Applications of Traditional and Concentrated Photovoltaic Technologies for Reducing Electricity Costs at Ontario Data Centers

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I. Executive Summary

Large electricity customers in Ontario have an opportunity to generate significant electricity cost savings using solar technology without economic incentives such as feed-in tariff (FIT) contracts. FIT contracts have guaranteed healthy returns on investment for solar installation investors in Ontario and have spurred significant growth in the province's solar industry. However, these contracts are controversial. Many have criticized the inflated rates paid per kilowatt-hour (kW) of solar electricity produced, and point to the FIT program as the reason for Ontario's ever-increasing electricity rates.

This thesis has uncovered a scenario under which solar energy investments in Ontario are profitable, and thus justifiable, *without* economic incentives. This particular scenario involves "offsetting," where the solar energy produced by an installation is consumed on-site by a commercial operation and offsets the consumption of an equivalent amount of electricity from the electrical grid. By *not* consuming electricity from the grid, consumption fees are foregone and electricity cost savings are generated.

This offsetting scenario applies to Class "A" electricity customers in Ontario – businesses that have peak energy demands exceeding three megawatts. In addition to being charged the wholesale price per kW of electricity consumed, Class "A" electricity customers also incur a "global adjustment" fee and a levy for electricity delivery, both of which are time dependent and mostly occur during afternoon hours when solar modules are producing electricity. According to this thesis, the average internal rate of return (IRR) for a photovoltaic (PV) investment under the offsetting scenario is projected to increase from 5.6% in 2016 to 13.0% in 2020 as specified by Figure 76 in Section 7.4.1. For concentrated PV technology, the average IRR is expected to rise from 6.0% in 2016 to 10.7% in 2020 as per Figure 79 in Section 7.4.3. The Class "A" customers in this thesis are data centers, but the offsetting scenario findings could apply to *any* Class "A" electricity customer in Ontario.

The findings of this thesis have immediate implications for solar developers, financiers, and installers. FIT program rates have declined from over CAD 0.80 per kilowatt-hour (kWh) in 2009 to between CAD 0.20-0.30/kWh today. As solar costs continue to decrease, the downward trend in FIT rates will likely continue. Solar industry organizations that once benefited from high FIT prices may need to look for new opportunities, and erecting solar installations at Class "A" electricity customers in Ontario may be a sound strategy. Moreover, offsetting may present a solution to counter the high electricity costs cited by numerous manufacturers and other energy-intensive operations in Ontario, and this could positively impact those organizations as well as the province's economy.

II. Abstract

Demand for cloud-based applications and remote digital storage is increasing. As such, data center capacities will need to expand to support this shift in computing. Data centers consume substantial amounts of electricity in support of their operations, and larger data centers will mean that more energy is consumed. To reduce electricity bills, data center operators must explore innovative options, and this thesis proposes leveraging solar technology for this purpose. Three different photovoltaic and concentrated photovoltaic costing scenarios, as well as four different Ontario-based electricity tariff scenarios – time-of-use, feed-in tariff, power purchase agreement, and a peak-dependent electricity charge involving the province's global adjustment fee – will be used to determine if there is a business case for using solar technology at data centers in Ontario to reduce energy costs. Discounted net present value, return on investment, internal rate of return, and levelized cost of electricity will be calculated to determine the economic viability of solar for this application, and both deterministic and stochastic results will be provided. Sensitivity of the four metrics to variability from energy yield, operations and maintenance costs, as well as system prices will also be presented.

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IV. Alphabetical List of Acronyms

AC	alternating current
BOS	balance of system
CAD	Canadian dollars
CdTe	cadmium telluride
CF	capacity factor
CI	confidence interval
CIGS	copper indium gallium (di)selenide
CLT	Central Limit Theorem
CO_2	carbon dioxide
CPV	concentrated photovoltaic(s)
CREST	California Renewable Energy Standard Tariff
CSA	Canadian Standards Association
CWEEDS	Canadian Weather Energy Engineering Datasets
DC	direct current
DCF	discount cash flow
DNI	direct normal irradiance
EDI	electronic data interchange
EPA	Environmental Protection Agency
FIT	feed-in tariff
GA	global adjustment
GW	gigawatt
HOEP	Hourly Ontario Energy Price
IEA	International Energy Agency
IESO	Independent Electricity System Operator
IHS	Information Handling Services
IP	Internet protocol
IPCC	Intergovernmental Panel on Climate Change
IRR	internal rate of return
ISO	International Standards Organization
IT	information technology
ITU	International Telecommunications Union
KEPC	Korea Electric Power Corporation
kW	kilowatt
kWh	kilowatt-hour(s)
kWh_{AC}/m^2	kilowatt-hours of alternating current per square meter
LCOE	levelized cost of electricity

LDC	local distribution company
LPOE	levelized profitability of electricity
LTEP	Long-Term Energy Plan
m^2	square meter
MJ	megajoule
MW	megawatt
MWh	megawatt-hour
NPV	net present value
O&M	operations and maintenance
OECD	Organization for Economic Cooperation and Development
PPA	power purchase agreement
PPM	parts per million
PUE	power usage effectiveness
PV	photovoltaic
R&D	research and development
RAM	Reverse Auction Mechanism
ReMAT	Renewable Market-Adjusting Tariff
ROI	return on investment
SPVP	Solar Photovoltaic Program
SWOT	strengths, weaknesses, opportunities, and threats
TOU	time-of-use
TW	terawatt
USD	United States dollars
W	Watt
WEEE	(The) Waste Electrical and Electronic Equipment (Directive)
Wh	Watt-hour
Wp	Watt-peak
WWW	World Wide Web

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Chapter 1: Introduction

The competitive nature of today's business environment implies that organizations must run their operations as efficiently as possible. For many, this means ensuring that critical information is readily available to the right people at the right time regardless of where the persons are located. Accordingly, older business mainstays such as filing cabinets containing hard-copy documents and local digital storage repositories are being replaced by advanced, remote data centers. These facilities are capable of storing massive amounts data that anyone with an Internet connected device and proper login credentials can access regardless of the person's location.

One of the key components enabling the abovementioned transition is electricity, a component so critical yet so common that its importance is often overlooked. Electricity enables electronic devices, such as computers and servers, to perform electronic business (e-business) functions that include running applications and storing data. It also powers other integral data center components, including cooling and security systems, as well as lighting for staff. Electricity is absolutely vital for data center operations, but it is also a commodity that can become rather costly for data center operators as they expand their facilities to keep pace with customer demand. This thesis will highlight the energy expense problem faced by data center operators and assess the business case for one possible solution.

1.1 Context and Research Question

Individuals and businesses alike are increasingly relying upon cloud computing services. Consequently, data centers, which are facilities that house remote application and storage servers that power cloud computing networks, are being built at a steady pace across North America where market demand for digital storage and application services "doubles every 18 months" according to Mondal and Keisling (2012). Although data storage facilities may not be physically close in

proximity to one another, links between facilities are established using electronic communication technologies to form what is commonly referred to as "the cloud" or "cloud computing networks."

Data centers are energy-intensive operations. Figures from 2009 projected that these facilities within the United States alone would consume 100 billion megawatt hours (MWh) of electricity on an annual basis by the year 2011 (Meisner, Gold, & Wenisch, 2009), a significant amount of electricity by any measure. Furthermore, according to Nazir (2012), electricity expenditures generally account for more than 50% of an individual data center's total operating costs, and this high proportion is an excellent target for cost-reduction initiatives.

As an increasing number of these facilities are constructed across North America, data centers will consume more and more electricity. Greater electricity consumption will likely result in increased data center operations costs, which may be passed along to end-users. Since cloud computing networks compete for customers on a global scale with an intense level of competition between providers, cost competitiveness in this burgeoning field is of utmost importance. Thus, creating a strategy to reduce electricity expenditures is a worthwhile endeavour for data center owners. This research will examine the merits of applying photovoltaic (PV) and concentrated photovoltaic (CPV) solar panels to data centers and using solar-generated power to offset the electricity charges incurred by the facility. Accordingly, the research question of this thesis asks: *is there a business case for using solar technology to offset electricity expenditures at data centers in Ontario?*

This research question includes two sub-queries. Firstly, what financial indicators, and what financial indicator values would strengthen or weaken the business case for using solar technology to offset data center electricity expenditures in Ontario? Secondly, considering variability in both the amount of solar power generated and the value of the energy produced, what is the expected range of financial indicator variability from a large-scale solar panel system installed at a data center in

Ontario? This research will provide answers to both of these sub-questions in order to work toward establishing or repudiating the business case for leveraging solar technology.

1.2 Scope of Research

This research will examine expected costs, revenues, and financial metrics associated with installing and operating PV and CPV systems at data centers. These three items are defined as follows:

1. **Costs:** monies spent on constructing and operating a solar installation, including:
    a. Expenses associated with solar panels and balance of system items, such as electrical inverters, support racks, and wiring.
    b. Services such as installation, maintenance, as well as teardown and module recycling at the end of the installation's operational lifetime.
2. **Revenues:** cost savings generated by either:
    a. Selling the solar-produced electricity back to the electrical grid operator to create a revenue stream.
    b. Consuming the solar-produced power on-site to offset charges associated with consuming electricity from the power grid.
3. **Financial Metrics:** four measures used to assess the business case for or against using solar technology at data centers:
    a. Discounted Net Present Value: the value today of future revenues generated by a solar installation. This applies to solar electricity sold to generate cash flow or used to offset existing data center electricity charges.
    b. Return on Investment: a comparison of the value generated by the solar installation over its operational lifetime to the initial outlay of capital spent on the installation. A positive return on investment indicates that all expenditures were recovered, while a negative value implies that associated costs outweighed the value produced.

c. Internal Rate of Return: a measure of the value produced by a solar investment. A project's internal rate of return is typically compared against a discount rate, which is unique to an individual investor or investment firm. If the internal rate of return exceeds the discount rate, then the project is likely a worthwhile investment. If, on the other hand, the opposite is true, then the investment is best avoided.
d. Levelized Cost of Electricity: the breakeven price of electricity production for any electricity-generating technology. If an energy generator was to sell all of the electricity it produced over its entire operational lifetime at the levelized cost of electricity, the value generated from the sale would exactly offset all of the costs involved in setting up and operating the energy-generating technology.

Precise values for all costs related to PV and CPV system operation will be sourced from the literature review. Three different pricing scenarios, one high cost, one low cost, and one average cost, will be created. Revenues, on the other hand, will be determined according to four different tariff scenarios. Two of these scenarios, power purchase agreement (PPA) and feed-in tariff (FIT), will generate revenues by selling all of the electricity produced by the solar installation to the electrical grid. The other two scenarios, time-of-use (TOU) and global adjustment (GA) tariff offsetting, will assume that all of the solar-produced electricity is consumed by the data center, and this offsets an equal amount of electricity that would have been consumed from the electricity grid. As a result of the latter, charges associated with consuming electricity from the power grid are avoided. The four pricing scenarios are defined in greater detail as follows:

1. **Power Purchase Agreement (PPA) Contract:** a power purchase agreement establishes a baseline rate paid for solar-produced electricity over a set period of time. In some cases, the baseline rate is either increased or decreased depending upon time of day and demand faced by the electricity grid.

2. **Feed-in Tariff (FIT):** created by Ontario's Green Energy Act in 2009, this program provides fixed payments to independent renewable energy technology operators for the electricity they generate based upon the size of their installation (Ontario Power Authority, 2013). Unlike a power purchase agreement, the rate paid for solar-produced electricity under the feed-in tariff scenario is static over the entire duration of the FIT contract.
3. **Time of Use (TOU):** prices paid for solar-produced energy depend upon the time of day. Generally speaking, electricity prices are higher during the morning and afternoon periods when electricity demand is high but lower in the evening on account of reduced demand (Ontario Energy Board, 2013).
4. **Global Adjustment (GA) Tariff Offsetting:** available only to a specific class of large energy consumers in Ontario, this tariff scenario encompasses charges based upon: the wholesale price of electricity; a customer's energy consumption during the previous year's five hours of greatest province-wide demand; and delivery of electricity to the customer. Typically, the consumption and delivery charges occur during daytime hours when solar panels are generating electricity.

In order to maintain a focus upon the business case for solar power, certain elements will remain outside of the scope of this research. Neither engineering perspectives related to solar PV and CPV technologies nor storage options for solar generated electricity will be included as part of this thesis. Although these items are relevant to the subject matter, they are not integral to this thesis. Furthermore, this research will focus solely upon the data center component of cloud computing networks. Although other components of these networks could be considered for energy cost reduction initiatives, this research will focus solely upon offsetting electricity expenditures at data centers.

1.3 Objectives of Research

As stated by the research question, the primary objective of this research is to determine if there is a business case for leveraging solar technology to offset electricity expenditures at data centers in Ontario. The business case will be derived from the values of the four financial metrics defined in the previous section. The secondary objective of this research is to determine an expected distribution of the values of those four financial metrics, and this will be accomplished by two separate procedures. Firstly, a Monte Carlo simulation will be employed to simulate solar installation energy yield variability. A statistical analysis performed on the results will determine the expected distribution of the metrics with 95% confidence. Secondly, three different system price and operations cost scenarios will be created based upon figures uncovered during the literature review. Using the inputs from these three distinct scenarios, discounted net present value, return on investment, internal rate of return, and levelized cost of electricity metrics will be calculated, yielding a range of expected values. Combining the results of the first and second procedures will reveal which source of variability, energy yield, system price, or operations cost, causes the greatest amount of fluctuation in the four financial metrics and, consequently, which of those three sources poses the greatest risk to PV and CPV solar installation investors. Finally, the tertiary objective of this research is to determine the optimal time to invest in a PV or CPV solar installation in Ontario between the years 2014 to 2020 under each of the four electricity tariff scenarios. The most favourable point in time to invest will be based upon the results of the four financial metrics.

1.4 Importance of Topic

This thesis highlights a contemporary problem confronting data center operators. While demand for data center services is increasing, so too are electricity prices. Thus, as data centers expand to accommodate growing demand, greater quantities of electricity are consumed and, consequently, greater amounts of money are spent

on electricity. Given that customer demands for data center services show no signs of abating and improvements to the internal components of servers and other information technology (IT) equipment can provide only limited energy efficiency improvements, data center operators would be wise to pursue innovative techniques to reduce energy expenditures. If solar technology proves capable of reducing data center electricity expenses, data center operators could divert funds previously spent on energy into other areas, such as improving internal data center equipment. Alternatively, they could return a portion of this money to their shareholders in the form of a dividend.

Solar technology continues to become increasingly prevalent in North America as associated costs drop and public perceptions change. As a result, solar installations are being installed at a greater variety of locations across the residential, commercial, and industrial sectors. This thesis will provide a comprehensive analysis to determine if data centers in Ontario are strong candidates for solar technology. If there is in fact a business case for employing solar installations at these facilities, then this thesis will provide justification for an application of solar technology in a location not particularly well known for high levels of irradiance. Moreover, these results will be of benefit to data center operators and solar industry players alike.

1.5 Research Methodology

This thesis will apply a *quantitative* research methodology to answer the research question posed in Section 1.1. Since the business case for employing solar technology at Ontario data centers will be determined using financial metrics, which will be calculated using numerical inputs such as PV system energy output, irradiance readings, solar installation costs, and energy tariffs, a quantitative methodology is the most appropriate approach. Furthermore, a Monte Carlo simulation will be used to simulate solar installation energy yield variability and a statistical analysis will be performed on the results to determine the expected

distribution of the financial metrics with 95% confidence. This too will require that a quantitative research approach be used as opposed to a qualitative methodology.

The required quantitative figures will be gathered from a variety of sources. PV system energy yield will be provided by Hydro Ottawa and will be used as historical inputs in the Monte Carlo simulation. For CPV, irradiance readings will be downloaded from a Government of Canada website and will be used to determine concentrated photovoltaic system output. Solar installation costing values will be collected as part of the literature review, and will include system installation costs, operation and maintenance fees, inverter replacement charges, and an expense for dismantling and recycling the solar modules at the end of their useful life. Academic journals, conference proceedings, and industry reports from reputable sources will be used to gather these figures. Finally, electricity tariff data will come from official sources in Ontario, including the Independent Electricity System Operator and Hydro Ottawa.

This quantitative study will look at three specific variables in order to answer the research question: system energy output, measured in kilowatt-hours; electricity tariffs, measured in dollars per kilowatt-hour; and revenue generated from solar energy production, measured in dollars. After calculating system energy output, the financial model will determine solar installation revenue figures according to each of the three costing scenarios and four tariff scenarios introduced in Section 1.2. Using these revenue figures, the financial model will also compute values for the four financial metrics of discounted net present value, return on investment, internal rate of return, and levelized cost of electricity.

Given the quantitative nature of this thesis, computer software will be heavily relied upon to analyze raw data and calculate results. The versatile software Microsoft Excel will be employed to create the financial model, perform statistical analysis, and carry out a Monte Carlo simulation. Macros will be used in Excel for the latter,

and they may also be employed to assist with formatting the large quantity of raw data required by this study.

As a final methodology note, no formal qualitative research methods will be included as part of this thesis. However, informal discussions may occur with persons who work in the solar industry, or academics with knowledge of photovoltaics or another topic presented within this study. These discussions would be held in order to garner recommendations or suggestions about the direction of the research, or to obtain feedback on any item contained within in this thesis.

1.6 Research Contributions

This research will provide pertinent, detailed information to Ontario data center operators on the economic viability of using solar technology to counter high electricity costs. A thorough study on this subject specifically for Ontario is lacking at the present time, possibly to the detriment of many. Outside of the province, data centers are already leveraging solar technology for their benefit. One example is Apple's Maiden, North Carolina data center that boasts an accompanying 20-megawatt (MW) solar farm as shown in Figure 1 (Apple Inc., 2013a):

Figure 1. Apple's 20MW solar panel installation next to its Maiden, North Carolina data center. This PV installation occupies 100 acres of land (Apple Inc., 2014).

Many organizations strive to follow examples set by industry leaders, and this research will provide important insights into the innovative practice of harnessing the sun's energy to reduce data center electricity costs. If there is indeed a business case for using solar technology at data centers in Ontario, the comprehensive analysis presented by this thesis will be valuable to data centers operators and even other similar, large energy consumers in the province. The findings of this research may cement the idea that solar technology investment is a smart business decision, which in turn could be a boon for those in the solar industry as well as companies looking to reduce their electricity expenditures.

The financial results of this study, if favourable, could encourage new solar investments in a locale not especially known for high levels of solar irradiance, and this would be beneficial for many in Ontario. Moreover, the study of two electricity tariff scenarios that do not include economic incentives may reveal that financial support mechanisms are not a prerequisite for profitable solar technology investment. A finding of this type could positively influence the perception of solar development in Ontario. Currently, many electricity ratepayers in the province hold

feed-in tariffs directly responsible for rising energy prices and therefore oppose the use of solar technology.

Quantifying the magnitude of financial metric fluctuations due to different sources of variability will also provide valuable insight. For instance, if this thesis determines that the values of the four financial metrics do not fluctuate significantly when solar installation energy yield varies, then more confidence could be placed in PV and CPV technologies and perhaps further research into other comparable applications of the technologies could be conducted. Moreover, this study's methodology, described in detail in Chapter 3, could be used as a basis for alternative studies involving other renewable energy technologies besides solar.

Finally, other academic works have opposed using the levelized cost of electricity to determine the economic attractiveness of renewable energy sources, but they have failed to provide a straightforward alternative. This study, on the other hand, will build upon the valuation ideas uncovered during the literature review to propose a new metric for assessing the financial attractiveness of solar energy. This proposed metric will be known as the levelized *profitability* of electricity (LPOE).

1.7 Organization of Thesis

The remainder of this thesis is organized as follows: Chapter 2 will contain the literature review; the financial model and methodology details will be provided in Chapter 3; Chapter 4 will summarize the financial model inputs and the electricity tariffs included in the analysis; Chapter 5 will be devoted to discounted net present value results; Chapter 6 will contain return on investment figures; Chapter 7 will include internal rate of return numbers; Chapter 8 will provide levelized cost of electricity metric findings; a summary of all results will be found in Chapter 9, as will a discussion pertaining to energy payment allocation factors and an analysis of Monte Carlo simulation input and output variability; the financial model used to calculate the financial metrics will be validated in Chapter 10; and finally the thesis'

conclusion will be presented in Chapter 11. Appendices "A" through "D," which contain normality test results, follow the conclusion chapter, and Appendix "E" summarizes the different combinations of tariff and pricing scenarios analyzed. The final section of the thesis contains a list of references.

Note that all monetary figures preceded by a "$" throughout this thesis are assumed to be in United States dollars.

Chapter 2: Review of Pertinent Literature

The literature review highlights important information related to e-business, cloud computing, and data centers, and demonstrates how each of these items are interrelated. Furthermore, it connects e-business, cloud computing, and data centers to the topic of energy efficiency. The topic of solar energy, with a focus upon the economics of solar energy production, will be covered thoroughly as well. For these topics especially, the methodologies, arguments, and conclusions of related works will be compared and evaluated in detail where applicable. Finally, literature concerning the risks of investing in solar energy will be evaluated to provide an examination of both risk assessment and risk management. Published works concerning e-business will be examined first because the current trends of this discipline are propelling the popularity of cloud computing and, consequently, energy consumption concerns.

2.1 e-Business

2.1.1 e-Business Introduction

The term "e-business" can broadly refer to communications, commerce, and organizational processes conducted electronically. Trites and Boritz (2013) define e-business as "the strategic use of technology, particularly the internet, to integrate and streamline the business processes, enterprise applications, and organizational

structure of a business to create a high-performance business model" (p. 6) This particular definition is important because it touches upon the relationship between e-business and business models. Electronic business, after all, is affecting traditional business models and creating new opportunities for organizations to attain competitive advantages with electronic means. According to Motiwalla, Khan, and Xu (2005), e-business can provide organizations with lower operating costs by electronically processing customer requests, superior supply chain efficiencies via "disintermediation" (p. 652) and an always-open online store capable of selling items to customers at any time of day. These and other benefits are empowering some relatively new e-business start-ups to compete successfully against the most established organizations. For instance, iTunes, Apple's digital download store, opened for business in 2003 and by 2008 it accounted for nearly 25% of all music sales in the United Sates (Waldfogel, 2010). By 2011, iTunes boasted a 70% market share of legal digital downloads and helped digital music sales surpass sales of compact discs and other physical forms of music for the first time in that year (Friedlander, 2012; Peng & Sanderson, 2014). The iTunes e-business model changed the way consumers purchased music, leaving popular, well-established music store chains, such as Tower Records in the United States and HMV in Canada and the United Kingdom, at a loss to keep pace in the burgeoning digital music marketplace (Young & Collins, 2010).

The purely digital retailer may have competitive advantages in certain areas over e-businesses that ship physical goods to their customers. However, energy consumption is likely one area where digital retailers, such as iTunes, are at a disadvantage. The iTunes digital download store, for instance, employs countless servers to store and deliver the electronic media purchased by customers on top of servers running applications that support the online store and digital transactions. On a daily basis, iTunes receives download requests for approximately 21,600,000 songs, 800,000 television episodes, and 350,000 movies (Apple Inc., 2013b; Apple Inc., 2013c). If Apple, the company operating iTunes, was to reveal the number of

servers required to satisfy this massive demand, the total and the corresponding electricity bill would probably be startling.

In comparison, IT energy intensity is not as crucial of an issue for an e-business selling goods online that are delivered via the mail system since physical products require warehouse storage area instead of server space. According to Weber, Koomey, and Matthews (2010), who compared the quantities of energy consumed while purchasing music, a miniscule amount of energy was used by data centers and computers for each physical album bought online and shipped via air or ground transportation to the customer from a warehouse. Comparatively, seven megajoules (MJ) of energy were consumed by data centers and computers – with negligible consumption attributed to the latter – during the purchase and download of a single digital music album from an online retailer such as iTunes (Weber et al., 2010). Thus, server energy consumption and related costs are more likely of a concern for e-businesses selling digital goods than those selling physical products. Despite its trade-offs, electronic business has proven itself beneficial to iTunes and scores of other organizations in many different sectors and it is highly probable that e-business will continue to be leveraged for its benefits.

2.1.2 e-Business Evolution

The electronic nature of business today has evolved significantly from its roots in the 1960's when basic electronic data exchanges were performed only by select groups of large organizations such as banks (Sarich, 1985; Trites & Boritz, 2013). Electronic data interchange (EDI) expanded beyond the finance industry over time into other sectors. For example, both the transportation and retail sectors began using EDI to manage cargo and inventory figures, respectively (Sarich, 1985). Despite the expansion into other sectors and industries, e-business was predominantly a back-office function limited to use by internal members of organizations until the late twentieth century. According to Li (2010), increased World Wide Web (WWW) usage in the 1990's significantly bolstered the popularity

of the Internet as an interaction mechanism for both businesses and individuals alike. Li's statement about the impact of the WWW and the Internet on communications is significant because this electronic revolution in communications spurred new methods of correspondence between individuals, between businesses, and between individuals and businesses (and vice versa).

Trites and Boritz (2013) support Li (2010) by stipulating that an "unprecedented change" (p. 2) occurred when companies began using the Internet for business purposes in the 1990's that affected the way with which commerce was conducted. As stated by Oudan (2010), this paradigm shift ushered in an era where new procedures were employed by firms to create greater customer value, bolster productivity, and augment profit margins in an increasingly competitive marketplace boasting new e-business initiatives. Further innovations and improvements to existing e-business practices will likely occur as companies continue to evolve their electronic business processes and applications.

There are few who would argue that e-business is merely a passing trend given its prevalence and the benefits it provides to companies. This viewpoint is supported by Heil and Prieger (2010) who conclude that e-business "will continue to expand into existing and future industries" (p. 7), providing many benefits including cost reductions and productivity improvements. With regard to individual organizations specifically, the same authors note that organizational performance, productivity, and task coordination, even between offices in different physical locations, will continue to improve due to the further development of e-business tools and applications (Prieger & Heil, 2010). New innovations and trends pertaining to the digital networks and infrastructure supporting online business activities help to spur the ongoing expansion and development of e-business. X. Wang (2012) continues where Prieger and Heil (2010) leave off by introducing a contemporary trend where applications, processes, and digital files traditionally stored on local computers are moving to remote computers on cloud networks. This trend will drive up the demand for data center services, spurring additional facilities into

operation. Consequently, data centers as a whole will consume an even greater amount of energy.

As X. Wang (2012) explains, a remote centralized cloud server allows organizations to provide powerful and flexible applications at a lower cost compared to physically providing those applications to many users across multiple locations. Supply chain management, for example, becomes much more efficient when various supply chain members are able to share pertinent information across a seamless cloud network, resulting in more effective "communication, coordination, and collaboration across organizational boundaries" (Cegielski, Jones-Farmer, Wu, & Hazen, 2012, p. 185). Cloud networks also provide an element of convenience to users. Cloud storage services, such as Dropbox and Google Drive, allow both businesses and individuals to store files on remote servers. These files can be accessed using different devices, including desktop computers, laptop computers, computer tablets, and smartphones, from anywhere in the world so long as an Internet connection is present. Moreover, these files stored on cloud computing networks can be shared with as many users as desired, which can assist with collaboration between parties in different locations without having to send documents to collaborators via e-mail, for instance.

X. Wang (2012) also sees mobile commerce (m-commerce) as becoming increasingly prevalent in more parts of the world due to the proliferation of cloud computing, which provides an ideal platform for m-commerce and enables timely information to be delivered quickly to the mobile shopper for efficient transactions. M-commerce is defined as using a wireless or mobile device to conduct "any transaction with a monetary value … via a mobile telecommunications network" (Zheng & Chen, 2003, p. 24).

However, X. Wang (2012) is dismissive over security, which is one of the most pertinent concerns associated with cloud computing. Although he acknowledges that security remains a chief concern for cloud computing networks, he suggests

that companies should not be particularly apprehensive about the vulnerability of their data when entrusting a cloud service provider with security (X. Wang, 2012). Unfortunately, even the most high profile companies are susceptible to online security breaches, and organizations that use cloud networks for storage and business processes must always keep this in mind. In June of 2011, for example, a software malfunction at Dropbox, a popular provider of cloud storage services, allowed user accounts to be accessed with either a correct password, an incorrect password, or simply no password upon login (Cachin & Schunter, 2011). This error essentially granted anyone visiting Dropbox's website with access to the contents of each user's account. Further security challenges associated with cloud computing will be covered in Section 2.2.4.

Li (2010) supports X. Wang (2012) by stating that m-commerce is an important contemporary e-business trend, but he also includes Web 2.0 and web services in his assertion. Web 2.0 is difficult to define precisely because there are numerous distinct definitions. On balance, Web 2.0 refers to a phase within the ongoing evolution of the World Wide Web where users, once lacking the tools and platforms to produce online content of their own, are now equipped with these items, thus empowering them with the unprecedented ability to generate and share content and ideas with others from all over the world (Hwang, Altmann, & Kim, 2009; Wijaya, Spruit, Scheper, & Versendaal, 2011).

Web services, on the other hand, can be defined as "self-contained modular applications described by a collection of operations that are network accessible through standardized web protocols" (Rodriguez-Mier, Mucientes, Vidal, & Lama, 2012, p. 2). The standard language conventions used by web services for communication eliminate many interoperability issues between applications running on disparate systems (Fensel, Facca, Simperl, & Toma, 2011). Web services applications can assist with reserving tickets for flights, tracking packages sent by couriers, converting currency values, and assessing inventory levels within supply chains (Y. Chen, Zhang, Kong, & Lin, 2013).

A countless number of web services exist in addition to the four examples from the previous paragraph. The growth and popularity of web services is placing excessive demands on servers at levels previously unseen according to Gilly, Juiz, and Puigjaner (2011). Unfortunately, overwhelmed servers can drop data packets during transmission thereby prolonging processing times for web services requests and diminishing the end-user's experience (Tari, Phan, Jayasinghe, & Abhaya, 2011). Given that web services operate on distributed servers (W3CSchools, n.d.), data centers are becoming the preferred host for these web-based applications because they are both "scalable and cost effective" (Tari et al., 2011, p. 141). If server capacity is stressed, data centers, generally speaking, are able to provide additional resources with minimal difficulty to relieve the digital congestion.

Li (2010) is correct in identifying m-commerce, Web 2.0, and web services as contemporary e-business trends that rely on servers for data and application storage, as well as transaction processing in some instances. However, he omits any mention of Web 3.0, which is the upcoming phase of the World Wide Web's evolution. In the Web 3.0 phase, computers will be able to understand web content, and as a result they will be able to search for, collect, and present information in a more effective and intelligent manner (Torre, 2009). Standards for labelling web content and website data will enable machines to seek and retrieve information in unprecedented ways: Feigenbaum, Herman, Hongsermeier, Neumann, and Stephens (2007) envision an era when a Wikipedia search for "films nominated for a Best Picture Academy Award before 1990 that ran longer than three hours" (p. 95) returns a precise list of such movies automatically compiled by a sophisticated software bot.

For businesses, Web 3.0 could entail using web-based applications to consolidate proprietary data with other data sources to extract customer purchase propensities hidden within the abundant amount of data, for example (Garrigos-Simon, Alcamí, & Ribera, 2012). Regardless, web services will be critically important to the

development and diffusion of Web 3.0 because they will enable exchanges of digital information between applications stored on remote servers (Fensel et al., 2011).

As organizations continue to leverage and adapt to using the aforementioned e-business trends for their benefit, a greater number of servers will be required to carry out digital processes. Accordingly, companies will be required to either establish a data center or centers to satisfy their server needs, or they will outsource their data center requirements to an external service provider specializing in this field (Stanoevska-Slabeva & Wozniak, 2010). In either case, data centers, which interconnect with one another to form cloud computing networks, are becoming increasingly popular to support e-business applications and functions. Literature pertaining to cloud computing is covered in the following section.

2.1.3 Summary

In summary, Section 2.1 of this literature review has established that e-business successfully challenged traditional business models, creating new opportunities for emerging ventures to compete against established incumbent firms. The growth in popularity of both the Internet and World Wide Web helped expand e-business into new areas, and as a result organizations began interacting with one another and their customers via newly created digital channels. Contemporary e-business trends, such as m-commerce, Web 2.0, web services, and the emerging Web 3.0 phase, are helping to spur a fundamental shift where applications, processes, and digital files traditionally stored on local computers are moving to remote servers in datacentres on cloud networks. It is probable that demand for digital storage and applications will continue to grow as e-business further evolves. Consequently, a greater number of data centers and a larger amount of energy will be required to house and power the servers running applications and storing digital data, respectively.

2.2 Cloud Computing

2.2.1 Cloud Computing Introduction

Cloud computing is emerging as a lucrative trend with a promising future. A Gartner research paper[1] from 2009 estimated that the value of the global cloud computing market would reach $150.1 billion in 2013, up from $56.3 billion in 2009 and $46.4 billion in 2008 (Owusu & Pattinson, 2012). Moreover, 72% of the technology specialists surveyed by the Pew Research Center in a 2010 study agreed with the notion that a greater number of people will be using cloud computing applications and services first and foremost over desktop software by the year 2020 (Ipri, 2011; Voida, Olson, & Olson, 2013). Furthermore, current figures indicate that the amount of cloud data center Internet Protocol (IP) traffic will grow from 2,419 petabytes[2] per year at the end of 2014 to 5,313 petabytes per year by the end of 2017 (Bloomberg L. P., 2014). The significant global value of cloud computing, which is steadily increasing, the suggestion that cloud computing will become the dominant computing platform in the relatively near future, and continuing growth in the already massive amount of cloud data center IP traffic are all indications that *the cloud* is becoming further entrenched in our society.

Owusu and Pattinson (2012) further contribute to the literature review by identifying the three principal cloud computing network components: data centers, which are buildings that house storage and application servers; communication networks, responsible for transporting data from the servers to the end-user; and user devices, including desktop computers, notebook computers, and smartphones. Notably, these three components must work congruently to retrieve data from storage servers, transfer the data through the communication network, and present the data in an appropriate manner to the end-user. Although each of these three

[1] Report available for a fee. See: Pring, B., Brown, R. H., Frank, A., Hayward, S., & Leong, L. (2009, March 18). *Forecast: Sizing the Cloud; Understanding the Opportunities in Cloud Services*. Retrieved from https://www.gartner.com/doc/914826

[2] One petabyte is approximately one billion megabytes (Perrons & Hems, 2013).

elements is important, the research contained within this thesis will be focused solely upon the data center component of the cloud computing network (data centers will be discussed in-depth in Section 2.3). The remaining literature review pertaining to cloud computing will cover definitions, benefits, concerns, and its environmental ties.

2.2.2 Cloud Computing Definitions

The myriad definitions of cloud computing uncovered during the research process indicate that a definitive definition of cloud computing has not yet been established. Most definitions unearthed tended to define cloud computing by either its components or its capabilities. For instance, Kalagiakos and Karampelas (2011) define the cloud as a metaphor for "a space where computing has been pre installed and exist[s] as a service; data, operating systems, applications, storage and processing power … on the web ready to be shared" (p. 1). In contrast, Baliga, Ayre, Hinton, and Tucker (2011) define cloud computing as "a model for enabling convenient, on-demand network access to a shared pool of configurable computing resources that can be rapidly provisioned and released with minimal management effort or service provider interaction" (p. 150). Even though they use different wordings, both of these cloud computing definitions underline crucial concepts. For one, each highlights the sharing of centralized resources. Moreover, the two definitions touch upon the idea of cloud computing as a service available for users whenever the need arises.

Of the many different definitions uncovered during the research process, one in particular is essential for inclusion in this thesis: Owusu and Pattinson (2012) define cloud computing as "a computing paradigm where the boundaries of computing will be determined by economic rationale rather than technical limits" (p. 1949) This definition is significant for two reasons. Firstly, although it is noticeably different from the definitions presented in the previous paragraph, economics unquestionably plays a vital role in determining whether cloud

computing networks will be constructed in the first place, expanded as necessary to meet projected consumer demand, or improved upon to incorporate newer technology to better serve users. Secondly, this particular definition of cloud computing alludes to the crux of this thesis, which involves determining whether there is a business case for leveraging solar technology to offset data center energy expenditures. If so, then the capital not spent on electricity could be applied to other activities such as data center expansion and improvement. Calculations and figures pertaining to the business case will be presented beginning in Chapter 5. Meanwhile, the literature review will remain on the topic of cloud computing by analyzing academic writings related to its benefits.

2.2.3 Cloud Computing Benefits

Cloud computing's upswing in popularity and promising future are largely attributable to the benefits that the service provides to its end-users. Firstly, as Stanoevska-Slabeva and Wozniak (2010) note, cloud computing is scalable meaning the cloud network can grow or shrink to adapt to dynamic customer needs. For instance, additional storage space for files can be added and computing power for application servers can be increased as an organization expands in size and customer requirements change. Scalability of the cloud is a key attraction for many businesses, especially for those firms outsourcing their cloud computing to a third party service provider. Under this type of arrangement, upgrades to the amount of storage space and enhancements to server capabilities can simply be purchased from the third party service provider. Although total storage capacity within a data center is restricted by both physical space and technological capability, increases in storage space and upgrades to cloud capabilities are typically straightforward whether the cloud network is owned and operated for the exclusive use of one organization (private cloud) or cloud computing space is leased from a service provider (public cloud) (Islam, Mollah, Huq, & Aman Ullah, 2012; Masiyev, Qasymov, Bakhishova, & Bahri, 2012; Nazir, 2012).

Secondly, cloud computing can relieve many of the IT burdens facing organizations today. As Islam et al. (2012), Masiyev et al. (2012), and Nazir (2012) also state, third party cloud computing service providers implement software patches and hardware upgrades to their servers and other IT equipment, alleviating organizations from having to perform these tasks in-house. As a result, businesses that outsource their cloud computing needs have less on-site server equipment to maintain and purchase as well as fewer overall IT responsibilities. This could lead to cost savings, particularly if fewer internal technical support staff are required to manage a reduced amount of IT resources and infrastructure. Moreover, a dedicated third party service provider likely has expertise pertaining to IT equipment, digital networking, and security management, and thus may be more apt at maintaining these components than a firm that is also concerned with other pressing business matters.

Thirdly, according to Islam et al. (2012), cloud computing can create greater organizational efficiencies because it centralizes the storage of data and digital files. Storing these types of resources on a cloud network allows users with appropriate access credentials to connect to the resources regardless of geographical location. This type of arrangement enables real-time collaboration amongst staff, even if they are located in different offices, and eliminates the task of sharing multiple versions of the same file via e-mail. As well, employees who work away from main offices remotely can access timely information from servers on a cloud computing network assuming they have a network connection and an appropriate mobile device. Consequently, these employees can stay informed with the most up-to-date information even while travelling or meeting clients in distant locations. Cloud computing may provide many benefits to its user base, but there are also concerns associated with the service. Chief cloud computing challenges are identified in the next section.

2.2.4 Cloud Computing Challenges

The challenges facing cloud computing are important to consider because they could discourage individuals and businesses from adopting the service outright. Some of the most prominent cloud computing challenges identified during the research process included data transfer limitations (Kant, 2009), service availability and resource accessibility concerns (Yoo, 2011), and apprehensions about data security (Nazir, 2012).

Each of these items represents a potential drawback for cloud network users. Firstly, since cloud computing enables processes to be executed on remote servers over the Internet, digital network congestion is a genuine concern. Ensuring timely access to vast amounts of data on low-latency networks is challenging, especially when multiple cloud tenants are sharing a finite amount of computing resources (Kant, 2009). An increase in the quantity or intensity of processes running on a cloud computing network could conceivably decrease the amount of available bandwidth and cause digital traffic bottlenecks (Mishra, Dutta, Kumar, & Mann, 2013). As a result, server response times pertaining to customer requests for resources stored within the cloud may worsen.

Secondly, cloud resources could become either partially or completely unavailable in the event of technical problems. Yoo (2011) points out that even the most popular cloud services provided by third parties, including Google's Gmail, the customer relationship management website Salesforce.com, and Amazon.com's cloud storage service, have been inaccessible at various times even though they are each considered highly reliable. Out of reach cloud resources can have adverse effects, including decreased productivity if e-mail ceases to function or lost sales if an online store becomes inoperative (Chakraborty, Ramireddy, Raghu, & Rao, 2010). However, even if data center and network operators have contingency plans in place to account for service failures, problems accessing cloud services could also originate from the end-user. For example, a completely discharged battery in a

mobile device, or lack of network or Internet connection could prevent an end-user from accessing cloud resources (Dihal, Bouwman, de Reuver, Warnier, & Carlsson, 2013). Therefore, it is plausible that issues related to accessing content stored within cloud networks could stem from either the service provider or end-user.

Finally, cloud network security could be compromised in numerous ways. Improper security protocols could leave either public or private clouds susceptible to intrusions by unauthorized individuals. Furthermore, as Nazir (2012) states, incorrect encryption methods could leave data vulnerable to snooping as it is transferred over communication networks. Organizations are continuing to examine the trade-offs between convenience and security afforded by cloud computing. For firms requiring a high degree of security for their digital data, however, the cloud may be eschewed for "a more controlled [storage] environment" (Mackay, Baker, & Al-Yasiri, 2012, p. 679). Thus, security concerns may actually prevent some from adopting cloud computing at the present time.

There are other cloud computing concerns besides the three identified in the previous paragraphs. However, an analysis of additional challenges will not be included as part of the literature review. While each cloud computing concern is relevant to a degree, a thorough review of every challenge is outside of the scope of this thesis. Instead, it is sufficient to understand that there are bona fide challenges facing cloud computing, such as the three previously stated examples, which can negatively affect many aspects of the discipline including the adoption rate and the cost of the service. With the focus of this thesis on the overarching concerns surrounding energy use and energy costs at data centers, the minutiae of each challenge are not necessarily relevant to examining the business case for using solar power. Prior to discussing energy usage and cost concerns at data centers, literature related to cloud computing and the environment will be presented.

2.2.5 Cloud Computing Environmental Concerns

The "environmental movement" (Uddin & Rahman, 2012, p. 4084) has made significant strides into the mainstream in recent years. Through their persistent efforts, environmental groups have been able to garner the attention of media, governments, and individuals in all corners of the world. Much of this success can be attributed to the rapid pace at which messages are transmitted via the Internet and social media and the broad reach of electronic communications in today's networked world. As a result, many more people have become aware of environmental initiatives and concerns, from conservation of natural habitats to energy efficiency.

The IT sector is not immune to environmental concern. As computers and electronics further encroach into more aspects of every day life, there are worries about our current and future energy demands. With regard to cloud computing specifically, high-profile environmental groups such as Greenpeace have criticized data centers over their energy consumption. As Pan, Maini, and Blevis (2010) state, Greenpeace characterizes data centers as "massive storage facilities that consume incredible amounts of energy" (p. 603) and believes that further efforts are required to make these buildings more energy efficient. Undoubtedly, other environmental groups share this same viewpoint regarding data centers. However, while environmental organizations are somewhat limited to calling attention to energy efficiency issues, governments, on the other hand, have the power to curb the amounts of energy consumed by data centers through legislation and statutes.

The United States government is a supporter of initiatives that promote energy efficiency improvements. As Uddin and Rahman (2012) indicate, current President Barack Obama has intentions of implementing measures that would increase energy efficiency at all new and existing buildings, including data centers, within the United States by varying degrees before the year 2030. However, even prior to Obama taking office, the United States government categorized data centers as significant

energy consumers and through the Department of Energy created a "National Data Center Energy Efficiency Information Program" (Anderson, 2010, p. 52) to establish metrics, tools, and training for helping data center operators consume energy more efficiently. Although the program is voluntary operators in compliance with the energy usage targets and best practices stipulated by the program are recognized as industry leaders (U.S. Department of Energy, 2008). This program is still in effect today and it continues to promote energy efficiency measures at data centers within the United States.

In addition to the Department of Energy, Sego et al. (2012) note that the Environmental Protection Agency (EPA), another United States government department, has both "environmental and economic concern[s]" (p. 1) about energy use and costs at domestic data centers. Owusu and Pattinson (2012) support this claim by stating that the EPA has investigated "data center energy use and opportunities for energy efficiency" (p. 1949), concluding that data centers do in fact expend significant amounts of money to consume vast quantities of electricity. The support for data center energy efficiency initiatives at the federal level in the United States is a telling sign of the scale of the concern. However, governmental concerns are not limited to the United States. The Japanese government, for example, has founded the "Japan Data Center Council" (Buyya, Beloglazov, & Abawajy, 2010, p. 2), which is a group assembled to contend with energy consumption issues amongst data centers in Japan. Although the literature review did not uncover any federal concerns regarding data center energy usage in Canada, the Canadian government's website states that data centers are "energy-intensive operations" (Government of Canada, 2013a, Demand for Processing Power Keeps Growing, para. 3) consuming approximately 1% of the total amount of electricity consumed in Canada on a yearly basis. The Government of Canada recommends that Canadian data centers use servers and other IT equipment adhering to standards established by the EPA's *Energy Star* program, which thoroughly tests electronics to ensure they meet specific performance and energy efficiency requirements (Government of Canada, 2013a; U.S. Department of Energy, 2008).

Uddin and Rahmin (2012) observe that specific motivations drive organizations to adopt green IT measures, including favourable public perception, adherence to environmental laws, and improved energy efficiency. Each of these motives has merit for businesses: favourable public perception can translate into more customers and potentially more sales; adherence to environmental laws can help avoid fines for non-compliance, which are detrimental to bottom lines; and improved energy efficiency can lead to cost-savings from fewer funds spent on electricity. However, for data center operators, abiding by environmental regulations and spending less money on energy are probably higher priorities than earning a positive public impression. Cloud computing users may be somewhat concerned about the environmental friendliness of the service, but quality and convenience are likely more important. Furthermore, customers requiring an all-encompassing, reliable cloud computing experience from a reputable company may have very limited options in terms of providers to choose from. Thus, in some cases, the environmental consciousness of the cloud provider may be ignored if its service matches the customer's needs.

Similar to any other business, cloud computing providers must follow all environmental regulations set by government bodies. Interestingly, governments are in a unique position when it comes to environmental policy: not only can they mandate that a minimum proportion of electricity be generated by renewable energy sources, but governments can also provide incentives, including subsidies and tax breaks, to help ensure that those minimum targets for green energy production are met (Stokes, 2013). These economic incentives are especially important for encouraging companies to invest in new renewable energy projects. Ultimately, corporations are motivated by profits and they must make strategic business decisions that will bolster their revenues and profitability. Thus, the decision to invest in a new green energy project will probably hinge upon the dollars and cents associated with the matter. Governments that are cognizant of this

notion are providing economic incentives to help green energy investments generate positive returns.

Accordingly, this research will determine whether investing in a new solar energy project can successfully offset data center electricity costs, and part of this analysis will examine the impact of government subsidies on investment. Although renewables can both improve energy consumption efficiency and benefit the environment, this body of research will focus upon the financial rewards created since the green energy produced by solar panels will not be consumed directly by the data center in this case. Instead, the energy will be sold to the electricity grid at a specified price to create a revenue stream. Compared to communication networks and end-user devices, data centers consume the most energy of the three main cloud computing network components (Owusu & Pattinson, 2012). The next section of the literature review will provide important background information about data centers and their related energy and cost concerns.

2.2.6 Summary

In Section 2.2, it was established that the global value of the cloud computing market is increasing, and the total amount of cloud data center IP traffic, already large enough to be measured in petabytes, is estimated to grow even further in the years to come. Additional data centers will be constructed to handle the demands of the growing IP traffic, meaning these facilities, as a whole, will be responsible for even more energy consumption. Data centers, communication networks, and end-user devices were indicated as the main components of cloud computing networks. Several benefits of cloud computing were mentioned, including scalability as well as organizational efficiencies resulting from the centralization of digital resources. However, the challenges of cloud computing, which included network congestion, service availability, and security concerns, were noted as potential barriers to the adoption of cloud computing. Environmental issues related to cloud computing were also touched upon, as were governmental apprehensions about the amount of

energy consumed by data centers. Finally, the section highlighted three important reasons why companies would adopt green IT practices and touched upon the role that governments can play in encouraging renewable energy investments.

2.3 Data Centers

2.3.1 Data Center Introduction

Data centers are a cornerstone of our electronically connected society. Uddin and Rahman (2012) specify that both private and public sector institutions employ data centers to enable e-commerce transactions, social media connections, and electronic government services among other activities. Every day, millions of individuals access digital data stored within these immense facilities via their smartphones, tablets, and computers for a multitude of purposes. Many people are completely oblivious to the fact that they interact with data stored on remote servers within data centers on a frequent basis.

Unlike the definition of cloud computing, there is greater consensus on the definition of "data center" amongst academic authors. Yuventi and Mehdizadeh (2013) define a data center as "any space whose main function is to house servers or computing devices that are … powered on and performing functions" (p. 91), distinct from an office building that may happen to contain a large amount of IT equipment to support a sizable workforce. Balodis and Opmane (2012) use similar terms in their definition by stating that a data center is a "facility intended for housing computer systems and associated components" (p. 181). This particular definition is slightly more precise than the one provided by Yuventi and Mehdizadeh since servers are sometimes purposely powered off in order to save electricity and related costs when data center demand is low. Knapp, Denney, and Barner (2011), on the other hand, define a data center as "a central repository for the storage, management, and dissemination of data supporting one or multiple organizations" (p. 533). Each of these distinct definitions illuminates key characteristics of data

centers, including their primary purpose and centralized nature. Other interpretations of "data center" uncovered during the research for this thesis were very similar and have not been included in the literature review for this reason.

Data centers have evolved significantly since their inception. Balodis and Opmane (2012) trace the beginning of the data center back to the 1950's and 1960's when computers required a great deal of storage area out of necessity. The large size of computers at this point in time restricted them to use by military, scientific, and eventually commercial institutions, which dedicated specific rooms or areas at their facilities to house these machines (Cortada, 1997). Advances in computing technology over the following decades would diminish the physical size of computers and increase processing speeds. Similarly, computer networks would expand well beyond their initial military use and server capabilities would improve significantly as well (Camarero, Martinez, & Beivide, 2013). Today, both large institutions and small organizations alike are able to take advantage of data centers. And even though computers and servers have become smaller, data center facilities continue to be built in large sizes to accommodate the increasing demand for cloud computing services. Schneider and Hardy (2011) note that Facebook has a data center in Forest City, North Carolina measuring 370,000 square feet in total area. Similarly, Islam et al. (2012) state that Microsoft has constructed a data center in Quincy, Washington that is over 469,000 square feet in size.

Spurring the construction and development of these large facilities is unprecedented growth in the amount of money spent on data center projects. Yuventi and Mehdizadeh (2013) illustrate this idea by stating that investments in data center projects grew from USD 15 billion in the year 2000 to USD 50 billion in the year 2010. A 2012 survey of data center vendors and end-users by the market research firm Datacenter Dynamics indicated that global investment in data center projects for the year 2013 was expected to reach USD 120 billion (Jones, 2012). Accompanying the positive growth and expansion of data centers are noteworthy issues in need of addressing. The two most important matters to be covered by this

research are the large quantities of energy consumed by these facilities and the accompanying significant energy costs. Literature pertaining to each of these items will be discussed in detail in the following subsections.

2.3.2 Data Center Energy Usage

Modern data centers require a substantial amount of energy to operate their various components, which according to the authors Balodis and Opmane (2012) can include computers and servers, primary and backup power equipment, cooling systems, humidity control systems, and fire suppression systems. Servers and cooling systems in particular demand a large quantity of electricity (Nazir, 2012). Estimates by Masanet, Brown, Shehabi, Koomey, and Nordman (2011) indicated that servers alone account for at least 50% of electricity demand in data centers. Berl et al. (2010) support this figure via their analysis of the e-commerce company Amazon.com. Of Amazon.com's total data center expenditures, 53% were "related to the cost and operation of the servers" (Berl et al., 2010, p. 1045), while 42% were related to energy split approximately between 19% on power and 23% on cooling systems.

The efficiency of the energy consumed by data centers is measured using a metric known as *power usage effectiveness* (PUE). This industry-standard measurement is the ratio of the total amount of energy used by facilities to the total amount of energy used by IT equipment (Brady, Kapur, Summers, & Thompson, 2013). According to a recent EPA study[3], PUE values for data centers typically fall between 1.25 and 3.75, with the average value being 1.91 (Garimella, Persoons, Weibel, & Yeh, 2013). Although PUE values approaching 1 are highly desirable, Brady et al. (2013) note that a PUE of exactly 1 is unattainable because "it will always take some form of energy consumption to support the IT equipment" (p. 156). Regardless, data

[3] Sullivan, A. (2010, February 4). *Energy Star for Data Centers*. Retrieved from: http://www.energystar.gov/ia/partners/prod_development/downloads/DataCenters_GreenGrid02042010.pdf

center operators are continuing to work towards reducing their PUE values to be as close to 1 as possible because energy efficiency improvements can translate into less money spent on electricity. Google, an industry leader in this field, has already made great strides with regard to lowering its PUE value as evidenced by Figure 2:

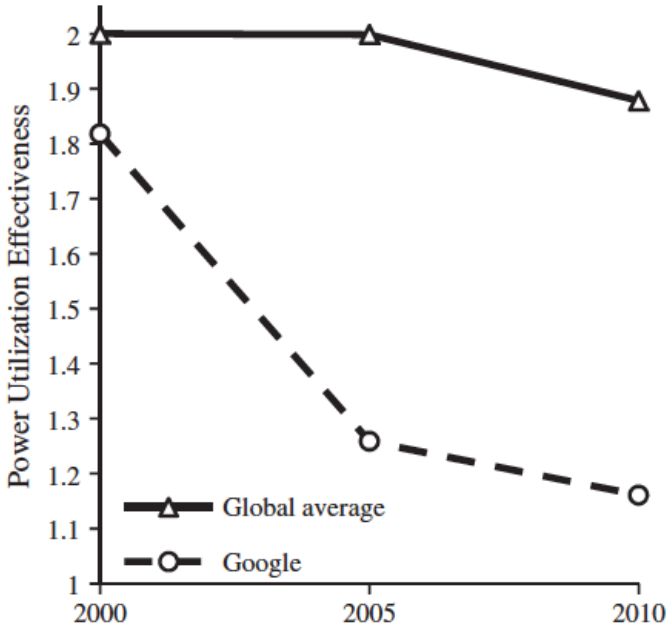


Figure 2. Comparison of Google's data center PUE to the global average from 2000 to 2010 (Garimella et al., 2013).

Tallying the total amount of electricity consumed by data centers within a single country helps to place energy consumption by these facilities into perspective. For the United States, 1.8% of all electricity sales - 69 billion kilowatt-hours (kWh) of electricity or the equivalent electrical consumption of over five million average American households - were attributed to data centers within the country for the year 2008 (Masanet et al., 2011; Uddin & Rahman, 2012). However, estimates from a report[4] cited by both Meisner et al. (2009) and Çavdar and Alagoz (2012) indicated that aggregate data center energy consumption for the year 2011 would reach 100 billion kWh of electricity in the United States alone. Statistics presented by the EPA confirmed the upward trend in the amount of energy used: data center

[4] Environmental Protection Agency. (2007). *Report to Congress on Server and Data Center Energy Efficiency Public Law 109-431*. Retrieved July 16, 2014 from http://www.energystar.gov/ia/partners/prod_development/downloads/EPA_Datacenter_Report_Congress_Final1.pdf

electricity consumption in the United States "nearly doubled between 2000 and 2005, and increased by approximately 36% between 2005 and 2010" (Environmental Protection Agency, 2012, Why Data Centers?, para. 1). Between 1.7% and 2.2% of all electricity used in the United States in 2010 was attributed to data centers (Environmental Protection Agency, 2012).

Considering individual data centers, the company Apple, in a recent environmental footprint report, stated that its Maiden, North Carolina data center consumed 104 million kWh of electricity during the 2012 fiscal year (Apple Inc., 2013a). The same report notes that Apple anticipates greater customer demand for its Maiden, North Carolina data center's services in the future, which will also increase the electricity requirements of the facility (Apple Inc., 2013a). In addition to Apple it appears as though demand for electricity at data centers is increasing by and large. Recent projections for data centers within the United States indicated that energy consumption would grow at a rate in excess of 9% for each year up until 2020 (Environmental Protection Agency, 2012). Moreover, Uddin and Rahmin (2012) state that energy usage by data centers at the present time is "doubling every five years" (p. 4079), while Mondal and Keisling (2012) indicate that demand for digital storage "doubles every 18 months" (p. 1). If these predictions are in fact correct, data center operators, in all probability, will have energy consumption concerns to contend with for the foreseeable future.

More data centers, and in turn more electricity to power those data centers, will be required as we continue to create digital documents, upload photos to social media websites, and transition from localized computer storage to cloud storage. This notion is echoed by Uddin and Rahman (2012) who state that "increased reliance on the storage, backups, transfer, and processing of digital information throughout all aspects of society has caused significant growth in data center energy use" (p. 4080). Unfortunately, data centers face multiple energy issues in addition to concerns about the amounts of their electricity expenditures and the quantities of energy consumed: Kant (2009) touches upon the power "distribution and

conversion" (p. 2941) problem by reporting that a noteworthy amount of electricity is lost through both inefficient power distribution routes from the electrical grid to the data center and multiple conversions from alternating current (AC) to direct current (DC); Yuventi and Mehdizadeh (2013) point out that the large quantities of energy used by data centers can lead to undue strain on the electric grid, resulting in possible electricity disruptions to the data center; furthermore Uddin and Rahmin (2012) allude that uncertain "energy availability" (p. 4080) in some regions could result in power constraints being imposed upon data centers, which could negatively impact data center performance and diminish the quality of service provided to customers; finally, Buyya et al. (2010) and Gandhi, Harchol-Balter, Das, and Lefurgy (2009) discuss the challenge of balancing acceptable service levels able to handle dynamic customer server traffic that periodically spikes and strains resources, with efficient energy consumption. Ignored, these data center energy issues will likely continue to present challenges for data center operators as our society becomes increasingly cloud-based.

As mentioned in the previous paragraph, quality of service is a particularly important data center issue. Data centers typically arrange minimum service standards and guarantees with customers in contracts known as *service level agreements*. Yuventi and Mehdizadeh (2013) note that in many cases data center operators prioritize dependability ahead of "energy consumption and efficiency" (p. 91) to ensure that customers remain satisfied and to fulfill service level agreements. Absolutely, satisfying customer needs and striving to comply with service level agreements are of utmost importance for data center operators. But relegating energy matters to a secondary or lesser concern in the name of service availability likely creates undesirable consequences, such as inefficient electricity consumption and increased electricity expenditures. Ultimately, energy matters should be at the forefront of data center operator concerns along with service availability, especially techniques for improving energy efficiency or reducing electricity expenditures while maintaining appropriate service levels. The amount of money spent on electricity is the second of the two most important matters concerning data centers,

and literature pertaining to this and other data center cost issues will be explored in the next subsection.

2.3.3 Data Center Costs

Data centers are expensive to both build and operate. The authors Harmon, Demirkan, Auseklis, and Reinoso (2010) indicate that large-scale data center facilities, such as those in operation by Google and Facebook, come attached with price tags between USD 500 million and USD 1 billion. These figures exclude operating costs, which are also substantial for data centers due in large part to significant amounts of electricity consumption. Meisner et al. (2009) and Çavdar and Alagoz (2012) both cite recent estimates placing the total cost of electricity consumption for all data centers within the United States at USD 7.4 billion per year. Analyzing individual companies, estimates indicated that that Google spent in excess of $38 million solely on electricity to provide power to more than 500,000 servers in 2007, while Rackspace, a cloud computing and IT services provider, spent at least $12 million on electricity to power some 50,000 servers in the same year (Qureshi, Weber, Balakrishnan, Guttag, & Maggs, 2009). According to Ganesh, Weatherspoon, Marian, and Birman (2013) Google is now estimated to have over 1 million servers or double the amount used in the preceding calculation. Hence, the amount of money spent by Google in one year to power their servers has likely also increased.

Interestingly, data center servers are not used at full capacity during all hours of the day and night. According to Shuja et al. (2012), data centers typically house extra servers to account for peak instead of average customer demand and this redundant server architecture adds to total energy consumption and costs. Meisner et al. (2009) echo this sentiment by stating that data center operators must account for levels of heightened customer demand, which in some cases can be more than three times the typical usage level, by employing additional servers to ensure continuous operations under heavy network traffic conditions. If data centers fail to account for spikes in the number of server requests and become overloaded, customers could

experience problems accessing data and service level agreements could become breached. Since "data centers should provide high availability and should be fault tolerant" (Çavdar & Alagoz, 2012, p. 3237), expenditures on supplementary components requiring additional electricity, such as servers, can be considered a necessity to keep data centers online and available at all times. Therefore, the very nature of their operations compels data centers to use significant amounts of electricity and spend significant sums on energy to ensure they are fully functional and in compliance with terms of service.

With concerns surrounding energy costs abounding, many data center operators are assessing strategic options to combat these matters. Given that costs associated with operations are "increasing at 20% per year with annual energy costs alone nearly matching the costs for new equipment" (Harmon et al., 2010, p. 4), data center operators should be aware of the gravity of the situation. The literature review identifies two notable approaches to confronting data center energy cost problems. The first involves improvements to internal data center components and how data centers manage customer traffic and demands: Baliga et al. (2011) and Berl et al. (2010) propose server improvements, including upgrades to processors that use less energy during operation, to reduce overall electricity demand and thus costs; Ge, Sun, and Wang (2013) and Qureshi et al. (2009) suggest routing customer traffic to data centers in geographic regions where electricity prices are off-peak and therefore less expensive; Çavdar and Alagoz (2012) advocate for scheduling data center tasks to be performed at specific times to alleviate server congestion and avoid peak electricity costs; finally, Shuja et al. (2012) encourage data center operators to predict periods of maximum customer traffic demands, switch on an appropriate number of servers to handle the peak, then put those additional servers back into stand-by mode once the spike in traffic abates to save electricity expenses.

The second approach to addressing data center energy cost concerns involves offsetting electricity demand or generating revenue with a supplemental energy source. According to Uddin and Rahmin (2012), data centers can benefit from

supplemental renewable energy sources under the right conditions. The *GreenStar Network*, a global computer network with nodes powered solely by hydroelectricity, solar, wind, and geothermal power, is a prime example of this concept (CANARIE, n.d.; K. K. Nguyen et al., 2012). Operating on the CANARIE network, one of the world's best computer networks in terms of transfer speed and capacity, a GreenStar Network data center powered by clean energy will perform operations until its renewable power supply becomes inadequate, at which time it will transfer its work to another data center on the network that has an adequate amount of renewable energy to continue or finish its tasks – all without any noticeable delay to the end-user (K. K. Nguyen et al., 2012). While the GreenStar Network reduces data center energy costs by significantly decreasing demand for electricity, this thesis, on the other hand, will examine how data center electricity costs can be offset via revenues generated using a renewable energy source.

According to Uddin and Rahmin (2012), businesses employing a great amount of IT equipment for their operations, such as data centers, are misunderstanding "the relationship between the falling capital cost of IT equipment and the rising costs of housing and powering" (p. 4080) these items, causing data center owners in some cases to experience financial difficulties. Even though IT equipment is less expensive to buy, the costs of running and providing accommodation for the equipment may negate any potential cost savings. Furthermore, when assessing data center costs, it is imperative that owners account for expenses that could be considered a by-product of their operations. For instance, in addition to expensive electricity bills, Le, Bianchini, Nguyen, Bilgir, and Martonosi (2010) state that data centers create large carbon footprints, which, if subjected to levies by governments, can entail further costs for their operators (Murugesan, 2008). Thus, there could be scenario where negative environmental impacts associated with data center operations translate into additional expenditures for owners.

However, at the present time there is a great deal of interest with regard to diminishing the environmental impact of IT-heavy operations such as data centers.

Several major standards organizations are supporting this endeavour by providing certifications and best practices for data center operators to follow. For instance, the International Telecommunications Union (ITU), a United Nations agency, has approved *Recommendation ITU-T L.1300*, which explains best practices related to IT equipment selection, cooling systems design, power management, and network layout in order lessen the environmental impacts of data centers (International Telecommunication Union, 2012). Moreover, a working group of the International Standards Organization (ISO) is currently developing guidelines for data centers related to resource efficiency from both environmental and economic perspectives (International Standards Organization, n.d.). As well, the Canadian Standards Association (CSA) is promoting a program that equips organizations with the means to estimate the quantity of IT greenhouse gas emissions avoided by using an environmentally friendly IT service provider (Canadian Standards Organization, n.d.).

The examples of the ITU, ISO, and CSA illustrate that there is support from major international bodies for environmental initiatives related to data centers. This is a positive development for the industry because of the additional benefits created by these strategies. For example, improvements in energy efficiency at data centers for the sake of the environment can also result in financial rewards for the owners through less money spent on electricity (Murugesan, 2008). In the next section of this thesis, solar PV technology will be introduced and the merits of its use as a renewable energy source for generating revenue to offset electricity expenditures at data centers will be discussed.

2.3.4 Summary

To summarize, Section 2.3 demonstrated that data centers play a key role in providing numerous digital services to countless people each and every day. The user base for data centers has expanded over time to include all types of organizations of various sizes, and the technology supporting the computers,

servers, and other internal electronic components of these facilities has advanced considerably during this time period as well. However, the enormous amounts of energy consumed by these facilities and the costs associated with this consumption are both prominent concerns for data center owners. With the demand for data center services and cost of operations set to rise over the coming years, data center operators must address their energy consumption practices and related electricity expenditures or face potential financial strains. Environmental initiatives, backed by major international organizations, were introduced as one method of assisting data center operators with improving energy efficiency and reducing energy costs. Alternatively, leveraging renewable energy sources to generate revenue that would offset electricity costs was also presented as an option for data center operators.

2.4 Solar Energy

2.4.1 Solar Energy Introduction

Solar energy, or "light and heat" (D. Y. Wang & Lee, 2008, p.3) from the sun, is a unique, economic, and reliable alternative fuel source to traditional fossil fuels. This energy resource does not require extraction from the Earth, and its price does not fluctuate according to market forces; it is always free of charge. Moreover, the sun will likely retain its status as a fuel source long after our planet's fossil fuel reserves are depleted. However, solar energy continues to face an uphill battle against traditional fuel sources, such as oil and coal, for widespread acceptance. Parts of this struggle will be highlighted in the following paragraphs of Section 2.4.1, while the ensuing subsections will cover how PV solar cells create electricity, a review of the materials used in said cells, the advantages and disadvantages of solar photovoltaics, trends associated with PV, and a selection of examples of solar technology use at data centers.

Several definitions of "solar energy" were uncovered during the research process, and each was concise. For instance, the EPA defines solar energy as "energy from the

sun, also known as solar radiation and short-wave radiation" (Environmental Protection Agency, n.d., Solar Energy, para. 1). Alternatively, Doğan and Tuğrul (2001), establish solar energy as a "portion of the electro-magnetic spectrum, which includes visible light, ultra-violet light and infrared light" (p. 243). Furthermore, Natural Resources Canada defines solar energy as "energy from the sun in the form of radiated heat and light" (Natural Resources Canada, 2013, Solar Energy, para. 1). The key takeaways from these brief definitions include the sun as a source of energy, and both light and heat as forms of energy.

The sun continually inundates Earth with solar radiation. However, if this energy is to be harnessed for a specific purpose, such as generating an electrical current, specific instruments are required. The concept of using apparatus to exploit energy from the sun is traceable back to the time before the Common Era, when individuals used materials to focus sunlight onto dry timber and kindling as a means to ignite the materials (Lamont, 2012). While this particular application of harnessing the sun's energy was relatively elementary, its principle of using a special object to absorb solar radiation for the purpose of producing a particular outcome is still applicable to photovoltaic technology today.

Solar PV is one of two methods employed to transform solar energy into a usable output (Canadian Solar Industries Association, 2011a; National Renewable Energy Laboratory, 2013b). One method, photovoltaics, transforms solar energy into electricity for use in light bulbs and other electronic devices, for instance (Labouret & Villoz, 2010). The other method, solar thermal, converts radiation from the sun into heat, which can be used to warm up water tanks within commercial and residential buildings, for example (Mills & Schleich, 2009). While each method is useful in its own regard, this body of research will focus solely upon solar photovoltaics.

Similar to the definitions of solar energy, definitions of photovoltaics were also defined succinctly. As an example, Parida, Iniyan, and Goic (2011) and The Boston

Consulting Group (2012) use similar, limited words to plainly describe solar PV simply as a method of converting light from the sun into electrical current. Both of these stated references echo the notion of Labouret and Villoz in the previous paragraph that photovoltaic technology is used to produce electricity. Other definitions uncovered during the research process were much alike and would be redundant if included.

The origins of solar PV can be traced back to 1839 when Edmund Becquerel, a physicist from France, uncovered the "photovoltaic effect" (R. Hill, 1994, p. 80) whereby a small amount of electricity was generated after certain materials were exposed to light (Theyel, Taylor, & Heffernan, 2011). This landmark observation marked the beginning of scientific study into photovoltaic technology. However, scientific progress was slow to advance, and the development of photovoltaic technology did not evolve significantly during Becquerel's lifetime (Blazev, 2012). According to Lamont (2012), this slow progress could have been attributed to a general disinterest in supporting an inefficient energy source that faced competition against a prolific supply of inexpensive fossil fuel, or a lack of understanding of the subject. From the 1860's until the mid 20th century, several curious scientists built upon Becquerel's initial findings, while other enterprising individuals developed practical applications of photovoltaic technology; despite their best intentions, however, both groups experienced limited success in their attempts to bring photovoltaic technology to the mainstream (Bradford, 2007). The challenges presented by PV technology were too great to overcome at the time.

However, a historic development for photovoltaic technology would eventually occur in 1954 when Bell Labs became the first commercial operation to patent a silicon-based solar cell (Theyel et al., 2011). The company's previous work with semiconductors was an asset for Bell Labs, and the knowledge obtained from this work helped the organization transform the solar cell from a scientific experiment to a viable product (Lamont, 2012). Bell Labs' initial patent would spur further PV technology research and development, resulting in cells with better but still limited

energy efficiencies and, in due course, interlinked solar cells that would form the first solar panels (Theyel et al., 2011). At this point in time, a new era for photovoltaic technology had begun, which would eventually see PV applied to projects both on terra firma and in outer space. But before these future successes would materialize, solar PV technology would once again encounter challenging times.

As Lamont (2012) states, PV technology's inefficiency and expensiveness in the mid-1950's were both unfavourable characteristics – solar cell efficiency was about only 6% at best and cost USD 250 per watt (W), which was much more than the USD 3 per watt cost of electricity from coal at the time. These two barriers to adoption proved to be serious for this innovative technology as both businesses and individuals lacked economic justification to procure this technology for their homes and operations. Nevertheless, the right opportunity for solar PV eventually emerged when space became a new frontier for exploration. According to Pizzini (2012), silicon-based PV solar cells were applied to satellites beginning in the latter part of the 1950's because of their practicality: the solar cells had long lifespans and direct access to the sun, their energy source, from orbit. R. Hill (1994) and Lamont (2012) support this idea by confirming *Vanguard I*, launched in 1958, as the first satellite to use solar cells.

Bradford (2007), who also acknowledges the initial space satellite application of solar cells, indicates there was a sense of optimism for photovoltaics after the technology proved useful as a power source for man-made objects in space during the 1960's. While widespread terrestrial solar PV applications remained out of reach during this decade, the notorious oil crisis of the 1970's prompted an "Alternative Energy Renaissance" (Blazev, 2012, p. 11) within the United States that prioritized renewable energy research and development. In light of "supply fears and the rapid rise in fuel prices" (Bradford, 2007, p. 98) attributed to the oil crisis, along with the realization that American dependency on foreign controlled sources of fuel was unsustainable, the United States government emphasized investing

public money into promoting solar energy and advancing solar research. Consequently, the future of solar PV technology appeared promising. However, challenges for PV technology would once again materialize with changes to American renewable energy policy in the 1980's.

When President Ronald Reagan entered the White House in 1981, solar PV research and development funding levels were at USD 155 million; when he left office in 1989, this funding had been cut to USD 35.5 million (Sklar, 1990). Solar technology programs sponsored by the federal government were either scaled back or abandoned altogether as a result of these cutbacks, and President Reagan even went so far as to remove solar panels from the roof of the White House that were installed by his predecessor, Jimmy Carter (Rahm, 1993). The United States created adverse conditions for solar PV technology, and this ideology spread to other countries. According to Bradford (2007), Reagan's funding cuts to renewable energy programs were emulated by those in charge of other nations, and these actions, combined with a downturn in global oil prices during the 1980's and the beginning of the 1990's, "diminished the perceived urgency to cultivate renewable-fuel options" (p. 98).

However, the most recent period of PV technology development, from the 1990's to the present day, has been rather positive for the industry. This era has seen new, independent energy-producing companies setup operations in response to governments deregulating energy producers, as well as growth in the area of commercialized renewable energy products (Fontana, 2012). During this time as well, Japan and Europe surpassed the United States in terms of domestic PV usage on account of new government programs, policies, and campaigns in those countries that enticed individuals and businesses to adopt solar energy technology (Lamont, 2012). Bradford (2007) supports this sentiment by designating both Japan and Germany as pioneers of solar PV promotion and adoption during this time period, and links the successes of their renewable energy policies to reductions in the overall cost of solar PV systems. Subsequently, other areas, including Ontario,

Canada, have enacted renewable energy policies based upon the favourable results experienced in countries such as Germany (Stokes, 2013).

Solar PV technology has faced adverse conditions on several occasions, but has managed to persevere. Today, solar energy is a promising alternative fuel source and its full potential has yet to be realized. This introduction to solar energy has provided context for the remaining subsections, which will begin with the workings of photovoltaic technology.

2.4.1.1 Solar Photovoltaic Technology

As mentioned in the previous section, solar energy capturing technologies can be divided into photovoltaic and thermal applications. PV can be further split into traditional photovoltaics and *concentrated* photovoltaics, which is an advanced application of PV technology. CPV involves the use of mirrors or transparent pieces of glass to focus light from the sun onto specially designed solar cells capable of absorbing concentrated sunlight (National Renewable Energy Laboratory, 2009a; Sala & Luque, 2007). Traditional solar cells, in contrast, absorb sunlight without the aid of external focusing materials. While this thesis will analyze financial results stemming from the use of both PV and CPV installations, the literature review will focus primarily upon PV technology since the amount of published material pertaining to CPV is comparatively small. However, information about CPV technology will be provided within this thesis where available and where appropriate.

The term "photovoltaic" is itself a combination of the words *photon*, which refers to light, and *voltage*, which refers to electricity according to National Renewable Energy Laboratory (2012). However, others opine the combination of words to be *photon* and *Volta*, which is a reference to Alessandro Volta, a scientist "for whom the Volt is named" (Factoran, 1995, p. 8). Nevertheless, the process of converting sunlight into electricity can be separated into three distinct activities: absorbing

light from the sun, creating an electrical charge, and producing an electrical current (Labouret & Villoz, 2010). Each of these events will be briefly explained in the following paragraphs.

During the first stage, a semiconductor material within the solar cell, such as silicon, absorbs solar energy, which is transferred to the valence (outer) electrons of the silicon atoms (U.S. Department of Energy, 2013a). The absorbed energy causes the electrons to become "excited into higher energy levels" (Hirst, 2012, p. 294). According to National Renewable Energy Laboratory (1982), electrons with higher energy levels can detach from bonded positions within silicon's atomic crystal structure. When this happens, the result is untethered, negatively charged electrons and vacant, positively charged electron holes (Labouret & Villoz, 2010). The electrons, which become increasingly excited as the semiconductor material's temperature increases, move in an unpredictable manner from electron hole to electron hole (National Renewable Energy Laboratory, 1982).

However, without some form of intervention the silicon electrons will eventually lose energy and cease their movements altogether after repeated pairing and decoupling with oppositely charged electron holes (Labouret & Villoz, 2010). In order to prevent this from occurring, additional elements with valence electron structures well suited to interact with silicon for this specific purpose – phosphorus and boron, for example – are inserted into silicon crystals through a process known as "doping" (Krauter, 2006, p. 21), which creates an excess of electrons and electron holes. Doped silicon containing an abundance of electrons is known as *n-type material*, whereas doped silicon with a surplus of electron holes is known as *p-type material* (National Renewable Energy Laboratory, 1982). The negative n-type material is placed alongside the positive p-type material in the solar cell, which allows bonds to form between electrons and electron holes along the edge of the p-type and n-type materials, respectively, in an area known as a "p/n junction" (U.S. Department of Energy, 2013b, PV Semiconductors, para. 2).

These bonds create an electrical charge at the p/n junction that acts as a barrier preventing additional bonds from forming between electrons and electron holes (National Renewable Energy Laboratory, 1982). The barrier ensures electrons are kept on the n-type material, while electron holes remain on the p-type material. The junction, however, permits excess electrons to move across the barrier from the p-type material to join electrons on the n-type material, and conversely it allows electron holes to move across the barrier to join electron holes on the p-type material within the solar cell (Archer & Hill, 2001). The movements permitted by the junction cause electrons to gather upon the n-type material and electron holes to gather upon the p-type material, and it is these clusters of free electrons and electron holes that are available to produce an electrical current (U.S. Department of Energy, 2013b). By linking the n-type material to the p-type material by means of an external electrical load, such as a light bulb, the electrons are able to flow in a current from the n-type material through the load and into the p-type material to pair with electron holes (Archer & Hill, 2001; National Renewable Energy Laboratory, 1982). This is a basic description of how solar cells produce an electrical current. Although a silicon-based solar cell was used for this illustration, solar cells can be produced using many different materials. A selection of different types of cells and their associated materials are discussed in the following paragraphs.

2.4.1.2 Solar Photovoltaic Cell Materials

Solar cells can be classified according to the materials used in their fabrication. Reddy (2012) differentiates solar cells into the following categories: silicon-based, including both crystalline and amorphous cells; advanced thin-film technologies and multi-junction cells, in which additional elements or compounds are incorporated into the cells; and "third generation cell technologies" (p. 7), which include solar cells with higher efficiencies and the capacity to absorb concentrated sunlight.

Crystalline silicon cells, according to Rardin and Xu (2011), are produced using "silicon wafers that can be either mono-crystalline or multi-crystalline structures"

(p. 3) depending upon the production method employed. Mono-crystalline silicon cells are created from a process beginning with a single "seed crystal" (Factoran, 1995, p. 10), the structure of which is replicated to produce a silicon "brick" that is eventually thinly sliced into wafers. Multi-crystalline silicon cells, on the other hand, contain crystals of different sizes and orientations as a result of a different production method, which involves moulding pure, melted silicon into a block-shaped bar that is also sliced into thin wafers (Labouret & Villoz, 2010). Approximately 80% to 90% of all solar cells manufactured today contain crystalline silicon (Schropp, 2014).

In contrast, amorphous silicon solar cells lack the crystalized structure found in crystalline solar cells and they are comparatively thinner (Meral & Dinçer, 2011). These thin-film solar cells are produced using a layering technique, where a homogenous layer of silicon and other elements are layered on top of a base material such as glass (R. Hill, 1994; Meral & Dinçer, 2011; Tyagi, Rahim, Rahim, & Selvaraj, 2013). The atomic structure of amorphous silicon is, by itself, not an ideal semiconductor, so hydrogen atoms are commonly used – instead of phosphorous or boron in the case of crystalline silicon solar cells – to enable an electrical charge to be produced (Labouret & Villoz, 2010). Kirchartz and Rau (2011), support this notion by also stating that hydrogen is commonly used in the production of amorphous silicon solar cells.

Some thin-film solar cells include chemical compounds such as "cadmium telluride (CdTe)" (Parida et al., 2011, p. 1628) and these particular cells are an example of the advanced thin-film technologies referenced by Reddy (2012). According to Lamont (2012), compounds are used to further improve solar cell efficiency, which is the ratio of the amount of electricity produced to the amount of light absorbed (Goetzberger & Hoffmann, 2005). The distinct layers of elements and compounds within the solar cell absorb light from different regions of the solar spectrum (Labouret & Villoz, 2010). When multiple elements are used within the solar cells, multiple junctions are formed, which is why these types of cells are classified as

multi-junction. Multi-junction solar cells typically have higher efficiencies because their combination of elements and compounds allows them to absorb a greater range of light from the solar spectrum (Meral & Dinçer, 2011).

Third generation solar cells incorporate many new technologies and concepts. (Reddy, 2012), for instance, categorizes solar cells containing three to five semiconductor compounds, as well as cells able to convert concentrated sunlight into electricity as part of CPV applications as third generation. However, both of these types of cells are prohibitively expensive at the present time for mass production (Reddy, 2012). Solar cells used in CPV applications require a concentrator to focus sunlight onto the advanced solar cells. The concentrator, typically aided by a computer and sophisticated software in order to move in parallel with the sun, adds additional complexities and costs (Friedman, 2012). Moreover, the moving components of tracking systems require maintenance, which increases operations costs and encroaches on the solar installation's profitability. Due to their additional complexities and costs, advanced solar cells will not be used as part of the data collection process for this body of research. Instead, the data will be collected from only non-concentrated, single junction crystalline silicon solar cells.

The materials used in solar cells affect the qualities and characteristics of said cells. As a result, some solar cells are more suitable for certain applications than others. Crystalline silicon, for example, could be chosen over amorphous silicon because the former is more efficient at generating electricity than the latter (Parida et al., 2011; Reddy, 2012). Furthermore, crystalline silicon is more capable of weathering the elements compared with amorphous silicon, which translates into a longer lifespan and slower degradation of the solar cells (Moore, 2010). Consequently, crystalline silicon solar cells are more appropriate for outdoor solar modules that provide electricity to a home or business, or to the existing power grid.

However, amorphous silicon solar cells have apt applications as well. For example, these types of solar cells are more effective at absorbing sunlight and "can be deposited on a wide range of substrates, both rigid and flexible" (Meral & Dinçer, 2011, p. 2180). The thin nature of amorphous silicon cells also means that fewer materials are required for their fabrication, which translates into lower costs (Aberle, 2009; Schropp, 2014). Their thinness also renders amorphous crystalline solar cells available to different applications compared with crystalline silicon solar cells, including use in consumer electronics such as calculators (Fraas & Partain, 2010). Nevertheless, thin-film solar cells are typically outlived by crystalline solar cells and are less efficient at producing electricity, which are both notable drawbacks (Theyel et al., 2011). Generally speaking, the literature pertaining to applications of crystalline and amorphous silicon support the notion that there are distinct, appropriate uses for each form of this popular semiconductor material.

2.4.1.3 Solar Photovoltaic Advantages and Disadvantages

Similar to various other technologies, solar PV has both appealing and uninviting features. For instance, solar PV technology can be installed in a variety of settings, including on the rooftops of residential and commercial buildings or on land neighbouring these properties (Canadian Solar Industries Association, 2011b). However, if the setting is in a predominantly cloudy, rainy area, the solar panels may not produce much electricity. Table 1 provides a summary of some advantages and disadvantages pertaining to solar PV technology:

Advantages	Disadvantages
• Fuel source is stable over long-term	• Upfront cost is typically large
• Operation and maintenance costs are reasonable	• Weather conditions may negatively affect availability of fuel source
• No staff required on-site to generate electricity	• Amount of energy produced is variable
• 20 or more years of operation	
• Energy created is clean	

Table 1. Advantages and disadvantages of solar energy. Adapted from Foster, Ghassemi, and Cota (2009).

In terms of the advantages, the sun continually provides free fuel for solar cells and unlike fossil fuels there is no concern over escalating prices of sunlight (Why renewable energy? 2012). Additionally, the sun can be counted upon to provide a steady stream of solar energy because it will be stable in its current form for at least the next three billion years (Golub & Pasachoff, 2014). Even the most optimistic estimates and calculations of how long the Earth's coal, oil, and gas reserves will last until depletion are no where near the sun's projected useful lifespan (Shafiee & Topal, 2009). Furthermore, silicon, a primary ingredient in solar cells, is "the second most abundant element in Earth's crust – second only to oxygen" (Stylos & Koroneos, 2014, p. 640), so the probability of depleting silicon reserves at any point in the near future is minimal. Operation and maintenance costs of PV systems are modest at approximately "1% of capital investment per year" (International Energy Agency, 2013a, p. 9), and the stationary nature of many rooftop and ground mounted solar installations minimizes operation and maintenance costs since there are few, if any, moving parts to service. In relation to this idea, solar installations do not require a team of workers on hand to monitor and adjust electricity production on an ongoing basis, unlike fossil fuel generation sources.

In terms of their functional timeframe, solar panels typically have an operating life of at least 20 to 25 years (Branker, Pathak, & Pearce, 2011). Zhang, Wang, Xiao, and Li (2012) support a similar timeframe, whereas Swift (2011) indicates that the useful operating life can reach 30 years. Zweibel (2010) notes that warranties on PV systems typically cover 25 years or more of operation and he is optimistic that photovoltaic installations will successfully operate for even longer periods of time in the future. The relatively long operating lifespans of PV systems and the minimal maintenance required is an appealing combination. Finally, unlike traditional fuels such as coal and oil, solar energy does not produce greenhouse gases during electricity production meaning solar energy is clean energy (Bradshaw, 2013).

However, the disadvantages of solar PV energy are well documented too. Firstly, the initial costs of setting up and installing a solar PV system can be considerable

(Timilsina, Kurdgelashvili, & Narbel, 2012). Sarzynski, Larrieu, and Shrimali (2012) echo this sentiment and note that economic incentives directed at reducing upfront costs would likely increase the number of prospective solar PV customers. Weather conditions can also negatively impact the performance of solar cells. Besides the commonly known negative effect of cloudiness on the amount of electricity generated by solar panels, Patt, Pfenninger, and Lilliestam (2013) also identify the adverse effects of hail, which can physically damage PV modules, lightning, which can devastate an improperly grounded PV system, extreme temperatures, which can reduce the efficiency of solar cells, and dust, which can accumulate on top of solar panels and block sunlight. Tyagi et al. (2013) also discuss the negative impact that higher temperatures have on solar PV cells and describe how a build up of dust particles may impede sunlight from reaching the solar cells. Noro et al. (2012) additionally touch upon the idea of weather impacting solar PV systems and acknowledge that solar power is prone to substantial electricity output variations over short periods of time because of changes in weather.

To combat the disadvantage of variable energy production from solar PV systems, Noro et al. (2012) propose a solution involving the use of batteries to store some of the energy produced by the solar panels for use during times when the solar panels are not producing energy. Hund, Gonzalez, and Barrett (2010) acknowledge the unfavourable impact that clouds can have on the electricity produced by PV systems and they too support the idea brought forward by Noro et al. (2012) of storing energy with batteries and releasing said energy at appropriate times to mitigate some of the variability. The important takeaway from the literature describing the advantages and disadvantages of solar PV systems is that certain conditions – particularly economic and climactic – must exist so that solar PV technology is able to prove advantageous. These conditions do exist as evidenced by some of the trends described in the following paragraphs.

2.4.1.4 Solar Photovoltaic Trends

Over a number of years, photovoltaics have grown out of obscurity into a rather well known technology. At the present time, solar power is providing opportunities to a wide range of groups that include "investors, manufacturers and technology adopters" (Theyel et al., 2011, p. 1048). After encountering multiple barriers to further development and adoption since its inception, photovoltaic technology finally appears to be gaining momentum on a global scale. It is estimated that solar energy could satisfy approximately 5% of the world's energy requirements in 2030 and 11% in 2050 (International Energy Agency, 2013a).

The total amount of solar PV capacity installed around the globe has increased over the years. One of the driving forces behind growing numbers of solar PV installations is carbon dioxide (CO_2) reduction. At the present rate, carbon dioxide levels will become critical by 2050 without some form of intervention, which, according to Razykov et al. (2011), should entail the installation of "about 20 TW [terawatts] of non-CO_2 energy to stabilize CO_2 in the atmosphere" (p. 1580). This is a lofty goal, but according to the same authors, solar is poised to be a prominent player within the mix of renewable energies used to provide the proposed 20 TW of green energy (Razykov et al., 2011).

In the year 2050, which was referenced in the previous paragraph, Timilsina et al. (2012) indicate that Greenpeace and the European Renewable Energy Council expect 2,033 GW (gigawatt) – or 2.033 TW – of solar PV capacity to be installed by this point in time. Additionally, the same authors note that the International Energy Agency (IEA) projects global solar capacity to range between 600 GW (0.6 TW) and 1100 GW (1.1 TW) depending upon which carbon dioxide scenario is realized in the years to come on planet Earth (Timilsina et al., 2012). Levels of CO_2 are on the rise according to recent atmospheric readings, which indicate that average carbon dioxide levels have risen from 317.45 parts per million (PPM) in 1958 to 399.65 PPM as of March 2014 (National Oceanic and Atmospheric Administration, 2014). A

recent Intergovernmental Panel on Climate Change (IPCC) report[5] appeals for carbon dioxide mitigation efforts in order to ensure global atmospheric CO_2 levels are kept at reasonable levels. In the report, a target of approximately 450 parts per million CO_2 in the year 2100 is prescribed, which would prevent global average temperatures from increasing by 2°C or more by that time (Edenhofer et al., 2014).

Interestingly, average global carbon dioxide levels have yet to reach 450 PPM according to the atmospheric data collected monthly since 1958 at a research station in Mauna Loa, Hawaii, yet there are already calls to begin CO_2 mitigation initiatives in order to achieve this target level. Ensuring atmospheric CO_2 concentrations of 450 PPM with "high confidence" (Edenhofer et al., 2014, p. 11) in the year 2100 will likely require that low-carbon energy sources account for about 60% of primary energy sources by 2050, an approximate 310% increase over 2010 levels. Assuming action is taken in response to these concerns over CO_2 in our atmosphere, solar energy demand could be poised for strong growth in the years to come.

Motivations for installing additional PV systems aside, the total amount of PV installed capacity has grown significantly during the early 21st century, and is expected to continue growing. Figure 3 illustrates the total gigawatts installed between the years 2000 and 2013, and projects installed capacity up until the year 2050:

[5] *Climate Change 2014: Mitigation of climate change*. Available: http://mitigation2014.org/report/final-draft/

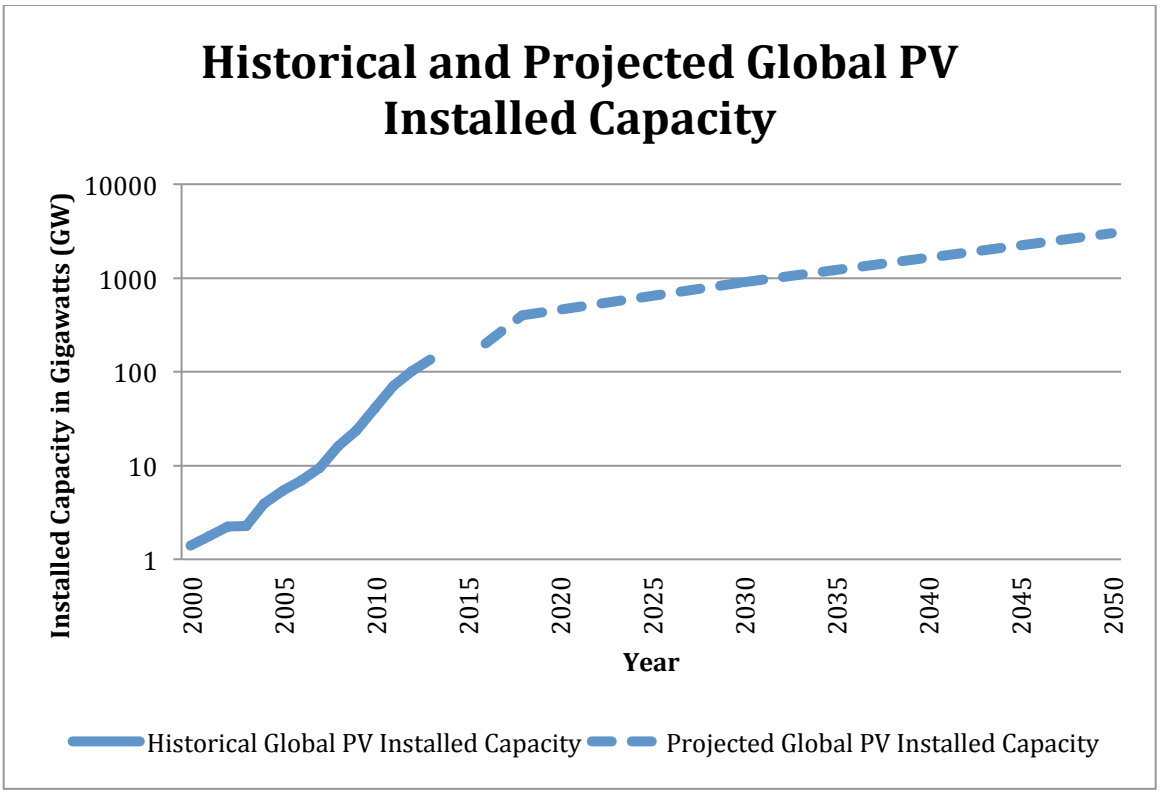


Figure 3. Total global installed PV capacity between 2000 and 2013, and projected capacity up until 2050. Adapted from European Photovoltaic Industry Association (2013).

As per Figure 3, total PV installed capacity climbed to 102.2 GW in 2012 (Pazheria, Othmanb, & Malik, 2014). Looking ahead, by 2016 total global installed PV capacity is expected to reach 200 GW and could extend as high as 400 GW by 2018 depending upon the policies and business conditions that promote solar energy and make it an attractive investment (European Photovoltaic Industry Association, 2013). The projected 200 GW of installed PV capacity by 2016 appears achievable since figures from the IEA indicate total installed capacity in 2013 reached at least 134 GW "with a firm level of certainty" (International Energy Agency, 2014, p. 6). Estimates looking even further into the future project a total installed capacity of 900 GW by 2030 and 3,000 GW (3 TW) by 2050 (International Energy Agency, 2013a).

From a Canadian perspective, total installed solar PV capacity reached 765.97 MW within the country's borders in 2012, up from 7.15 MW in 2000 and only 0.96 MW in 1992 (Luukkonen et al., 2013). Notably, the province of Ontario, which recently

adopted measures promoting the use of solar and other renewable energy technologies, had 645 MW of operational solar PV in 2012 representing 70% growth over the province's 2011's total installed capacity (Bateman, Dignard-Bailey, & Poissant, 2013). While the amount of PV installed worldwide is on the uptrend, the costs associated with solar PV technology are moving in the opposite direction.

The prices and costs of solar PV modules and systems have decreased over the years and this trend is expected to continue. PV modules consist of a series of interconnected solar cells, and are commonly referred to as solar panels (Yuventi, 2012). PV systems, on the other hand, include solar modules along with components such as "cabling, support structures, and, if applicable, electricity storage, optics and sun trackers" (Turkenburg et al., 2012, p. 828). As mentioned in the introduction to solar energy, the United States began investing heavily in solar research and development during the 1970's. From that time until the end of the 20th century, the price of PV modules declined drastically from USD 70.00-80.00/Watt-peak (Wp) to USD 2.00-3.00/Wp (Krauter, 2006). Between 2000 and 2010, prices continued to descend and eventually standard solar modules achieved price levels between USD 1.50-2.00/Wp (U.S. Department of Energy, 2012). In 2012, the year from which the most recent data is available, the cost per watt for typical PV modules had reached levels as low as USD 0.80/Wp (U.S. Department of Energy, 2013c).

In Canada, prices for typical solar modules between the years 2000 and 2012 decreased from approximately CAD 10.70/Wp to CAD 1.15/Wp with a nearly 50% decline between 2010 and 2012 alone (Luukkonen et al., 2013). On a worldwide scale, estimates from 2012 predicted that the global average price for a solar PV module would be USD 0.74/Wp in 2013 (Feldman et al., 2012).

PV systems have experienced similar price declines recently (U.S. Department of Energy, 2013c). Between 1998 and 2011, for instance, price reductions for PV systems of all sizes in the United States averaged between 5-7% per year resulting in median installation costs in 2011 of USD 6.13/Wp for systems 10 kilowatts (kW)

or less, USD 5.62/Wp for systems 10-100 kW, and USD 4.78/Wp for systems greater than 100 kW (Feldman et al., 2012). In 2012, installation prices for large PV systems ranged between USD 1.50-3.00/Wp, while smaller rooftop system installation prices spanned USD 2.40-6.00/Wp (International Energy Agency, 2013b). Comparatively, an IEA survey of 19 countries indicated that PV system installation prices typically ranged between USD 2.40-3.70/Wp in 2012, with an average price of USD 2.80/Wp and a lowest system installation price of USD 1.60/Wp (International Energy Agency, 2013c). For the year 2013, system prices were expected to range between USD 2.00-4.95/Wp for distributed systems and USD 1.60-3.30/Wp for utility-scale systems (Feldman et al., 2013).

PV system prices in Canada followed a comparable trend. Grid-connected PV systems 10 kW or less were priced at CAD 20.00/Wp in the year 2000, whereas the price for the same sized system ranged between CAD 3.00-5.00/Wp in 2012 (Luukkonen et al., 2013). In 2005, the first year of available data for grid-connected systems greater than 10 kW, PV system prices were CAD 12.60/Wp, while in 2012 that price had dropped to between CAD 2.80-4.00/Wp (Luukkonen et al., 2013).

The downward trending PV system prices in the United States and Canada are indicative of a global trend. Referring to other countries, Germany, mentioned earlier as a leader in PV promotion and utilization, also continues to experience declining PV prices as evidenced by Figure 4:

German prices of installed PV systems < 100 kW (€/Wp), 1/2009 to 1/2014

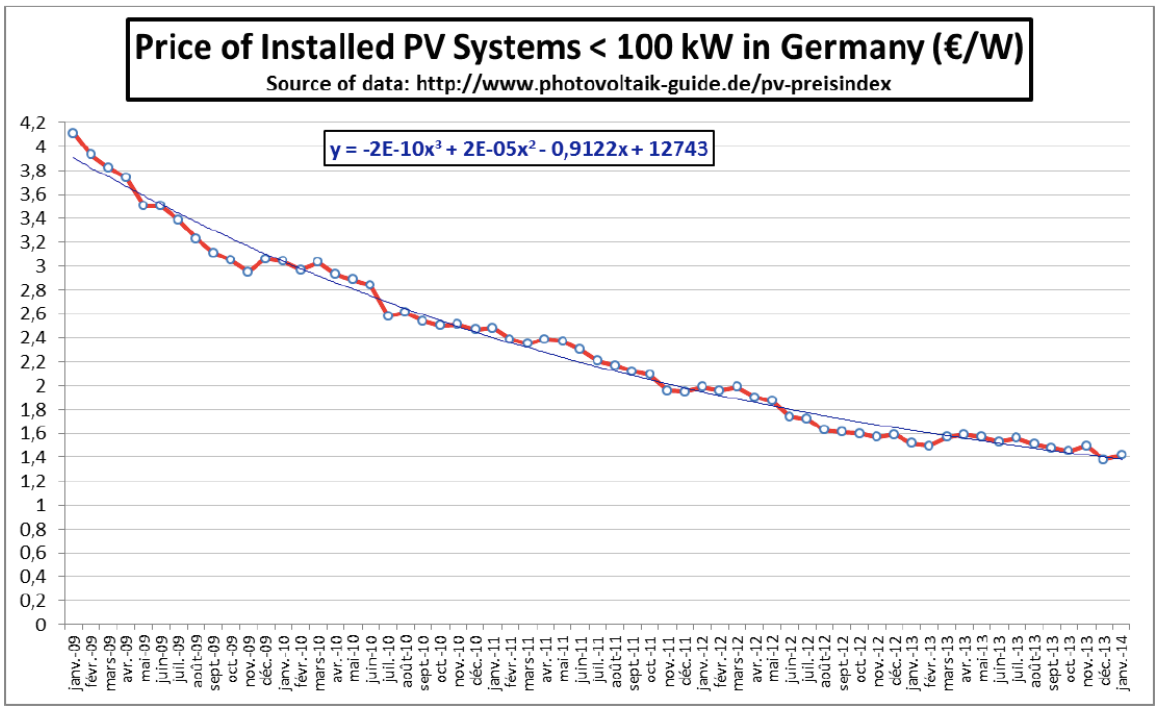


Figure 4. Installation prices for solar PV in Germany from 2009 to January 2014 (Chabot, 2014).

In terms of future price trends, Feldman et al. (2013) predict average distributed PV system prices will range from USD 2.00/Wp to USD 4.75/Wp by the end of 2014, while utility-scale systems prices will be even lower at USD 1.50/Wp to USD 3.15/Wp. U.S. Department of Energy (2012) projects that PV system costs for commercial rooftop installations could reach as low as USD 1.25/Wp in 2020 if its *SunShot* Initiative[6] is able to achieve its objectives. Zweibel (2010) is optimistic that PV system installation prices of USD 1.00/Wp could be achieved at some point between 2010 and 2020 for large-sized systems, and this figure precisely matches projected utility-scale solar installation costs in the year 2020 by U.S. Department of Energy (2012).

The cost competitiveness of electricity generated by solar energy is expected to improve against electricity produced by traditional fuel sources. As a result of the

[6] The U.S. Department of Energy's SunShot Initiative promotes solar energy research and development. One of its goals is to reduce cots associated with PV technology.

previously mentioned declining PV module and system costs, the cost of electricity from solar sources is in decline. The levelized cost of electricity generated from solar sources, for example, is expected to decline from approximately USD 0.16-0.31/kWh at the present time to USD 0.065-0.135/kWh between 2030 and 2050 (International Energy Agency, 2013a). Concurrently, electricity prices are on the rise. In the United States, for instance, the price of electricity generation for residential customers is expected to increase from USD 0.061/kWh in 2014 to USD 0.097/kWh in 2032 (U.S. Energy Information Administration, 2014b). These pricing figures exclude electricity transmission and distribution charges. Comparatively, Ontario's *Long-Term Energy Plan* indicates that the average electricity price for residential customers will increase from approximately CAD 0.098/kWh in 2014 to CAD 0.13/kWh in 2032 (Ontario Power Authority, 2014). When transmission and distribution charges are taken into account, residential electricity prices in both the United States and Canada are even higher. These pricing figures indicate that solar generated electricity could become cost competitive with, if not less expensive in some cases than, grid-produced electricity in the relatively near future.

Moreover, solar technology is capable of further reducing electricity consumption costs for specific types of electricity consumers. In Ontario, for example, the bulk of electricity charges for larger energy consumers in the province stem from a consumption charge based upon the wholesale price of electricity, a distribution charge, and a global adjustment fee. Notably, the latter two costs are based upon peaks in energy use during specific time periods for large energy consumers (Independent Electricity System Operator, n.d.e), and on a $/kWh basis for the hours in which the peak occurs, the costs can be several times greater than the wholesale price of electricity (Independent Electricity System Operator, n.d.d). However, the demand peaks used to calculate global adjustment fees, for instance, typically occur in the summertime during the afternoon (Independent Electricity System Operator, n.d.d), and afternoons happen to be when the amount of energy produced by solar modules regularly peaks (Borenstein, 2012). Therefore, the use of solar panels could offset electricity demand during peak timeframes, resulting in the

avoidance of a certain amount of electricity charges. This idea in particular will be explored in the analysis section of this thesis.

Finally, the efficiencies of solar cells have also improved over time, and this trend as well is forecast to stay the course of continuing improvement. When silicon solar cells were first patented, their efficiencies ranged from 4% to 11% at best (Theyel et al., 2011). Since this time, research and development has both improved the efficiencies of these cells and spurred the development of new types of solar cells. Figures from 2014 indicate that *peak* efficiency can be as great as 25% for single crystal silicon solar cells and 20.4% for multi-crystalline silicon cells (National Renewable Energy Laboratory, 2014). Information from the IEA provides support for the trend of improving efficiencies by indicating that *average* PV module efficiencies "are expected to increase from 16% in 2010 to 25% in 2030" (International Energy Agency, 2013a, p. 22), while advanced PV technologies incorporating multiple semiconductors could reach efficiencies approaching 40% by the year 2050. The IEA provides estimates of expected efficiencies of commercially available silicon solar cells in Table 2:

	2010-2015	2015-2020	2020-2030/2050
Single-crystalline	21%	23%	25%
Multi-crystalline	17%	19%	21%

Table 2. Efficiency targets of commercial crystalline PV modules. Adapted from International Energy Agency (2013a).

From the figures in Table 2, the efficiencies of commercially available solar panels trail the best efficiency values reported by the National Renewable Energy Laboratory. Although single crystal solar cells have already achieved peak efficiencies of 25% (National Renewable Energy Laboratory, 2014), commercial solar cells capable of reaching these same efficiency levels may not be available in the marketplace until at least 2020 if these projections hold true.

The literature also states that there are discrepancies between best-recorded efficiencies and the efficiencies of commercially available thin-film solar cells. At the present time, the peak recorded efficiencies for thin-film silicon, copper indium

gallium (di)selenide (CIGS), and CdTe are 13.4%, 20.8%, and 20.4%, respectively (National Renewable Energy Laboratory, 2014). Commercial targets for these same thin-film solar cells are displayed in Table 3:

	2010-2015	2015-2020	2020-2030
Thin-film Silicon	10%	12%	15%
CIGS	14%	15%	18%
CdTe	12%	14%	15%

Table 3. Efficiency targets of commercial thin-film PV modules. Adapted from International Energy Agency (2013a).

The figures in Table 3 indicate that the efficiency targets for commercially available CIGS and CdTe thin-film solar cells will lag behind peak reported efficiencies of these same cells. While the discrepancies may appear at first glance to be an issue, they could also indicate that solar cell manufacturers have leeway to further improve upon solar cells to match these peak efficiency values.

In addition to thin-film and crystalline solar cells, many additional types of cells, such as those mentioned towards the end of Section 2.4.1.2, are also undergoing further research and development. As these cells continue to be worked upon, they too will likely achieve better efficiencies, perhaps in different strides than silicon based solar cells because of the unique materials and compounds used in their fabrication. As noted by Tyagi et al. (2013), best-recorded solar cell efficiencies of 45% could be expected in the near future and, eventually, efficiencies of 50% could be achieved. National Renewable Energy Laboratory (2014) supports this idea by indicating that three-junction concentrated solar cells have already reached best-recorded efficiency levels of 44.4%; for non-concentrated solar cells, a peak efficiency value of 38.8% has been achieved by a four-junction cell. The literature pertaining to PV trends indicates, overall, that more capacity is being installed, the costs of solar PV are declining, and the efficiencies of the solar cells are increasing. Each of these trends is a positive development for solar PV technology, particularly declining costs and increasing solar cell efficiencies. As these trends make PV technology more attractive, solar energy is being applied to relatively new areas such as data centers.

2.4.1.5 Solar Photovoltaic Power and Data Centers

To conclude the introduction to solar energy, PV technology's application at data centers will be explored briefly. In certain jurisdictions where solar power is a good fit both economically and climatically, some data center operators have already erected solar installations either on top of the roofs of their data centers or on adjacent land. For instance, DuPont Fabros Technology Inc., a data center operator that leases space within its facilities to various clients (DuPont Fabros Technology, 2014), has installed a 2.17 MW solar installation on the rooftop of its 1,000 foot long *NJ1* data center in Piscataway, New Jersey as shown in Figure 5 (Miller, 2012):

Figure 5. DuPont Fabros Technology Inc.'s Piscataway, New Jersey data center. The facility includes a large rooftop solar installation (Miller, 2012).

The large size of this data center with its expansive, flat rooftop provides an ideal location for a solar installation. However, when rooftop conditions are unfavourable and additional land would be required to build a solar installation, data center operators should consider the optics of purchasing said land for a solar installation. In some cases, it is possible that the land acquisition could be met with resistance if

the area is considered ecologically or environmentally sensitive (Why renewable energy? 2012).

In addition to DuPont Fabros Technology Inc. and the organizations previously mentioned in this thesis, several other companies are in the process of adding solar power to their data centers or have already implemented solar installations: The McGraw-Hill Companies announced in June, 2011 that it would construct a 14.1 MW solar installation at its data center located in East Windsor, New Jersey, which, at the time, was labelled as "the largest privately-owned, net-metered solar project in the Western Hemisphere" (The McGraw-Hill Companies, 2011, 14.1 MW Project Planned for McGraw-Hill Facility in East Windsor, NJ, para. 3); In 2012, eBay announced that it had covered the rooftop of one of its data centers in South Jordan, Utah with a 665 kW system consisting of "72,000 square feet of solar panels" (Brewer-Hay, 2012, eBay's Topaz Data Center Gets Even Greener, para. 2); and Cisco has installed a 264 kW solar installation that features over 1,000 solar panels on its data center in Richardson, Texas (Smith, 2014).

Data center operators have an incentive to look at innovative ways to save costs on electricity. Section 2.3.3 of this literature review highlighted the large fees incurred by data center operators for electricity. With high costs, even modest reductions have a noticeable impact. For example, considering Google's estimated $38 million annual expenditure on electricity for its servers a few years ago, "a modest 3% reduction [in this amount] would therefore exceed a million dollars [in savings] every year" (Qureshi et al., 2009, p. 123). This insight is noteworthy because a small reduction target of 3% is realistic and electricity savings of over $1 million every year is significant. Even for smaller organizations, notable savings could likely be realized from modest reductions making this type of endeavour both an attractive and feasible proposition for data centers of many sizes. Although a multitude of organizations have already assembled solar installations at their data centers in multiple regions, there is a lack of literature pertaining to solar PV technology and its application at data centers in Ontario, Canada. This thesis will help bridge this

knowledge gap by examining the economic viability of applying solar PV technology to data centers within this province.

2.4.1.6 Summary

In Section 2.4.1 it was established that solar energy involves converting light and heat from the sun into electricity. Some of the advancements and setbacks experienced by solar energy over the course of its existence were also covered. The process by which electricity is generated using solar cells was touched upon, which includes absorbing sunlight, creating an electrical charge, and finally producing an electrical current. The materials used in the fabrication of solar cells were also discussed and included silicon-based cells – both crystalline and amorphous, advanced thin-film cells containing chemical compounds, and other new solar cells containing multiple junctions and the capacity to absorb concentrated sunlight. The advantages and disadvantages of solar energy were also identified and analyzed. Furthermore, recent trends in solar energy, including increasing solar cell efficiencies, growing amounts of global installed capacity, and decreasing prices were described. Finally, examples of data centers that have deployed solar installations were provided. The following section will remain on the topic of solar energy, but its focus will be upon the economics of solar energy production.

2.4.2 Introduction to the Economics of Solar Energy

The decision to implement a solar installation at a data center is a complicated matter. Questions about the size of the PV system, the orientation of the modules, the type of solar cells to use, and whether or not to use a stationary or tracking setup are just a sampling of the numerous matters requiring resolution before any physical infrastructure is erected. Whether a firm is self-funding the solar installation or whether outside investors are providing initial capital, the costs of, and the expected revenues generated by, the PV system should be estimated and scrutinized ahead of time to determine the potential economic viability of the

project. The following sections will detail the literature surrounding the economics of solar installations.

According to Masters (2004), "the most important inputs to any economic analysis of a PV system are the initial cost of the system and the amount of energy it will deliver each year" (p. 544). Sarzynski et al. (2012) and Timilsina et al. (2012) support the first component of this statement by mentioning that high initial costs associated with solar installations can act as a roadblock to technology utilization. The initial cost of installing a PV system – typically measured in dollars per watt-peak ($/Wp) – covers both the cost of the solar modules and all balance of system (BOS) costs, which can include labour to install the PV system, inverters to convert direct current produced by solar modules to alternating current used by most electronic devices, electric wiring, and support structures for the PV panels (Masters, 2004). These costs can vary depending upon the location and size of the PV system (Swift, 2011). For instance, average installation costs for residential PV systems are for the most part less expensive in Japan and Europe than the United States (Branker et al., 2011). According to Barbose, Darghouth, Weaver, and Wiser (2013), this pricing discrepancy between countries is likely attributable to differences in "soft costs" (p. 20), which can include expenditures related to acquiring new customers, PV marketing materials and campaigns, taxes on items sold, and operating costs (Seel, Barbose, & Wiser, 2013). Utility sized systems, which are larger in size than residential and commercial systems, usually have lower installation costs (Feldman et al., 2013). Ranges for present day PV installations costs were provided in Section 2.4.1.4.

In most cases, the energy produced by a PV system directly impacts the amount of revenue generated. Thus, the quantity of energy yielded by a solar installation is an important figure. Solar panel manufacturers label PV modules with a measure of the theoretical maximum amount of electricity the solar panels could produce under ideal circumstances known as "Standard Test Conditions" (Castellano, 2010, p. 59). As Balfour, Shaw, and Nash (2013) indicate, creating Standard Test Conditions in a

laboratory requires adjusting the temperatures of the solar cells to 25°C, setting solar irradiance – or the intensity of the sun – at 1,000 watts per meters squared (W/m^2), and simulating a specific atmospheric environment. Under these ideal circumstances, a 100 W solar module, for example, could produce a full 100 W of energy, but outdoors in practice, solar panels rarely, if ever, produce the maximum power they are capable of due to cloud, temperature variations, interference from dust, dirt, and sand particles, and energy losses during electricity transmission (Papadopoulou, 2011). The metric *capacity factor* (CF) is routinely used to illustrate how much energy is actually produced by a PV module compared with the amount of energy that *could* be produced under ideal conditions (Reichelstein & Yorston, 2013). Consequently, CF should be taken into account when determining the amount of solar capacity required for a particular project.

Besides the initial system cost and the amount of energy expected to be produced, additional factors that can influence PV system economic viability must also be taken into consideration. Masters (2004) summarizes these items:

> Whether the system is economically viable depends on other factors – most especially, the price of the energy displaced by the system, whether there are any tax credits or other economic incentives, and how the system is to be paid for. A detailed economic analysis will include: estimates of operation and maintenance costs; future costs of utility electricity; loan terms and income tax implications if the money is to be borrowed, or personal discount rates if the owner purchases it outright; system lifetime; costs or residual value when the system is ultimately removed; and so forth. (p. 544)

Knowing the price of the energy displaced in favour of solar energy provides a baseline level for determining either the costliness or inexpensiveness of solar-generated electricity. The typical metric used to compare the prices of different energy sources is *Levelized Cost of Electricity* (LCOE) (Branker et al., 2011; Timilsina

et al., 2012), which will be discussed in greater detail in Section 2.4.2.2. At the present time, energy from solar modules is generally more expensive compared with traditional energy sources such as nuclear, coal, and natural gas; over the long-term, however, this gap is expected to lessen to the point where solar energy becomes cost competitive against energy produced by these dispatchable energy sources (REN21, 2013; The Boston Consulting Group, 2012). Economic incentives, such as tax credits, are intended to reduce the financial challenges associated with PV systems (International Energy Agency, 2013c) and encourage investment (Theyel et al., 2011). Other popular economic incentives supporting solar energy, such as feed-in tariffs, will be discussed in detail Section 2.4.2.3. Finally, the funding method will also affect the economic viability of a PV system. Loan payments and associated interest charges, for instance, must be taken into account since they can add to the overall cost of implementing a solar installation (Masters, 2004).

This thesis will include one additional expense in the calculation of PV system economic viability: the cost of recycling photovoltaic modules. The cost associated with PV module recycling is important because solar panels contain materials that can be hazardous to humans and the environment if improperly handled at the end of their useful life (McDonald & Pearce, 2010). Moreover, proper PV recycling procedures are also required as a way to confront the challenges of using rare elements in solar cells. Tellurium, according to Marwede and Reller (2012), is a relatively rare element used in certain solar cells, and deficient tellurium supply levels could limit the potential "market growth" (p. 36) of PV cells containing this metalloid. El Chaar, Lamont, and El Zein (2011) support this idea and indicate that greater inventories of this rare element could affect prices of CdTe solar cells, which contain tellurium. Choi and Fthenakis (2014) also highlight the relationship between "natural resources scarcity and material price increases" (p.443) of certain elements used in PV cells. Potentially, PV module recycling programs could assist with creating larger inventories of these in-demand rare elements.

Multiple different methods are employed to separate, remove, and recycle desired elements from photovoltaic modules, which can be reused in new PV applications. For instance, Kang, Yoo, Lee, Boo, and Ryu (2012), and Klugmann-Radziemska and Ostrowski (2009) mention the use of chemical solvents and chemical etching, respectively, to extract sought-after materials. Additionally, Granata, Pagnanelli, Moscardini, Havlik, and Toro (2014), as well as T. Wang, Hsiao, and Du (2012) describe a procedure where a thermal process is used to remove valuable elements, such as silicon, contained within solar modules that have first been physically crushed into smaller pieces. There are different expenses associated with these processes, and PV module recycling cost figures are presented in the next paragraph.

Assuming a solar module of 1 m^2 in size, McDonald and Pearce (2010) indicate that recycling costs are approximately $9.00/module for CdTe solar panels, $20.24/module for CIGS solar panels, and $32.11/module for silicon-based solar panels. However, these values are in reference to studies from 1998 and 2000. Di Francia (2013) provides updated costs for dismantling and recycling solar panels in accordance with "The Waste Electrical and Electronic Equipment (WEEE) Directive" (p. 979), which assigns ownership of recycling and all related costs to certain equipment manufacturers, including solar panel makers, in Europe (Cherrington, Goodship, Longfield, & Kirwana, 2013). Scaling the figures provided by Di Francia (2013) to presume a 1 m^2 solar module, the cost for dismantling and recycling is on average €13.55 per silicon-based module. Di Francia's recycling figures will be used as part of the financial analysis of solar installation investment in this thesis. With a lack of data pertaining to the dismantling and recycling of concentrated photovoltaic modules, Di Francia's PV recycling figures will also be applied to CPV technology.

The opening paragraphs of Section 2.4.2 have outlined several different factors that can affect the economic viability of PV installations. Taking these details into account, financial metrics can be calculated to uncover the economic characteristics of an investment in a photovoltaic installation. The following section will delve into

some of the routinely used financial metrics associated with investments in solar energy.

2.4.2.1 Photovoltaic Financial Metrics

Projected measures of PV system profitability can be determined by analyzing all applicable costs and revenues associated with a PV system over its lifetime. This analysis generally begins by calculating projected yearly cash flows over a period of 25-years – the typical lifespan of solar modules – but this timeframe has some upward latitude (Branker et al., 2011). From these yearly cash flows, the *net present value* (NPV) of all cash flows can be determined. Baker and English (2011) define net present value as "the sum of the discounted cash flows (inflows) less the sum of the discounted costs (outflows)" (p. 60). A positive NPV indicates that a project will generate large enough sums of cash over its operational lifetime to recover all initial costs, and provide a rate of return greater than a predefined required rate of return (Swift, 2013). In other words, an organization will likely end up in a better financial position by investing in a project with a projected positive NPV value because the investment will create a net monetary benefit. Conversely, if the NPV of a project is negative, the investment is probably unwise since the initial amount of funds invested may not be recovered and the return on investment (ROI) will likely be less than the required rate of return (Masters, 2004).

Calculating NPV for a solar installation involves considering the cash flows generated by the solar modules during each year of operation, the degradation of said modules, operation and maintenance costs, loan costs, and a discount rate (Branker et al., 2011). While cash flow values are calculated simply by comparing the amount of money disbursed with the amount of money received during each year of PV system operation, the values of the other components are based upon generally accepted ranges of numbers defined by scientific sources and academic researchers. The ranges for each of these items will be discussed in the following paragraphs.

Once operational, the maximum possible amount of energy produced by solar modules declines as time moves forward via a phenomenon known as *degradation*. The degradation rate, as it is commonly referred to, varies between different sources: Zweibel (2010) indicates that annual degradation rates between 0.2-0.5% are realistic; Branker et al. (2011) note that most financial models use degradation rates between 0.5% to 1.0% per year, but also support Zweibel (2010) by stating that "in general, a degradation rate of 0.2-0.5% per year is considered reasonable given technological advances" (p. 4476); Lowder, Mendelsohn, Speer, and Hill (2013) make known that degradation rates for crystalline silicon solar cells have been steady around 0.5% based upon data collected over the past 20 years; and finally, Di Francia (2013) uses a linear degradation rate equal to 0.7% per year in his PV financial analysis.

Similar to degradation rates, operation and maintenance cost estimates vary within a range of acceptable values depending upon the source of information and method of calculation. For instance, Hernández-Moro and Martínez-Duart (2013) set out "annual operation and maintenance costs of 1.5% … of the total cost of the [PV] system" (p. 123). In contrast, National Renewable Energy Laboratory (2013a) uses a *dollar per kilowatt per year* figure, and indicates average operation and maintenance (O&M) costs for PV systems between 10-100 kW are $19/kW/year, with a standard deviation of $15/kW/year. Drury, Lopez, Denholm, and Margolis (2013) provide an O&M cost range of $22-$28/kW/year with a reference value of $25/kW/year for stationary PV systems in the United States, while Di Francia (2013) indicates that O&M figures "ranging between 0.4% up to 1% of the total PV plant cost have been reported" (p. 980). More recently, T. Nguyen, Spendelow, and Margolis (2014) state that O&M costs could be as low as $12/kW/year for PV commercial systems in the United States, while Klise, Balfour, and Keating (2014) note that operation and maintenance costs are estimated to be approximately 1% of total system investment each year. Assuming a $500,000 baseline capital investment as the analysis in this thesis will, both the spot estimate by T. Nguyen et al. (2014) and the proportional

estimate by Klise et al. (2014) fall within one standard deviation of the mean given by National Renewable Energy Laboratory (2013a). Operation and maintenance figures for CPV are a challenge to find at the present time. Consequently, this thesis will apply PV operation and maintenance costs for a 2-axis tracker to CPV technology in the financial analysis. According to Drury et al. (2013), PV installations with 2-axis trackers can incur additional O&M costs ranging between $0.00-$37.50/kW/year compared with fixed-tilt PV installations. With additional components to maintain, the CPV O&M costs used in the analysis will be greater than PV operation and maintenance expenses. As a final note about these particular expenses, operation and maintenance costs have less of an impact on PV system financial viability than installation costs. Muneer, Bhattacharya, and Cañizares (2011) add to this point by stating, "solar PV investment planning models are not significantly affected by their operating costs" (p. 2548).

The last two components of the NPV calculation, the cost of money loaned and discount rate, are also variable. Firstly, the cost of a loan will vary since the terms of the loan agreement and assigned interest rate will likely depend upon the lender's unique conditions and the financial status of the loan acquirer (Branker et al., 2011). Secondly, the discount rate, defined by Marks, Robbins, Fernandez, Funkhouser, and Williams (2009) as "the rate of return an investor would require to be induced to invest in the cash flow stream being discounted" (p. 563), must be high enough to entice investors. A summary of discount rates from recent literature for both PV and CPV installations is shown in Table 4:

Source	Type	Discount Rate
(Swift, 2013)	PV	7%
(Hernández-Moro & Martínez-Duart, 2013)	PV	10-12%
(Bazilian et al., 2013)	PV	5-10%
(International Renewable Energy Agency, 2013)	PV	10%
(REN21, 2013)	PV	7%
(International Energy Agency, 2013a)	PV	10%
(Reichelstein & Yorston, 2013)	PV	8%
(G. L. Barbose et al., 2013)	PV	7%
(Mabeea, Mannion, & Carpenter, 2012)	PV	8%
(Timilsina et al., 2012)	PV	10%
(Poullikkas, Hadjipaschalis, & Kourtis, 2013)	CPV	2-10%

Table 4. PV and CPV discount rates collected from the literature review.

In Table 4, discount rates applied to PV projects range between 5% and 12%. This span of discount rates is indicative of different risk levels associated with different PV investments. With regard to CPV technology specifically, the range of discount rates in Table 4 represents the span of inputs used in a sensitivity analysis performed by Poullikkas et al. (2013) for a prospective CPV installation as opposed to discount rates from an actual CPV system. Since CPV technology is relatively nascent and has yet to achieve the same scale as PV technology, many items such as discount rates, operation and maintenance costs, and other numerical figures pertaining to CPV investment projects are challenging to obtain at the present time. Figure 6 below provides a visual of the different discount rates from Table 4. Data points connected by a brace in Figure 6 indicate a range of discount rate values provided by the authors:

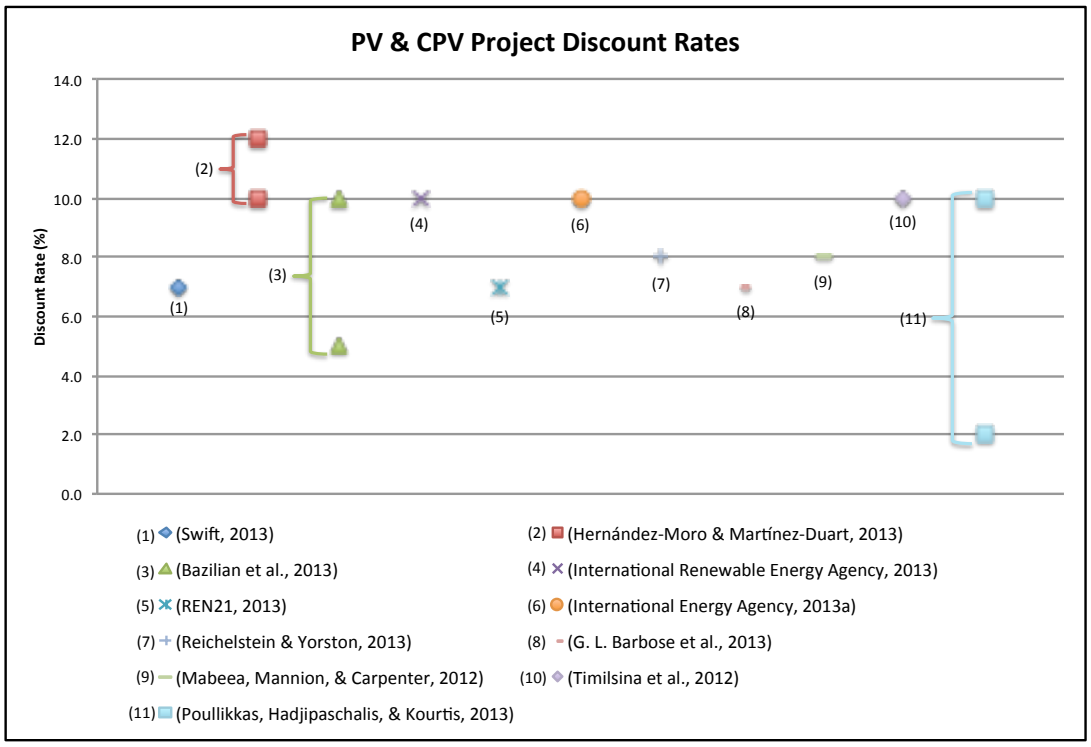


Figure 6. A visual of PV and CPV project discount rates uncovered during the literature review.

A second financial metric applicable to PV installation financial analysis is return on investment. The ROI is defined as "the ratio of money gained or lost (whether realised or unrealised) on an investment relative to the amount of money invested" (G. Liu, Baniyounes, Rasul, Amanullah, & Khan, 2013, p. 1929-1930). In other words, ROI compares the initial amount of money invested to set up the solar installation with the net present value of the amount of money generated over the entire operational lifetime of the PV installation. A solar installation project with a positive return on investment indicates the project has recovered all of the initial capital invested and generated additional funds, while a negative return on investment is indicative of a project that has neither recuperated all of the initially outlaid capital nor generated any additional funds.

Lastly, the metric internal rate of return (IRR) will be incorporated as part of the study of solar installation economic attractiveness. This particular financial measure "is defined as the interest rate at which present worth of the cash flows of a project are zero" (Odeh, Yohanis, & Norton, 2006, p. 854), or the discount rate associated

with a project that would produce a net present value of zero (Ayyub, 2003). Generally speaking, a project should be pursued when the IRR is greater than the discount rate (also known as the required rate of return), and a project should be avoided when the IRR is less than the discount rate (Bierman Jr., 2002). The financial analysis to be performed for this thesis will include each of the previously mentioned NPV, ROI, and IRR calculations.

It should be noted that these three financial metrics are not exhaustive by any means. Additional measures could be used to further assist with determining the economic viability of a proposed solar installation project. For example, Masters (2004) indicates that the breakeven point of a solar project, which is when the PV system begins to generate a profit, is another commonly used calculation. However, for the purposes of this thesis, NPV, ROI, and IRR calculations will sufficiently detail the economic attractiveness of potential solar installation investments.

2.4.2.2 The Levelized Cost of Electricity

Introduced earlier in the literature review, LCOE will now be discussed in greater detail. LCOE is typically used to compare the cost of generating electricity from different energy sources (Timilsina et al., 2012), and is usually expressed in either $/kWh or dollars per megawatt hour ($/MWh) format. Darling, You, Veselka, and Velosa (2011) describe LCOE as the "fairest comparison between energy supply technologies ... which takes into account the lifetime energy production and lifetime costs associated with a system" (p. 3133). Technically speaking, "LCOE is the average cost of production per kWh over the technology investment life" (Davis & Owens, 2003, p. 1593), and is the average price at which energy must be sold over the energy source's operational lifetime in order to breakeven on the initial investment (Darling et al., 2011). LCOE values can be computed for both traditional and renewable energy sources (Reichelstein & Yorston, 2013).

Calculating the LCOE involves several inputs, including: the initial investment or installed cost, which is sometimes referred to as the CAPEX; operation and maintenance costs, otherwise referred to as OPEX; a discount rate; loan and interest costs; the annual amount of electricity generated; and the expected operational lifetime of the system (Branker et al., 2011; Vanbuggenhout & Masson, 2011). Specifically for solar energy, the degradation rate of the solar panels is also taken into account (Hernández-Moro & Martínez-Duart, 2013; Swift, 2013).

With respect to the inputs mentioned in the previous paragraph, the literature review reveals a lack of consensus on specific input values used in LCOE calculations. Analogous to the NPV formula inputs mentioned in Section 2.4.2.1, LCOE inputs are each typically associated with a range of acceptable values in addition to an assumed or average figure. Using O&M costs as an example, Reichelstein and Yorston (2013) calculate the LCOE for a utility-scale PV installation exceeding 1 MW in size using O&M costs ranging between $15-$20/kW/year depending upon the solar cell technology. National Renewable Energy Laboratory (2013a), alternatively, indicates an acceptable O&M cost range of $10-$30/kW/year – with an average O&M cost figure of $20/kW/year – for utility-scale PV installations greater than 1 MW in size.

Ranges of acceptable degradation rates were provided in Section 2.4.2.1. Additionally, Reichelstein and Yorston (2013) used constant degradation rates ranging between 0.35% and 0.75% in four different LCOE calculation scenarios, but propose that degradation rates are not necessarily linear and should instead be higher during the initial years of PV system operation with eventual decreases over time. Contrasts in system costs are also evident between different sources. G. Barbose et al. (2014) indicate installed costs for utility-scale PV systems ranged between $2.30-$6.80/Wp in 2012. In comparison, International Renewable Energy Agency (2013) quotes installed costs for the year 2012 between $2.00-$3.60/Wp for systems of the same size. It should be noted that G. Barbose et al. (2014) included both fixed and tracking PV installations, as well as both crystalline and thin-film

solar cells in their assessment, which could explain their larger price span compared with International Renewable Energy Agency (2013).

These ranges of acceptable inputs will ultimately lead to a certain amount of variability when calculating the LCOE. In addition to input fluctuation, environmental variables, too, can cause the LCOE to vary. One such variable is the amount of solar irradiance the PV system receives, and this depends in part upon the latitude where the installation is located (Reichelstein & Yorston, 2013). Traditional PV technology can "take advantage of both direct and diffuse irradiation" (Hernández-Moro & Martínez-Duart, 2013, p. 125), meaning numerous potential installation locations exist worldwide. Generally speaking, however, photovoltaic installations are strategically placed to take advantage of higher levels of solar irradiance (Kucuksari et al., 2014; Lave & Kleissl, 2011).

But even within geographic locations where irradiance levels are favourable, other factors that could vary the LCOE must be considered. Cloudiness, for instance, will fluctuate depending upon the weather conditions at different latitudes, which can in turn influence irradiance levels and, consequently, the output of a PV system (Byea & Ceccaroli, 2014). Since LCOE calculations include the amount of electricity outputted by a PV system (Branker et al., 2011; Vanbuggenhout & Masson, 2011), a comparison of multiple PV installations from similar latitudes could theoretically yield different LCOE values due to site-specific environmental variables such as cloudiness. Thus, a consideration to make with respect to LCOE values is that they are not necessarily fixed and definitive due to the variable nature of the inputs used in their calculation.

To account for the variable nature of inputs, LCOE calculations may be performed more than once using multiple input figures chosen from an acceptable range of values, or, depending upon the context, different irradiance and cloudiness figures from varying geographical locations. This process is known as a sensitivity analysis (Reichelstein & Yorston, 2013), the output of which is several LCOE values that can

be compared to one another in order to determine the effect of declining capital costs, lower O&M expenses, or installing the PV system in a different region, for example.

Current LCOE values associated with solar PV are provided by multiple sources. Borenstein (2012) presented solar-generated electricity LCOE values between roughly $0.09/kWh and $0.45/kWh, a rather large range due to the fact that the author aggregated estimates from multiple sources, and these sources assumed different sizes of PV installations, capacity factors, project lifetimes, and subsidy amounts. Another estimate, provided by The Boston Consulting Group (2012), indicated that the levelized cost of solar energy for sunny locations within the United States could be between $0.17/kWh to $0.25/kWh depending upon the use of economic incentives. Additionally, figures from 2013 indicated that LCOE values for rooftop solar PV ranged from $0.20/kWh to $0.46/kWh in countries belonging to the Organization for Economic Cooperation and Development (OECD) and $0.28/kWh to $0.55/kWh for non-OECD countries (REN21, 2013).

Current projections indicate that solar PV LCOE values are expected to decline in the near future. U.S. Energy Information Administration (2014a) estimates that the LCOE for a new solar PV installation coming online in 2019 will be $0.13/kWh. This value is higher than the future LCOE estimates for silicon-based PV systems provided in Figure 7 based on Reichelstein and Yorston (2013):

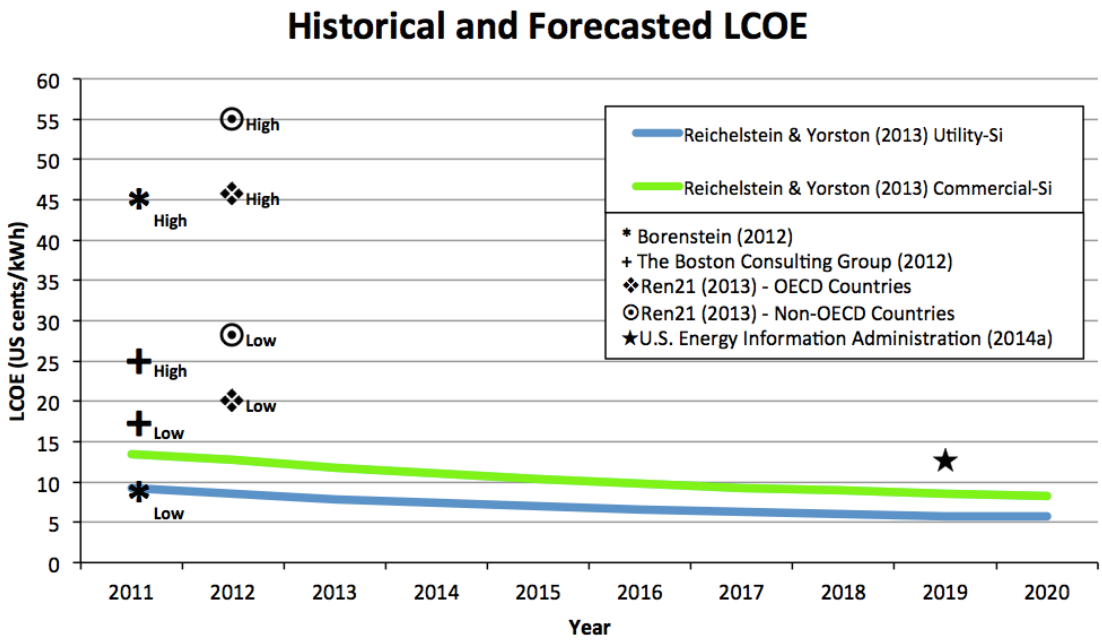


Figure 7. LCOE projections (green and blue lines) by Reichelstein and Yorston (2013) and other LCOE values from previously referenced authors. Note that the estimates from Borenstein (2012) encompass the years 2008-2011, inclusive. All points are approximate. Adapted from Reichelstein and Yorston (2013).

The LCOE values associated with solar PV technology are generally greater than those of other energy producing technologies. The highest LCOE estimate for solar provided by Borenstein (2012) was $0.45/kWh, which is significantly greater than the same author's highest LCOE estimate for coal power – approximately $0.12/kWh – and nuclear energy – roughly $0.15/kWh. Nevertheless, LCOE should not be the only consideration when comparing different energy producing technologies. Other factors, according to Bazilian et al. (2013), including the "value a particular technology brings to a power system" (p. 334), or the fact that "PV generation, in some locations, matches periods of higher demand and hence can be of high value" (p. 334) should be considered as well.

Unfortunately, the intrinsic value created by PV technology can be challenging to quantify unless solar power is sold at prices truly reflective of supply and demand levels. This would be possible in areas where wholesale electricity marketplaces operate, including the provinces of Ontario and Alberta (National Energy Board, 2013) and more than 30 states in the U.S. (Hummon, Denholm, & Margolis, 2013).

Furthermore, the cost of energy produced by solar technology is often compared to other generating technologies using the LCOE metric (Borenstein, 2012). Thus, reducing PV's LCOE likely has merit, and the following paragraph highlights ways in which reductions could be achieved.

According to Reddy (2012), lowering system costs, as well as operation and maintenance costs would lessen LCOE values. Moreover, increasing PV module energy output via solar cells with higher efficiencies, or tracking the sun's movement during daylight hours so that more electricity is produced can potentially assist with this endeavour (Reddy, 2012). Incentives, to be discussed in the next section of the literature review, and subsidies could also make solar energy more economically attractive compared with traditional sources of energy such as coal and nuclear power (The Boston Consulting Group, 2012). However, in order to specifically reduce solar PV's LCOE, subsidies would need to assist with reducing initial system costs or ongoing operation and maintenance expenses.

The use of the LCOE metric may be an established method of comparing the costs of energy from different generating technologies. However, some authors perceive the many different sources of variability associated with the LCOE as a cause for concern, and they cast doubt upon the validity of the metric. Branker et al. (2011) note that the LCOE "is deceptively straightforward" (p. 4471) and could be used to misrepresent the true cost of energy if the inputs are not clearly stated or are unrealistic. This is where the previously mentioned range of acceptable input values could create issues, and Darling et al. (2011) make known that the variability of the acceptable input numbers into the LCOE formula could result in a misreported LCOE value. Joskow (2011) indicates that using the LCOE to compare renewable energy sources with conventional energy sources is flawed because this method does not account for the true value of the energy provided by the renewable source. Borenstein (2012) supports this particular idea and elaborates upon it by stating that solar energy is typically produced in highest quantities during midday, which generally happens to coincide with peak electricity grid demand and, potentially,

peak prices for electricity. With respect to this phenomenon, Borenstein (2012) concludes, "the average economic value of generation from solar is greater than if it produced the same quantity of power on average at all hours of the day" (p. 74); unfortunately, the LCOE calculation does not take this facet of PV energy production into account.

Joskow (2011) also indicates that the economic attractiveness of a solar installation should be based upon factors besides LCOE, including its expected profitability and value of the electricity produced. Solar energy has the capacity to provide economic benefits besides a revenue stream from electricity produced and sold, including value from electricity *not* consumed from the electrical grid. Along with calculations and comparisons of LCOE figures, this thesis will quantify the value of avoiding electricity consumption and associated charges for said consumption by generating photovoltaic electricity as part of the analysis. A specific analysis will focus upon electricity charges and costs unique to large energy consumers within the province of Ontario. This analysis will assist with determining the true value of solar energy when used to offset existing demand and associated demand costs.

As solar cell efficiencies continue to improve, and as the various costs associated with PV systems continue to decline, PV's LCOE will proceed to edge closer to retail electricity price values. Grid parity is certainly feasible, and this is already the case in certain parts of the world. In Germany, for instance, longstanding policies promoting PV adoption have created conditions where the LCOE for residential and commercial solar installations is currently lower than retail electricity rates (European Photovoltaic Industry Association, 2013). The example of Germany, however, is more of an exception rather than the rule, since the LCOE of solar generated electricity is typically greater than retail electricity rates in most other areas. In such regions where solar generated electricity is unattractive due to its high cost, incentives can be used to entice both investment in, and the use of, solar energy. One particularly popular incentive program model, the *feed-in tariff*, will now be discussed in detail.

2.4.2.3 Feed-in Tariffs

The total amount of photovoltaic installed capacity worldwide has increased steadily since the turn of the century, and is expected to continue to grow for the foreseeable future (Moosavian, Rahim, Selvaraj, & Solangi, 2013). Incentives, which entice users to adopt photovoltaic technology, have undoubtedly contributed to this growth (G. Barbose et al., 2014; Guidolin & Mortarino, 2010). These inducement vehicles can come in the form of tax credits and advantageous financing terms for PV projects, subsidies that bolster the price paid for solar produced electricity, and rules stipulating that solar energy must be purchased even if it is more expensive than other sources of energy (Timilsina et al., 2012). This latter point describes feed-in tariffs, a program widely implemented in many jurisdictions to date and seen as one of the more favoured methods of enticement (Mabeea et al., 2012).

According to Couture and Gagnon (2010), feed-in tariff programs are "increasingly considered the most effective policy at stimulating the rapid development of renewable sources" (p. 955). Evidence of this effectiveness is illustrated not only by the previously mentioned example of Germany, but also by the example of Japan. According to Theyel et al. (2011), in Japan, a country that has used feed-in tariffs for many years to promote the use of solar energy, subsidies are no longer required to make PV produced electricity competitive with retail electricity on cost. Although not all FIT programs have been as successful as Germany's and Japan's to date, the characteristics of FIT programs are somewhat similar across jurisdictions.

Timilsina et al. (2012) state that FIT "refers to a premium or tariff or payment to new and renewable energy technologies which are relatively expensive or may not be competitive with conventional technologies for electricity generation" (p. 457). The objective of FIT programs is to ensure a reasonable rate of return on funds invested into a solar installation over the project's lifespan (The Boston Consulting Group, 2012). Moreover, FIT programs assist with both ensuring the payback period of the initial investment is less than the operational lifetime of the PV system

(Würtenberger, Bleyl, Menkveld, Vethman, & van Tilburg, 2012), and reducing the risks associated with PV system investments, which can in turn decrease the financing costs associated with these projects (Wüstenhagen & Menichetti, 2012).

The popularity of FIT programs can be illustrated by recent utilization figures. As of the beginning of 2013, the combined number of American states and Canadian provinces with FIT programs is 28, while the total number of countries with FIT policies in place is 71 (REN21, 2013). Among these different jurisdictions, the tariff amounts paid to solar energy producers can vary greatly depending upon the location and the size of the solar installation (Timilsina et al., 2012). For example, the tariff associated with a 100 kW rooftop solar installation in the province of Ontario today is CAD 0.343/kWh (Ontario Power Authority, n.d.), while in the state of Oregon, a solar installation of the same size can expect to receive between USD 0.16/kWh and USD 0.175/kWh depending upon its location within the state (State of Oregon Public Utility Commission, 2014). A 100 kW stand alone solar installation in the United Kingdom, comparatively, can expect to receive £0.0899/kWh on average today (Office of Gas and Electricity Markets, 2014), which at the time of writing was approximately CAD 0.16/kWh.

Since the data collected and used in this thesis are from the Ottawa area, the most recent FIT price schedule for solar projects in Ontario is displayed in Table 5:

Renewable Fuel Project Size	Tranche	FIT Price (CAD/kwh)
Solar (PV) (Rooftop)	≤ 10 kW	0.384
	>10, ≤ 100 kW	0.343
	>100 kW	0.316
Solar (PV) (Non-Rooftop)	≤ 10 kW	0.289
	>10 kW	0.275

Table 5. FIT tranches and prices for PV as of September 30, 2014 (Ontario Power Authority, n.d.).

The price paid for solar generated electricity under the Ontario FIT program is guaranteed by 20-year contracts (International Energy Agency, 2013c). These prices represent the third iteration of FIT subsidies in Ontario since the program's

inception in 2009, and are much lower than the program's initial tariffs (Winfield & Dolter, 2014). According to Luukkonen et al. (2013), these cost reductions are specifically attributable to the "decreasing cost of modules and other system components" (p. 18). The declining Ontario FIT program subsidies are in line with an assertion by International Energy Agency (2013a), indicating that FIT programs should decrease incentive amounts over time in order to motivate PV manufacturing companies to innovate and improve upon the cost efficiency of their products.

As alluded to by the number of jurisdictions currently employing feed-in tariff programs, FITs "are currently the most commonly used incentive tools for renewable energy production worldwide" (Würtenberger et al., 2012, p. 46). Governments oversee the administration and application of FIT programs in most instances (Verbruggen & Lauber, 2012). As well, governments overall appear to be more focused on developing FIT programs, which "focus on market creation, production increases and removal of deployment barriers" (Stokes, 2013, p. 491) instead of creating and funding PV technology research and development (R&D) programs. Ayoub and Yuji (2012) substantiate this idea by indicating that overall R&D spending on energy by developed nations has declined significantly from maximum levels achieved in the 1980's.

The popularity of feed-in tariffs is at least in part attributable to the many advantages of the program. Verbruggen and Lauber (2012) note that the pricing structure of FIT contracts is generally well defined and thus predictable over the entire lifetime of the agreement. Couture and Gagnon (2010) indicate that the transparency of FIT pricing assists with reducing risk to investors, which in turn helps to create an environment that fosters solar energy market growth. Along with reducing risk, feed-in tariffs typically provide a "reasonable return on investment" (Zhu & Venkatesh, 2010, p. 816) to those providing the initial capital. Ambec and Crampes (2012) view FIT programs as vehicles that reduce the attractiveness or competitiveness of nuclear, coal, and oil energy producing technologies, which in

turn helps to bolster the ongoing development of alternative energy producing technologies such as photovoltaics. Moreover, and perhaps most importantly, FIT programs, according to Ayoub and Yuji (2012), do more than simply provide a premium price to solar energy producers because in the long-term, these tariffs help to create a marketplace for PV energy. Stokes (2013) supports this idea by indicating that new jobs are usually created in jurisdictions that implement FIT programs. Also within these areas, both PV system component manufacturing plants and PV equipment installers typically reap at least some net benefit in the form of new jobs created and heightened demand for their products and services. As an illustration of this point, Pearce (2010) notes that after the FIT program was implemented in Ontario in 2009, many companies with ties to the PV sector set up operations in the province at "a breathtaking pace" (p. 29).

However, several authors also highlight the drawbacks of FIT programs. Timilsina et al. (2012) note firstly that feed-in tariffs fail to reduce the high upfront costs of PV systems, which can be a major investment hurdle, and secondly that FIT programs increase the price of electricity paid by energy consumers in the short-term. Wüstenhagen and Menichetti (2012) and Winfield and Dolter (2014) both support this latter point by indicating that critics in Germany and Ontario, respectively, have denounced PV FIT programs for adding to the cost of energy in those regions. FIT program pricing transparency, previously expressed as a benefit, can also act as a drawback. Although beneficial for investors, the transparency of FIT prices makes them well suited for attack from opponents, notes Stokes (2013).

Continuing with drawbacks, FIT programs are typically funded by electricity ratepayers, and if a particular region has an insufficient threshold of electricity consumers to draw upon for funding, the FIT program may not be feasible (The Boston Consulting Group, 2012). As well, FIT programs can be subject to change, and governments may modify FIT rates or renegotiate contracts under certain circumstances (The Economist Intelligence Unit, 2011). If FIT contract renegotiation occurs, the original return on investment calculated at the time of contract signing

could be reduced if the incentive rate is unexpectedly cut. While this is not a common occurrence, Yatchew and Baziliauskas (2011) indicate that the Ontario government has said it is "willing to adjust [FIT contract] prices out-of-schedule" (p. 3892) if the need arises.

A summary of the previously mentioned FIT program characteristics are indicated in a strengths, weaknesses, opportunities, and threats (SWOT) analysis in Table 6:

Strengths	Weaknesses
• Revenue stream is relatively predictable	• Does not address high upfront costs of PV systems
• Incentive prices are known ahead of time for duration of contract	• Increases electricity rates to a certain extent in the short-term
• Incentive stability reduces investor risk	• Transparent prices make FIT programs ripe for criticism
• Provides at least an acceptable return on investment	• May not be appropriate for all areas
Opportunities	**Threats**
• Can create new marketplaces for solar, which includes new jobs	• Political pressures or changes in governments may impact FIT programs
• Helps with further developing photovoltaic technology	• Public support may deteriorate if electricity rates increase

Table 6. FIT program SWOT analysis. Adapted from (Würtenberger et al., 2012).

Of all the strengths of FIT programs, perhaps the most important is the program's ability to reduce investor risk. In the following section, literature covering PV's risk identification, assessment, and management will be covered in further detail.

2.4.2.4 Summary

In Section 2.4.2, it was determined that economics play a large role in determining whether or not a solar installation will receive investment money and consent to be built. Related to this point, the high up-front cost of installing a PV system was identified as a major hurdle that could impede some from setting up an installation. Additionally, the projected amount of energy produced by a PV system is also an

important consideration when forecasting expected profits since energy output is linked to the amount of revenue generated. Other profitability factors, such as the availability of tax credits, favourable financing methods and terms, operation and maintenance costs, and the expected useful lifespan of the PV system were also identified. Some financial metrics used to measure the economic attractiveness of a solar installation were introduced, which included net present value, return on investment, and internal rate of return. A method of comparing the cost of electricity from different generating sources, levelized cost of electricity, was introduced and discussed, and the merits of using this metric for solar energy were analyzed. Current solar LCOE values were presented and compared against coal and nuclear LCOE figures. This comparison indicated that, at the present time, coal and nuclear produced energy is less expensive than energy produced by solar cells. Finally, the idea of feed-in tariffs was introduced as a popular method of incentivizing solar energy production. A discussion of FIT program characteristics and prices paid for energy produced under this program was provided, as was a FIT program SWOT analysis.

2.4.3 Solar Photovoltaic Risks

Many of the risks associated with PV technology have already been highlighted in this literature review, including the risks associated with providing a large amount of upfront capital for PV system construction (Timilsina et al., 2012), PV's vulnerability to different weather conditions (Patt et al., 2013; Tyagi et al., 2013), and variable PV module output (Noro et al., 2012). Moreover, McDonald and Pearce (2010) noted the danger posed by some chemical elements contained within certain solar cells, while Yatchew and Baziliauskas (2011) touched upon the prospect of wavering political support for solar power.

There are different levels of risk associated with each of the items touched upon in the previous paragraph, and some items may be more suitable for some form of risk management than others. Regardless, each of these items represents a potential

drawback of using, or investing in, PV technology, and protections against these deterrents are sought. With respect to the renewable energy sector, the importance of guarding against risk is noted by Borghesi and Gaudenzi (2013) who state "risk management is required to protect ... investments and help ensure that the renewables industry continues to develop" (p. 112). The following sections will cover the identification and assessment, as well as management, of risks commonly associated with photovoltaics. Additional risks tied to PV technology will also be highlighted throughout the upcoming sections.

2.4.3.1 Risk Identification

According to Ayyub (2003), risks should be identified by drawing upon the viewpoints of multiple stakeholders with previous, related experiences. One benefit of garnering input from multiple perspectives is that this approach can help identify a more inclusive list of potential risks (Ackermann, Howick, Quigley, Walls, & Houghton, 2014; Letens, Van Nuffel, Heene, & Leysen, 2008). As per the literature, some of the risks inherent to photovoltaic energy projects specifically can include: technology risk, although for PV this may be limited to newer types of solar cells; financing risk, which could refer to undetermined future electricity prices or the likelihood of recovering the initial outlay of capital used to construct the PV installation; and competition risk from other electricity generating sources which may be less expensive than solar-produced electricity (National Renewable Energy Laboratory, 2005). As well, risk can be associated with: construction contractors, if they are unable to deliver as per contractual obligations on specifications and costs of a PV system; the vulnerability of PV equipment to theft, damage and in rare cases vandalism; regulatory risks, where incentives supporting the use of PV technologies can be reduced or revoked; and natural disasters or catastrophic global events such as volcanic eruptions that could devastate the physical structure of a photovoltaic system or the ability of a PV system to produce energy (Agrawal, 2012).

Much of the risk attributed to PV investments, however, is tied to uncertainty, and one major source of uncertainty is the amount of electricity that a PV system will produce (Thevenard & Pelland, 2013). The quantity of PV system energy yield is related to the amount of solar irradiance the system receives, which is in turn impacted by meteorological conditions. The physical locations of solar modules, as well as weather conditions at these locations "often play key roles in contributing to potential risks" (Speer, Mendelsohn, & Cory, 2010, p. 1).

A map illustrating the amount of electricity that could be generated by a solar installation may be referenced to identify areas for a prospective photovoltaic system at a high-level. Figure 8 shows a map of Canada with estimates of yearly photovoltaic energy yields:

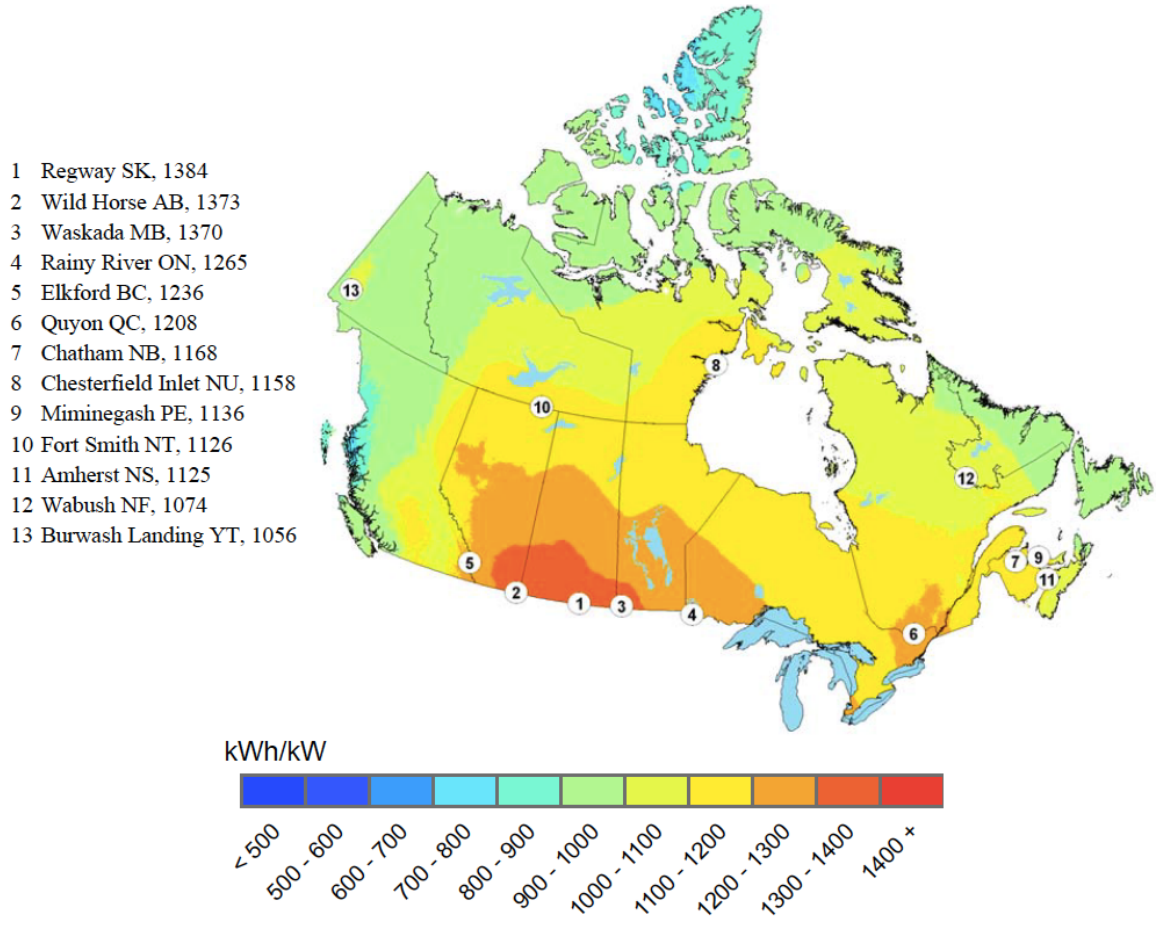


Figure 8. Energy yield estimates in kWh/kW/year across Canada featuring 13 of the best locations for PV systems. Note that Ottawa, the area of focus for PV investment in this thesis, is within a section of higher irradiance levels than much of the surrounding area (Pelland et al., 2006).

Clearly, some regions have better PV potential than others according to Figure 8. However, to better gauge PV potential for a precise area, solar irradiance readings should also be collected from instruments at the exact location. According to Vignola, Grover, Lemon, and McMahan (2012), data measurements from irradiance-reading instruments placed at the location of interest can compliment satellite data to curtail the risk of miscalculating the amount of solar irradiance in a given area. Schnitzer, Johnson, Thuman, and Freeman (2012) also note the how site-specific data "generally leads to a more accurate assessment of the solar resource than modeled data or surface-based reference data sources, leading to greater confidence in corresponding energy estimates" (p. 3056). This thesis will utilize a combination of data that includes raw energy yields from more than one PV installation from the Ottawa area as well as publically available irradiance and meteorological datasets for the Ottawa region produced by scientific agencies.

Returning to Figure 8, this map illustrates that different regions have varying amounts of solar potential even at similar latitudes. One possible explanation for this phenomenon is local weather patterns, which are dynamic in nature and a direct cause of PV energy yield uncertainty. Understanding local weather conditions, and recognizing the likelihood that a particular area will have favourable conditions for solar PV – a greater number of sunnier rather than cloudy days, for instance – is a vital part of the risk identification process (Vignola et al., 2012). While a region that is notorious for its overcast and rainy conditions may be dismissed outright as a location for a photovoltaic system, other areas with more variable weather conditions may require in-depth analysis. Several authors have looked at the use of weather forecasting to determine the overall riskiness of a location for a PV system. For example, Detyniecki, Marsala, Krishnan, and Siegel (2012), Shi, Lee, Liu, Yang, and Wang (2012), Pelland, Galanis, and Kallos (2013), and Chicco, Cocina, Di Leo, and Spertino (2014) each assessed the accuracy of models that predict the amount of electricity generated by PV installations based upon weather forecasts and found that energy output can indeed be predicted within a certain degree of confidence.

Related to weather conditions are temperatures, which can also impact the performance of PV modules. For example, Kim, Lim, Song, Chang, and Jeon (2011) note that the largest effect of ambient temperature on photovoltaic modules is "the overall decrease in the maximum power of a PV module as the temperature increases" (p. 406). Meral and Dinçer (2011) echo this sentiment and note also that lower temperatures can elevate PV cell voltage levels. Makrides, Zinsser, Phinikarides, Schubert, and Georghiou (2012) add to this topic by stating that it is the efficiency of *crystalline* silicon solar cells that decrease when ambient temperatures rise. As an example of this, a study of photovoltaic systems in Saudi Arabia by Rehman and El-Amin (2012) found that when the ambient temperature in July ranged between 30-40°C, the temperature of the surface of the PV panels under study could exceed 70°C, causing performance losses of the solar cells. This cell temperature is much warmer than the standard test condition temperature of 25°C for solar cells mentioned in Section 2.4.2. The risks posed by weather and temperatures, as well as the myriad risks identified at the beginning of this section, are important considerations when determining a suitable location for a PV installation. Once risks have been identified, attention should turn to assessment. The following section will discuss how risks related to PV can be assessed.

2.4.3.2 Risk Assessment

This literature review has uncovered three common methods for assessing risks, including quantitative risk assessment, qualitative risk assessment, and semi-quantitative risk assessment. Quantitative risk assessments, for example, use data as input for analyses that associate values with risks (Ayyub & Amin, 2007), allowing different risks to be compared with one another (Aven, 2011). Comparing and contrasting risks can help to determine which risks are more significant, or if a particular risk is justifiable against a specific risk threshold. Simulations and sensitivity analyses are both types of quantitative risk assessments (Kendrick, 2009), and this thesis will employ one or both of these techniques using empirical data in the analysis section.

In contrast, qualitative risk assessment "is distinguished primarily by its lack of reliance on numerical expressions of risk" (Yoe, 2011, p. 223) and "aims to describe each risk using words and phrases" (Hillson, 2004, p. 108). Ostrom and Wilhelmsen (2012) support Hillson (2004) by providing examples of words used to describe risk, including 'minimum,' 'moderate,' and 'maximum.' Although less technical in nature, qualitative risk assessments may be more appropriate in situations where data is unavailable to perform a quantitative risk assessment, when time does not permit a lengthy or more involved quantitative assessment, when the risks are minimal and a simpler qualitative assessment is sufficient, and as a broad risk assessment prior to a more detailed quantitative assessment (Rausand, 2011).

Finally, semi-quantitative risk assessments are a sort of middle-ground between purely quantitative and qualitative risk assessments, where quantitative values can be associated with qualitative words or categories to enhance a risk evaluation (Loosemore, Raftery, Reilly, & Higgon, 2006). According to Bowden, Lane, and Martin (2001), this type of risk assessment, for instance, could consist of a matrix of qualitative risks ranked by probability of occurrence. Cox Jr. (2008), however, cautions that semi-quantitative risk assessments may over-simplify pertinent information, lack transparency, and be overly subjective in nature. Since this thesis will use quantitative data, the literature review will next focus upon two quantitative risk assessment methodologies that can be applied to PV technology.

Firstly, Dobos, Gilman, and Kasberg (2012) present the idea of an "exceedance probability" (p. 2), which is typically used to assess energy production risk (Kleissl, 2013). An exceedance probability is the likelihood that the quantity of electricity generated by a solar installation will exceed a certain number of kilowatts over the course of one year (Dobos et al., 2012). For example, a P90 value means, "there is a 10% chance that this level [of energy output] will not be met" (Gray, Watson, Silva, & Gramacy, 2013, p. 20). Thus, a P90 value of 1,000 kWh signifies there is a 10%

chance that a photovoltaic system will not produce 1,000 kWh of electricity over the course of one year.

Even if a "P" value classifies a PV installation as risky, Würtenberger et al. (2012) note that higher risks can be accounted for "by applying a high discount rate or requiring a higher return on investment to compensate for the risk" (p. 17). Thus, a lower discount rate could indicate modest risk, while a higher rate points to greater risk. Exceedance probabilities can be calculated using modeled datasets or site-specific data from operational PV modules (Schnitzer et al., 2012).

Secondly, as an alternative to calculating exceedance probabilities, a simulation could be used to calculate and quantitatively model the uncertainty associated with PV investments. Simulations can be powerful tools, as they have the ability to account for many different variables, including variability in energy yields and prices paid for PV-produced electricity. A specific type of simulation, known as a Monte Carlo simulation, is commonly used to quantify the risks associated with PV installations.

A Monte Carlo simulation is a powerful forecasting tool, described by Kritzman (1993) as "a numerical technique that allows us to experience the future" (p. 17). While this assertion may contain a degree of hyperbole, it is not completely inaccurate. Whiteside (2008) indicates that "the true power of Monte Carlo simulation is in data extrapolation, or forecasting beyond the known data points and understanding the range of outcomes expected" (p. 1).

The Monte Carlo technique assigns new values to variables each time a simulation is performed, and after repeating the simulation numerous times, "the outcome is a probability distribution of the overall system calculated through the iterations of the model" (Kwak & Ingall, 2007, p. 45). Darling et al. (2011) provide a similar description by indicating that Monte Carlo simulations create "models of possible results through the substitution of range values – a probability distribution – for any

factor that has inherent uncertainty" (p. 3137), and present not only what is expected in the future, but also the probability of the outcome. This "probabilistic result" (Collins & Crowther, 2011, p. 6266) enables key statistics to be calculated, which aids with analysis of the simulation results. With respect to the exceedance probabilities mentioned previously, Whiteside (2008) remarks that a Monte Carlo simulation can be used to compute P50 values.

Monte Carlo simulations are commonly used as a tool to quantify risks (Kwak & Ingall, 2007), which can help with decision-making since "probability distributions [from Monte Carlo simulations] are an informative method for describing uncertainty" (Darling et al., 2011, p. 3137). This specific simulation technique has been applied in many fields, including commerce applications, engineering explorations, scientific studies, and financial analyses (Thomopoulos, 2013). As well, the Monte Carlo technique has been applied to photovoltaics: Collins and Crowter (2011) used a Monte Carlo simulation to model the energy output from PV modules given uncertainty in sunlight; Branker et al. (2011) noted that the Monte Carlo technique can be applied to the inputs used to calculate the LCOE, thus determining the sensitivity of the LCOE, while Darling et al. (2011) ran Monte Carlo simulations to gauge the sensitivity of PV system LCOE values; Goodrich, James, and Woodhouse (2012) employed a Monte Carlo simulation to determine a distribution of PV system prices for residential, commercial, and utility-scale PV installations; Parida et al. (2011) made reference to a study where a Monte Carlo simulation was employed to predict the quantity of energy produced by distributed PV systems; and Muneer et al. (2011) leveraged the Monte Carlo technique to determine the NPV of a large-scale PV installation using variable discount rates and energy yields.

This thesis will employ the Monte Carlo technique to assess the risks associated with both uncertain electricity prices and variable energy yields from PV systems. While the Monte Carlo technique has been applied by some of the authors in the previous paragraph to observe variability in PV system energy yields, the technique has, thus far, seen limited application to electricity prices. Jung and Tyner (2014)

used a Monte Carlo simulation on electricity prices as part of their economic analysis of PV systems in the state of Indiana. However, this literature review did not uncover any previous instances where a Monte Carlo simulation had been used to simulate variability of Ontario's electricity prices as part of a PV economic analysis.

Once risks have been identified and assessed, focus can then turn to management. The next section will discuss how risks associated with photovoltaics are managed.

2.4.3.3 Risk Management

Some risks are simply beyond one's control, while others are manageable. For risks that are amenable to proactive measures, Kendrick (2009) highlights three methods of responses to risk "including avoidance, mitigation, and transfer" (p. 182). According to Webb (2003), risk avoidance involves "choosing a course of action in which the risk is not encountered" (p. 98). It can entail negating a specific component of a project in order to reduce overall risk (G. M. Hill, 2010), but it can also include abandoning a project all together. Dropping an entire project to avoid risk, however, is a drastic course of action that is usually undertaken only if there are overwhelming concerns about moving forward with a venture (Edwards & Bowen, 2005).

Risk mitigation, on the other hand, "is an action, consciously taken by management, to counteract, in advance, the effects on the business of risk events materializing" (Kenett & Raanan, 2010, p. 29). According to Agrawal (2012), renewable energy projects risks can be mitigated via insurance policies, contracts, and selecting specific project details so as to minimize threats. "Business interruption insurance" (Lowder et al., 2013, p.21), for example, is commonly used to protect against operational disruptions that suspend revenue generation once a PV system is in working order. However, risk can also be mitigated prior to PV system construction via the use of real options (Bensoussan, 2009).

Real options are somewhat related to their financial counterparts, which are typically used as insurance against unfavourable market movements. Martinez-Cesena, Azzopardi, and Mutale (2013) define a *real option* as "the right, without obligation … to adjust the project in response to the evolution of uncertainty" (p. 251), which could include the adjustment of delaying project investment, for example. Conversely, Greden, Glicksman, and Lopez-Betanzos (2005) define a *financial option* as a contractual agreement that provides the "owner [of a financial asset] the right, but not the obligation, to purchase (or sell) a financial asset … for a specified price on or by a certain date" (p. 204). The idea of the *right* but not the *obligation* to act is the essence of options. If the financial option definition provided by Greden et al. (2005) was applied to solar energy investment, it could be said that the owner of the location where a solar installation is to be constructed has the right, but not the obligation, to build a PV system at a future capital cost at a later point in time.

The notion of associating value with the ability to delay project investment – especially for those projects with irreversible capital expenditures – is brought forward by Boomsma, Meade, and Fleten (2012), who characterize PV installations as having irreversible capital costs and "high uncertainty" (p. 226) with regard to earnings during operation. Doan and Menyah (2013) echo this sentiment by noting that for infrastructure projects with irreversible capital costs, the option of postponing construction until a future point in time does indeed have value. Menegaki (2008) agrees as well that there is value stemming from the flexibility to defer renewable energy investment to a later period in time. In reference to the high uncertainty mentioned by Boomsma et al. (2012), Davis and Owens (2003) state that overall "the more volatile the environment, the more valuable the option to wait" (p. 1599). This particular idea alludes that the ability to defer investment until a later, less volatile period in time has value since waiting avoids the higher risks associated with investing during turbulent market conditions.

Unfortunately, the mathematics used to calculate the true value provided by real options is outside of the scope of this thesis. This research will, however, incorporate real options as part of its analysis from a simplified standpoint by examining the present value of discounted cash flows from PV investments made at regular intervals in time. The results of the net present value calculations will indicate whether or not investment in a PV system should be initiated soon or postponed until later.

Several authors have noted the differences between the traditional net present value method and the real options approach, as well as the inadequateness of the former to provide proper valuation under some circumstances. For example, Martinez-Cesena et al. (2013) uncover which factors impact the decision to delay investment in photovoltaic technology, and note that traditional discount cash flow (DCF) and NPV analyses only "either recommend abandoning the project or investing immediately" (p. 250). Ergo, these particular traditional investment assessment methods are rigid and may not be particularly useful as valuation tools when future capital costs and PV module efficiencies are subject to variability, or when PV projects can be altered once they have been initiated.

Other authors share similar points of view. Siddiqui, Marnay, and Wiser (2007) state that the value of *altering* an investment is "often overlooked by the DCF approach," (p. 267) but is accounted for by real options. Letens et al. (2008) note that the DCF method assumes a static discount rate and cannot account for dynamic risk over the course of a project's lifetime, whereas real options can incorporate fluctuating risk levels. Even Calabrese, Gastaldi, and Ghiron (2005), who performed a real options study about PV manufacturing, found that the net present value method cannot properly assess the value of the option to expand capacity of the manufacturing facility.

This thesis, however, will incorporate capital cost projections that follow a predetermined declining trend line over time and subsume improvements in PV

module efficiencies. Furthermore, it will assume that PV system investment is irreversible once it has been made and that there is no option to upgrade the PV installation once it has been constructed. By incorporating PV module efficiency improvements into projected capital costs and by presuming that the PV investment is irreversible and unalterable, the NPV methodology is sufficient in this case to valuate both current and future PV investments. Additionally, in response to Siddiqui et al. (2007) who state the discount cash flow method "does not consider uncertainty in the cash flows" (p. 267), this thesis will introduce cash flow variability by use of the Monte Carlo simulation method mentioned in the previous section.

Even though there exist differences between the discount cash flow method and real options approach, Martinez-Cesena et al. (2013) note that real options are not a replacement for NPV analysis. Calabrese et al. (2005) agree and state that the real options approach "is not proposed as an alternative that supplants classical methods; on the contrary it supports these methods" (p. 190). Menegaki (2008) substantiates this idea further by noting that both "risk-adjusted discount rates and options theory … are complementary approaches" (p. 2429) to evaluating risk. Thus, while the real options approach may be the most suitable method to valuate flexible investments, the traditional NPV methodology is perfectly appropriate for valuating other types of investments, such as those contained within this thesis. The net present value analysis proposed by this research is one method of managing risk internally, but in some cases the best option is to transfer risk outside of the organization.

Risk transfer, the third of the three previously identified preventative responses to risk, involves handing over risk to another party (Reynolds, 2012). When risk is transferred, the transferee assumes responsibility for said risk and is compensated appropriately via an insurance or risk premium, for instance (Ayyub, 2003). Based upon the literature review, insurance is one of the more popular means of protecting PV systems from risks. The Economist Intelligence Unit (2011), for

instance, states that insurance policies are the most popular means of transferring renewable energy risk. Previous PV financial analyses account for insurance expenses using the following quantities: Fthenakis, Mason, and Zweibel (2009) stated insurance costs to be approximately 2% of capital costs; Darling et al. (2011) noted that the cost of insurance was "assumed to be 0.5% of the installation cost" (p. 3135); and Branker et al. (2011) factored in an insurance cost equal to "1.5% of the total system cost" (p. 4477) for their example of a PV system set in Ontario. Also for PV, many solar module manufacturers include warranties with their products. If a problem arises with the product, the onus is on the manufacturer to fix the issue. Lowder et al. (2013) note that warranties can include a 25-year promise that the output from the solar modules will stay above a certain threshold, as well as a warranty on the PV module materials and labour used to install the system. However, Speer, et al. (2010) indicate that warranties cover only limited items, and so additional insurance is still required in many cases.

However, as Leblanc (2008) notes, the renewable energy insurance industry is an emerging field of study with limited insurance claim data, and insurers typically account for this uncertainty within the premiums charged to customers. Aside from insurance, risk can be transferred by other means. For instance, risk can be transferred using contractual obligations – in the form of a liability waiver, for example – or through the transfer of property ownership where an asset and its associated legal responsibilities are signed over to another party (Speer et al., 2010; Voorhees & Woellner, 1998).

There are different approaches risk management. The appropriate method will depend upon the risk tolerance of the organization and the risk characteristics of the project or initiative at hand. For PV projects, a *quantitative* approach to either *avoid* or *mitigate* risk is likely the most suitable course of action, and the various tools mentioned in Section 2.4.3.3 have been developed in order to assist with properly managing PV investment risks.

2.4.3.4 Summary

Section 2.4.3 highlighted several topics pertaining to photovoltaic risks. It was noted that different levels of risk exist, and some risks may be more suitable for risk management initiatives than others. Risk identification, assessment, and management were detailed in this section. The risk identification process should incorporate multiple viewpoints in order to gather a more robust sense of risks, which, for photovoltaics, can include risks related to technology and financing. The largest source of PV risk was identified as uncertainty, particularly with regard to the uncertainty of variable electricity output from photovoltaic modules. Methods of identifying PV risks related to variable electricity output, including levels of solar irradiance, weather patterns, and temperatures were discussed. Next, risk assessment was presented and divided into quantitative, qualitative, and semi-quantitative methods, each with its own benefits and applications. Exceedance probabilities and Monte Carlo simulations were highlighted as quantitative risk assessment techniques with applicability to photovoltaics. Lastly, risk management was mentioned and categorized into risk avoidance, mitigation, and transfer. A simplified real options approach was proposed as a risk mitigation technique to be analyzed by this thesis, which will assist with determining when to invest in a PV installation. This concludes the review of relevant literature for this thesis. In the next chapter, the research and financial models will be introduced and discussed.

Chapter 3: Financial Modelling Methodology

3.1 Financial Modelling Methodology Introduction

This chapter will describe two key models employed by this thesis. Firstly, the *research model*, used to guide the overall direction of investigation and study of the research topic, will be introduced. Secondly, the *financial model*, which employs inputs of energy yields, solar installation costs, and electricity tariffs to calculate the outputs of levelized cost of electricity, net present value, return on investment, and

internal rate of return, will be covered in detail. An example using formulas from the global adjustment tariff offsetting scenario will be presented to show how cost savings are generated from avoiding the use of grid-produced electricity and from counteracting two electricity consumption charges. For the other three tariff scenarios, only the "tariffs" component of the financial model is different. Additionally, formulas for calculating LCOE, NPV, ROI, and IRR will be provided and discussed, and a sample NPV calculation will be included in-text for reference.

3.2 Research Model

To determine if there is a business case for solar offsetting at data centers in Ontario, this thesis will apply the research model framework shown in Figure 9. The framework concisely illustrates how the research question stated in Section 1.1 of this thesis will be answered.

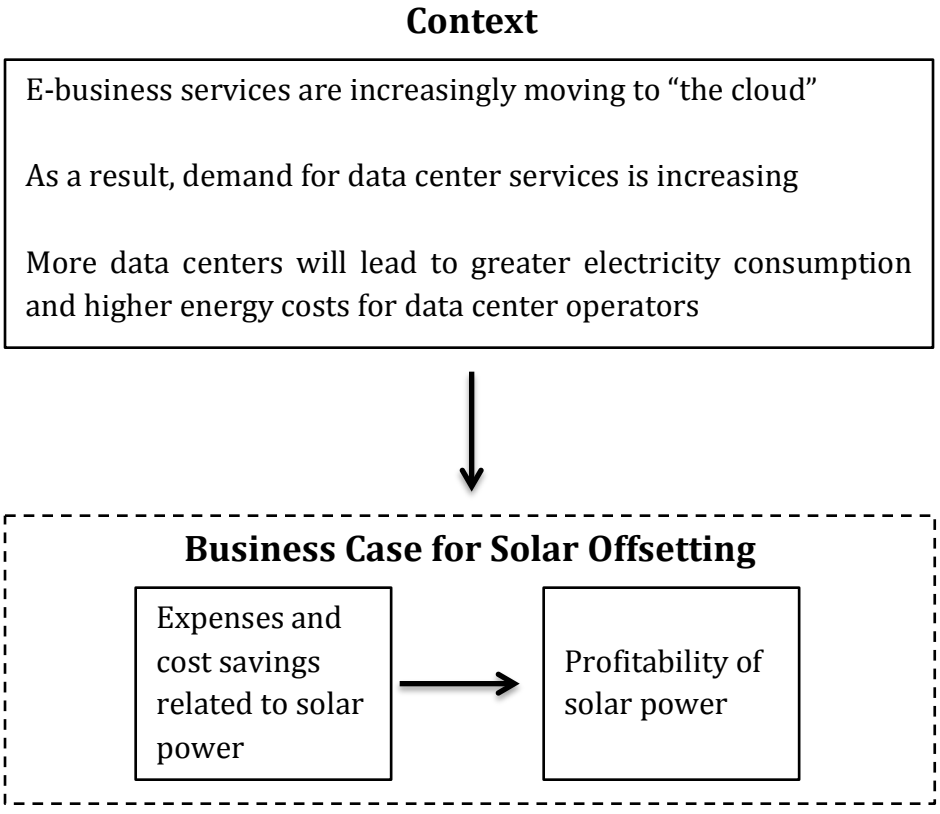


Figure 9. The research model framework.

The context provides the motivation for assessing the business case for using solar to offset electricity costs at data centers. Support for the context in Figure 9 was established in Sections 2.1 through 2.3 of the literature review. In terms of the items within the *Business Case for Solar Offsetting* box in Figure 9, this thesis will analyze the expenses and cost savings associated with offsetting to determine the profitability of using solar power in this manner. Expenses will encompass costs to install the system, ongoing operation and maintenance fees, the price of replacing the inverter that converts direct current to alternating, and the charge for dismantling and recycling the solar modules at the end of their useful life. Cost savings represent the amount of money saved by consuming solar-produced electricity *instead of* electricity from the electrical grid. Finally, profitability is the present value of discounted future cash flows, which, if positive, represent cost savings. Measures of profitability for photovoltaics were discussed in Section 2.4.2.1 of the literature review.

The research model framework contains assumptions relating to future trends for e-business services, electricity demand, and data center business models. Firstly, it presupposes that as the amount of e-business services offered via cloud computing networks grows, the number of data centers required to support these services will grow too. Secondly, it assumes that electricity prices will increase in the years to come in the province of Ontario, and data center operators wishing to reduce their electricity expenditures while maintaining or expanding existing operations must introduce a new element, such as photovoltaic offsetting, to help achieve this goal. Finally, it supposes that data center operators are motivated to reduce electricity costs, since these expenses represent a high proportion of total data center expenditures.

3.3 Research Methodology and Design

3.3.1 Financial Model

This thesis will employ a quantitative research methodology, incorporating numeric data into the financial model from several different sources. This quantitative approach is the most appropriate approach for determining if there is a business case for using photovoltaic offsetting at data centers in Ontario: the financial results will be the determinant and they are quantitative in nature; the inclusion of variables representing energy yields, solar installation expenses, and electricity prices mean that this research requires quantitative analysis; and under a quantitative approach the financial model in this thesis can be validated using the inputs from other, similar studies. The financial model is shown in Figure 10, and each of its inputs and outputs will be discussed in the following sub-sections.

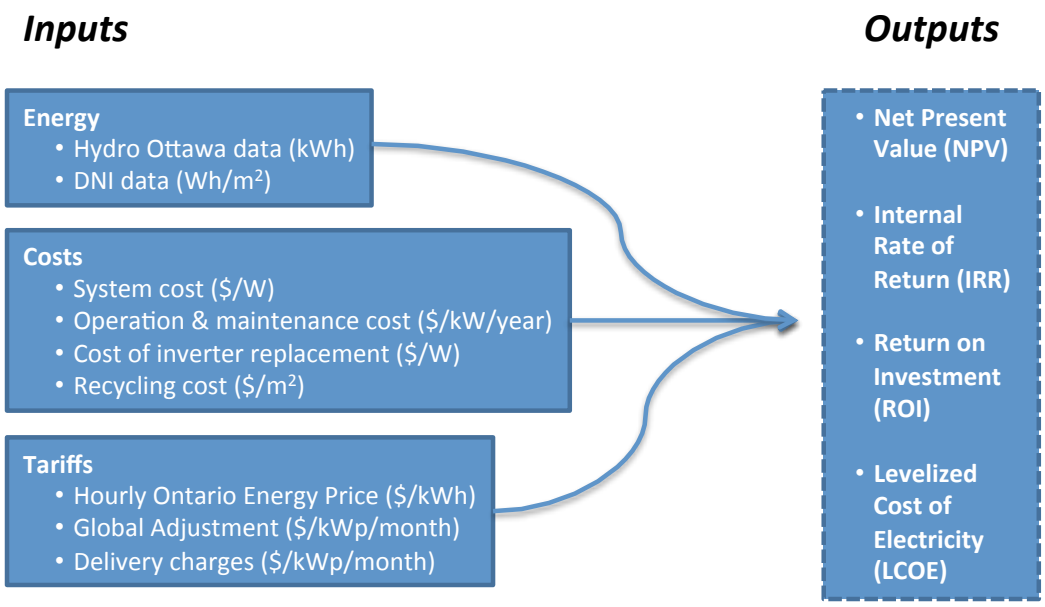


Figure 10. The financial model. In this model, either Hydro Ottawa data or DNI data are combined with costs and tariffs to calculate outputs.

3.3.1.1 Energy

Data comprising the energy component of Figure 10 were gathered from two distinct sources. Firstly, empirical energy yield data consisting of hourly

measurements of photovoltaic electricity output were collected from PV installations located at different sites within the city of Ottawa, Ontario. The mount type and tilt angle of these six solar installations, which are owned and operated by Hydro Ottawa, are shown in Table 7:

Installation	Mount Type	Tilt
A	Pole	50°
B	Pole	45°
C	Roof	30°
D	Roof	10°
E	Roof	5°
F	Full tracker	Dual-axis tracker

Table 7. Mount type and tilt angle of the six Hydro Ottawa solar installations that provided PV energy yield data (Haysom, Benedet, Wright, & Tomosk, 2013a).

Solar modules situated in the northern hemisphere are typically oriented towards the south to help them capture as much solar radiation as possible (Chang, 2009; Šúri, Huld, Dunlop, & Ossenbrink, 2007; Yadav & Chandel, 2013). Since Ottawa is situated at just over 45° north of the equator (Government of Canada, 2014), each of the solar installations in Table 7 faces either directly south or east of south (Haysom et al., 2013a). The kWh electricity output data from the directly south-facing Installation *B* were chosen for the analysis in this thesis since the tilt of this particular installation is both closest to Ottawa's latitude and nearest to the optimal 40° solar module tilt for PV offsetting projects in Ottawa, Ontario (Haysom, Benedet, Wright, & Tomosk, 2013b).

Secondly, for the CPV offsetting analysis, direct normal irradiance (DNI) data were obtained online from the publically accessible Canadian Weather Energy and Engineering Datasets (CWEEDS) (Government of Canada, 2013b). The data files from CWEEDS, which consist of various weather and climactic measurements in hourly intervals typically spanning the years 1953 to 2005 (Government of Canada, 2013b), provided an ample amount of data for this analysis. Since DNI data cover many years, they include any impacts from extreme events, such as a major volcanic eruption, that occurred during the collection time period. As well, these data

incorporate other atmospheric phenomena including increased (decreased) atmospheric dust due to increasing (decreasing) industrialization, for example.

Each energy-related data file, one containing Hydro Ottawa's empirical kWh output and the other consisting of CWEEDS DNI readings for Ottawa, included a significant number of hourly measurements. The latter in particular, with hourly DNI readings encompassing January 1st, 1953 to December 31st, 2005, contained 464,592 rows of measurements in a standard Excel spreadsheet. To make working with these data files easier, averages for hourly intervals were calculated for each month of the year from the raw data. To illustrate this process, consider the month of January, which has 31 days. Each one of those days has 24 one-hour intervals beginning with 00:00 – 01:00 and continuing to 23:00 – 23:59. Hourly DNI averages for January 1953, for example, were calculated by summing all of the raw DNI readings observed during each hourly interval for each day of this particular month and then dividing by 31, the number of days in the month. This process was repeated for all months over all years covered by the data. To demonstrate the depth of the CWEEDS data file spanning 1953 to 2005, inclusive, consider that each hourly interval calculation for January, for instance, was the average of 1,643 DNI readings.

Once these calculations were complete, the final average hourly DNI measurements were tabulated in a 12 by 24 matrix with the 12 calendar months as a column down the left-hand side and the 24 hourly intervals as a row across the top of the matrix. The same computation and arrangement of average hourly photovoltaic energy yield readings from the empirical Hydro Ottawa data was also performed.

At this point, the data were not yet in the preferred format and additional calculations were required to transform the figures into kilowatt-hours of alternating current per square meter (kWh_{AC}/m^2), the desired unit of measurement for the energy data. For the empirical Hydro Ottawa PV kWh output data, the conversion to kWh_{AC}/m^2 entailed dividing each hourly interval from the 12 by 24 matrix mentioned in the previous paragraph by the area (m^2) of the PV installation

from which the data were obtained. In contrast, conversion of the CWEEDS DNI measurements to kWh_{AC}/m^2 called for additional calculations since, in this case, irradiance data was being converted instead of solar module energy yield output data. Given that the CWEEDS DNI data was used to model electricity output from a CPV installation, the additional calculations assumed that CPV *module* efficiency was 30% (National Renewable Energy Laboratory, 2014), while CPV *rest of system* efficiency, also known as the system performance ratio, ranged between 80-90% as per figures provided by King et al. (2014) who noted that CPV performance ratio figures ranged from 86% to 95% depending upon the time of year. King et al. (2014) measured CPV performance ratios using a CPV installation in the warm climate of Albuquerque, New Mexico. However, Hashimoto, Kurtz, Sakurai, Muller, and Otani (2013) demonstrated that CPV performance ratios declined due to spectral and temperature effects during winter months in Okayama, Japan. Given that this analysis is concerned with the comparatively latitude of Ottawa, Ontario, a city that experiences wintertime conditions, this thesis will use a lower performance ratio value compared with the range provided by King et al. (2014). To account for performance ratio, each hourly interval of average DNI data readings from the data file – in kilowatt-hours per square meter (kWh/m^2) – was multiplied by 0.3, the amount of direct current produced by the system per m^2, and then by a system performance ratio of 0.85 to calculate the amount of electricity in kWh_{AC}/m^2 generated by the CPV system each hour. With both the empirical Hydro Ottawa data and the CWEEDS DNI data converted to the same units per square meter, the amount of electricity generated could be scaled according to the physical size of the solar installation, also measured in square meters.

As a final note with regard to energy, the financial model presumed that the solar modules experienced degradation at linear rates between of 0.1% per year and 0.7% per year. This meant that the maximum energy output from the solar panels diminished over the operational lifetime of the system. The chosen range of 0.2% to 0.7% for PV systems was in line with PV degradation estimates provided by Branker et al. (2011), Di Francia (2013), Lowder et al. (2013), and Zweibel (2010) in Section

2.4.2.1. The linear degradation of 0.1% was estimated as a best-case scenario for CPV. With a discussion of energy yield now complete, costs, the second input from Figure 10 will now be analyzed.

3.3.1.2 Costs

Three of the four costs indicated in Figure 10 were discussed as part of the literature review in Chapter 2. For PV technology, ranges of present-day and projected capital costs – also known as system costs – were provided in Section 2.4.1.4, the mean and standard deviation of current operation and maintenance costs were given in Section 2.4.2.1, and the cost of dismantling and recycling solar modules was provided in Section 2.4.2. The fourth cost, replacing the inverter that converts the direct current produced by the solar modules into alternating current in year 13 of operation, varied depending upon the year of replacement. Haysom et al. (2013b) used an inverter replacement cost of $0.16/Wp, an amount slightly lower than the average commercial PV system inverter replacement cost in 2012 of $0.19/Wp stated by Bazilian et al. (2013). However, a recent report by Pérez, Báez, and Luternauer (2014) projected costs for commercial-scale inverters in Euro cents per Watt-peak up to and including the year 2030 using a learning curve. In 2013, this amount was slightly less than €0.12/Wp and was expected to decline to just under €0.08/Wp in 2030. This thesis used these projected figures to determine the cost in USD of replacing an inverter in year 13 of a solar installation project commencing in the years 2014 through 2020, inclusive. A summary of operation and maintenance, inverter replacement, and dismantling and recycling costs used by the financial model in this thesis is shown in Table 8. All costs shown in the table are in United States dollars (USD).

Cost Category	Technology	Cost	Reference	Note
Operation and maintenance	PV	Range between average of $19.00/kW/year and ± $15.00/kW/year	(National Renewable Energy Laboratory, 2013a)	σ = ± $15.00/kW/year. Analysis will use lower and upper O&M cost values within ± 1σ.
	CPV	Range between $19.00/kW/year and upper limit of $19.00/kW/year + $37.50/kW/year	(Drury et al., 2013)	Analysis will use PV O&M cost values ≥ $19.00/kW/year and below upper limit of $19.00/kW/year + $37.50/kW/year.
Inverter replacement	PV	Range between $0.112/W for a project beginning in 2014 and $0.098/W for a project beginning in 2020	(Pérez et al., 2014)	Converted from € to USD using average 2014 exchange rate at time of writing.
	CPV	Range between $0.112/W for a project beginning in 2014 and $0.098/W for a project beginning in 2020	(Pérez et al., 2014)	Assumed to be same as PV
Dismantling and recycling	PV	$18.25/m^2	(Di Francia, 2013)	Converted from € to USD using average 2014 exchange rate at time of writing
	CPV	$18.25/m^2	(Di Francia, 2013)	Assumed to be same as PV

Table 8. Operation and maintenance, inverter replacement, and dismantling and recycling costs used by the financial model. All costs are in USD.

Although PV costing figures were relatively straightforward to obtain, CPV costing figures from reputable sources were more than challenging to acquire at the present time. With cost figures pertaining to both the replacement of a CPV system's inverter, as well as the dismantling and recycling of CPV solar modules unavailable, the financial model assumed that these expenses were the same as their PV counterparts. Similarly, a lack of available CPV operation and maintenance costing numbers also meant that this thesis had to presume CPV O&M costs. For the purpose of this thesis, CPV operation and maintenance costs were presumed to be within the range of O&M costs for dual-axis PV trackers, which also have the additional technical components used by CPV installations to track the movement of

the sun. Fortunately, CPV system cost figures from an academic source were available at the time of writing, and the financial model in this thesis included these pricing values. The next several paragraphs will detail multiple aspects of both the PV and CPV system prices used by the financial model.

Data for PV system prices were obtained from two distinct sources. Firstly, National Renewable Energy Laboratory published a report containing projected PV installation costs corresponding with the U.S. Department of Energy's SunShot initiative (Ardani et al., 2013), which was briefly touched upon in Section 2.4.1.4. The system cost price projections between the present time and 2020 in this report were ideal for this thesis, since this research aims to determine when to optimally initiate PV investment in the near future. The system prices from the report for each of the years 2014 through 2020 are shown in the left-hand column of Table 9 and exclude the customer acquisition costs that were included as part of the original total system prices.

	National Renewable Energy Laboratory	McKinsey & Company
Year	**System Cost ($/W)**	**System Cost ($/W)**
2014	3.51	1.82
2015	3.14	1.70
2016	2.76	1.58
2017	2.36	1.48
2018	1.97	1.38
2019	1.60	1.28
2020	1.22	1.20
Source	(Ardani et al., 2013)	(Aanesen, Heck, & Pinner, 2012)

Table 9. PV system cost projections in $/W from National Renewable Energy Laboratory and McKinsey & Company.

Secondly, research firm McKinsey & Company produced a report titled *Solar Power: Darkest Before Dawn* also containing PV system cost projections. In the report, attention was drawn to PV system price projections for the years 2015 and 2020 (Aanesen et al., 2012). Using these PV system prices for 2015 and 2020, the exponential trend line $y = 1.945e^{-0.07x}$ connecting the two points was calculated in Microsoft Excel and then used to compute system costs for each of the years 2014

through 2020 to match the timeframe from NREL's report. The results of this calculation were shown in the right-hand column of Table 9.

The disparity between the two projections of system prices in Table 9 provided an opportunity to explore the financial attractiveness of PV investments at different system prices. As a result, this thesis examined the results of PV investment for the years 2014 through 2020 using McKinsey & Company's costs as a "pessimistic" pricing scenario, National Renewable Energy Laboratory's figures as an "optimistic" pricing scenario, and an average of the two values for each year as an "average" pricing scenario. A summary of the PV system prices used by the financial model in this thesis is shown in Table 10 below:

Year	Pessimistic ($/W)	Average ($/W)	Optimistic ($/W)
2014	3.51	2.67	1.82
2015	3.14	2.42	1.70
2016	2.76	2.17	1.58
2017	2.36	1.92	1.48
2018	1.97	1.67	1.38
2019	1.60	1.44	1.28
2020	1.22	1.21	1.20

Table 10. PV system costs in $/W for the years 2014 through 2020 used by the financial model.

Turning to CPV system prices, Haysom, Jafarieh, Anis, Hinzer, and D. Wright (2014) used CPV installation deployment volume data provided by the research firms Information Handling Services (IHS) and Yole Développement (Yole) as part of a learning curve analysis to project average CPV system prices for each of the years 2014 through 2020. IHS provided one estimate of CPV deployment volume between 2014 and 2020, while Yole supplied both an optimistic and a conservative volume projection over the same timeframe. From these average estimates, the authors also computed an upper and lower system price confidence interval (CI) for each year. Each of the upper CI, lower CI, and average system prices for the years 2014 through 2020 under the one IHS and two Yole CPV deployment volume scenario estimates is shown in Table 11.

	IHS			Yole Optimistic			Yole Conservative		
	System Cost ($/W)			System Cost ($/W)			System Cost ($/W)		
Year	Lower CI	Average	Upper CI	Lower CI	Average	Upper CI	Lower CI	Average	Upper CI
2014	1.89	2.36	2.97	1.94	2.42	3.02	2.04	2.52	3.12
2015	1.50	1.96	2.58	1.57	2.04	2.65	1.72	2.19	2.80
2016	1.24	1.69	2.30	1.30	1.76	2.37	1.49	1.96	2.57
2017	1.07	1.50	2.11	1.10	1.54	2.15	1.30	1.76	2.37
2018	0.94	1.36	1.96	0.96	1.38	1.98	1.15	1.59	2.20
2019	0.85	1.25	1.84	0.85	1.25	1.84	1.02	1.44	2.05
2020	0.78	1.17	1.75	0.75	1.13	1.71	0.91	1.32	1.92
Source	(Haysom et al., 2014)								

Table 11. Average CPV system prices in $/W for the years 2014 through 2020 from Haysom et al. (2014).

Three pricing scenarios were created instead of incorporating each one of the prices shown in Table 11 into the financial model. The three pricing scenarios consisted of a "pessimistic" pricing scenario that included the highest price each year from the "Upper CI" values, an "optimistic" pricing scenario composed of the lowest system price each year from the "Lower CI" pricing figures, and an "average" pricing scenario made up of the mean of the three "average" system prices each year. The final CPV system prices selected and calculated in the manner described in the prior sentence are shown in Table 12:

Year	Pessimistic ($/W)	Average ($/W)	Optimistic ($/W)
2014	3.12	2.44	1.89
2015	2.80	2.06	1.50
2016	2.57	1.80	1.24
2017	2.37	1.60	1.07
2018	2.20	1.45	0.94
2019	2.05	1.31	0.85
2020	1.92	1.21	0.75

Table 12. Exact CPV system costs in $/W for the three pricing scenarios analyzed by this thesis.

Generally speaking, system costs weigh heavily on the profitability of both PV and CPV installations since they represent a significant proportion of all system expenses. Tariffs, to be introduced and discussed in the next section, are also a

major factor of PV and CPV system profitability since they determine the value of the energy produced by a solar installation in an offsetting application.

3.3.1.3 Tariffs

This section will delve into the details of the global adjustment tariff offsetting scenario to illustrate the "tariffs" component of the financial model from Figure 10 in Section 3.3.1. This scenario is the most complex of the four tariffs under analysis and requires thorough explanation. Specifics pertaining to the other three tariff scenarios will be presented in Section 4.3.

Electricity customers in Ontario with peak demand exceeding 3 MW, which can include those in mining, manufacturing, cold storage warehousing, and data center services (Independent Electricity System Operator, n.d.b), are subject to the following three energy tariffs: the wholesale price of electricity – also known as the Hourly Ontario Energy Price (HOEP) – per kWh of electricity consumed; a global adjustment charge based upon the amount of kilowatts consumed by the customer during Ontario's five greatest province-wide hourly demand peaks from the previous year as a proportion of all electricity consumed in the province during those five hours; and a monthly distribution charge from the local distribution company (LDC) based upon the customer's highest kW demand peak each month. Further details pertaining to these three tariffs will be covered later in this section.

Data pertaining to the three tariffs were obtained online from the Independent Electricity System Operator (IESO) (Independent Electricity System Operator, n.d.c; Independent Electricity System Operator, n.d.d), the Government of Ontario (Ontario Power Authority, 2014), and Hydro Ottawa (Hydro Ottawa, 2014). The IESO oversees the operation of the electricity market in Ontario and calculates the wholesale price of electricity based upon electricity market forces (Independent Electricity System Operator, n.d.a). Current and historical wholesale electricity pricing data as well as costing information related to global adjustment charges

were provided by the IESO free of charge on its website and were used by this thesis. The Government of Ontario, at the current time, publishes forecasts of both HOEP pricing data and global adjustment fees up to and including the year 2032. These data were especially important for analyzing the financial attractiveness of solar offsetting in future years, one of the two research objectives of this thesis. Finally, Hydro Ottawa, the local distribution company for the purpose of this thesis, provided delivery costing data for large electricity customers within its jurisdiction on its website.

In the solar offsetting application employed by this thesis, the use of PV-generated electricity to offset the three tariffs produced cost savings as opposed to revenues. The value cost savings was dependent upon both the amount of electricity produced and the time at which the electricity was produced by the solar installation. With regard to the amount, this thesis assumed that the quantity of solar electricity produced and consumed by the customer on-site displaced an equal amount of electricity that would have been procured from the electricity grid. By foregoing grid-supplied energy, the large electricity customer was not charged the wholesale Hourly Ontario Energy Price per kWh of electricity consumed. As well, the customer avoided accompanying regulatory and debt retirement charges. In terms of the timing, research showed that global adjustment demand peaks tended to occur between midday and the late afternoon (Independent Electricity System Operator, n.d.d), while distribution charge peaks also occurred during the afternoon for more than half of the year (Haysom et al., 2013b). Coincidentally, the timing of these two tariff charges happens to coincide with when solar modules typically produce their greatest output of energy.

The manner in which the financial model determined the dollar amount of cost savings from offsetting over an assumed 25-year operational timeframe was somewhat complex. The financial model needed to account for both present and future Hourly Ontario Energy Prices, global adjustment fees, and distribution charges. As well, it was required to shadow the expected average future values for

each tariff according to projections from the Government of Ontario's Long-Term Energy Plan (LTEP) from Ontario Power Authority (2014). The following example net present value analysis for a PV project commencing in 2014 illustrates how the financial model calculated the value of cost savings generated from offsetting each of the three tariffs.

To start, historical HOEP and GA data were used to calculate an average HOEP baseline value and an average GA baseline charge for year zero of the NPV analysis. These initial values for 2014 were then used in ratio calculations, where ratios of baseline HOEP and GA charges to future average HOEP and GA charges provided by the LTEP were calculated for each year of system operation. Figure 11 displays projected average HOEP and GA values converted to USD from the Long-Term Energy Plan. Values up to and including the year 2032 were provided by the LTEP, while values for the years 2033 through 2045, inclusive, were calculated using linear regression.

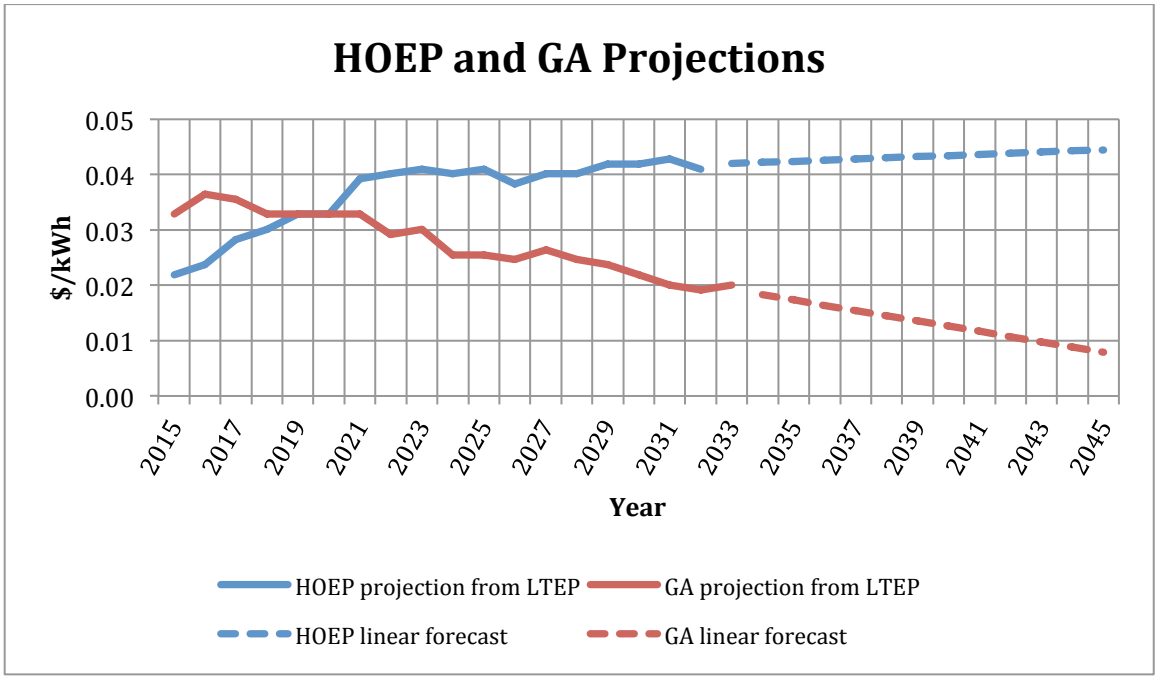


Figure 11. HOEP and GA projections from the most recent Ontario LTEP converted to USD. The GA projection from the LTEP continues into 2033 since GA charges are based upon the previous year's GA value. The linear forecasts extend until 2045 to account for a project commencing in 2020 and operating for 25 years (Ontario Power Authority, 2014).

According to Figure 11, a CPV project commencing in 2014 and operating over 25 years until 2039 should benefit greatly from selling electricity at the HOEP, which is expected to approximately double by the year 2022 and then remain somewhat constant until 2032. However, the value of offsetting the GA consumption charge is expected diminish over the same timeframe. The monthly peak delivery tariff is expected to remain fairly static over the 25-year operational timeframe as per a large energy customer example case from the LTEP (Ontario Power Authority, 2014). Since the monthly peak delivery tariff is customer specific, current and projected average values, such as those displayed in Figure 11 for the HOEP and GA, are unavailable. Since this value is approximately 1.015 times greater than the calculated baseline average HOEP figure of USD 0.02156/kWh, the value of *not* consuming electricity from the electrical grid in 2015 was 1.015 times greater than the baseline average value. On top of that, displacing demand for grid electricity meant that the associated regulatory and debt retirement fees were eschewed. At the time of writing, regulatory and debt retirement charges for large electricity customers within Hydro Ottawa's jurisdiction represented approximately 53.4% of the baseline average HOEP figure of USD 0.02156/kWh (Hydro Ottawa, 2014). To capture the value from offsetting these additional fees, the cost savings from offsetting HOEP charges were scaled up by a factor of 1.534. Thus, the total value of foregoing grid-produced electricity in year one, 2015, was $1.015 \times 1.534 = 1.557$ times greater than the baseline value in year zero. This same ratio calculation was repeated for each remaining year of the 25-year NPV analysis according to the future average HOEP prices from Figure 11, so that a different scaling value was determined for each year. However, the 1.534 scaling factor for regulatory and debt retirement charges was assumed to be static throughout the 25-year timeframe.

A separate calculation was performed to determine the amount of cost savings produced by offsetting global adjustment charges. However, unlike the HOEP ratio calculation there were no supplementary charges to take into account. The ratio of the calculated baseline average GA charge of USD 0.029/kWh to the average GA values provided by the LTEP was calculated for years two through 25 of the NPV

analysis since each year's global adjustment charge is based upon the previous year's electricity consumption. In 2016, the first year in which the GA is offset in this example NPV analysis, this ratio was USD 0.036/kWh ÷ USD 0.029/kWh = 1.250. Thus, the value of reducing the GA charge in year two of the net present value analysis was about 1.250 times greater than in the baseline global adjustment charge in year zero.

To determine the value of offsetting the monthly distribution charge, an average of the HOEP ratio – without the additional regulatory and debt retirement multiplier of 1.534 – and the GA ratio was calculated for each year of operation. In the year 2016, for example, the value of diminishing the delivery tariff was $(1.015 + 1.250) \div 2 =$ 1.333 times greater than in the baseline year of the NPV analysis.

These ratio calculations were performed for each year of solar installation operation. The values derived from the ratio calculations were used to either scale up or down the value of cost savings from offsetting HOEP, GA, and distribution charges each year against baseline tariff values. In the succeeding paragraphs, the formulas used to calculate the value of cost savings from offsetting each of the three tariffs will be presented and discussed. Each of the formulas includes a variable, referred to as a "multiplier," for the scaling value obtained from the ratio calculations discussed in the preceding paragraphs. The discussion will begin with the formula for offsetting the Hourly Ontario Energy Price and supplementary regulatory and debt retirement charges.

Calculating the amount of cost savings generated by offsetting the HOEP and accompanying charges was fairly straightforward. It involved multiplying the average energy yield for each hourly interval in a month by the average HOEP value corresponding with the same hourly interval. Using the month of January as an example, the product of the 24 calculations from the previous sentence was summed and then multiplied by 31, resulting in a partial monthly offsetting figure. At this point, the previously calculated and mentioned HOEP multiplier of 1.557,

which incorporates the value of offsetting regulatory and debt retirement charges, was applied to determine the total value of HOEP offsetting for the month. This calculation is represented by the following equation:

$$HOEP_{CS}(t) = \sum_{m,h} E_{mh}(t)\ x\ (t)\ p_{mh}\ n_m \qquad (1)$$

In (1), $HOEP_{CS}(t)$ stands for the amount of cost savings generated by offsetting the HOEP and supplemental electricity charges in year t, $E_{mh}(t)$ is the average kWh energy yield at month m and hour h in year t, $x(t)$ represents the HOEP multiplier in year t, p_{mh} denotes the average Hourly Ontario Energy Price at month m and hour h, while n_m symbolizes the number of days n in month m.

Determining the cost savings produced by offsetting global adjustment charges required a separate calculation. In Ontario, the GA charge is based upon energy consumption during the five hours of greatest province-wide demand from the previous year. As stated earlier, the IESO tracks the occurrences of these hours and provides this data on its website (Independent Electricity System Operator, n.d.d). Using this historical data, each hourly interval of each month of the year was assigned a probability of being one of the five peak hours where a global adjustment charge was incurred. For hourly intervals with a probability greater than zero, the probability figure was multiplied by the average energy yield produced by the solar modules during this same hourly time period. These products were then summed to determine the total quantity of kilowatts expected to go towards offsetting GA charges. This amount of kilowatts was then multiplied by the 2013 global adjustment charge of USD 24.35/kW/month (Independent Electricity System Operator, n.d.c; Independent Electricity System Operator, n.d.d). At this point, the previously mentioned 2016 global adjustment scale up value of 1.250 was applied to compute a monthly GA offset figure. Then, by multiplying this monthly GA offset quantity by 12, the total yearly amount of cost savings resulting from reducing GA

charges in 2016 was calculated. The formula for this calculation is depicted by the following equation:

$$GA_{CS}(t+1) = \sum_{m,h} E_{mh}(t)\, y(t)\, \pi_{mh} \times 24.35 \times 12 \qquad (2)$$

In (2), $GA_{CS}(t+1)$ stands for the amount of cost savings generated by offsetting global adjustment charges in year $(t+1)$, $E_{mh}(t)$ is the average kWh energy yield at month m and hour h in year t, $y(t)$ denotes the global adjustment multiplier in year t, and π_{mh} symbolizes the probability of an hourly interval being part of the global adjustment in month m and hour h as per historical data. The number 24.35 represents the USD global adjustment charge per month for years two through 25, inclusive, and 12 refers to the number of months in one year.

The calculation of cost savings from reducing distribution charges employed yet another formula. Similar to the GA calculation, the delivery offsetting calculation incorporates hourly intervals. However, unlike the global adjustment calculation there are no probabilities assigned to the hourly intervals since historical data pertaining to distribution charges are customer-specific. The hourly intervals used in the distribution charge calculation corresponded to when peak demand occurred each month. For this thesis, the hourly intervals were assumed to occur between 09:00 and 10:00 from November to March and between 13:00 and 14:00 from April to October. For each month of the year, the average energy yield corresponding to the appropriate hourly interval was multiplied by a USD 6.42/kW distribution charge for large Hydro Ottawa customers (Hydro Ottawa, 2014). The sum of these products was then multiplied by the previously mentioned 2016 distribution charge multiplier of 1.333 to arrive at the total cost savings of reducing delivery tariffs for 2016. Equation (3) below shows the formula for this calculation:

$$D_{CS}(t) = \sum_{m,h} E_{mh}(t)\, z(t) \times 6.42 \quad (3)$$

In (3), $D_{CS}(t)$ is the amount of cost savings generated by reducing electricity distribution charges in year t, $E_{mh}(t)$ is the average kWh energy yield at month m and hour h in year t, $z(t)$ represents the distribution charge multiplier in year t, and 6.42 is the monthly distribution charge for large Hydro Ottawa customers per kilowatt in USD for years one through 25, inclusive.

The total amount of cost savings generated by offsetting is calculated by summing Equations (1), (2), and (3) as per Equation (4):

$$S(t) = HOEP_{CS}(t) + GA_{CS}(t+1) + D_{CS}(t) \quad (4)$$

In (4), $S(t)$ stands for the sum of cost savings in year (t), and $HOEP_{CS}(t)$, $GA_{CS}(t+1)$, and $D_{CS}(t)$ are Equations (1), (2), and (3), respectively.

The calculation in Equation (4) was performed for each year of the NPV analysis. Table 13 below illustrates the complete NPV analysis for the an example PV project commencing operations in 2014 and operating until 2039 using the information and formulas stated throughout this section. This NPV analysis assumed: a $500,000 system investment and a capital cost of $1.82/W; A discount rate of 8%; linear degradation each year of 0.2%; operation and maintenance costs each year of $10/kW; an inverter replacement cost in year 13 of $0.112/W; and a recycling cost in year 25 of $18.25/m^2. The energy yield figures for the example PV project were empirical Hydro Ottawa PV installation output data and they were scaled up to represent a 274.73 kW installation of 1,831.50 m^2.

Year	Cost Savings ($)	Degradation (%)	Cost savings with Degradation ($)	Inverter Replacement Cost ($)	Recycling Cost ($)	Operation & Maintenance Cost ($)	Net Cost Savings ($)	Discount Rate (%)	Present Value of Net Cost Savings ($)
0	-500,000.00	0.000	-500,000.00	0.00	0.00	0.00	-500,000.00	0.08	-500,000.00
1	20,183.00	-0.002	20,142.63	0.00	0.00	2,747.25	17,395.38	0.08	16,106.83
2	58,862.05	-0.004	58,626.60	0.00	0.00	2,747.25	55,879.35	0.08	47,907.53
3	61,057.26	-0.006	60,690.92	0.00	0.00	2,747.25	57,943.67	0.08	45,997.55
4	59,206.10	-0.008	58,732.45	0.00	0.00	2,747.25	55,985.20	0.08	41,150.79
5	61,153.05	-0.010	60,541.52	0.00	0.00	2,747.25	57,794.27	0.08	39,333.81
6	61,153.05	-0.012	60,419.22	0.00	0.00	2,747.25	57,671.96	0.08	36,343.12
7	65,695.95	-0.014	64,776.20	0.00	0.00	2,747.25	62,028.95	0.08	36,193.30
8	62,146.09	-0.016	61,151.75	0.00	0.00	2,747.25	58,404.50	0.08	31,554.13
9	63,844.78	-0.018	62,695.58	0.00	0.00	2,747.25	59,948.33	0.08	29,989.09
10	57,947.24	-0.020	56,788.30	0.00	0.00	2,747.25	54,041.05	0.08	25,031.46
11	58,596.23	-0.022	57,307.11	0.00	0.00	2,747.25	54,559.86	0.08	23,399.79
12	55,599.56	-0.024	54,265.17	0.00	0.00	2,747.25	51,517.92	0.08	20,458.48
13	58,996.96	-0.026	57,463.03	30,769.23	0.00	2,747.25	23,946.55	0.08	8,805.10
14	56,897.53	-0.028	55,304.40	0.00	0.00	2,747.25	52,557.15	0.08	17,893.66
15	57,145.79	-0.030	55,431.42	0.00	0.00	2,747.25	52,684.17	0.08	16,608.25
16	55,046.37	-0.032	53,284.89	0.00	0.00	2,747.25	50,537.63	0.08	14,751.45
17	53,595.93	-0.034	51,773.67	0.00	0.00	2,747.25	49,026.42	0.08	13,250.32
18	51,248.25	-0.036	49,403.32	0.00	0.00	2,747.25	46,656.06	0.08	11,675.63
19	52,986.28	-0.038	50,972.80	0.00	0.00	2,747.25	48,225.55	0.08	11,174.44
20	51,089.60	-0.040	49,046.02	0.00	0.00	2,747.25	46,298.77	0.08	9,933.32
21	50,148.71	-0.042	48,042.47	0.00	0.00	2,747.25	45,295.22	0.08	8,998.16
22	49,207.83	-0.044	47,042.68	0.00	0.00	2,747.25	44,295.43	0.08	8,147.72
23	48,266.94	-0.046	46,046.66	0.00	0.00	2,747.25	43,299.41	0.08	7,374.55
24	47,326.05	-0.048	45,054.40	0.00	0.00	2,747.25	42,307.15	0.08	6,671.81
25	46,385.16	-0.050	44,065.90	0.00	33,427.57	2,747.25	7,891.08	0.08	1,152.24
							Net Present Value		**29, 902.53**

Table 13. Example complete net present value calculation for a PV offsetting project commencing in 2014 and operating for 25 years until 2039.

The complete NPV analysis shown in Table 13 took into account the energy yield data from Section 3.3.1.1, PV costing figures from Section 3.3.1.2, and tariff charges from Section 3.3.1.3. Equation (4) was used to calculate the "Cost Savings" column. Additional items used in the NPV analysis, such as degradation and discount rate, were mentioned in other sections of this thesis. Since the NPV in Table 13 is positive, this particular investment project would be deemed worthwhile assuming

the costs, expenses, and tariff amounts used by the analysis were in fact real. A full NPV analysis was included in Table 13 to illustrate how this thesis will calculate this important financial metric. However, net present value is only one of the outputs that will be calculated as part of this research. Along with net present value, the formulas of the three other outputs identified in Figure 10 will now be covered in detail.

3.3.1.4 Outputs

To evaluate the economic attractiveness of both PV and CPV offsetting projects, the analysis calculated levelized cost of electricity, net present value, return on investment, and internal rate of return. These financial measures, which are the final component of the financial model shown in Figure 10 to be discussed, are metrics that are essential to investigating the business case for solar power offsetting projects in Ontario.

Levelized cost of electricity is an energy industry standard and thus must be included as part of the analysis. Since this metric was thoroughly discussed previously in Section 2.4.2.2, this section will focus solely upon the LCOE formula. The following equation will be used by this thesis to calculate levelized cost of electricity:

$$LCOE = \frac{\mathrm{I} + \frac{Inv}{(1+r)^{13}} + \frac{Rec}{(1+r)^{25}} + \sum_{t=1}^{T} M(t) \,/\, (1+r)^{t}}{\sum_{t=1}^{T} E(0)(1-dt) \,/\, (1+r)^{t}} \tag{5}$$

In (5), $LCOE$ stands for levelized cost of electricity, I is the total system cost, Inv refers to the cost of replacing the inverter that converts solar-produced DC into AC in year 13, while Rec is the cost of dismantling and recycling the solar modules in year 25. Both Inv and Rec are discounted at the risk-adjusted discount rate r. Continuing, $M(t)$ represents expenses related to operation and maintenance in year t, $E(0)$ symbolizes energy yield at the time of installation, d denotes the degradation

rate of the solar modules, and finally T is the maximum number of years of system operation (Tomosk, Wright, Haysom, & Hinzer, 2015).

In Section 2.4.2.2 of this thesis, several authors, including Branker et al. (2011), Darling et al. (2011), Joskow (2011), and Borenstein (2012), questioned using the LCOE to gauge financial attractiveness. As a result of their arguments, the business case analysis in this thesis also incorporated the financial metrics of net present value, return on investment, and internal rate of return. Net present value was defined and described in Section 2.4.2.1. The NPV formula used by this thesis is shown in Equation (6), which has been adapted from (McCrary, 2010):

$$NPV = -I + \frac{CF(1)}{(1+r)^1} + \cdots + \frac{CF(N)}{(1+r)^N} \tag{6}$$

In (6), NPV stands for *net present value*, I denotes the total system cost in year zero, CF represents cash flow or rather the value from offsetting HOEP, GA and delivery tariffs as per Equation (4), r is the risk-adjusted discount rate, and N symbolizes the final year of system operation. For all NPV calculations in this thesis, $N = 25$.

The net present value calculation in Equation (6) is subject to the Equations (7), (8), and (9):

$$CF(t) = S(t) - M(t) \tag{7}$$

In (7), the cash flow in year t – or more precisely the value generated in year t from offsetting – is equal to $S(t)$, the total amount accrued from offsetting HOEP, GA, and distribution charges in year t, minus $M(t)$, the operation and maintenance expenses in year t.

$$CF(13) = S(t) - M(t) - Inv \tag{8}$$

In (8), the value from photovoltaic offsetting in year 13 includes the additional cost of replacing the direct current to alternating current inverter, Inv.

$$CF(25) = S(t) - M(t) - Rec \tag{9}$$

Finally, in (9) the value derived from offsetting in year 25 includes Rec, which is the additional cost of dismantling and recycling the solar modules.

The next financial metric, return on investment, was also defined and discussed in Section 2.4.2.1. All return on investment calculations in this thesis used the following ROI formula:

$$ROI = \frac{NPV}{I} \tag{10}$$

In (10), ROI stands for return on investment, NPV is an abbreviation for *net present value*, which was defined by Equation (6), and I refers to the total system cost of the solar installation. Equation (10) will compute return on investment as a percentage.

The final financial metric considered by this thesis was internal rate of return, which too was explained in Section 2.4.2.1 and defined as "the interest rate at which present worth of the cash flows of a project are zero" (Odeh et al., 2006). In the absence of a spreadsheet or financial calculator, IRR is typically calculated by trial and error. For simplicity, this thesis used Microsoft Excel's "IRR" function to calculate internal rate of return.

With all components of the financial model now thoroughly discussed, the next section of Chapter 3 will proceed to explore the particulars of the research design of this thesis.

3.4 Research Design

This research was designed to explore two important topics related to photovoltaic offsetting investment in Ontario. The first topic explored by the analysis was the optimal time to invest in a photovoltaic offsetting project in Ontario. To determine when best to invest, net present values for both PV and CPV installation projects for each of the years 2014 through 2020 were computed as per Equation (6). System prices for PV and CPV installations from Table 10 and Table 12, respectively, were used as part of these NPV calculations. The projected average Hourly Ontario Energy Prices and global adjustment charges from Figure 11 were also incorporated into these computations. To compare future net present values to their worth at the present time, NPV figures from 2015 to 2020, inclusive, were discounted back to 2014 using an appropriate United States Treasury rate depending upon the number of years. This procedure enabled the analysis to compare the value of investing in photovoltaic offsetting today versus the value of investing in photovoltaic offsetting at a future point in time. Furthermore, the discounted NPV figures illustrated when PV and CPV offsetting projects in Ontario become profitable and under which capital cost scenario given the trends of declining system prices and global adjustment tariffs, as well as rising wholesale electricity prices.

Secondly, in addition to determining the financial attractiveness of investing in solar offsetting projects at different points in time, this research also determined the impact of variability of select inputs on the outputs mentioned in Section 3.3.1.4. Variability was introduced to the financial model inputs of *Hydro Ottawa data*, *DNI data*, and *Hourly Ontario Energy Price* via the Monte Carlo simulation method described in Section 2.4.3.2. Specific details pertaining to the Monte Carlo simulation input data, including calculations and distributions of the input values, are discussed in Section 3.4.1.

To assess its impact on the financial viability of photovoltaic offsetting, variability generated by the Monte Carlo simulation was implemented in stages according to the four scenarios shown in the table below:

Scenario	Hydro Ottawa PV Energy Yield or DNI Variability	Hourly Ontario Energy Price Variability
1	No	No
2	Yes	No
3	No	Yes
4	Yes	Yes

Table 14. The four different energy yield and energy price variability scenarios under the global adjustment tariff offsetting scenario.

In Scenario 1, variability did not exist for either energy yield or energy price input. The NPV analysis in Table 13 illustrated an example of this, where the yearly cost savings figures were based upon unchanging amounts of energy yield and energy prices. As a result, the revenue figures followed a somewhat predictable pattern. In Scenarios 2 and 3, variability was introduced separately to energy yields and Ontario's electricity prices. By isolating variability in this manner, this thesis was able to determine whether either energy yield variability or electricity price variability had a greater impact on levelized cost of electricity, net present value, return on investment, and internal rate of return. Finally, in Scenario 4, variability was extended to both energy yields and electricity prices. The results from each scenario were compared to one another to uncover the impact of variability on the business case for solar offsetting in Ontario.

3.4.1 Monte Carlo Simulation Input Details

A Monte Carlo simulation uses the inputs of a mean, standard deviation, and probability distribution in order to generate new values. The mean and standard deviation are calculated from the historical raw data, while the probability value is generated separately via, for example, computer software. In this particular type of simulation, the distribution of the mean and standard deviation calculated from the input data must be known. This section will detail the process used to determine the distribution of the Monte Carlo simulation input data, which included direct normal

irradiance data, Ontario electricity tariffs, and PV energy yield figures from a Hydro Ottawa photovoltaic installation. To begin, a brief discussion on analyzing irradiance data will be presented.

When analyzing solar irradiance figures, the raw data is typically averaged by hourly interval. Although the sun's position in the sky for a particular hourly interval is different at various times of the year and these different positions affect the quantity of solar irradiance recorded on Earth, the day-to-day variation of the sun's position for a specific hourly interval within a given month is relatively minute. Therefore, the raw data can be averaged by hourly interval across each month of the year, and this particular format is preferred as opposed to a larger number of readings from smaller time intervals. This data configuration has been in use for a number of years. Masters (2004), for example, includes tables of average Watt hour (Wh) per square meter values for specific latitudes and solar panel tilt angles for each month's daytime hours in Appendix C of his book *Renewable and Efficient Electric Power Systems*.

The Monte Carlo simulation required that the historical data associated with the three inputs – direct normal irradiance, Hourly Ontario Energy Price, and Hydro Ottawa PV energy yield – be in the same format. Accordingly, averages for the 24 hourly intervals in a day for each month of the year were calculated from the raw direct normal irradiance, Hourly Ontario Energy Price, and Hydro Ottawa PV installation energy yield data. The final values were arranged in a matrix with the 12 months of the year listed down the far left-hand column and the 24 hourly intervals across the top row. Figure 12 below shows an example of part of a matrix of average DNI data used to calculate CPV energy yield in Ottawa, Ontario:

	00:00	01:00	02:00	03:00	04:00	05:00	06:00	07:00	08:00	09:00	10:00	11:00	12:00
January	0	0	0	0	0	0	0	0	203.19269	306.53615	359.66392	391.64643	398.44923
February	0	0	0	0	0	0	0	116.77658	311.70793	387.82012	442.45189	469.67444	475.07344
March	0	0	0	0	0	0	89.852153	304.97013	397.978	447.38126	475.5307	490.25901	488.86645
April	0	0	0	0	0	62.85391	275.80945	357.29308	402.02377	424.14591	430.69623	436.53282	432.41003
May	0	0	0	0	3.7642492	231.30832	342.53366	396.3271	427.72256	435.27574	438.30821	426.71196	414.78719
June	0	0	0	0	25.931669	258.33583	351.42381	413.0084	444.73771	455.67936	449.50661	441.84509	429.93097
July	0	0	0	0	4.4666114	231.53269	341.64125	416.40529	460.04255	473.53741	469.84874	445.35652	425.45789
August	0	0	0	0	0	118.65205	307.74576	385.30725	436.06264	457.43245	459.33985	437.58403	407.86282
September	0	0	0	0	0	1.4029774	225.63772	342.84713	391.03722	417.38087	423.87021	406.71562	393.42997
October	0	0	0	0	0	0	48.816714	242.05984	317.1333	342.82143	352.64064	354.69954	347.46423
November	0	0	0	0	0	0	0	82.905654	184.03656	226.76237	244.26674	247.16844	242.81555
December	0	0	0	0	0	0	0	0.9982539	165.95481	247.89837	290.87469	315.17856	313.93564

Figure 12. Part of a matrix showing average DNI values in Wh/m² for each hourly interval of each month in Ottawa, Ontario from the CWEEDS dataset (Government of Canada, 2013b).

The values within the table represent the average amount of direct normal irradiance in Watt-hours per square meter in Ottawa, Ontario for a particular hourly interval in a given month. For example, the mean DNI in Ottawa for the hourly interval of 12:00-13:00 in January between the years 1953 and 2005 is approximately 398.449 Wh/m². After calculating and arranging the input data for the three simulation variables by month and hourly interval, the next step was to determine the distribution of the raw data used as part of these calculations. If the distribution of the data points was defined, then the raw data could be inputted into the Monte Carlo Simulation. However, if the distribution of the raw data was undefined, then additional calculations would have to be employed before inputting any DNI, HOEP, or PV energy yield data into the Monte Carlo simulation.

Normality tests were performed on the raw DNI, HOEP, and PV energy yield datasets to determine the distribution of the data. Figure 13 illustrates the results of a normality test on DNI data observed during the hourly interval of 12:00-13:00 in January. Red x's of DNI data readings were plotted against blue squares of expected values from a normal distribution calculated using the mean, standard deviation, and number of data points for that particular hour's DNI data. In total, there were 1,643 DNI readings in the CWEEDS dataset for this hourly interval in January. Since each of the 31 days in January has one 12:00-13:00 hourly interval, this figure is equal to the product of 53 years of data multiplied by 31.

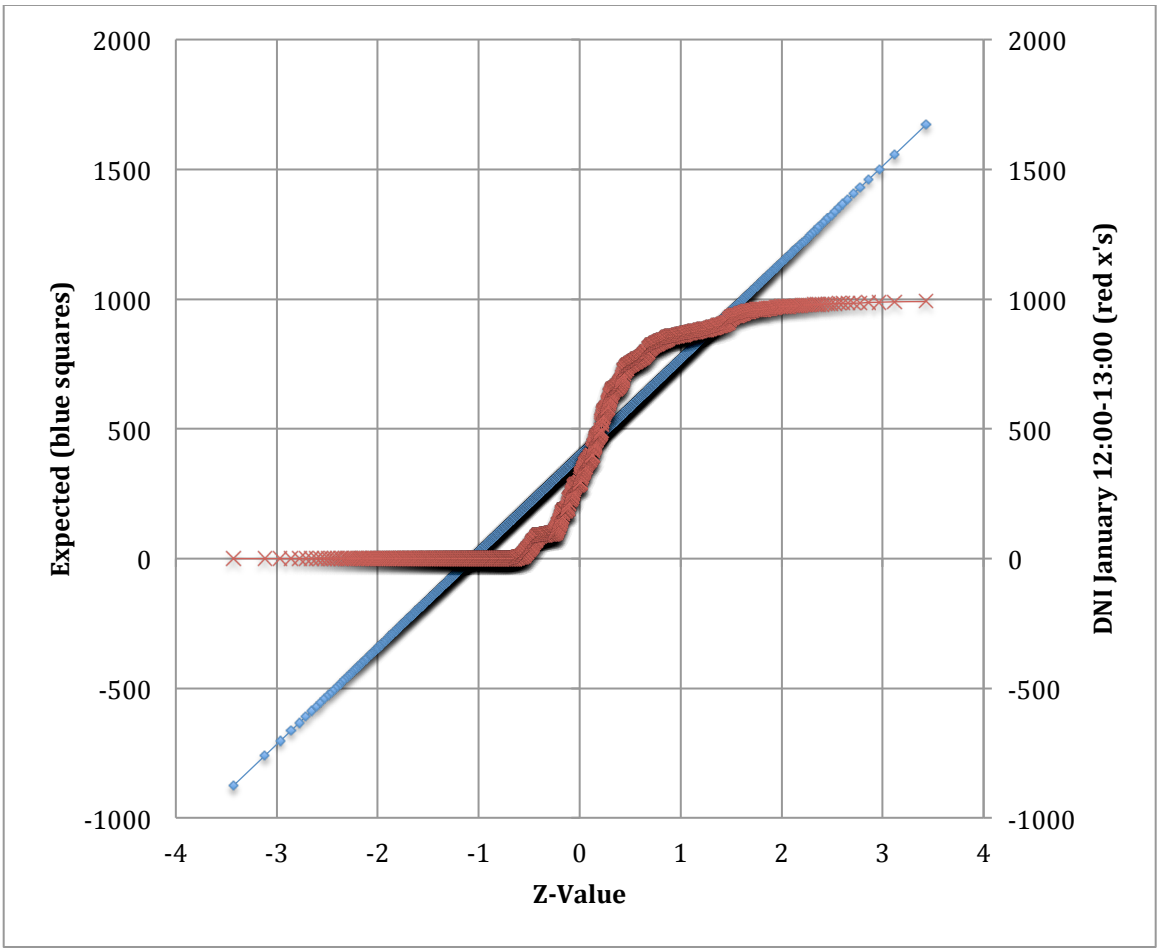


Figure 13. A normality test of DNI values observed between 12:00 and 13:00 for each day in the month of January over the years 1953 to 2005 in Ottawa, Ontario. If the raw DNI data were normally distributed, the plot of observed DNI values (red x's) would roughly match up with the expected values (blue squares).

Since the red x's do not follow the linear plot of blue squares, there is sufficient evidence to indicate that the raw DNI data is not normally distributed. This same normality test was repeated on DNI data observed during different hourly intervals from different months of the year, and each test produced evidence to conclude that the raw DNI data was not normally distributed. Subsequently, the same normality test was also performed on both the raw HOEP data and the raw PV energy yield data. The results, which included the testing of a number of hourly intervals over several different months of the year, indicated that these two sets of raw data were also not normally distributed. Plots of the normality tests performed on the raw direct normal irradiance, Hourly Ontario Energy Price, and Hydro Ottawa PV energy yield data are provided in Appendix A. Given the non-normal distribution of the raw

data, additional calculations had to be performed on the input data in order to define the distribution. Appropriately, the Central Limit Theorem (CLT) was applied to assist with defining the distribution of the data for input into the Monte Carlo simulation.

At a high-level, the Central Limit Theorem holds that the distribution of means calculated from a set of raw data is approximately normal unless the data indicate otherwise. More specifically, as stated by Dekking, Kraaikamp, Lopuhaä, and Meester (2005), "the central limit theorem provides a tool to approximate the probability distribution of the average or the sum of independent identically distributed random variables" (p. 199). Furthermore, as Wilcox (2010) notes, "provided each mean is based on a reasonably large sample size, the plots of the means will follow, approximately, a normal curve" (p. 36). The raw DNI data displayed in Figure 13 followed an unknown distribution, and this presented a problem since the distribution of the Monte Carlo simulation input data must be defined, To define the distribution of the data, the Central Limit Theorem can be used to calculate a set of means that will almost certainly be normally distributed unless a test for normality indicates otherwise. A normal distribution of data is ideal to work with since it can be easily characterized via just a mean and standard deviation. The following paragraphs will detail how the CLT was applied to each of the DNI, HOEP, and PV energy yield data to compute means and to test those calculated means for normality. Graphs illustrating the results of these normality tests will be provided as well.

To begin, a raw data substitution of sorts was made. The raw data was used to calculate yearly averages of the raw data for each year within the dataset. These calculated means then became the new raw data. To clarify, consider the 1,643 data points mentioned previously and used in the normality test shown in Figure 13. The 1,643 data points of DNI values observed between 12:00 and 13:00 in January over the years 1953 to 2005, inclusive, were sorted into columns by year resulting in 53 columns of 31 data points. The average of each year's 31 DNI data points was

calculated, which produced a total of 53 average data points. The formula used to calculate these 53 average data points is illustrated by Equation (11):

$$\overline{DNI}_{mh}(t) = \frac{\sum_{j=1}^{n_m} DNI_{mh}(t,j)}{n_m} \tag{11}$$

In (11), $\overline{DNI}_{mh}(t)$ stands for the average DNI for month m and hour h during year t, $DNI_{mh}(t,j)$ is the DNI in hour h of month m on day j in year t, while n_m represents the number of days n in month m. After calculating $\overline{DNI}_{mh}(t)$ for each year and each hourly interval in the data file, the average of the 53 calculated means for each hourly interval was computed using Equation (12):

$$\overline{DNI}_{mh} = \frac{\sum_{t=1}^{y} \overline{DNI}_{mh}(t)}{y} \tag{12}$$

In (12), $\overline{DNI}_{mh}$ is equal to the average DNI at hour h of month m, while $\overline{DNI}_{mh}(t)$ is the average DNI for month m and hour h during year t. The letter y denotes the total number of years.

The 53 calculated means were then subjected to the same normality test mentioned earlier in this section. The results of this normality test, shown as a plot of the 53 calculated means against expected values in Figure 14, illustrate that the means are in fact approximately distributed. In other words, Figure 14 demonstrates that there is insufficient evidence to conclude that the means of the data are not normally distributed.

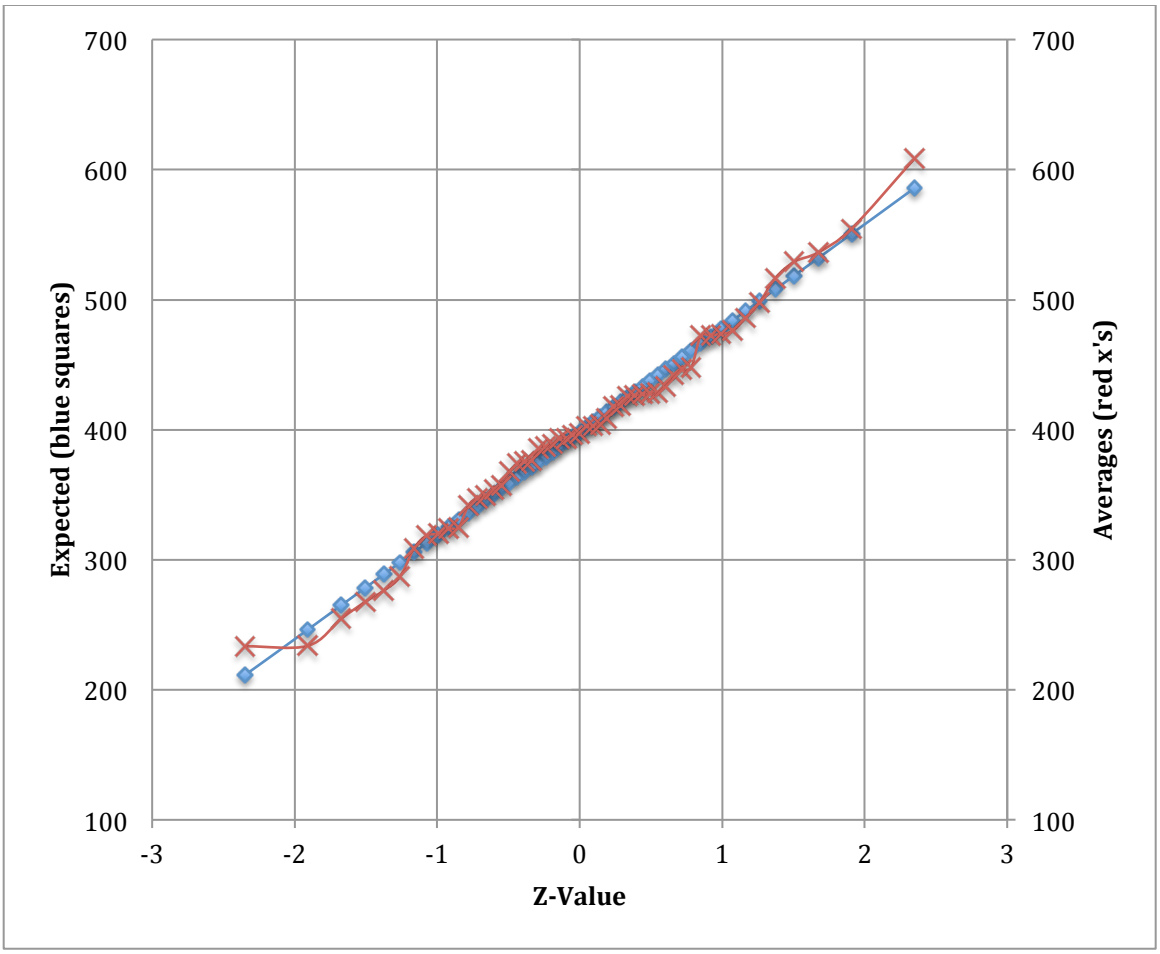


Figure 14. A normality test of the average DNI values observed between 12:00 and 13:00 in the month of January over the years 1953 to 2005 in Ottawa, Ontario. Since the plot of the 53 calculated means (red x's) matches well with the expected values (blue squares), the averages are approximately normally distributed.

This same normality test using the calculated means of the DNI data as inputs was performed using other hourly intervals and other months of the year. The resulting graph from each test indicated that there was not enough evidence to suggest that the means were not normally distributed. Additional graphs of normality tests of calculated means can be found in Appendix B.

With the distribution of the 53 calculated means now defined, the standard deviation of those means was calculated using the following equation modified from Black (2010):

$$\sigma(DNI_{mh}) = \sqrt{\frac{\sum_{t=1}^{y}(DNI_{mh}(t) - \overline{DNI}_{mh})^2}{y-1}} \quad (13)$$

In (13), $\sigma(DNI_{mh})$ stands for the standard deviation of DNI during hour h of month m, $DNI_{mh}(t)$ represents DNI from hour h of month m during year t, y denotes the total number of years, and $\overline{DNI}_{mh}$ is the average amount of DNI for hour h of month m.

The 53 calculated means from the DNI dataset provided a large number of data points with which to test for normality. However, the datasets of the other two variables of HOEP and PV system energy yield did not have the same large quantity of historical data, and thus the number of calculated means for these two items was smaller. The raw data for the Hourly Ontario Energy price, for example, spanned from May 1st, 2009 to December 31st, 2014. From this amount of data, only five or six calculated means could be produced to test for normality depending upon the month, and this is a significantly smaller number than the 53 means calculated from the CWEEDS DNI dataset. Nevertheless, means could be calculated and the computation of the HOEP calculated means is shown in Equation (14):

$$\overline{HOEP}_{mh}(t) = \frac{\sum_{j=1}^{n_m} HOEP_{mh}(t,j)}{n_m} \quad (14)$$

In (14), $\overline{HOEP}_{mh}(t)$ represents the average HOEP for month m and hour h during year t, $HOEP_{mh}(t,j)$ is the HOEP in hour h of month m on day j in year t, while n_m denotes the number of days n in month m. Once the five or six means were calculated, an average of these values was computed for each hourly interval as per Equation (15):

$$\overline{\overline{HOEP}}_{mh} = \frac{\sum_{t=1}^{y} \overline{HOEP}_{mh}(t)}{y} \quad (15)$$

Equation (15) indicates that $\overline{HOEP}_{mh}$ is the average HOEP at hour h of month m, and $\overline{HOEP}_{mh}(t)$ stands for the average HOEP for month m and hour h during year t. The total number of year is symbolized by y.

While there is no definitive rule as to how many raw data points are needed to test for normality using the Central Limit Theorem, more data points will generally yield better results (Wilcox, 2010). According to Black (2010), a "sufficiently large sample" (p. 230) means using at least 30 or more data points to calculate a single average using the CLT. For each of the DNI, HOEP, and PV energy yield variables, 30 or 31 data points were used depending upon the month to compute one calculated mean for all hourly intervals except for those during the month of February. In that particular month, either 28 or 29 data points were used to compute a single calculated mean. While the number of data points for February is just below the desired number of data points according to Black (2010), the results of the normality tests performed on the calculated means reveal that these values are approximately normally distributed given that 28, 29, 30, or 31 points of raw data were used when calculating each average depending upon the month. The results of several normality tests performed on calculated means from the DNI and HOEP datasets are provided in Appendix B. The PV energy yield raw data was too small to calculate enough means for normality testing.

Since the number of days in a month provides a sufficient amount of data points to calculate a mean under the Central Limit Theorem, normality tests were performed on the small number of HOEP calculated averages using Equations (14) and (15) for various hourly intervals over several different months. Figure 15 below shows the results of the normality test of the calculated averages corresponding to the hourly interval of 12:00-13:00 during the month of January.

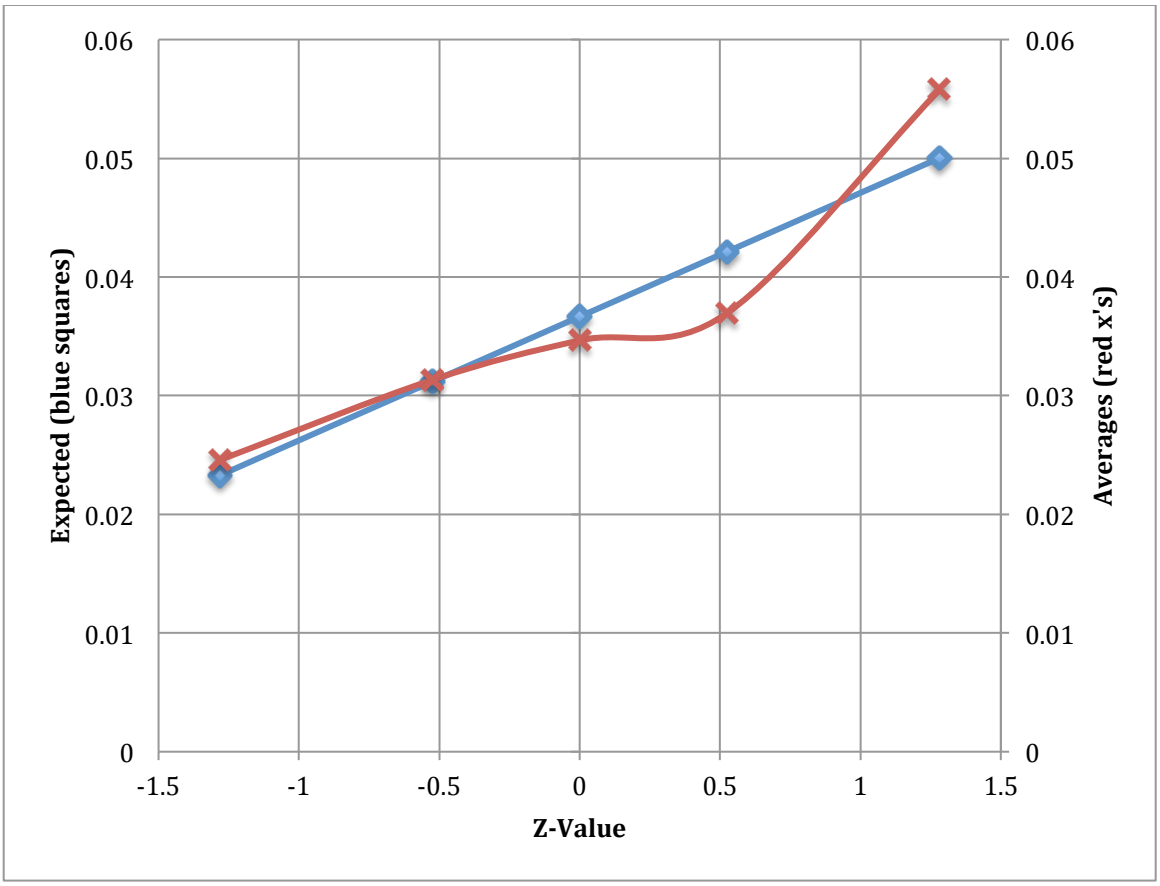


Figure 15. A normality test of average Hourly Ontario Energy Prices for the hourly interval of 12:00-13:00 in the month of January between 2010 and 2014. The calculated averages (red x's) match fairly well with the expected values (blue squares).

The six calculated means match up relatively well with the expected values, illustrating that there is insufficient evidence to demonstrate that the calculated means are not normally distributed. Additional normality tests were performed using the HOEP data from other hourly intervals and from different months, and several of these normality test graphs have been included in Appendix B. Compared with the normality tests performed using the DNI data calculated means, the HOEP calculated mean normality tests contained fewer data points and more deviations from the expected values. Regardless, the normality test graphs showed that the HOEP calculated means approximately followed the trend line of expected values in all instances. With the knowledge that the calculated means were roughly normally distributed, a standard deviation of the five or six means was calculated using the previously stated Equation (13).

Given the small number of calculated means from the HOEP dataset, additional normality tests were performed to validate the analysis and ensure the normality tests on the calculated means worked properly. These validation tests involved replacing the calculated means with new values generated using the calculated mean and standard deviation of a particular hourly interval. Excel's NORM.INV function, which returns a new value based upon a mean, standard deviation, and a probability (Briand & Hill, 2013), was invoked for this task. The probability in this case was calculated using Excel's *RAND()* function, which returned a randomly generated probability greater than zero but less than one from a uniform distribution. Returning to the example from Figure 15, the mean and standard deviation of the six average HOEP data points corresponding to the hourly interval of 12:00-13:00 in January were used in conjunction with six different probabilities generated using *RAND()* to create six new values representing average HOEP data points. A mean and standard deviation were then calculated from these six new values, and then the six values were plotted against expected values as per the previously mentioned normality test. In each instance, the normality test chart showed that the new values followed the trend line of the expected values. Figure 16 below illustrates the result of one of the normality tests performed on the generated means, while Appendix C provides additional charts of normality tests performed on the generated means.

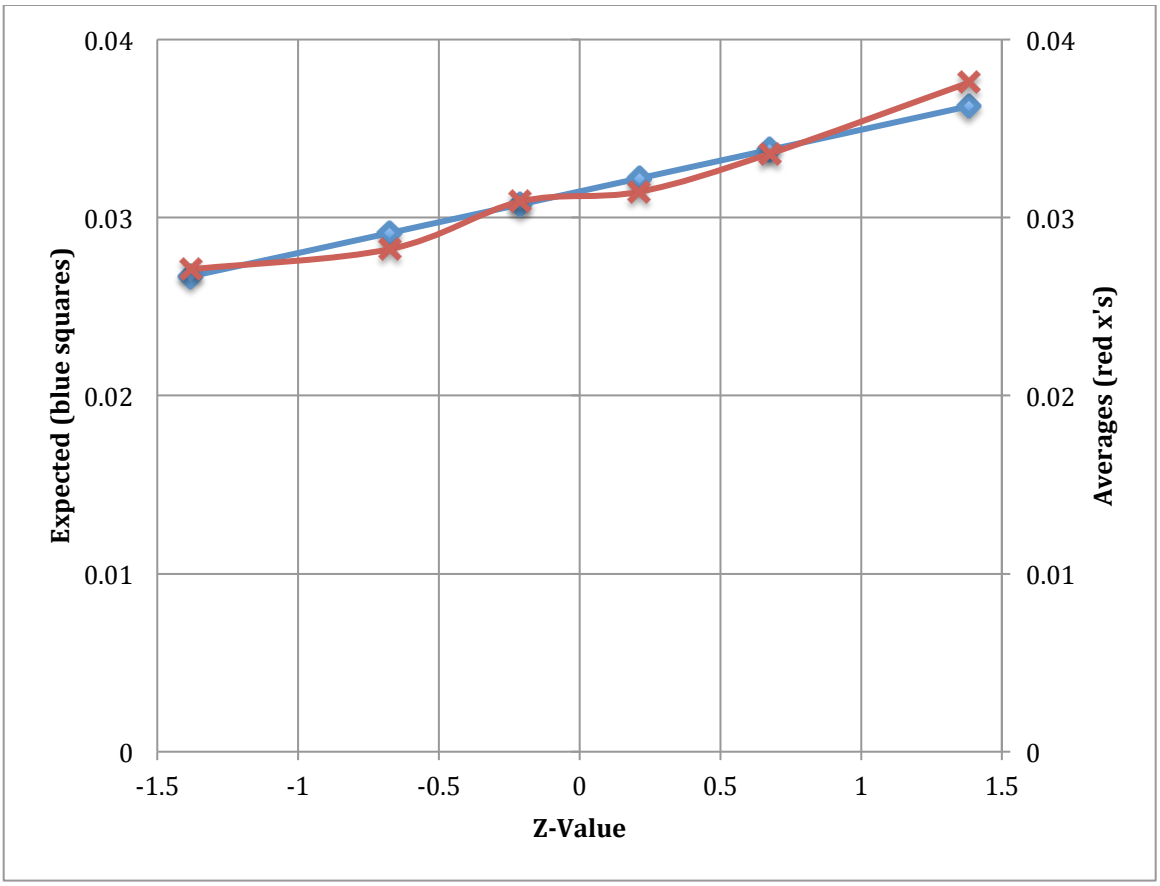


Figure 16. A normality test of six numbers generated using the standard deviation and mean of the five HOEP calculated means for the hourly interval of 12:00-13:00 in the month of January between 2009 and 2014. The calculated averages (red x's) match very well with the expected values (blue squares).

The third variable to be included in the Monte Carlo simulation, PV energy yield, had the least amount of historical data compared with the DNI and HOEP datasets. PV energy yield data ranged from May 1st, 2011 to December 31st, 2012, meaning each hourly interval had either one or two calculated averages depending upon the month. This quantity of raw data was enough to calculate a mean for each hourly interval. If only one year of data was available, the average would be calculated as simply:

$$\overline{PVY}_{mh}(t) = \frac{\sum_{j=1}^{n_m} PVY_{mh}(t,j)}{n_m} \tag{16}$$

In Equation (16), $\overline{PVY}_{mh}(t)$ stands for the average PV energy yield for month m and hour h during year t, $PVY_{mh}(t,j)$ is the PV energy yield in hour h of month m on day j in year t, while n_m denotes the number of days n in month m.

If two years of data were available then Equation (16) was calculated twice, once for each year of data. Afterwards, Equation (17) was used to calculate the average of the two means: the mean was calculated in two steps beginning with Equation (17) below:

$$\overline{PVY}_{mh} = \frac{\sum_{t=1}^{y} \overline{PVY}_{mh}(t)}{y} \tag{17}$$

In 17, $\overline{PVY}_{mh}$ symbolizes the average PV energy yield in hour h of month m, while $\overline{PVY}_{mh}(t)$ represents the average PV energy yield for month m and hour h during year t. The y stands for the total number of years.

Whether one mean or two means were calculated, the number of data points used in the calculation was 29, 30, or 31, approximately the number of data points recommended by Black (2010) for calculating a mean according to the Central Limit Theorem. As mentioned previously, normality tests on the PV energy yield means were not performed since only one or two calculated averages were produced for each hourly interval.

The raw data did not span enough years to produce a sufficient number of calculated means from which a standard deviation could be computed. Ultimately, computing a standard deviation from two mean data points would not produce an accurate result and calculating the standard deviation of one mean data point is impossible. Nevertheless, the Central Limit Theorem provided a solution to calculating standard deviation in this case. Even though this dataset contained a smaller number of values than either the DNI or HOEP datasets, there was a lack of evidence to *not* rely on the Central Limit Theorem.

To calculate the standard deviation in such a scenario, the CLT states that "regardless of the distribution of the individual values in the population" (Lee, Lee, & Lee, 2013, p. 354), the standard deviation can be calculated by dividing σ by $\sqrt{n}$, where σ represents the standard deviation of the entire populate and n is the number of data points. For this analysis, n equalled 31 regardless of the number of days in the month for which the standard deviation was being calculated. This was because the months of January through April in the dataset had daily PV energy yield data points from only 2011, while all other months in the dataset had data points from both 2011 and 2012. By setting $n = 31$ for all PV energy yield standard deviation calculations, the calculations were consistent across all hourly intervals and all months of the year. Thus, the standard deviation of the PV energy yield was calculated using the following equation:

$$\sigma(PVY_{mh}) = \frac{\sigma}{\sqrt{31}} \tag{18}$$

In (18), $\sigma(PVY_{mh})$ stands for the standard deviation of the PV energy yield during hour h of month m, and σ represents the standard deviation of all of the raw data points whether one or two years of data were available.

At this point, the empirical direct normal irradiance, Hourly Ontario Energy Price, and PV energy yield data were in compatible formats. Moreover, all of the data had a defined distribution on account of the Central Limit Theorem. The next step involved inputting the calculated means and standard deviations of these three variables into the Monte Carlo simulation to generate new values as per the four variability scenarios presented in Table 14. To accomplish this task, the previously mentioned Excel function NORM.INV was used to generate new values for each of the three variables. The NORM.INV function combined each hourly interval's calculated mean and a standard deviation with a probability generated by Excel's *RAND()* function. The results of the Monte Carlo simulations, as well as results from

other scenarios listed as part of the research objectives in Section 1.3 will be presented in next chapter.

3.5 Summary

Chapter 3 covered the financial modeling methodology associated with this thesis. The *research model* was presented, which included both the context for exploring this area of research and a high-level look at how the business case for solar offsetting was assessed. The *financial model* was also introduced, and it was shown to contain the inputs of: solar energy yield, from both empirical Hydro Ottawa PV installation data and DNI data from Environment Canada, a Government of Canada research department; solar installation costs, which encompassed costs for system installation, operation and maintenance, inverter replacement, and module recycling; and electricity tariffs, including the Hourly Ontario Energy Price, as well as global adjustment and electricity distribution charges. Formulas for calculating the value of offsetting each of the three tariffs were provided. The financial model's outputs were listed as levelized cost of electricity, net present value, return on investment, and internal rate of return. Formulas for calculating LCOE, NPV, and ROI were provided. Finally, the research design section noted that this thesis will analyze both the optimal time to invest in PV and CPV offsetting projects in Ontario between 2014 and 2020 and the impact of energy yield and electricity price variability on the outputs mentioned in Section 3.3.1.4. In reference to the latter, four scenarios for assessing the impact of variability were proposed: no energy yield or electricity price variability; energy yield variability, but no electricity price variability; no energy yield variability but electricity price variability; and both energy yield and electricity price variability. The details of the Monte Carlo simulation were provided, including the desired format of the historical input data, the fact that the distribution of the input data must be defined, the use of the Central Limit Theorem to calculate normally distributed means as well as standard deviations regardless of the number of calculated means, and a brief explanation of how the simulation will generate new values for each of the three variables. The

next section will present a summary of the inputs used by the financial model as well as an over view of all tariff scenarios.

Chapter 4: Financial Model Input Summary and Overview of Tariff Scenarios

In Chapter 4, financial model inputs, which include the previously mentioned capital costs, operation and maintenance fees, degradation and discount rates, as well as inverter replacement expenses, will be concisely summarized in tables. Additional inputs, including the cost to dismantle and recycle the solar modules at the end of the installation's useful operational lifetime, the presumed module and system efficiencies, and the assumed operational lifetime will also be stated. For both PV and CPV technologies, all of these inputs will be combined in the financial model under three different costing scenarios to calculate the outputs of net present value, internal rate of return, return on investment, and levelized cost of electricity. The PV scenarios will be defined in Section 4.1 by the inputs given in Table 15 and Table 16, while Table 19 and Table 20 in Section 4.1 will provide the inputs used by the CPV scenarios.

Risk-free interest rates will also be presented in Section 4.1. These rates are used to calculate the interest accrued on the assumed USD 500,000 of investment capital available in 2014 to fund either a PV or CPV installation. If the project investment is deferred to a later year, the principal amount will accumulate interest at a risk-free rate according to the number of years of investment postponement. The rates are presented in Table 17, where further details about how interest is accumulated are also presented.

Section 4.3 will provide specifics pertaining to the four tariff scenarios to be analyzed by this thesis, beginning with time-of-use pricing, followed by feed-in tariffs, power purchase agreements, and finally global adjustment tariff offsetting,

which also include the offsetting of Hourly Ontario Energy Prices and distribution charges. Time-of-use pricing and power purchase agreements were not discussed previously in this thesis, so Section 4.3 will include a thorough examination of these two tariff scenarios. Brief references to the previously mentioned feed-in tariffs and global adjustment tariff offsetting scenario will also be provided in this section.

4.1 PV Analysis Input Summary

A summary of the PV figures inputted into the financial model is displayed below in Table 15. Many of the input values vary depending upon the year in which the PV project begins generating electricity, and this table illustrates input value differences where applicable. Table 15 also divides the inputs into "pessimistic," "average," and "optimistic" scenarios, which were determined based upon the range of acceptable values uncovered during the literature review.

The categorization of the input values into three scenarios was designed to simplify the analysis. If the analysis were to include calculations using every possible combination of the inputs shown in Table 15, the result would be an excessively large amount of data due to the large number of possible combinations. As a result, this approach was deemed unrealistic. Instead, this analysis clustered the higher system price, operation and maintenance cost, degradation rate, and discount rate into a "pessimistic" scenario, while the lower system price, operation and maintenance cost, degradation rate, and discount rate were grouped into one "optimistic" scenario. Intermediate input values were organized to form an "average" scenario. Consequently, the results illustrate the range between all of the input parameters being low, all of the input parameters being high, and an average scenario in which all of the input parameters are medium.

Component	Year	Pricing Scenario and Value			Reference(s)
		"Pessimistic"	"Average"	"Optimistic"	
System price ($/W)	2014	3.51	2.67	1.82	(Aanesen, Heck, & Pinner, 2012); (Ardani et al., 2013)
	2015	3.14	2.42	1.70	
	2016	2.76	2.17	1.58	
	2017	2.36	1.92	1.48	
	2018	1.97	1.67	1.38	
	2019	1.60	1.44	1.28	
	2020	1.22	1.21	1.20	
Operation and maintenance ($/kW/year)	2014-2020	30.00	19.00	10.00	(National Renewable Energy Laboratory, 2013a)
Degradation rate (%)	2014-2020	0.7	0.5	0.2	(Branker et al., 2011); (Di Francia, 2013); (Lowder et al., 2013); (Zweibel, 2010)
Discount rate (%)	2014-2020	9.0	8.5	8.0	(Bazilian et al., 2013); (Mabeea et al., 2012); (Reichelstein & Yorston, 2013)
Inverter replacement cost in year 13 of operation ($/W)	2014	0.112	0.112	0.112	(Pérez et al., 2014)
	2015	0.110	0.110	0.110	
	2016	0.107	0.107	0.107	
	2017	0.105	0.105	0.105	
	2018	0.102	0.102	0.102	
	2019	0.100	0.100	0.100	
	2020	0.098	0.098	0.098	

Table 15. The PV inputs used in the financial analysis divided into "pessimistic," "average," and "optimistic" scenarios. All dollar values are in USD.

Additional financial model inputs that do not change regardless of the scenario or the year in which the project begins are displayed in Table 16:

Component	Value	Reference(s)
Dismantling and recycling cost in year 25 ($/m²)	18.25	(Di Francia, 2013)
Assumed module efficiency (%)	15.0	(National Renewable Energy Laboratory, 2014)
Assumed system efficiency (%)	85.0	(Reich et al., 2012)
Project lifespan unless otherwise stated (years)	25	(Branker et al., 2011; Muneer et al., 2011; Swift, 2013)

Table 16. Additional financial model inputs used by the PV analysis.

In Table 16, the module efficiency percentage was based upon the efficiency of a typical PV module in operation today, whereas the reference, National Renewable

Energy Laboratory (2014), provided the best cell efficiencies achieved under laboratory settings. In a real-world application, observed module efficiency may be lower than the efficiency observed under ideal laboratory conditions. The system efficiency, also known as a performance ratio, was an assumed value assigned to the Hydro Ottawa installation that provided the PV energy yield data. The performance ratio value was determined based upon research by Reich et al. (2012) who studied the performance ratios of 100 PV systems in Germany and found that the median performance ratio of these systems was 84%. Since Germany's climate is not too hot, this performance ratio could likely also apply to Ottawa, Ontario.

The amount of capital available for investment in 2014 was assumed to be USD 500,000. If investment in a solar installation was deferred to a future year, this analysis assumed that the capital was re-invested until required at the risk-free interest rate. Since all of the costs used by the financial model were in United States dollars, United States Treasuries were assumed to be the risk-free investment vehicle. Table 17 below provides rate information on the United States treasuries used in this thesis:

	Period	Average 2014 Rate (%)	Project Start Year	Reference
Risk-free rate (United States Treasuries)	1-year	0.110	2015	(U.S. Department of the Treasury, 2014)
	2-year	0.438	2016	
	3-year	0.875	2017	
	5-year	1.645	2019	

Table 17. United States Treasury rates used to calculate the interest accrued on the capital available in 2014 when solar investment was deferred until a later year.

The average 2014 rates shown in Table 17 were collected as of the time of writing. They represent the average of the daily Treasury yield values for the time period of January 1, 2014 to October 30, 2014, inclusive. A PV project deferred until 2015 would collect interest according to the 1-year average 2014 rate, while a deferral until 2016 would mean that the USD 500,000 accrued interest at the 2-year average 2014 rate. Note that Treasury rates compound semi-annually (U.S. Department of the Treasury, 2011). For years in between the periods in which US Treasuries were provided, this analysis assumed that a PV investment project deferred until 2018

accrued interest for 4 years at 0.875% and a PV investment project deferred until 2020 accrued interest for 6 years at 1.645%.

Taking interest accrued into account, the amount of capital available for investment each year is provided in Table 18 below under the column "Total Investment ($)." Table 18 also provides an overview of the size of the PV installation in both in kW and m^2 given a system price in $/W. Additional figures, including annual energy yield, are provided as well.

PV Pricing Scenario	Project Start Year	System Price ($/W)	Total Investment ($)	Size of Installation (kW)	Size of Installation (m^2)	Cost of Installation ($/$m^2$)	Energy Production* (kWh/year)
Pessimistic	2014	3.51	500,000.00	142.45	949.67	526.50	166,827.57
	2015	3.14	500,551.13	159.41	1,062.74	471.00	186,691.16
	2016	2.76	504,392.94	182.75	1,218.34	414.00	214,025.18
	2017	2.36	513,264.53	217.48	1,449.90	354.00	254,703.08
	2018	1.97	517,763.79	262.82	1,752.16	295.50	307,801.26
	2019	1.60	542,690.86	339.18	2,261.21	240.00	397,225.82
	2020	1.22	551,656.84	452.18	3,014.52	183.00	529,558.72
Average	2014	2.67	500,000.00	187.27	1,248.44	400.50	219,312.65
	2015	2.42	500,551.13	206.84	1,378.93	363.00	242,235.63
	2016	2.17	504,392.94	232.44	1,549.59	325.50	272,216.35
	2017	1.92	513,264.53	267.33	1,782.17	288.00	313,072.54
	2018	1.67	517,763.79	310.04	2,066.92	250.50	363,094.90
	2019	1.44	542,690.86	376.87	2,512.46	216.00	441,362.02
	2020	1.21	551,656.84	455.91	3,039.43	181.50	533,935.24
Optimistic	2014	1.82	500,000.00	274.73	1,831.50	273.00	321,738.89
	2015	1.70	500,551.13	294.44	1,962.95	255.00	344,829.55
	2016	1.58	504,392.94	319.24	2,128.24	237.00	373,866.76
	2017	1.48	513,264.53	346.80	2,312.00	222.00	406,148.16
	2018	1.38	517,763.79	375.19	2,501.27	207.00	439,397.45
	2019	1.28	542,690.86	423.98	2,826.51	192.00	496,532.28
	2020	1.20	551,656.84	459.71	3,064.76	180.00	538,384.70
*** Assumes no variability**							

Table 18. PV installation characteristics. All dollar values are in USD.

According to Table 18, as the capital cost decreased and the amount of capital available for investment increased over time, the area and kW size of the PV installation expanded. Accordingly, the amount of electricity produced grew larger too as indicated by the "Energy Production" column. In the next section, the input values and the installation characteristics for CPV technology will be provided.

4.2 CPV Analysis Input Summary

Table 19 below displays the inputs used in the CPV financial model. The CPV system prices, operation and maintenance costs, degradation rates, and discount rates have been grouped together to form "pessimistic," "average," and "optimistic" scenarios in the same manner as the PV scenario, which was illustrated by Table 15 in Section 4.1. As well, Table 19 makes clear when an input value is dependent upon the year in which the CPV project commences.

Component	Year	Pricing Scenario and Value			Reference(s)
		"Pessimistic"	"Average"	"Optimistic"	
System price ($/W)	2014	3.12	2.44	1.89	Haysom et al. (2014)
	2015	2.80	2.06	1.50	
	2016	2.57	1.80	1.24	
	2017	2.37	1.60	1.07	
	2018	2.20	1.45	0.94	
	2019	2.05	1.31	0.85	
	2020	1.92	1.21	0.75	
Operation and maintenance ($/kW/year)	2014-2020	45.00	32.00	19.00	(Drury et al., 2013)
Degradation rate (%)	2014-2020	0.5	0.3	0.1	(Gerstmaier et al., 2014)
Discount rate (%)	2014-2020	10.0	9.0	8.0	(Poullikkas et al., 2013)
Inverter replacement cost in year 13 of operation ($/W)	2014	0.112	0.112	0.112	(Pérez et al., 2014)
	2015	0.110	0.110	0.110	
	2016	0.107	0.107	0.107	
	2017	0.105	0.105	0.105	
	2018	0.102	0.102	0.102	
	2019	0.100	0.100	0.100	
	2020	0.098	0.098	0.098	

Table 19. The CPV inputs used in the financial analysis divided into "pessimistic," "average," and "optimistic" scenarios. All dollar values are in USD.

Additional CPV data used in the financial analysis that do not depend upon the year in which the project begins or the costing scenario are displayed in Table 20:

Component	Value	Reference(s)
Dismantling and recycling ($/m²)	18.25	(Di Francia, 2013)
DNI solar resource (kWh/m²/year)	1,456	(Government of Canada, 2013b)
Module efficiency (%)	30.0	(National Renewable Energy Laboratory, 2014)
System efficiency (%)	85.0	(King et al., 2014)
Project lifespan unless otherwise stated (years)	25	(Ellis, 2014)

Table 20. Additional financial model inputs used as part of the CPV analysis. All dollar values are in USD.

Analogous to the PV analysis, interest accrued semi-annually at the same risk-free rates shown in Table 17 on deferred CPV investments. The CPV analysis also assumed that an investment deferred until 2018 accrued interest for 4 years at 0.875%, while a PV investment project deferred until 2020 accrued interest for 6 years at 1.645%.

Table 21 below provides an overview of the CPV system characteristics, including the size of the CPV installation in both kW and m^2 given a system price in $/W and a total amount of investment capital used for each of the years 2014 to 2020 in United States dollars. The additional figures of the cost of the installation per m^2 and energy production per year in kWh are provided as well.

CPV Pricing Scenario	Project Start Year	System Price ($/W)	Total Investment ($)	Size of Installation (kW)	Size of Installation (m²)	Cost of Installation ($/m²)	Energy Production* (kWh/year)
Pessimistic	2014	3.12	500,000.00	160.26	534.19	936.00	198,470.65
	2015	2.80	500,551.13	178.77	595.89	840.00	221,396.78
	2016	2.57	504,392.94	196.26	654.21	771.00	243,061.82
	2017	2.37	513,264.53	216.57	721.89	711.00	268,209.27
	2018	2.20	517,763.79	235.35	784.49	660.00	291,467.32
	2019	2.05	542,690.86	264.73	882.42	615.00	327,853.27
	2020	1.92	551,656.84	287.32	957.74	576.00	355,834.99
Average	2014	2.44	500,000.00	204.92	683.06	732.00	253,782.14
	2015	2.06	500,551.13	242.99	809.95	618.00	300,927.66
	2016	1.80	504,392.94	280.22	934.06	540.00	347,038.27
	2017	1.60	513,264.53	320.79	1,069.30	480.00	397,284.99
	2018	1.45	517,763.79	357.08	1,190.26	435.00	442,226.28
	2019	1.31	542,690.86	414.27	1,380.89	393.00	513,052.83
	2020	1.21	551,656.84	455.91	1,519.72	363.00	564,630.73
Optimistic	2014	1.89	500,000.00	264.55	881.83	567.00	327,634.09
	2015	1.50	500,551.13	333.70	1,112.34	450.00	413,273.98
	2016	1.24	504,392.94	406.77	1,355.89	372.00	503,765.23
	2017	1.07	513,264.53	479.69	1,598.95	321.00	594,071.01
	2018	0.94	517,763.79	550.81	1,836.04	282.00	682,157.56
	2019	0.85	542,690.86	638.46	2,128.20	255.00	790,704.95
	2020	0.75	551,656.84	735.54	2,451.81	225.00	910,937.58
* Assumes no variability							

Table 21. CPV installation characteristics. All dollar values are in USD.

The CPV values in Table 21, as well as the PV values from Table 18, were used to assess the attractiveness of solar investment using four distinct tariff scenarios where the price paid for solar-produced electricity or the value derived from offsetting electricity consumption from the electrical grid depended upon one of the following: time-of-use electricity prices; a feed-in tariff; a power purchase agreement; or, global adjustment tariff offsetting. A discussion of these tariff scenarios begins in the next section, commencing with the time-of-use pricing scenario.

4.3 Tariff Scenarios Summary

4.3.1 Time-of-Use (TOU)

Under the time-of-use offsetting scenario, electricity produced by the solar installation was consumed on-site and as a result offset an equal amount of

electricity that would have been consumed from the electrical grid. Consequently, the costs of purchasing the foregone electrical grid electricity were avoided and cost savings were generated. The time-of-use electricity prices varied depending upon the time of day and month of the year according to an established schedule set by Hydro Ottawa. As well, the electricity prices available under this fixed schedule were available only to small business customers in Ottawa, Ontario. To qualify as a small business, the composition of the data center was modified. Instead of the assumed data center configuration of one large building housing numerous servers, the time-of-use scenario assumed that the data center was divided into multiple smaller *distributed* data centers. This data center arrangement was unique to the time-of-use scenario compared with the other tariff scenarios.

Under the distributed format, data centers are spread out geographically in a network that could span almost any amount of distance: the distributed network could consist of data centers spread across a single city or province, or the network could transverse multiple countries or even continents (Gu, Zeng, Li, & Guo, 2014). For the purpose of this thesis, the analysis assumes several small data centers distributed around the Ottawa, Ontario region because this area is where the energy yield data and tariff values are applicable.

There are several reasons to opt for the smaller, distributed data center arrangement instead of a single, large data center. Firstly, an operator could use a distributed network of data centers to reduce both risk and costs. In terms of the former, multiple data centers can reduce the risk of service downtime and lessen latency periods for processing requests (S. Chen, Wang, & Pedram, 2014). As well, according to Forestiero, Mastroianni, Meo, Papuzzo, and Sheikhalishahi (2014), "the dynamic migration of workload among data centers has become an opportunity to improve several aspects: better resiliency and failover management" (p. 324). For example, if one data center experiences a malfunction or a power disruption rendering it unavailable in a distributed network, the other data centers can likely compensate for the outage. The risk associated with an outage or failure is spread

across multiple facilities, and this reduces the probability that a problem will have a noticeable effect.

In terms of costs, Rappos, Robert, and Riedi (2013) state that distributed data centers can "reduce the infrastructure costs via economies of scale or efficient use of the hardware infrastructure" (p. 175). The infrastructure supporting the transfer of data packets from the end-user to the data center and back again can become expensive for data centers, especially for those that have a large number of users or those that store a large amount of data. Mazmanov, Curescu, Olsson, Ton, and Kempf (2013) found that "the cost of providing bandwidth per subscriber in a big data center eventually exceeds the cost of operating a distributed cloud" (p. 470), which is evidence to support the idea that the data center model can bring about cost savings compared with operating a single large data center.

A second reason why the distributed data center network model may be preferred is to leverage renewable energy technologies. These technologies, such as solar PV and CPV, produce electricity only when their energy source is available. Thus, the ability to disburse tasks to a data center or data centers where the sun is shining is vital for data center networks that want to incorporate renewable energy sources into their power mix (Rahman, Liu, & Kong, 2013). According to Kiani and Ansari (2015), algorithms can be used to schedule workloads at distributed data centers in order to maximize the use of renewable energy so that non-renewable energy is purchased "only when the green energy generation is not adequate to serve all incoming workload" (p. 26). The GreenStar Network mentioned in Section 2.3.3 is an example of a distributed Canadian cloud computing network that incorporates renewable energy and, in a manner unnoticeable to the end-user, transfers tasks from one data center to the other based upon the availability of intermittent renewable energy.

However, a network of mini distributed data centers contained within the limits of one city is subject to the same weather patterns. If conditions were cloudy at one data center, chances are that all data centers in the area would be experiencing the

same cloudy conditions. The ability of the network to shift a workload to another data center in order to use solar-produced electricity would not be counted an advantage of the mini distributed data center network. Nevertheless, distributed mini data centers offer a unique advantage over a single, large data center in that the dispersed servers can be used to heat the buildings that store them. In a 2011 research paper titled *The Data Furnace: Heating Up with Cloud Computing*, researchers from Microsoft and the University of Virginia proposed using the servers that store data and run cloud processes as the main heat source in both residences and workplaces (J. Liu et al., 2011). In Ottawa, a city subject to cold or cool conditions for a large portion of each year, the distributed network of mini data centers may benefit household and business owners by providing a free heat source in exchange for housing a small number of computer servers. While a financial analysis of heating a home or business with heat waste from servers is outside of the scope of this thesis, a distributed network of mini datacenters that uses solar power to offset electricity costs and is contained within a single city can provide benefits even when the sun is not shining.

As mentioned at the beginning of this section, the distributed data center model was chosen for the time-of-use analysis in order to qualify for electricity rates available for small businesses in Hydro Ottawa's service territory. This electricity utility and its rates were selected because the PV energy yield data used in this analysis were obtained from a solar installation operating within Hydro Ottawa's service area, and matching these energy yield data points with electricity prices from another service territory would be ill-advised. According to Hydro Ottawa, a small business is defined as having a peak electricity demand below 50 kW (Hydro Ottawa, 2014), which is comparable to the electricity demand of approximately five average households.

Hydro Ottawa's time-of-use electricity rates for small businesses are structured to include off-peak, mid-peak, and on-peak time periods. Table 22 details the timing of these time periods as well as the current electricity rates.

Season	Peak Type	Time	CAD/kWh	USD/kWh
Winter (November 1st to April 30th)	Off-peak	19:00 – 07:00	0.077	0.070
	Mid-peak	11:00 – 17:00	0.114	0.104
	On-peak	07:00 – 11:00; 17:00 – 19:00	0.140	0.128
Summer (May 1st to October 31st)	Off-peak	19:00 – 07:00	0.080	0.073
	Mid-peak	07:00 – 11:00; 17:00 – 19:00	0.122	0.111
	On-peak	11:00 – 17:00	0.161	0.147

Table 22. Hydro Ottawa small business time-of-use electricity prices. Average USD conversion rate was 0.9119 at the time of writing.

According to Table 22, the ratio of the off-peak to on-peak electricity price during the summer months is slightly greater than two. Generally speaking, the higher the ratio between the off-peak and on-peak electricity prices, the more likely that a solar installation will produce value from offsetting since the on-peak prices typically occur midday when solar modules are producing their greatest amount of electricity. However, a high ratio does not necessarily guarantee a favourable return on investment. If, for instance, the off-peak electricity price was $0.02/kWh and the on-peak price was $0.08/kWh, the 4:1 off-peak to on-peak ratio may be attractive. However, given current LCOE figures provided in Section 2.4.2.2, which represent the price at which power must be sold over all years of PV system operation to break even, it is unlikely that profitability will be achieved given these low hypothetical electricity prices.

The summertime peak electricity price of CAD 0.161/kWh in Table 22 is an attractive price for solar offsetting, but the total value of offsetting incorporates the mid-peak and off-peak rates as well, the latter of which is significantly lower. The analyses of the financial attractiveness of investing in PV and CPV technology in Ottawa beginning in Chapter 5 will reveal if these time-of-use electricity prices are conducive to generating profitability as measured by discounted net present value, return on investment, and internal rate of return.

Hydro Ottawa provides only current time-of-use prices and does not forecast any future electricity rate values. Since this analysis assumed that a PV or CPV installation would operate for 25 years and that an installation could commence operations in any of the years 2014 through 2020, future time-of-use rates had to be projected. The projections used in this analysis were based upon forecasted electricity prices from the Government of Ontario's Long-Term Energy Plan, as well as Hourly Ontario Energy Prices. Ratios of the average energy price in a future year to the average energy price at the present time were calculated. For each year of solar installation operation, this ratio was applied to the amount of value generated from selling the solar-produced electricity at time-of-use electricity prices to either scale up or scale down the total amount of value generated. A detailed discussion of the several steps involved in calculating these ratios follows.

Firstly, a baseline HOEP value was calculated using the historical HOEP data spanning May 1st, 2009 to December 31st, 2014 that was mentioned in Section 3.4.1. This calculation is shown in Equation (19) below:

$$HOEP_{Baseline} = \frac{\sum \overline{HOEP}_{mh}}{288} \tag{19}$$

In (19), $HOEP_{Baseline}$ is the average of the historical calculated HOEP means, and $\overline{HOEP}_{mh}$ stands for the historical calculated HOEP means at month m and hour h. Since the 12 by 24 matrix of historical calculated HOEP means contained 288 values, the baseline value was calculated by dividing the sum of the average HOEP values by 288.

For each future year of PV or CPV system operation, the ratio of the predicted average HOEP value provided by the Government of Ontario's Long-Term Energy Plan to the value of the baseline HOEP from Equation (19) was computed. Equation 20 shows this calculation:

$$HOEP_{Ratio}(t) = \frac{\overline{HOEP}_{LTEP}(t)}{HOEP_{Baseline}} \quad (20)$$

Equation (20) states that the $HOEP_{Ratio}$ is equal to $\overline{HOEP}_{LTEP}(t)$, the average HOEP value provided by the Long-Term Energy Plan in year t, to $HOEP_{Baseline}$, which was calculated in Equation (19).

Secondly, the ratio of the forecasted average global adjustment value provided by the LTEP to the historical average GA value from 2013 was calculated for each year of operation. Equation (21) illustrates this calculation:

$$GA_{Ratio}(t) = \frac{\overline{GA}_{LTEP}(t)}{\overline{GA}_{LTEP}(2013)} \quad (21)$$

In (21), the global adjustment ratio GA_{Ratio} is equal to the average global adjustment value provided by the Long-Term Energy Plan in year t of operation, $\overline{GA}_{LTEP}(t)$, to the average global adjustment value provided by the LTEP in 2013, $\overline{GA}_{LTEP}(2013)$. Since 2014 is the first year in which a PV or CPV project could commence, the average global adjustment value from 2013 was selected as the baseline value.

The ultimate value used to escalate – or in some years deescalate – time-of-use prices in future years was the average value of the ratio calculated in Equation (20) and the ratio calculated in Equation (21). This calculation is shown in Equation (22) below:

$$Scaling(t) = \frac{HOEP_{Ratio}(t) + GA_{Ratio}(t)}{2} \quad (22)$$

In Equation (22), $HOEP_{Ratio}(t)$ was calculated in Equation (20) and $GA_{Ratio}(t)$ was calculated in Equation (21). $Scaling(t)$ represents the factor used to either escalate

or deescalate time-of-use prices in future years. All dollar values used in the calculations of the ratios were converted to USD. A chart of the ratios calculated by Equation (22) between the years 2015 and 2045 is shown in Figure 17:

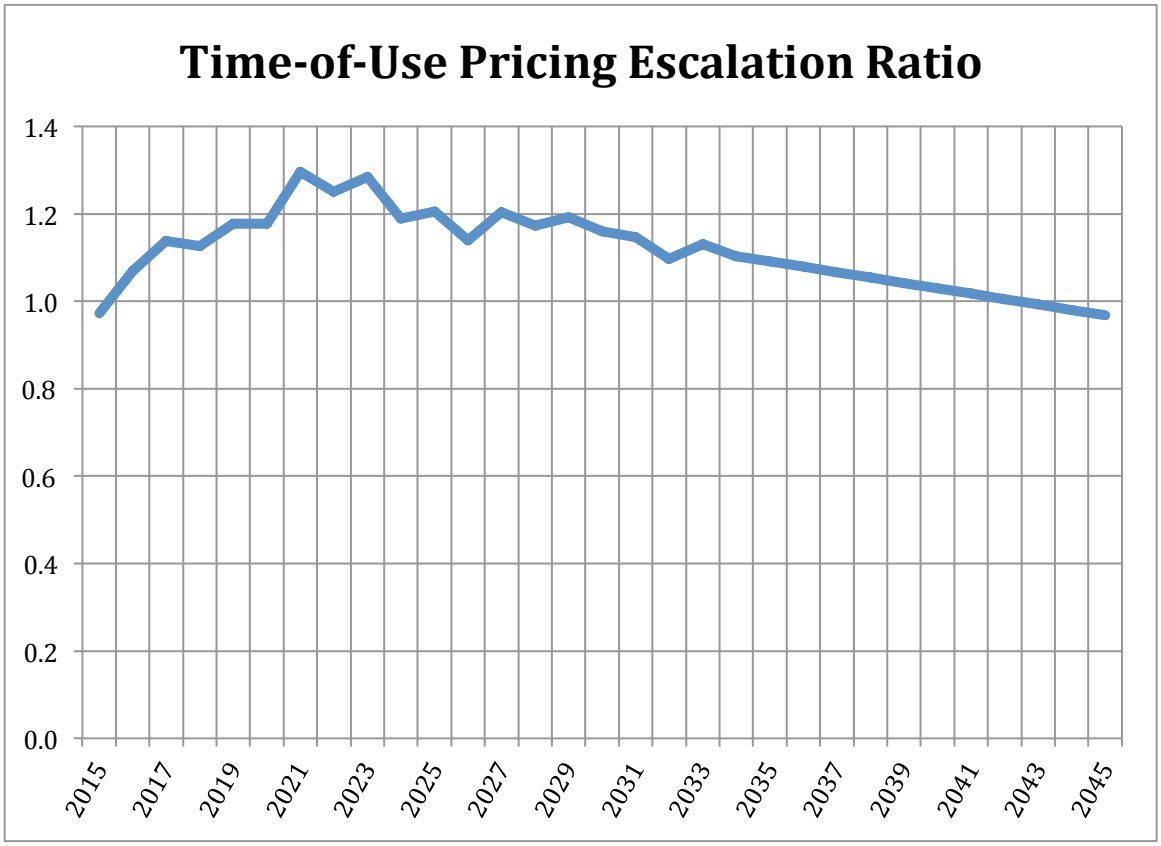


Figure 17. Time-of-use pricing ratio used to forecast future time-of-use prices.

As per Figure 17, the calculated average from Equation (22) increased until the year 2021, and then decreased afterwards. This same ratio was used to calculate the value by which distribution charges were scaled up or down for the global adjustment tariff offsetting scenario, which will be discussed in Section 4.3.4 after the power purchase agreement and feed-in tariff scenarios, the latter of which follows in the next section.

4.3.2 Feed-in Tariff (FIT)

With the feed-in tariff scenario, the price paid for solar-produced electricity was set according to a rate established by the Ontario Power Authority and guaranteed under contract for 20 years. Feed-in tariffs were introduced and thoroughly

discussed in Section 2.4.2.3. In that same section, Table 5 provided the most up-to-date FIT rates for solar projects in the province of Ontario.

Since the Ontario Power Authority did not provide projections of future feed-in tariff prices, this analysis used historical FIT rates to forecast feed-in tariff rates for solar projects commencing between 2015 and 2020. Instead of a linear regression, a logarithmic regression was used to forecast FIT prices since a linear extrapolation of past FIT prices would become negative and an exponential decline is more realistic. Figure 18 below shows average historical feed-in tariff prices for rooftop solar installations less than 500 kW as well as FIT prices that were calculated using a logarithmic regression. Both the historic and future FIT prices were calculated by the logarithmic regression were included in order to illustrate the fit of the data.

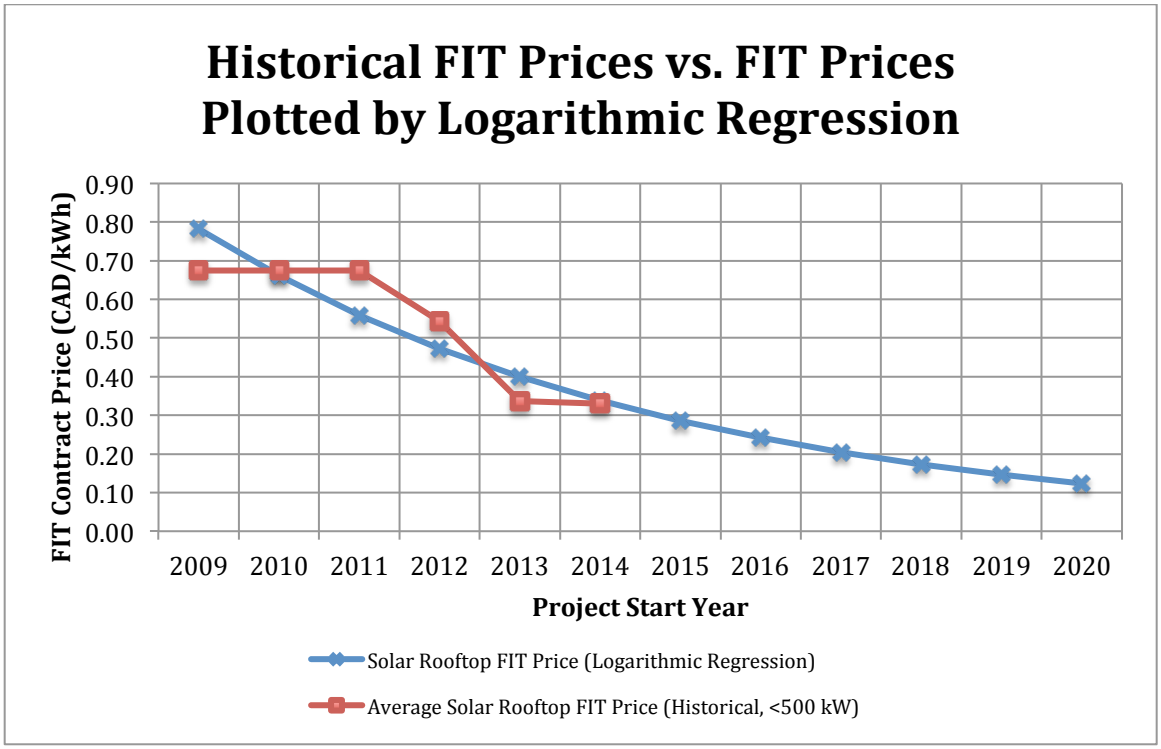


Figure 18. A comparison of historical rooftop solar FIT prices (average of all tranches <500kW) with FIT prices calculated using a logarithmic regression.

In Figure 18, the logarithmic regression produced a smooth, downward trending curve of FIT prices that, if continued, would continue downward but never cross the CAD 0.00/kWh FIT price. The value of average historic FIT prices for rooftop solar

represented by red squares decreased between 2009 and 2014, but not in the same smooth nature. However, the line of FIT prices generated by the logarithmic regression fit well with the average historical FIT prices, especially in the years 2010 and 2014 where prices from both data sets were nearly equal to one another.

Table 23 below shows historical FIT prices, and the "Average FIT Price" values in the far right-hand column were used in the logarithmic regression.

FIT Contract Start Date	Rooftop Installation Size (kW)	FIT Contract Price (CAD/kWh)	Average FIT Price (CAD/kWh)	USD/ kWh
September 24, 2009	> 10, ≤ 250 kW	0.713	0.674	0.615
	> 250, ≤ 500 kW	0.635		
July 2, 2010	> 10, ≤ 250 kW	0.713	0.674	0.615
	> 250, ≤ 500 kW	0.635		
April 5, 2012	> 10, ≤ 100 kW	0.548	0.544	0.496
	> 100, ≤ 500 kW	0.539		
August 26, 2013	> 10, ≤ 100 kW	0.345	0.337	0.307
	> 100 kW	0.329		
September 30, 2014	> 10, ≤ 100 kW	0.343	0.330	0.301
	> 100, ≤ 500 kW	0.316		

Table 23. Historical rooftop solar feed-in tariff prices. Average USD conversion rate was 0.9119 at the time of writing.

Since the PV solar installations analyzed by this thesis span in size from 142.45 kW to 452.18 kW, and the CPV installations span in size 160.26 kW to 287.32 kW, historical fit prices for installations greater than 10 kW but less than 500 kW were selected and then averaged so that each of the years between 2009 and 2014 were associated with a single FIT price. Note that the FIT price in 2011 was the same as the FIT price in 2010 since there was no update to the schedule. The base 10 logarithm of each of the average FIT prices was computed, and then a linear regression was performed on these six values.

To determine the value of future FIT prices, the following equation was used:

$$y = 10^{a+bx} \tag{23}$$

In Equation (23), y stands for the predicted FIT price value, a, is the intercept coefficient and was calculated to be 146.296 from the regression performed on the values in Table 23, b, symbolizes the year coefficient and was determined to equal -0.073 from the regression, while x represents the year for which the FIT price is being forecasted. Accordingly, the values of x ranged between 2015 and 2020, inclusive. Note that the $a + bx$ component of Equation (23) is an exponent of the base 10, and the purpose of this was to remove the logarithm. Table 24 below presents both the historical and forecasted FIT prices used in this analysis by both PV and CPV technologies:

Year	Contract Price (CAD/kWh)	Contract Price (USD/kWh)
2009	0.674	0.615
2010	0.674	0.615
2011	0.674	0.615
2012	0.544	0.496
2013	0.337	0.307
2014	0.330	0.301
2015	0.286*	0.261
2016	0.242*	0.221
2017	0.204*	0.186
2018	0.173*	0.158
2019	0.146*	0.133
2020	0.124*	0.113
*Forecasted		

Table 24. Historical and forecasted FIT prices for installations smaller than 500 kW. Future FIT prices were forecast using logarithmic regression. Average USD conversion rate was 0.9119 at the time of writing.

Note that none of the contract prices escalated during any of the operational years. Under the feed-in tariff scenario, the operational lifetime of PV and CPV installations was assumed to be 20 years – the length of a FIT contract. This was in contrast to the time-of-use tariff scenario where the operational lifetime was assumed to be 25 years or the typical useful lifespan of solar modules. The cost of dismantling and recycling solar modules was not included in the FIT scenario analysis because solar panels typically have at least a 25-year lifespan (Branker et al., 2011; Muneer et al.,

2011; Swift, 2013). In the next section, another scenario involving contractually set rates for solar-produced electricity will be introduced.

4.3.3 Power Purchase Agreement (PPA)

A power purchase agreement is an arrangement where a customer purchases electricity at a specified rate from a solar installation that is operated by a third-party. Typically, according to Zeng, Klabjan, and Arinez (2015), “a third-party developer designs, installs, owns, operates and maintains solar panels on the user's roof and the user or host procures electricity from developer-owned solar panels” (p. 296) at an agreed upon price. Similarly, the United States Environmental Protection Agency defines a power purchase agreement as “a financial arrangement in which a third-party developer owns, operates, and maintains the photovoltaic system, and a host customer agrees to site the system on its roof or elsewhere on its property and purchases the system's electric output from the solar services provider for a predetermined period” (Environmental Protection Agency, 2014, What Is a Solar Power Purchase Agreement (SPPA)?, para. 1).

Kulatilaka, Santiago, and Vakili (2014) note that the price paid for electricity as part of a power purchase agreement may increase over time at an agreed upon rate. Alternatively, some PPA’s include clauses whereby the price paid for electricity either escalates or deescalates depending upon the time of day (Southern California Edison, 2009). Regardless, the well-defined electricity prices found in a power purchase agreement are advantageous according to Davies (2014) because they can help customers with "business planning" (p. 27) by eliminating the risk associated with both fluctuating and unknown future electricity prices. National Renewable Energy Laboratory (2009b) indicates that power purchase agreements are attractive from a customer's perspective because they: relieve the customer of most if not all up-front system costs, which are typically absorbed by the third-party; secure electricity prices over 15 to 25 years, since "in a PPA, the electricity rates are predetermined, explicitly spelled out in the contract, and legally binding with no

dependency on fossil fuel or climate change legislation" (p. 3); and transfer all responsibility for system design, as well as operation and maintenance away from the customer to a third-party. From the third-party's perspective, the major attraction of power purchase agreements is that they stipulate that all of the electricity produced be purchased by the end-user (National Renewable Energy Laboratory, 2009b).

According to the Ontario Ministry of Energy, a power purchase agreement is comparable to a FIT contract (Ontario Ministry of Energy, 2014). With a FIT contract, the Government of Ontario represents the customer paying for solar-produced electricity while the independent solar producers throughout the province are the third-party responsible for setting up and maintaining solar installations. FIT contracts were discussed in Section 2.4.2.3 and Section 4.3.2. In this thesis, the analysis assumed that the data center operator took on the role of the third-party that owned the solar installation and sold the solar-produced electricity into the existing electrical grid.

While the terms of power purchase agreements signed within Ontario were challenging to come by, one PPA from 2010 was widely made public. Under this particular agreement, the Government of Ontario signed a PPA with Samsung and Korea Electric Power Corporation (KEPC) to develop 2,500 MW of solar and wind power generation in the province (Ontario Power Authority, 2011). Under this PPA, which was almost identical to a FIT contract, the province agreed to pay the 2010 ground mount solar FIT price of CAD 0.443/kWh for solar-produced electricity, plus an economic development adder of CAD 0.0143/kWh (Ontario Power Authority, 2011). Since the terms of the PPA signed with Samsung and KEPC were very similar to those of a FIT contract, this analysis used FIT rates for the baseline price paid for electricity under the power purchase agreement tariff scenario. However, ground mount FIT rates were used instead of rooftop FIT prices in order to follow the Ontario PPA example and to differentiate the PPA tariff scenario from the FIT scenario presented in Section 4.3.2. Keeping with the characteristics of a FIT

contract, this analysis also assumed that the length of a power purchase agreement was 20 years, the same length of time established by feed-in tariff contracts.

In parallel with the FIT scenario, the PPA tariff scenario used historical prices and a logarithmic regression to determine future PPA rates between the years 2015 and 2020. The historical ground mount FIT prices used by the PPA scenario are shown in Table 25 under the "FIT Contract Price" column. The base 10 logarithms of the values in this column were used in the regression calculation.

FIT Contract Start Date	Ground Mount Installation Size (kW)	FIT Contract Price (CAD/kWh)	USD/kWh
September 24, 2009	> 10 kW	0.443	0.404
August 13, 2010	> 10 kW, ≤ 10 MW	0.443	0.404
April 5, 2012	> 10 kW, ≤ 500 kW	0.388	0.354
August 26, 2013	> 10 kW	0.288	0.263
September 30, 2014	> 10 kW, ≤ 500 kW	0.275	0.251

Table 25. Historical ground mount solar feed-in tariff prices. Average USD conversion rate was 0.9119 at the time of writing.

Equation (23) from Section 4.3.2 was used to remove the logarithm and calculate the future PPA rates. Table 26 below shows both the historical and forecasted PPA prices used in this analysis by both PV and CPV technologies. Note that an economic development adder equal to 3.2% of the PPA price in each year was included in the contract prices (the economic development adder received by Samsung and KEPC was equal to 3.2% of their power purchase agreement rate of CAD 0.443/kWh in 2010).

Year	Contract Price (CAD/kWh)	Contract Price (USD/kWh)
2009	0.457	0.417
2010	0.457	0.417
2011	0.457	0.417
2012	0.401	0.366
2013	0.297	0.271
2014	0.284	0.259
2015	0.271*	0.247
2016	0.243*	0.222
2017	0.218*	0.199
2018	0.196*	0.179
2019	0.176*	0.160
2020	0.157*	0.143
*Forecasted		

Table 26. Historical and forecasted ground mount solar FIT prices for installations less than or equal to 500 kW. Future prices were forecast using logarithmic regression.

Figure 19 provides a visualization of the historical ground mount solar FIT prices as well as a plot of ground mount FIT rates calculated by logarithmic regression. The two plots fit well with one another:

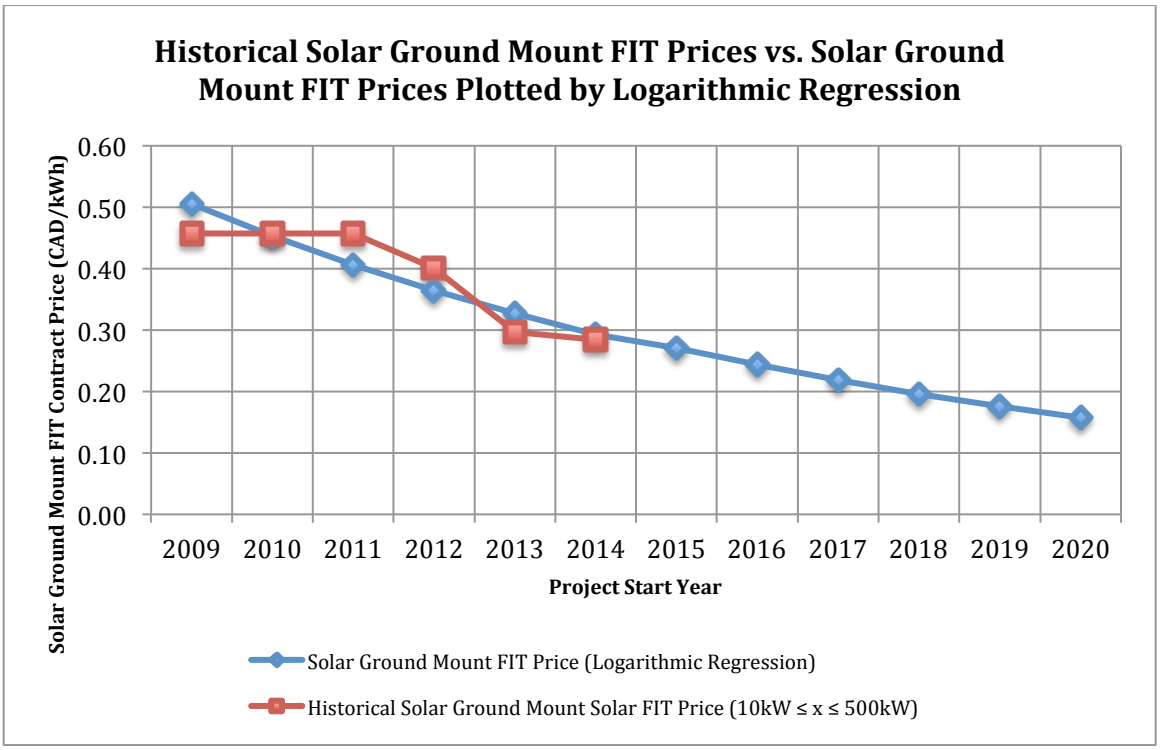


Figure 19. A comparison of historical ground mount solar FIT prices (all tranches >10kW and <500kW) with FIT prices calculated using a logarithmic regression. Both plots include a 3.2% economic development adder.

To further differentiate the PPA tariff scenario from the FIT scenario, energy payment allocation factors were employed by this analysis. Energy payment allocation factors are values that scale the price paid for electricity either up or down according to a predetermined schedule and were alluded to in the second paragraph of this section. The increase or decrease applies to the fixed price set by the power purchase agreement, and this arrangement is distinct from a PPA where electricity prices escalate according to a set rate during each year of the agreement. In this thesis, the power purchase agreement tariff scenario assumed that the price set by the PPA did not escalate over time.

Southern California Edison, a large electricity utility in California, has organized large solar projects that incorporate energy payment allocations factors within the power purchase agreements it signs with independent solar producers operating within the utility's service territory (Southern California Edison, 2009). The energy payment allocation factors used by Southern California Edison in its power purchase

agreements vary depending upon the time of day, and Table 27 shows the energy payment allocation factors from four publicly available power purchase agreements arranged by Southern California Edison:

Season	TOU Period	Time	Notes	Energy Payment Allocation Factor			
				California Renewable Energy Standard Tariff (CREST)	Renewable Market-Adjusting Tariff (ReMAT)	Solar Photovoltaic Program (SPVP)	Reverse Auction Mechanism (RAM)
Summer (June 1 - Sept 30)	On-Peak	12:00 - 18:00		3.13	1.22	2.64	1.29
	Mid-Peak	08:00 - 12:00; 18:00 - 23:00		1.35	1.11	1.27	1.04
	Off-Peak	23:00 - 08:00	Weekend rate	0.75	0.94	0.82	0.94
Winter (Oct 1 - May 31)	Mid-Peak	08:00 - 21:00		1.00	1.05	0.96	1.10
	Off-Peak	06:00 - 08:00; 21:00 - 00:00	Weekend rate	0.83	1.01	0.87	0.96
	Super Off-Peak	00:00 - 06:00	Weekend rate	0.61	0.85	0.74	0.95
Source				(Southern California Edison, 2009)	(Southern California Edison, 2014)	(Accion Group, 2014)	(Accion Group, 2015)

Table 27. Energy payment allocation factors from four power purchase agreements in California.

In Table 27, the price paid for solar-produced electricity scaled up during peak consumption times when electricity prices increased, while the price scaled down when demand subsided and the price of electricity decreased. For this thesis, the energy payment allocation factors from the four PPA's in Table 27 were averaged to create the following scaling values:

Season	Peak Class	Average Energy Payment Allocation Factor
Summer	On-Peak	2.07
	Mid-Peak	1.19
	Off-Peak	0.86
Winter	Mid-Peak	1.03
	Off-Peak	0.92
	Super Off-Peak	0.79

Table 28. Average energy payment allocation factors based upon four California power purchase agreements.

Besides those details announced by the Government of Ontario with Samsung and KEPC, no other power purchase agreement figures or characteristics for solar projects within the province of Ontario were available online. Therefore, to study the impact of energy payment allocation factors on the attractiveness of solar investment, the average figures provided in Table 28 from California were applied to the power purchase agreement tariff scenario for Ontario in this thesis. Justification for using these figures from an external jurisdiction was provided by examining the time-of-use rates from the previous tariff scenario. A calculation was performed on Hydro Ottawa's small business time-of-use rates to determine the ratios of the on-peak to off-peak, mid-peak to off-peak, and off-peak to off-peak electricity prices. These electricity prices were shown in Table 22 in Section 4.3.1. The values from these ratio calculations are shown beside the California average energy payment allocation factors from Table 28 in the following table:

	California		Ontario	
	Period	Factor	Period	Ratio
Summer	On-Peak	2.07	On-peak	2.01
	Mid-Peak	1.19	Mid-peak	1.53
	Off-Peak	0.86	Off-peak	1.00
Winter	Mid-Peak	1.03	On-peak	1.82
	Off-Peak	0.92	Mid-peak	1.48
	Super Off-Peak	0.79	Off-peak	1.00

Table 29. Comparison between average energy payment allocation factors from California and electricity prices for small businesses within Hydro Ottawa's service territory.

The ratios from Ontario are reasonably similar to the average energy payment allocation factors from California given the geographical distance between the two locations. Under the time-of-use tariff scenario from Section 4.3.1, the price paid for solar-produced electricity in Ottawa during on-peak hours was 2.01 times greater than during off-peak hours. According to the average energy payment allocation factors shown in Table 29, the price paid for solar-produced electricity during on-peak hours was 2.40 times greater than during off-peak hours. These two figures are relatively close to one another. Although the mid-peak and off-peak ratios are higher than the corresponding average energy payment allocation factors, the difference is not enormous by any means. The average energy payment allocation factors shown

in Table 28 were applied to the forecasted PPA prices from Table 26 according to the time-of-use periods for Ottawa, Ontario from Table 22.

As a final note, the cost of dismantling and recycling solar modules was not included as part of the PPA scenario because typical solar modules have a useful lifespan in excess of 20 years. This was analogous to the FIT scenario analysis presented in the previous section. In the next section, the final tariff scenario involving global adjustment tariff offsetting will be analyzed by this thesis. While elements of global adjustment tariff offsetting were presented in Section 3.3.1.3, the following will provide a more thorough discussion and review.

4.3.4 Global Adjustment (GA) Offsetting

In parallel with the time-of-use scenario from Section 4.3.1, the global adjustment tariff offsetting scenario did not involve the signing of any contracts and the solar-produced electricity was not sold for a fee. Instead, solar power was used to offset the consumption of electricity from the electrical grid and cost savings were generated instead of revenues.

As mentioned in Section 3.3.1.3, this tariff scenario was applicable only to businesses that have a peak demand in excess of 3 MW. The electricity bills received by this class of customers are composed of three separate charges. Firstly, a global adjustment fee dependent upon the customer's electricity consumption during Ontario's five greatest province-wide demand peaks from the previous year. Secondly, the Hourly Ontario Energy Price per kWh of consumed power, and thirdly a distribution charge for each monthly kW demand peak. Importantly, historical data indicate that the global adjustment peaks tend to occur during the afternoon hours of summer months (Independent Electricity System Operator, n.d.d), which is precisely the time when solar modules typically create their greatest quantity of electricity. Given that global adjustment charges can be quite substantial, the ability to offset these particular electricity charges would likely be viewed positively from

many large businesses in Ontario. As an aside, the previously mentioned distribution charges were assumed to occur during the afternoon hours over the summer months, which also represents an opportunity for additional cost savings from employing solar technology (Haysom et al., 2013b).

The value of offsetting over the 25-years of system operation under this tariff scenario was dependent upon the fluctuating cost of electricity (HOEP), global adjustment, and distribution charges. Accordingly, average future values of the former two fees were sourced from the Government of Ontario's Long-Term Energy Plan, while the latter was calculated as an average of the two fees. Figure 11 in Section 3.3.1.3 illustrated projected HOEP and GA values between 2015 and 2045, while Figure 17 from Section 4.3.1 showed forecasted distribution charge values over the same timeframe. For each year of PV or CPV system operation, the amount of cost savings generated from offsetting Hourly Ontario Energy Price charges, global adjustment charges, and distribution charges was calculated using Equations (1), (2), and (3) from Section 3.3.1.3, respectively. The total amount of offsetting in a given operating year was computed by Equation (4), which summed Equations (1), (2), and (3) together.

Under the time-of-use, feed-in tariff, and power purchase agreement tariff scenarios, the system energy yield was the only variable in the Monte Carlo simulation. The price paid for solar-produced electricity was set by a contract for feed-in tariffs and power purchase agreements, while for time-of-use pricing the value generated from not consuming electricity from the electrical grid was dependent upon the rates set by Hydro Ottawa. While electricity prices varied depending upon the time of day under the time-of-use and power purchase agreement tariff scenarios, this was categorically different than the current global adjustment scenario where the price per kilowatt-hour of electricity was determined by market forces. Accordingly, in this scenario energy *price* variability was introduced to the Monte Carlo simulation since the average Hourly Ontario Energy Price fluctuates every hour of every day. Whereas the financial attractiveness of solar investment under the time-of-use,

feed-in tariff, and power purchase agreement tariff scenarios was tested assuming only two scenarios – zero variability and energy yield variability – the financial attractiveness of solar investment under the global adjustment tariff offsetting scenario was tested assuming zero variability, energy yield variability, and energy yield *as well as energy price variability*. Table 14 in Section 3.4 summarized the variability scenarios tested by the global adjustment tariff offsetting scenario.

4.4 Summary

In Chapter 4, the numerical inputs used by the financial model for both PV and CPV technologies were defined. This included values for system prices, operation and maintenance fees, inverter replacement costs, as well as degradation and discount rates. Additional values for the cost of dismantling and recycling the solar modules after their useful lifetime, as well as assumed module and system efficiencies were also provided. The remainder of the chapter was devoted to presenting useful details and formulas corresponding to the time-of-use, fee-in tariff, power purchase agreement, and global adjustment tariff offsetting scenarios. Appendix E provides a table summarizing the combinations of pricing, tariff, and variability scenarios under which the four financial metrics mentioned in Section 3.3.1.4 will be calculated.

Prior to reviewing the PV and CPV results, two key points about the results in Chapters 5 through 8 must be emphasized. The first is that the PV results were based upon historical empirical alternating current electricity data gathered from operational Hydro Ottawa photovoltaic installations. The second point is that the CPV results were based upon historical direct normal irradiance figures, which, through a series of calculations touched upon in Section 3.3.1.1, were converted into alternating current electricity data. The distinction between the two sources of data is important to comprehend while reviewing the results.

Chapter 5: Discounted Net Present Value Results

5.1 Time-of-Use Discounted Net Present Value Results

5.1.1 Deterministic Results

5.1.1.1 Photovoltaic Technology

Chapter 5 presents the discounted net present value results for each of the four tariff scenarios discussed in Section 4.3. For each of these scenarios, the results stemming from the use of photovoltaic technology will be presented first, followed by the results related to concentrated photovoltaic technology.

Assuming zero variability in PV energy yield, Figure 20 below illustrates discounted net present value figures for each of the "pessimistic," "average," and "optimistic" costing scenarios. These discounted net present values stem from input values provided by Table 15 and Table 16 in Section 4.1. During each of the PV installation's 25 operational years, the amount of cost savings generated was discounted back to start date of the project as per the discount rate assigned to each scenario from Table 15. Additionally, if the project was deferred to commence operations in any year after 2014, the net present value of cost savings was discounted back to 2014 using a risk-free Treasury rate from Table 17 in Section 4.1 based upon the number of elapsed years. The purpose of double discounting was to determine the value today – in 2014 – of the future value of a PV investment. Accordingly, each data point on the charts in this section represents the value of investing in a PV project in 2014 even if that project commences operations at some point after 2014. For example, Figure 20 below indicates that the value today of investing in a PV installation commencing operations in the year 2020 and running until the year 2045 under the "optimistic" costing scenario is approximately USD 80,000:

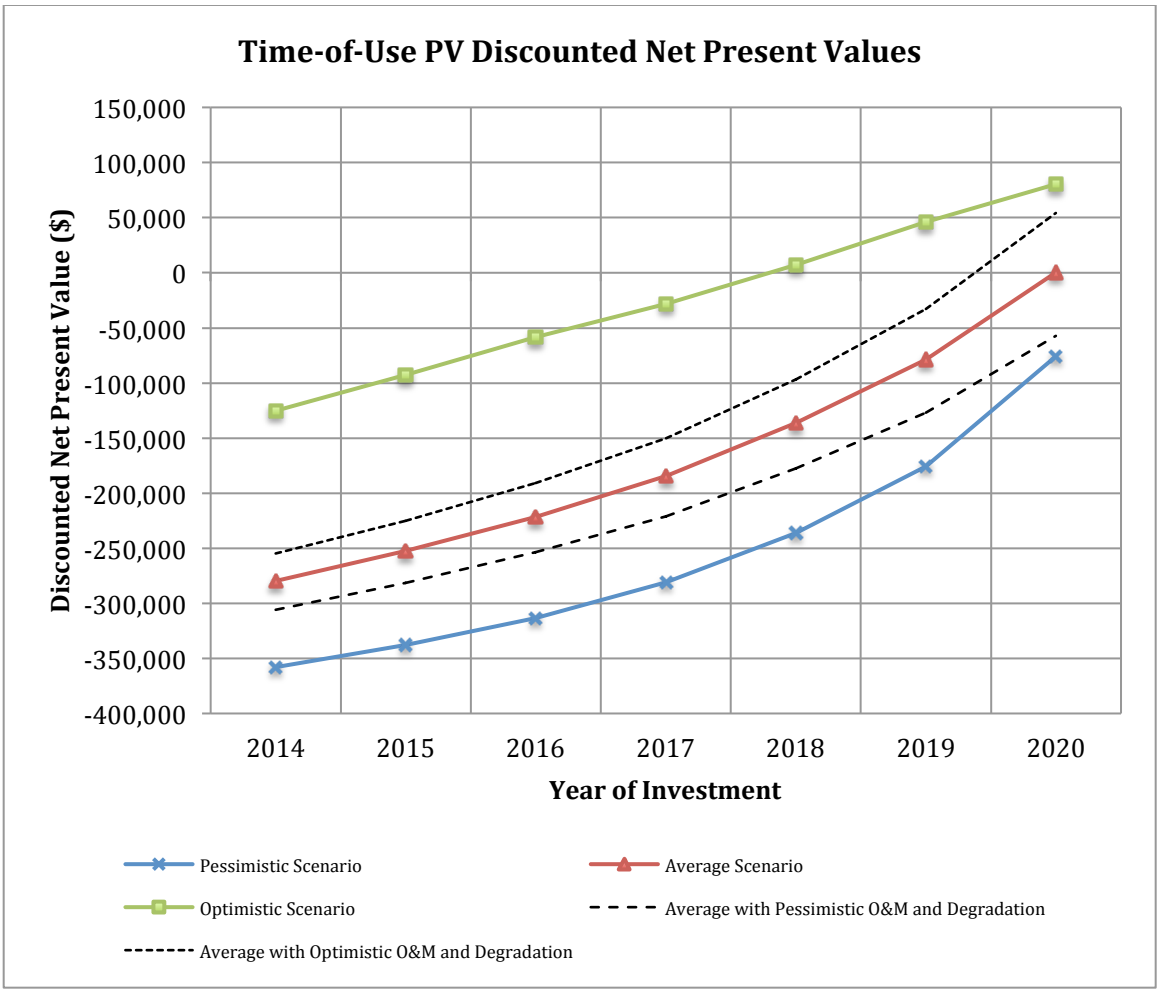


Figure 20. Discount net present values for a PV installation situated in Ottawa, Ontario that sells the electricity it produces at Hydro Ottawa's time-of-use rates for small businesses.

Figure 20 also included two additional plots of discounted net present value figures. One represented the discounted net present values of the "average" scenario with the operation and maintenance cost, as well as degradation rate from the "pessimistic" scenario. The other represented the discounted net present values of the "average" scenario with the operation and maintenance cost, as well as degradation rate from the "optimistic" scenario. The O&M costs and degradation rates for each costing scenario were provided in Table 15.

Plots of these two lines were added to provide a range of discounted net present values related to the "average" costing scenario. The operation and maintenance cost, as well as the degradation rate were selected for this additional calculation

involving the “average” scenario because they represented two items that could not necessarily be controlled once the system was operational. While the $/W cost to install a PV system, for example, could be secured via a contract, operation and maintenance fees may vary depending upon the environmental conditions under which the solar system operates. Furthermore, the degradation rate may not be exactly as predicted, possibly as a result of imperfect manufacturing processes, for instance. Interestingly, according to Figure 20, the discounted NPV under the “average” scenario with the “optimistic” O&M cost and degradation rate was USD 54,337.17 in 2020 compared with USD 133.61 in the same year under the standard “average” scenario. This represented a significant discounted NPV increase of over 40,567% as a result of a 47.37% decrease to the yearly operation and maintenance cost and a 60% decline in the yearly degradation rate.

5.1.1.2 Concentrated Photovoltaic Technology

Turning to CPV technology, Figure 21 illustrates discounted net present values as per the inputs from the “pessimistic,” “average,” and “optimistic” scenarios presented in Table 19, as well as the additional inputs from Table 20 in Section 4.2:

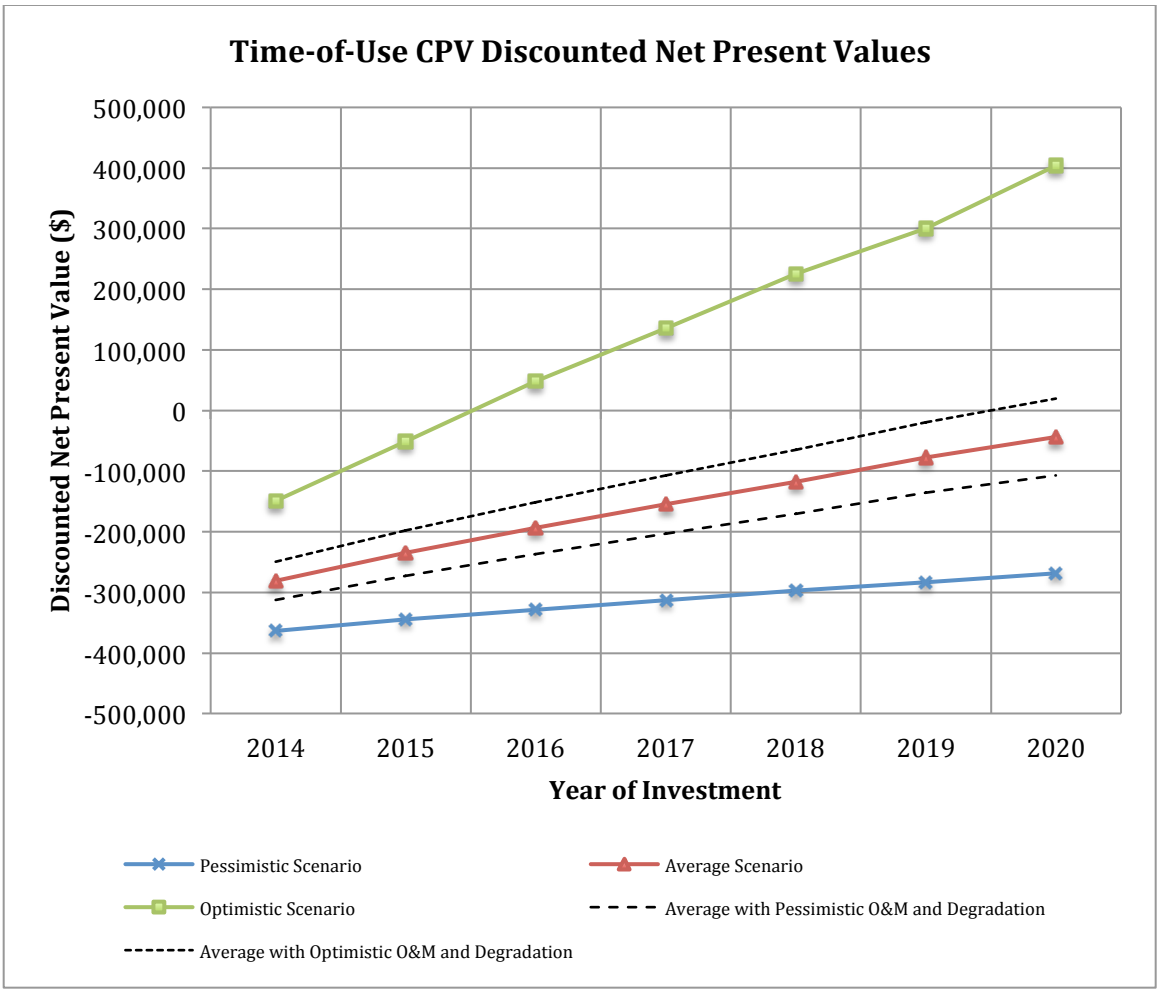


Figure 21. Discount net present values for a CPV installation situated in Ottawa, Ontario. The electricity produced by the installation offsets electricity-grid consumption at Hydro Ottawa's time-of-use rates for small businesses.

In the same manner as the PV results in Figure 20, Figure 21 illustrated discounted net present values for CPV technology by showing the results from the three costing scenarios, as well as a range of values for the "average" scenario that accounted for both "optimistic" and "pessimistic" O&M fees, and degradation rates. Both CPV operation and maintenance costs as well as degradation rates for all three costing scenarios were provided in Table 19. Analogous to the PV results, the "average" CPV costing scenario showed a positive discounted NPV in 2020 with the O&M and degradation rate from the "optimistic" costing scenario.

There were, however, some differences between the PV and CPV discounted net present value results. For example, a positive discounted NPV was not observed

until the year 2018 under the "optimistic" PV results, whereas a positive discounted NPV was seen by the year 2016 under the "optimistic" CPV results. Not only did the positive discounted net present values occur earlier for CPV technology, but there were also a greater number of total positive discounted NPV results for CPV technology compared with PV technology. The plots of the "average" and "pessimistic" PV discounted net present values curved upwards in a much steeper manner than the "average" and "pessimistic" plots of the CPV discounted net present values. As well, the CPV "optimistic" scenario discounted net present values were much higher than the PV "optimistic" discounted net present values. This was likely attributable to the lower $/W system costs for CPV compared with PV from the year 2015 onwards as shown by Table 15 and Table 19. Note that the forecasted $/W system cost figures used by this thesis subsume improvements in cell efficiencies.

5.1.2 Energy Yield Variability Results

5.1.2.1 Photovoltaic Technology

In this section, system energy yield variability will be introduced as part of the discounted net present value calculations. The purpose of introducing this new factor is to observe the extent of discounted NPV variability resulting from fluctuating system energy output. Analyzing the impact of variability on discounted net present values is important because it can be used as part of a risk assessment, for example, either by a prospective solar installation operator or by a bank considering loaning capital to finance a new PV or CPV system. Literature pertaining to solar risk identification, assessment, and management was reviewed in Sections 2.4.1, 2.4.2, and 2.4.3, respectively.

Energy yield variability was introduced to the discounted net present value calculations via a Monte Carlo simulation, which generated new values based upon a mean and standard deviation of historical data, as well as a random probability. Details pertaining to the Monte Carlo simulation were discussed in Section 3.4.1,

including the distribution of input values and the equations used to calculate variability as part of the simulation.

The charts in this section display the mean discounted NPV after 250 Monte Carlo simulations. The plots of the average discounted net present values looked very similar to the static energy yield charts from the previous section. Figure 22 provides evidence of this and compares plots of the discount net present values with zero energy yield variability on the left to the average discounted net present values calculated from 250 Monte Carlo simulations from each of the years 2014 through 2020 on the right. The similarities between the plots contained within two charts were expected, since the calculations to compute both the no-variability and energy variability results relied upon the same inputs.

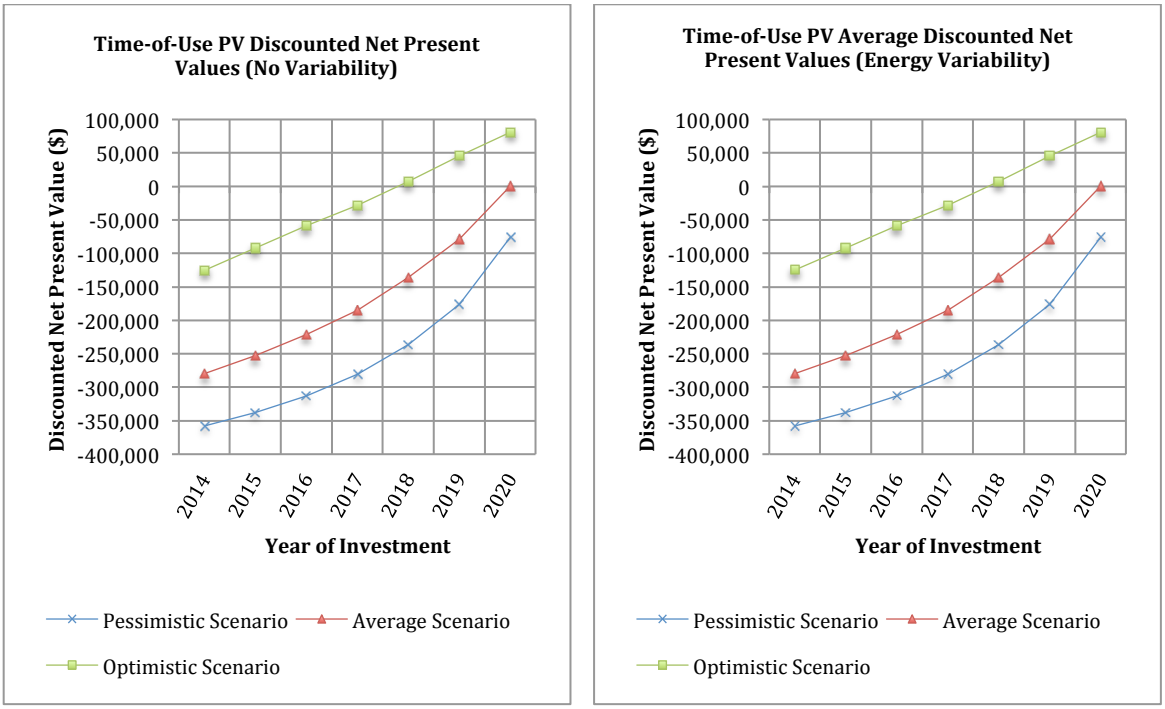


Figure 22. A comparison of PV discounted net present values when there is no energy variability (left) and energy variability (right).

Numeric discounted net present value results from the PV technology Monte Carlo simulation, including the standard deviation, minimum, average, maximum, and range of values observed after 250 simulations, are shown below in Table 30:

Scenario	Year	Standard Deviation	Minimum ($)	Average ($)	Maximum ($)	Range ($)
Pessimistic	2014	474.61	-359,084.90	-357,696.19	-356,469.61	2,615.29
	2015	585.34	-339,578.11	-337,511.40	-335,539.62	4,038.49
	2016	640.80	-315,190.39	-313,097.81	-311,334.14	3,856.25
	2017	749.36	-282,873.78	-280,908.61	-278,864.12	4,009.66
	2018	967.21	-239,214.84	-236,285.32	-233,717.15	5,497.69
	2019	1088.17	-178,443.24	-175,819.25	-172,458.45	5,984.79
	2020	1386.35	-80,088.54	-75,858.89	-71,862.08	8,226.46
Average	2014	654.78	-281,291.54	-279,585.65	-278,001.66	3,289.87
	2015	720.35	-254,265.20	-252,417.91	-250,717.67	3,547.53
	2016	834.33	-223,694.75	-221,362.50	-218,841.00	4,853.75
	2017	943.62	-186,511.95	-184,461.99	-181,775.79	4,736.17
	2018	1078.46	-138,848.17	-135,980.46	-132,775.78	6,072.39
	2019	1264.22	-81,826.07	-78,728.32	-74,856.08	6,970.00
	2020	1629.74	-3,102.84	112.61	4,945.79	8,048.64
Optimistic	2014	974.56	-127,825.53	-125,125.15	-122,175.69	5,649.84
	2015	1102.43	-95,729.09	-92,550.23	-89,816.92	5,912.17
	2016	1200.91	-61,350.34	-58,384.82	-54,905.99	6,444.35
	2017	1259.70	-31,621.12	-28,047.87	-24,386.31	7,234.81
	2018	1372.72	3,908.60	7,465.20	11,278.15	7,369.55
	2019	1485.24	41,464.17	45,718.98	48,778.23	7,314.06
	2020	1675.37	76,172.31	80,486.42	85,237.65	9,065.34

Table 30. PV discounted net present value, standard deviation, minimum, average, maximum, and range figures from the time-of-use Monte Carlo simulation results. All figures are in USD.

The calculated ranges shown in Table 30 tended to increase as time moved forward. This could be due to the fact that system prices decreased each year while at the same time an increased amount of capital was available to spend on investment in a PV installation. One result from this relationship was that larger PV installations were constructed as time moved forward[7], and from the increasing range values it appeared as though energy yield variability was amplified by the larger installations. The standard deviations of the data also increased between the years 2014 and 2020 likely for the same reason.

[7] PV installation sizes for each of the years 2014-2020 were provided in Table 18.

A chart illustrating a part of the results from Table 30 is shown in Figure 23 below. This chart provides a visualization of variability by including 95% confidence intervals on both sides of the means for each of the three pricing scenarios:

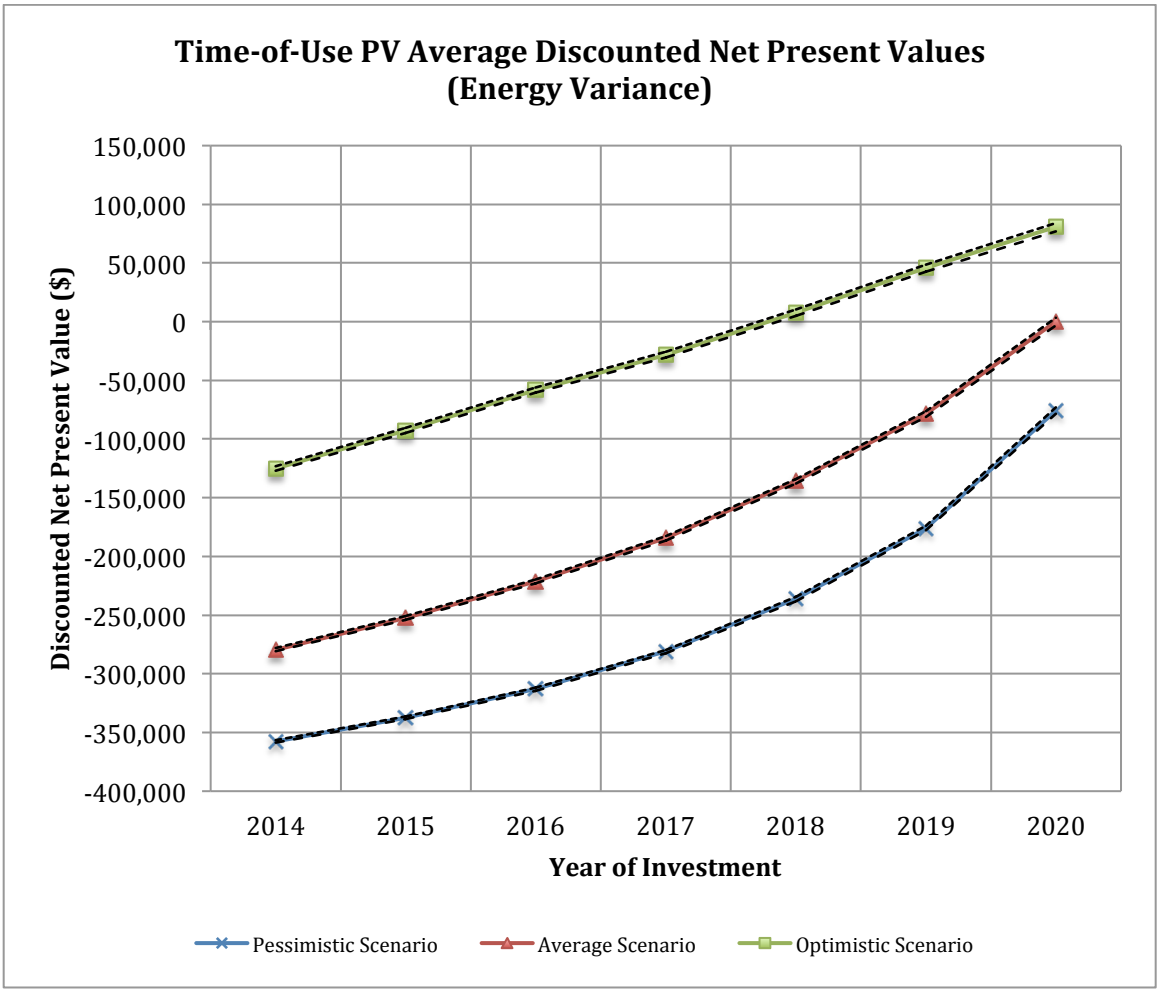


Figure 23. Average PV discounted net present values with energy variability 95% confidence intervals under the time-of-use tariff scenario.

Since the input figures used to calculate the discounted net present values were normally distributed, the 95% confidence intervals shown in Figure 23 were computed using the following equation:

$$DNPV_{95\%CI}(t) = DNPV_{\mu}(t) \pm 1.96(DNPV_{\sigma}(t)) \quad (24)$$

In (24), $DNPV_{95\%CI}(t)$ stands for the discounted net present value 95% confidence interval for year t, $DNPV_{\mu}(t)$ represents the average discounted NPV from the 250

Monte Carlo simulations in year t, while $DNPV_{\sigma}(t)$ denotes the discounted net present value standard deviation of the 250 simulation results in year t. The number 1.96 corresponds to the Z-value of a 95% confidence interval under a normal distribution curve.

The 95% confidence intervals in the above chart were rather difficult to see. Below, a close-up of a portion of Figure 23 shows the Monte Carlo simulation results for the "optimistic" scenario between the years 2017 and 2020:

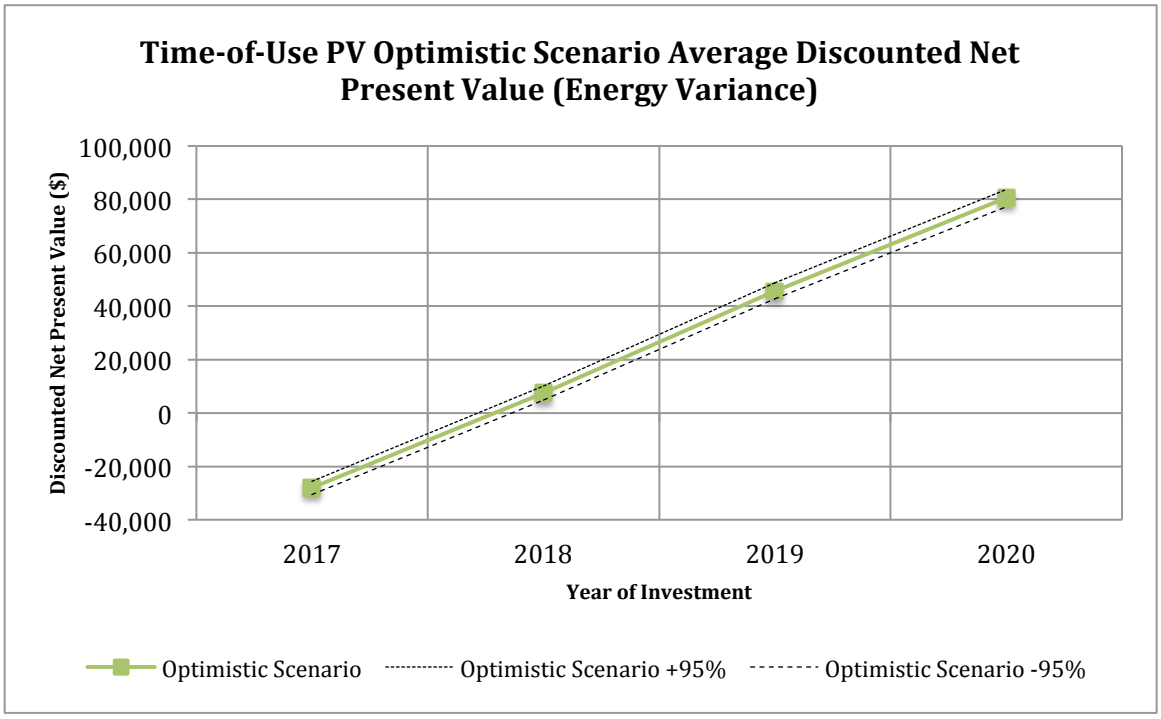


Figure 24. Close-up of the PV "optimistic" scenario's average discount net present values after 250 Monte Carlo simulations with the +95% and -95% confidence interval on each side of the mean for the years 2017 to 2020.

Even though it was more distinctive close-up, the 95% confidence interval shown by Figure 24 was still quite narrow. This meant that 95% of the time the discounted NPV for any of the years shown would be located within this thin confidence interval band. Notably, the ranges of the 95% confidence intervals under the "average" and "pessimistic" scenarios were even narrower. This type of information was useful for risk assessment. From the charts presented thus far in this section, the risk of a discounted NPV falling significantly away from the mean in any of the years 2014 through 2020 was rather small.

Normality tests, which were introduced and defined in Section 3.4.1, were performed on the simulated data to ensure the data were in fact normally distributed. Figure 25 below shows one such normality test on 250 time-of-use discount net present values that were generated by the Monte Carlo simulation for the 2014 PV "average" costing scenario:

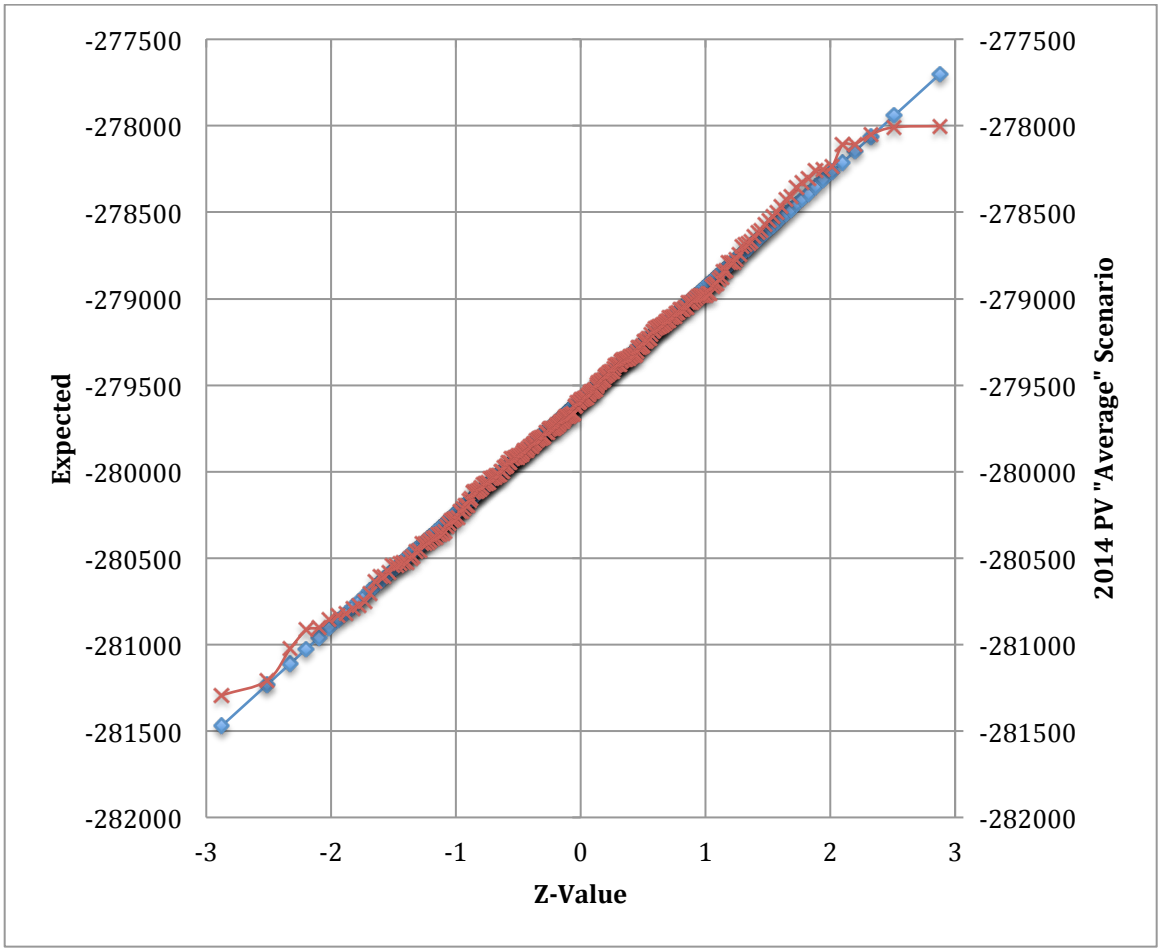


Figure 25. Normality test of the 250 discounted net present values generated by the Monte Carlo simulation for PV technology.

Since the red x's of observed values closely followed the blue squares of expected values, the 250 simulated values were considered normally distributed because of a lack of evidence to suggest otherwise. Additional normality tests results for photovoltaic technology under the time-of-use tariff scenario have been included in Appendix D. In the next section, further analysis pertaining to discounted NPV variability under the time-of-use tariff scenario will be presented.

5.1.2.2 Photovoltaic Technology Variability Analysis

In this section, three sources of variability and their impacts on discounted NPV variability will be analyzed. Firstly, variability due to system energy yield will be analyzed. This was introduced in Section 5.1.2.1 and stemmed from the Monte Carlo simulation. Secondly, variability due to the range of possible operations and maintenance costs, as well as degradation rates as provided by the literature review will be examined. This idea was presented in Sections 5.1.1.1 and 5.1.1.2 and was illustrated by the dashed plot lines of discounted net present values above and below the solid-red plot line of mean discounted net present values in Figure 20, for instance. Finally, variability due to the different system costs, which were also collected from the literature review, will be investigated. This variability was introduced via the "pessimistic," "average," and "optimistic" plots of discounted net present values in Figure 20, Figure 21, and Figure 22, for example, in the in the previous three sections.

For variability due to O&M and degradation, as well as system costs, the variability was in terms of what discounted net present values *could* be possible. For example, under system cost variability, it was assumed that the $/W price of a system could fall anywhere between the "pessimistic" and the "optimistic" system costs presented by Table 15 in Section 4.1 for PV technology and Table 19 in Section 4.2 for CPV technology in each of the years 2014 to 2020. The same was true for O&M and degradation, meaning that operations and maintenance costs as well as degradation rates could fall anywhere between the "pessimistic" and "optimistic" values provided by the same tables. This, in turn, would affect the final discounted net present value.

To provide further insights into the variability of the results, the coefficient of variation was calculated for each pricing scenario. The coefficient of variation "is defined as the ratio of a series' standard deviation to its mean" (Cuddy & Valle, 1978, p. 79). Another way of thinking about the coefficient of variation is in terms of

the ratio of risk to expected value. Although not identical to a standard risk/return ratio calculation, the coefficient of variation still has value to prospective investors.

Continuing with 95% confidence intervals, the coefficient of variation was used as part of the following formula to determine how close 95% of the discounted net present values were in relation to the mean:

$$DNPV_{95\%}(t) = \pm 1.96\left(\frac{DNPV_{\sigma}(t)}{DNPV_{\mu}(t)}\right) \tag{25}$$

In (25), $DNPV_{95\%}(t)$ stood for 95% of the discounted net present values at time t, $DNPV_{\sigma}(t)$ denoted the standard deviation of the 250 discounted net present values at time t, and $DNPV_{\mu}(t)$ represented the mean of the 250 discounted net present values at time t. The figure 1.96 defined the Z-score associated with 95% of the data under normal distribution conditions.

Using Equation (25), Table 31 below lists the percentage of variability due to energy yield as a proportion of the mean. Note that in instances where the mean value was close to zero, the percentage of variability figure was considered an outlier. Siegel (2011) noted that the coefficient of variation did not work well when values close to zero were involved in the calculation, and so these particular values are identified using a * in the tables throughout Chapter 5.

Discounted Net Present Value Variability due to Energy Yield				
Year	**% Above/Below Central Estimate**	**Pessimistic Scenario**	**Average Scenario**	**Optimistic Scenario**
2014	% above central estimate	0.26%	0.46%	1.53%
	% below central estimate	-0.26%	-0.46%	-1.53%
2015	% above central estimate	0.34%	0.56%	2.33%
	% below central estimate	-0.34%	-0.56%	-2.33%
2016	% above central estimate	0.40%	0.74%	4.03%
	% below central estimate	-0.40%	-0.74%	-4.03%
2017	% above central estimate	0.52%	1.00%	8.80%
	% below central estimate	-0.52%	-1.00%	-8.80%
2018	% above central estimate	0.80%	1.55%	36.04%*
	% below central estimate	-0.80%	-1.55%	-36.04%*
2019	% above central estimate	1.21%	3.15%	6.37%
	% below central estimate	-1.21%	-3.15%	-6.37%
2020	% above central estimate	3.58%	2836.48%*	4.08%
	% below central estimate	-3.58%	-2836.48%*	-4.08%

Table Notes:

- "Central estimate" is the mean discounted net present value from the Monte Carlo simulation
- The above figures represent variability as a proportion of the mean with 95% confidence
- *Values that are exceptional due to the central estimate being close to zero

Table 31. Percentage of discounted net present value variability due to energy yield for PV technology under the time-of-use tariff scenario.

Over all, the figures in Table 31 indicated energy yield variability had only a small impact on discounted NPV. Excluding the values marked by a *, 95% of discounted net present values were within plus or minus 8.80% of the mean at most when system energy yields were variable. For the years where PV investment was profitable, 2020 under the "average" scenario, and 2018-2020 under the "optimistic" scenario, an investor would be wise to wait to invest in 2020 under the "optimistic" scenario since profitability was highest and the interval of % above/below the central estimate from Table 31 was smallest.

Below, Table 32 summarizes the extent of how system price as well as O&M and degradation could vary discounted NPV by indicating how much higher (lower) discounted NPV is in each year above (below) the central estimate due to lower (higher) system costs and, separately, lower (higher) O&M and degradation values.

The central estimate referred to in the previous sentence is the discounted net present values associated with the "average" pricing scenario:

Discounted NPV Variability due to System Cost and O&M and Degradation			
Year	**% Above/Below Central Estimate**	**System Cost⊙**	**O&M and Degradation❖**
2014	% above central estimate	55.21%	8.90%
	% below central estimate	-27.96%	-9.36%
2015	% above central estimate	63.31%	10.86%
	% below central estimate	-33.73%	-11.43%
2016	% above central estimate	73.63%	13.79%
	% below central estimate	-41.45%	-14.52%
2017	% above central estimate	84.83%	18.66%
	% below central estimate	-52.24%	-19.66%
2018	% above central estimate	105.51%	29.04%
	% below central estimate	-73.74%	-30.63%
2019	% above central estimate	158.19%	58.02%
	% below central estimate	-123.38%	-61.25%
2020	% above central estimate	60203.43%*	40567.68%*
	% below central estimate	-56828.35%*	-42877.05%*

Table Notes:

- ⊙Range from literature: Aanesen, Heck, and Pinner (2012), Ardani et al. (2013).
- ❖Range from literature: Branker et al. (2011), Di Francia (2013), Lowder et al. (2013), National Renewable Energy Laboratory (2013a), Zweibel (2010).
- "Central estimate" is the "average" discounted net present value with zero variability
- *Values that are exceptional due to the central estimate being close to zero

Table 32. Percentage of discounted net present value variability due to system cost, as well as O&M and degradation for PV technology under the time-of-use tariff scenario.

According to Table 32, system cost could vary discounted NPV to a greater extent than O&M and degradation during each of the years 2014 to 2020, and the magnitude of variation under both sources of variability increased over these seven years. Thus, when deciding when to invest in a PV installation under the time-of-use tariff, an investor could expect greater discounted NPV variability, and thus more risk, in projects that commenced operations closer to 2020. Below, Table 33 provides the ratio of variability due to system cost to variability due to O&M and degradation using the figures from Table 32:

Ratio of Variability due to System Cost to Variability due to O&M and Degradation		
Year	**Ratio Above/Below Central Estimate**	**Ratio**
2014	Ratio above central estimate	6.20
	Ratio below central estimate	2.99
2015	Ratio above central estimate	5.83
	Ratio below central estimate	2.95
2016	Ratio above central estimate	5.34
	Ratio below central estimate	2.85
2017	Ratio above central estimate	4.55
	Ratio below central estimate	2.66
2018	Ratio above central estimate	3.63
	Ratio below central estimate	2.41
2019	Ratio above central estimate	2.73
	Ratio below central estimate	2.01
2020	Ratio above central estimate	1.48
	Ratio below central estimate	1.33

Table Note:

- "Central estimate" is the "average" discounted net present value with zero variability

Table 33. Ratio of variability due to system cost compared with variability due to O&M and degradation for PV technology under the time-of-use tariff scenario.

Table 33 indicated that system cost variability was always greater than O&M variability since all values in the table were greater than 1. The ratios also indicated that the magnitude of discounted NPV variability could have been greater above the mean compared with below the mean.

In a final assessment of discounted net present value variability for PV technology under the time-of-use tariff scenario, Table 34 below calculates how much more discounted NPV variability could have varied from O&M and degradation, which was indicated in Table 32, compared with energy yield, which was indicated in Table 31:

Ratio of O&M and Degradation Variability to Energy Yield Variability				
Year	**Ratio Above/Below Central Estimate**	**Pessimistic Scenario**	**Average Scenario**	**Optimistic Scenario**
2014	Ratio above central estimate	34.22	19.39	5.83
	Ratio below central estimate	35.99	20.39	6.13
2015	Ratio above central estimate	31.96	19.42	4.65
	Ratio below central estimate	33.63	20.44	4.90
2016	Ratio above central estimate	34.38	18.67	3.42
	Ratio below central estimate	36.20	19.65	3.60
2017	Ratio above central estimate	35.69	18.61	2.12
	Ratio below central estimate	37.61	19.61	2.23
2018	Ratio above central estimate	36.20	18.68	0.81*
	Ratio below central estimate	38.17	19.70	0.85*
2019	Ratio Above central estimate	47.83	18.43	9.11
	Ratio below central estimate	50.49	19.46	9.62
2020	Ratio above central estimate	11325.51*	14.30	9943.42*
	Ratio below central estimate	11970.23*	15.12	10509.47*

Table Note:

- "Central estimate" is the mean discounted net present value from the Monte Carlo simulation
- *Values that are exceptional due to the central estimate being close to zero

Table 34. A comparison of how much more discounted net present value variability is due to O&M and degradation compared with energy yield for PV technology under the time-of-use tariff scenario.

Excluding the values marked with a *, which included values in the above table calculated from a value marked with a * from Table 31 and Table 32, discounted NPV variability due to O&M and degradation was between 2.12 and 50.49 times greater than variability due to energy yield. The ratio values were consistently smallest under the "optimistic" scenario, and largest under the "pessimistic" scenario. The ratio values under the "average" scenario were the most stable of the three scenarios between 2014 and 2020.

5.1.2.3 Concentrated Photovoltaic Technology

Moving to CPV technology, discounted net present value standard deviation, minimum, average, maximum, and range figures are shown below in Table 35:

Scenario	Year	Standard Deviation	Minimum ($)	Average ($)	Maximum ($)	Range ($)
Pessimistic	2014	942.57	-365,557.35	-363,709.92	-361,862.49	3,694.87
	2015	1,086.12	-346,366.03	-344,237.23	-342,108.44	4,257.60
	2016	1,219.50	-330,415.53	-328,025.31	-325,635.08	4,780.44
	2017	1,410.50	-315,658.99	-312,894.41	-310,129.84	5,529.16
	2018	1,488.29	-300,176.15	-297,259.10	-294,342.06	5,834.09
	2019	1,665.16	-286,211.39	-282,947.68	-279,683.96	6,527.42
	2020	1,723.84	-271,854.78	-268,476.05	-265,097.32	6,757.46
Average	2014	1,328.12	-283,395.54	-280,792.43	-278,189.32	5,206.23
	2015	1,515.56	-237,793.75	-234,823.24	-231,852.74	5,941.01
	2016	1,865.26	-197,300.19	-193,644.28	-189,988.36	7,311.83
	2017	2,055.62	-158,894.11	-154,865.10	-150,836.08	8,058.03
	2018	2,400.16	-122,101.15	-117,396.84	-112,692.53	9,408.62
	2019	2,684.54	-82,640.67	-77,378.97	-72,117.27	10,523.40
	2020	2,803.58	-49,183.03	-43,688.02	-38,193.01	10,990.02
Optimistic	2014	1,747.04	-152,332.20	-148,908.01	-145,483.83	6,848.38
	2015	2,278.21	-54,914.29	-50,448.99	-45,983.70	8,930.58
	2016	2,856.36	42,378.29	47,976.75	53,575.21	11,196.93
	2017	3,181.58	129,560.51	135,796.41	142,032.31	12,471.80
	2018	4,167.23	217,493.93	225,661.70	233,829.48	16,335.54
	2019	4,494.51	291,416.21	300,225.46	309,034.70	17,618.49
	2020	4,934.89	394,707.47	404,379.85	414,052.23	19,344.76

Table 35. CPV discounted net present value, standard deviation, minimum, average, maximum, and range figures from the time-of-use Monte Carlo simulation results. All figures are in USD.

In tandem with the PV results, the CPV standard deviation and range figures increased as time moved towards the year 2020. A chart showing a plot of the mean discounted net present values for the three costing scenarios is presented in Figure 26. This chart includes the 95% confidence interval on either side of the mean for each year. The confidence intervals were calculated using Equation (24), which was defined earlier in Section 5.1.2.1.

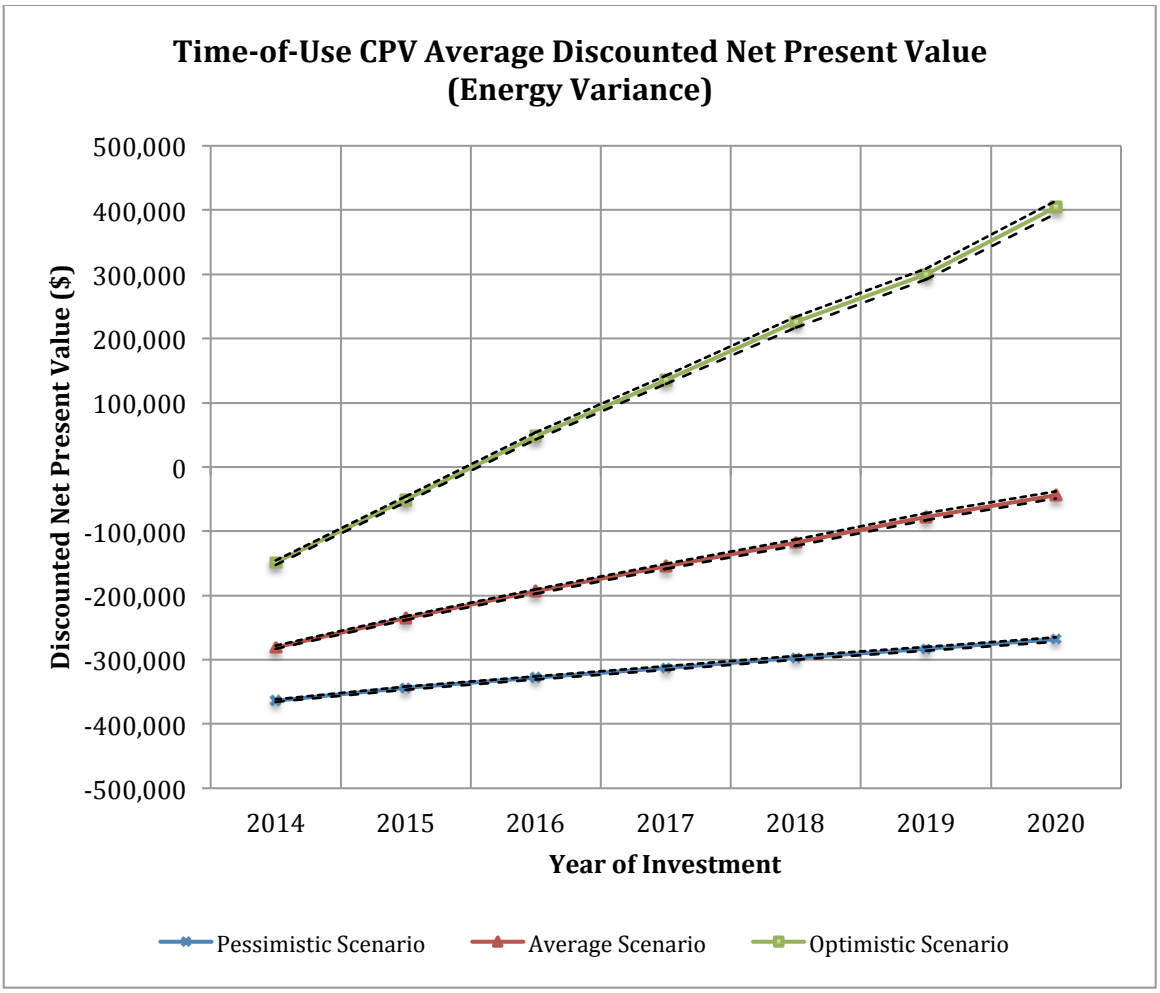


Figure 26. Average CPV discount net present values with energy variability 95% confidence intervals under the time-of-use tariff scenario.

The 95% confidence intervals associated with the CPV results were wider than those from the PV results, but were still narrow overall. For each of the years 2014 through 2020, the standard deviations of the CPV discounted NPV results were larger than the standard deviations of the PV discounted NPV results under the three costing scenarios. The smallest difference between standard deviation values in any year between the PV and CPV results was 3,259.52 in the year 2020 under the "optimistic" scenario.

In Figure 26, the upper 95% confidence interval was distinguished by tightly spaced rectangular dashes, while the lower 95% confidence interval was identified by larger, rectangular dashes with wider spacing. Focusing on the "optimistic" scenario,

which was the only situation where profitability was realized, the confidence intervals grew wider as time progressed towards 2020. Nevertheless, these intervals were not excessively wide at any point and did not imply that there was a large amount of risk associated with energy yield variability. Given that the standard deviations of the discounted net present values also increased over time, this was not unexpected. A close-up of the "optimistic" scenario mean discounted net present values with 95% confidence intervals between the years 2017 to 2020 is shown in Figure 27:

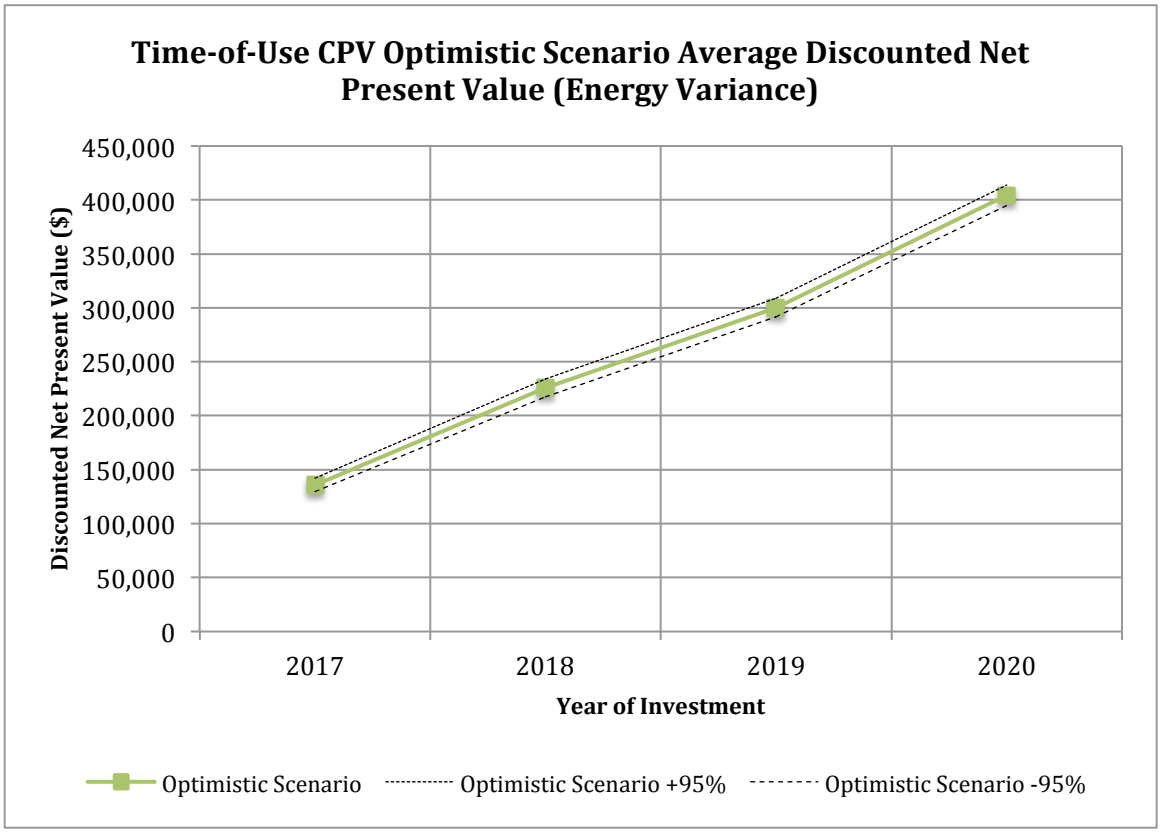


Figure 27. Close-up of the CPV "optimistic" scenario's average discount net present values after 250 Monte Carlo simulations with the +95% and -95% confidence interval on each side of the mean for the years 2017 to 2020.

The enlarged plot of the CPV "optimistic" scenario between the years 2017 and 2020 illustrated that the 95% confidence interval on either side of the mean was fairly narrow. This meant there was only a 5% chance that the discounted NPV would fall outside of the slim band represented by the two dashed line plots in Figure 27, and this narrowness was considered a positive from a risk management perspective.

Normality tests were performed on the CPV discounted net present values generated by the Monte Carlo simulation to ensure that simulated values were normally distributed. Figure 28 below displays one such normality test on the 250 values generated for the 2014 CPV "optimistic" scenario:

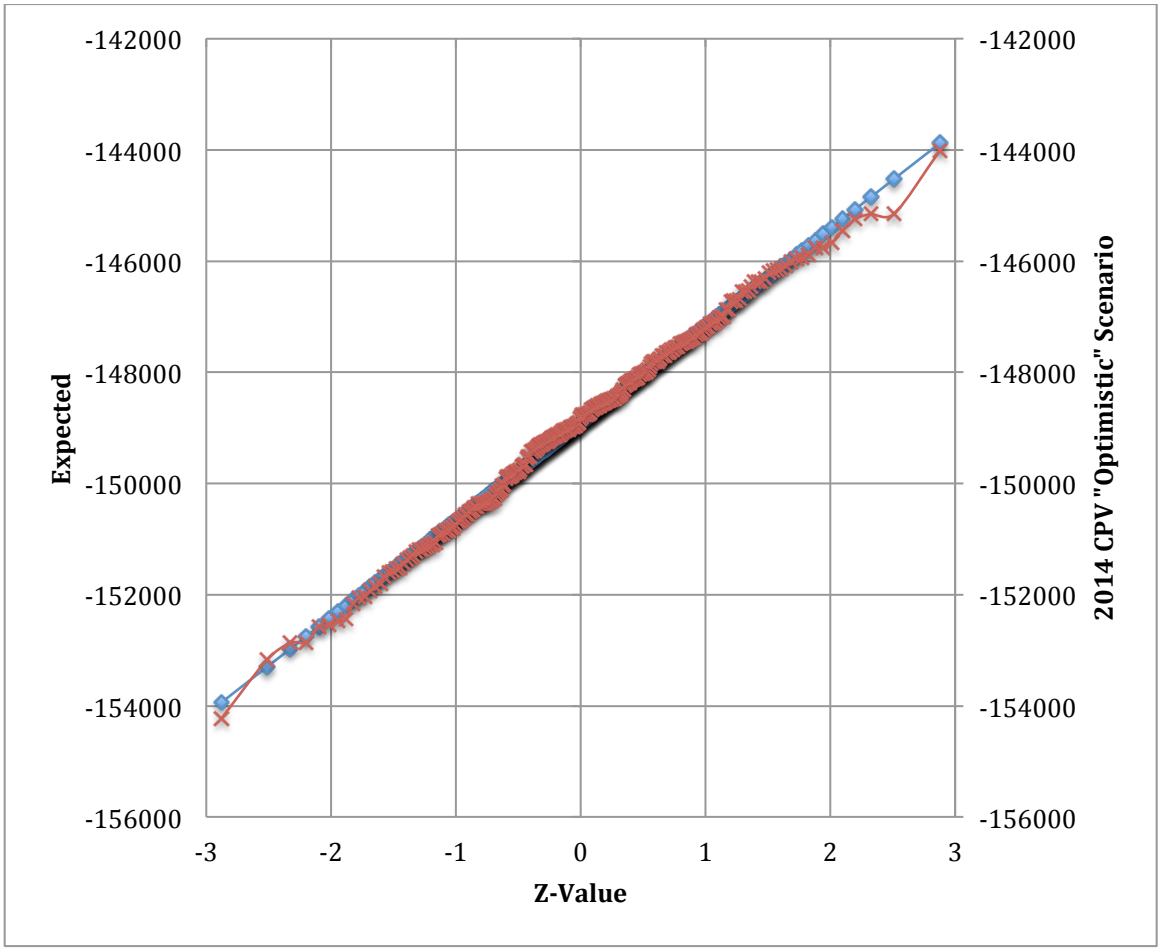


Figure 28. Normality test of the 250 discounted net present values generated by the Monte Carlo simulation for CPV technology.

The red x's in Figure 28, which denote observed values, matched the expected values that were represented by blue squares. Consequently, the 250 simulated discount net present values could be considered normally distributed. The results of additional normality tests results for CPV technology are available in Appendix D. Further analysis of discounted net present value variability for CPV technology follows in the next section.

5.1.2.4 Concentrated Photovoltaic Technology Variability Analysis

Using Equation (25) from Section 5.1.2.2, the following table defines energy variability as a proportion of the mean:

Discounted Net Present Value Variability due to Energy Yield				
Year	**% Above/Below Central Estimate**	**Pessimistic Scenario**	**Average Scenario**	**Optimistic Scenario**
2014	% above central estimate	0.51%	0.93%	2.30%
	% below central estimate	-0.51%	-0.93%	-2.30%
2015	% above central estimate	0.62%	1.26%	8.85%
	% below central estimate	-0.62%	-1.26%	-8.85%
2016	% above central estimate	0.73%	1.89%	11.67%
	% below central estimate	-0.73%	-1.89%	-11.67%
2017	% above central estimate	0.88%	2.60%	4.59%
	% below central estimate	-0.88%	-2.60%	-4.59%
2018	% above central estimate	0.98%	4.01%	3.62%
	% below central estimate	-0.98%	-4.01%	-3.62%
2019	% above central estimate	1.15%	6.80%	2.93%
	% below central estimate	-1.15%	-6.80%	-2.93%
2020	% above central estimate	1.26%	12.58%	2.39%
	% below central estimate	-1.26%	-12.58%	-2.39%

Table Notes:

- "Central estimate" is the mean discounted net present value from the Monte Carlo simulation
- The above figures represent variability as a proportion of the mean with 95% confidence
- *Values that are exceptional due to the central estimate being close to zero

Table 36. Percentage of discounted net present value variability due to energy yield for CPV technology under the time-of-use tariff scenario.

According to Table 36, 95% of the discounted net present values were at most within plus or minus 12.58% of the mean. Profitability was observed for projects starting between 2016 and 2020 under the "optimistic" pricing scenario. For an investor concerned about the impact of energy yield variability on discounted NPV, it was best to defer investment as long as possible since discounted net present value *variability* was lowest and discounted net present *value* was highest in 2020 under the "optimistic" scenario.

Table 37 compares discounted NPV variability due to system cost against the variability due to O&M and degradation:

Discounted NPV Variability due to System Cost and O&M and Degradation			
Year	**Above/Below Central Estimate**	**System Cost⊙**	**O&M and Degradation❖**
2014	% above central estimate	46.99%	11.23%
	% below central estimate	-29.56%	-11.23%
2015	% above central estimate	78.55%	15.87%
	% below central estimate	-46.46%	-15.87%
2016	% above central estimate	124.82%	22.03%
	% below central estimate	-69.37%	-22.03%
2017	% above central estimate	187.88%	31.01%
	% below central estimate	-102.35%	-31.01%
2018	% above central estimate	292.31%	45.03%
	% below central estimate	-153.28%	-45.03%
2019	% above central estimate	488.38%	75.51%
	% below central estimate	-265.50%	-75.51%
2020	% above central estimate	1028.17%	144.92%
	% below central estimate	-516.13%	-144.92%

Notes:

- ⊙Range from literature: Haysom et al. (2014).
- ❖Range from literature: Drury et al. (2013), Gerstmaier et al. (2014).
- "Central estimate" is the "average" discounted net present value with zero variability
- *Values that are exceptional due to the central estimate being close to zero

Table 37. Percentage of discounted net present value variability due to system cost, as well as O&M and degradation for CPV technology under the time-of-use tariff scenario.

Above the mean, discounted net present values could have varied to a greater extent compared with below the mean on account of $/W system prices between 2014 and 2020. The extent to which discounted net present values could vary on either side of the mean due to variable O&M and degradation was equal, and this was due to the evenly spaced values used for CPV operations and maintenance costs and degradation rates. These figures were provided in Table 19 in Section 4.2.

Ratio of Variability due to System Cost to Variability due to O&M and Degradation		
Year	**Ratio Above/Below Central Estimate**	**Ratio**
2014	Ratio above central estimate	4.19
	Ratio below central estimate	2.63
2015	Ratio above central estimate	4.95
	Ratio below central estimate	2.93
2016	Ratio above central estimate	5.67
	Ratio below central estimate	3.15
2017	Ratio above central estimate	6.06
	Ratio below central estimate	3.30
2018	Ratio above central estimate	6.49
	Ratio below central estimate	3.40
2019	Ratio above central estimate	6.47
	Ratio below central estimate	3.52
2020	Ratio above central estimate	7.09
	Ratio below central estimate	3.56

Table Note:

- "Central estimate" is the "average" discounted net present value with zero variability

Table 38. Ratio of variability due to system cost compared with variability due to O&M and degradation for CPV technology under the time-of-use tariff scenario.

According to Table 38 above, system cost variability was greater than O&M plus degradation variability in each of the years 2014 to 2020 even though the values from both sources of variability increased over time. The extent to which system cost variability was greater than O&M and degradation variability also increased in each year between 2014 and 2020. With system profitability increasing in each of the years 2016 through 2020 under the "optimistic" scenario, an investor looking to maximize profitability by investing in a later year would need to accept greater amounts of possible risk due to variability of system cost as well as O&M and degradation.

Turning to a different comparison of variability sources, O&M and degradation variability was between 1.79 and 115.15 times greater than energy yield variability:

Ratio of O&M and Degradation Variability to Energy Yield Variability				
Year	**Ratio Above/Below Central Estimate**	**Pessimistic Scenario**	**Average Scenario**	**Optimistic Scenario**
2014	Ratio above central estimate	22.10	12.11	4.88
	Ratio below central estimate	22.10	12.11	4.88
2015	Ratio above central estimate	25.67	12.55	1.79
	Ratio below central estimate	25.67	12.55	1.79
2016	Ratio above central estimate	30.23	11.67	1.89
	Ratio below central estimate	30.23	11.67	1.89
2017	Ratio above central estimate	35.10	11.92	6.75
	Ratio below central estimate	35.10	11.92	6.75
2018	Ratio above central estimate	45.89	11.24	12.44
	Ratio below central estimate	45.89	11.24	12.44
2019	Ratio Above central estimate	65.47	11.10	25.74
	Ratio below central estimate	65.47	11.10	25.74
2020	Ratio above central estimate	115.15	11.52	60.59
	Ratio below central estimate	115.15	11.52	60.59

Table Note:

- "Central estimate" is the mean discounted net present value from the Monte Carlo simulation
- *Values that are exceptional due to the central estimate being close to zero

Table 39. A comparison of how much more discounted net present value variability is due to O&M and degradation compared with energy yield for CPV technology under the time-of-use tariff scenario.

While the ratio values under the "average" scenario in Table 39 remained relatively unchanged between 2014 and 2020, ratio values under the "optimistic" and "pessimistic" scenarios increased over time. With variability due to O&M and degradation steadily increasing, the ratio values from the "optimistic" scenario overtook those from the "average" scenario in Table 39 in 2018.

5.1.3 Section 5.1 Summary

In Section 5.1.1, discounted net present values for PV and CPV offsetting under time-of-use pricing were presented. The discounted net present values with zero energy yield variability were presented in Sections 5.1.1.1 and 5.1.1.2. In these two sections, the "average" costing scenario was combined with operation and maintenance costs, as well as degradation rates from the "optimistic" and "pessimistic" costing scenarios to illustrate a range of possible discounted net present values under average system prices. The discounted net present values stemming from these

tests were shown in Figure 20 for PV technology and Figure 21 for CPV technology. From these two charts, significant amounts of profitability from offsetting time-of-use rates for small businesses did not occur until approximately the year 2019 for PV technology and 2016 for CPV technology.

The energy yield variability results in Section 5.1.2 indicated that the discounted net present values associated with CPV technology experienced greater variability than the discounted net present values associated with PV technology. On a kWh/m^2 basis, the standard deviations of the CPV system output calculated from DNI data were larger than the standard deviations of the Hydro Ottawa PV system kWh output data. Accordingly, the energy yield from the CPV system varied more than the energy yield from the PV system. The 95% confidence intervals on either side of the mean for both PV and CPV technologies were relatively narrow. Further variability analysis uncovered that system cost had the largest impact on varying discounted net present values, followed by O&M and degradation and then system energy yield. 95% of the discounted net present values fell within plus or minus 8.80% of the mean under PV technology and 12.58% of the mean for CPV technology. From a risk management perspective, this meant that an investor could be very confident that the actual discounted net present value would be close to the predicted mean. In the next section, the discounted net present values from the feed-in tariff pricing scenario will be analyzed.

5.2 Feed-in Tariff Discounted Net Present Value Results

5.2.1 Deterministic Results

5.2.1.1 Photovoltaic Technology

Discount net present values were calculated in this section using the system prices, operation and maintenance costs, degradation rates, discount rates, and inverter replacement cost from Table 15, as well as the additional PV inputs from Table 16 in

Section 4.1. The prices paid for solar-generated electricity under a feed-in tariff contract were provided in Table 24 in Section 4.3.2, and additional information about FIT contracts was provided in Section 2.4.2.3. Instead of cost savings created under the time-of-use pricing scenario in the previous section, revenue was generated under the feed-in tariff scenario. The value of future FIT revenue streams was also discounted back to the year 2014 according to the appropriate discount rate from Table 15 in Section 4.1. As well, if the decision to invest in a PV or CPV project was delayed until a future year, the value of future revenues was discounted back to 2014 using the appropriate risk-free Treasury rate from Table 17 depending upon the number of years the project was deferred. These calculations determined the value of the future revenue stream in 2014.

Below, Figure 29 provides discounted net present values for the "pessimistic," "average," and "optimistic" costing scenarios for a PV project selling electricity according to the USD feed-in tariff prices shown in Table 24. Two additional plots of discounted net present values were added to Figure 29 in addition to those from the three standard pricing scenarios. Firstly, a scenario was added where the "average" system price, discount rate, and inverter cost from Table 15 in Section 4.1 were combined with the "optimistic" operation and maintenance cost, as well as degradation rate from the same table. A second scenario was added where the "average" system price, discount rate, and inverter cost were combined with the "pessimistic" O&M cost and degradation rate from the same table. Note that under the FIT scenario, the PV project was assumed to operate for 20 years instead of 25 because the length of a FIT contract is 20 years.

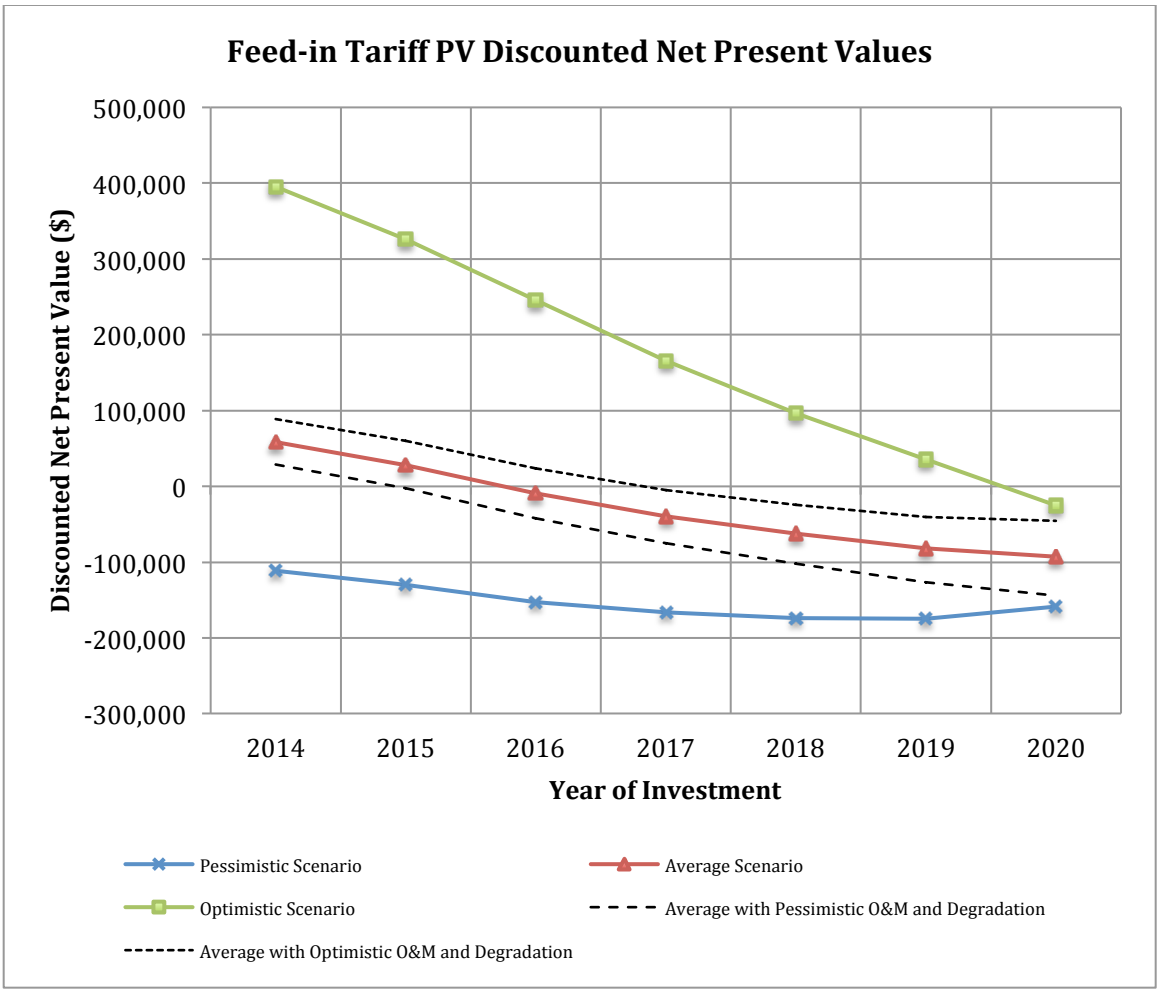


Figure 29. Discount net present values for a PV installation situated in Ottawa, Ontario that sells the electricity it produces under a feed-in tariff contract.

In Figure 29, the plots of the discounted net present values decreased as time moved forwards towards 2020. This was in contrast to the previous time-of-use tariff scenario where the discounted net present values from Figure 20 in Section 5.1.1.1 increased as time progressed. The price paid for solar-produced electricity under a FIT contract did not increase over time or fluctuate depending upon the time of day. Since an introduction in 2009, FIT prices have been decreasing as the costs associated with solar installations decline. Figure 18 in Section 4.3.2 illustrated historical FIT prices, as well as future feed-in tariff prices forecasted for use in this analysis. The future prices were forecasted using logarithmic regression. Given that FIT prices are expected to continue to diminish over time, an investor would want to

secure a feed-in tariff contract sooner rather than later to take advantage of the higher prices paid for solar-produced electricity now.

However, the discounted net present value results in this section considered not only diminishing FIT prices but also declining PV and CPV system costs. Taking these two downward trending factors together, the discounted net present value results in Figure 29 indicated that the reduction in system prices was not keeping pace with the downtrend in FIT prices, which was why the "average" and "optimistic" plots of discounted net present values decreased over time. Thus, as indicated by Figure 29, an investor was better off investing early if the system prices followed either the "average" or "optimistic" costing scenarios.

In terms of the magnitude of FIT price decreases over time, the 2014 average solar rooftop FIT rate for installations greater than 10 kW but less than 500 kW was less than half the average rate for installations of the same class and size in 2009. Accordingly, profitability between 2014 and 2020 was not observed under all of the pricing scenarios in Figure 29. While the most favourable costing scenario, the "optimistic" scenario, saw healthy profits during the years 2014 through 2018, the "average" costing scenario ceased to be profitable after 2015 and the "pessimistic" costing scenario did not realize and profitability. The additional plot comprised of discounted net present values calculated using the "average" scenario's system price with "optimistic" scenario O&M expenses and degradation rate showed a small amount of profitability in the year 2016. In contrast, the standard "average" pricing scenario illustrated by the solid red line Figure 29 did not show profitability in this year.

Interestingly, the range defined by the plots of "Average with Optimistic O&M and Degradation" and "Average with Pessimistic O&M and Degradation" widened as time progressed towards 2020. In all likelihood, this phenomenon was due to the larger PV installations that were built as a result of PV investment being deferred until a later year. Additional capital was available for investment into these

installations since the initial USD 100,000 of assumed capital available in 2014 was invested at a risk-free interest rate until required. Table 18 in Section 4.1 illustrated the amounts of capital available in each of the years 2014 through 2020 for PV installation investment. The same table also provided details about the sizes of PV installations constructed during each of those years in both kW and m^2. A PV installation constructed in the year 2020, for example, produced over 200% more kilowatt-hours of electricity output per year compared with a PV system in 2014. As evidenced by the widening dashed lines in Figure 29: the larger the system size, the bigger the change in discounted NPV when the O&M cost and degradation rate inputs were modified.

5.2.1.2 Concentrated Photovoltaic Technology

For CPV technology, the three costing scenario inputs from Table 19 and supplemental inputs from Table 20 were combined with the USD feed-in tariff prices from Table 24 to calculate discounted net present values over a 20-year timeframe. The results are shown in Figure 30 below:

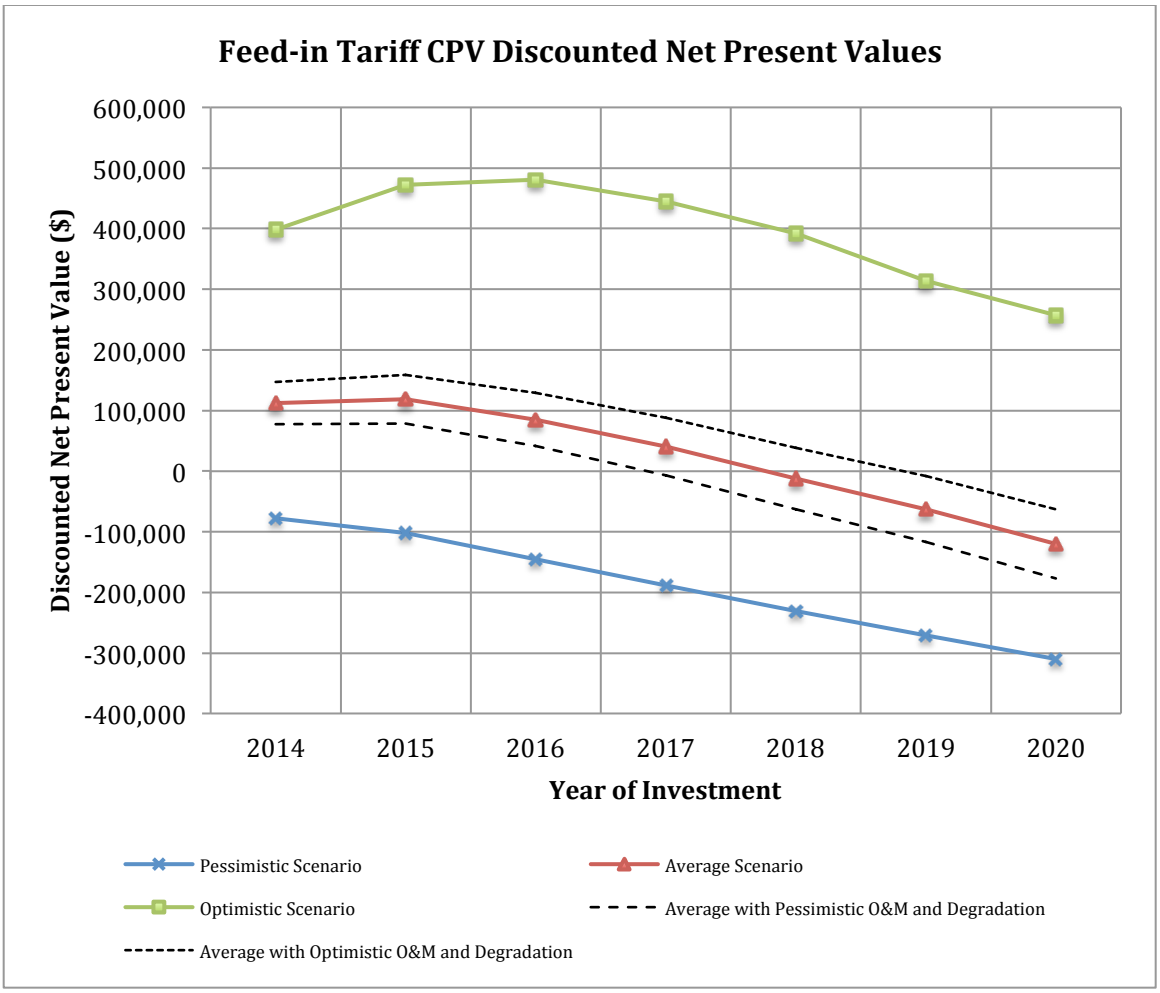


Figure 30. Discount net present values for a CPV installation situated in Ottawa, Ontario that sells the electricity it produces according to a feed-in tariff contract.

The plots shown in Figure 30 followed an intriguing pattern. While the discounted net present values associated with the "pessimistic" scenario trended downwards as time moved forward, the discounted net present values from the "average" and "optimistic" costing scenarios increased and then began decreasing in future years creating the conditions where the optimal year to invest in a CPV installation with a FIT contract was not 2014. According to Figure 30, the best time to invest in a CPV installation if a FIT contract was secured under the "optimistic" costing scenario was in 2016, while the ideal time to invest under the "average" pricing scenario was in 2015. The dashed plots did not affect the most favourable time to invest under the "average" pricing scenario.

The reason for the unique shape of the "optimistic" and "average" plots in Figure 30 was likely due to the interaction between the declining capital costs and the decreasing feed-in tariff prices. In Section 2.4.1.3, Timilsina, Kurdgelashvili, and Narbel (2012) noted that the initial expenditure on a solar installation is usually substantial, and the amount of capital spent has a large impact on system's profitability. The curved plot lines in Figure 30 above illustrate this idea. Consider the "average" scenario, where the system cost was USD 2.44/W in 2014 and the net present value of a CPV project commencing in 2014 and operating for 25 years was USD 112,550.43. In 2015 with a system cost of USD 2.06/W, the discounted net present value increased to USD 118,884.64 even when the effect of discounting was taken into consideration. However, had the 2015 $/W capital cost been USD 2.44/W, the same as 2014, or nearly any amount greater than USD 2.06/W, the 2015 discounted NPV would have decreased instead of increasing as observed. Figure 31 illustrates this concept, with a series of hypothetical capital costs between USD 2.44/W in 2014 and USD 2.06/W in 2015:

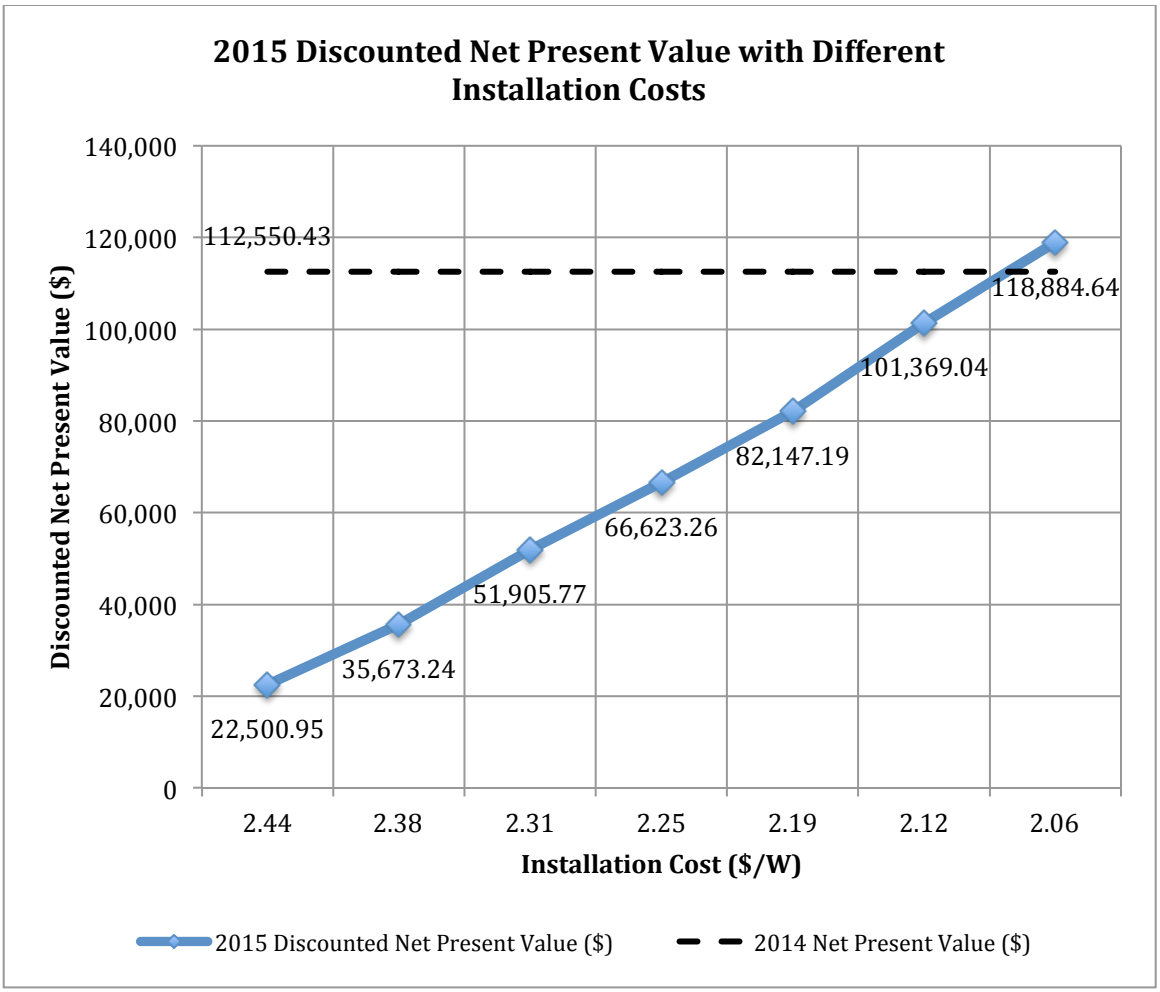


Figure 31. Possible discounted net present values in 2015 given the actual installation cost of $2.06/W and hypothetical installation costs greater than $2.06/W. All figures are in USD.

As per Figure 31, the $/W installation costs above USD 2.06/W would have caused the discounted NPV to decline in 2015. However, at USD 2.06/W, the discounted net present value actually increased in that year. In this case, the $/W drop is large enough to offset the decline in the feed-in tariff price even when discounting was taken into account. Note that the installation prices between USD 2.44/W and USD 2.06/W were purely hypothetical and used only for illustrative purposes.

Looking to the year 2016 under the "average" scenario in Figure 30, the decline in $/W installation cost was not enough to offset the decrease in FIT price, from USD 0.261/kWh in 2015 to USD 0.221/kWh in 2016 as per Table 24 in Section 4.3.2. Figure 32 demonstrates this fact:

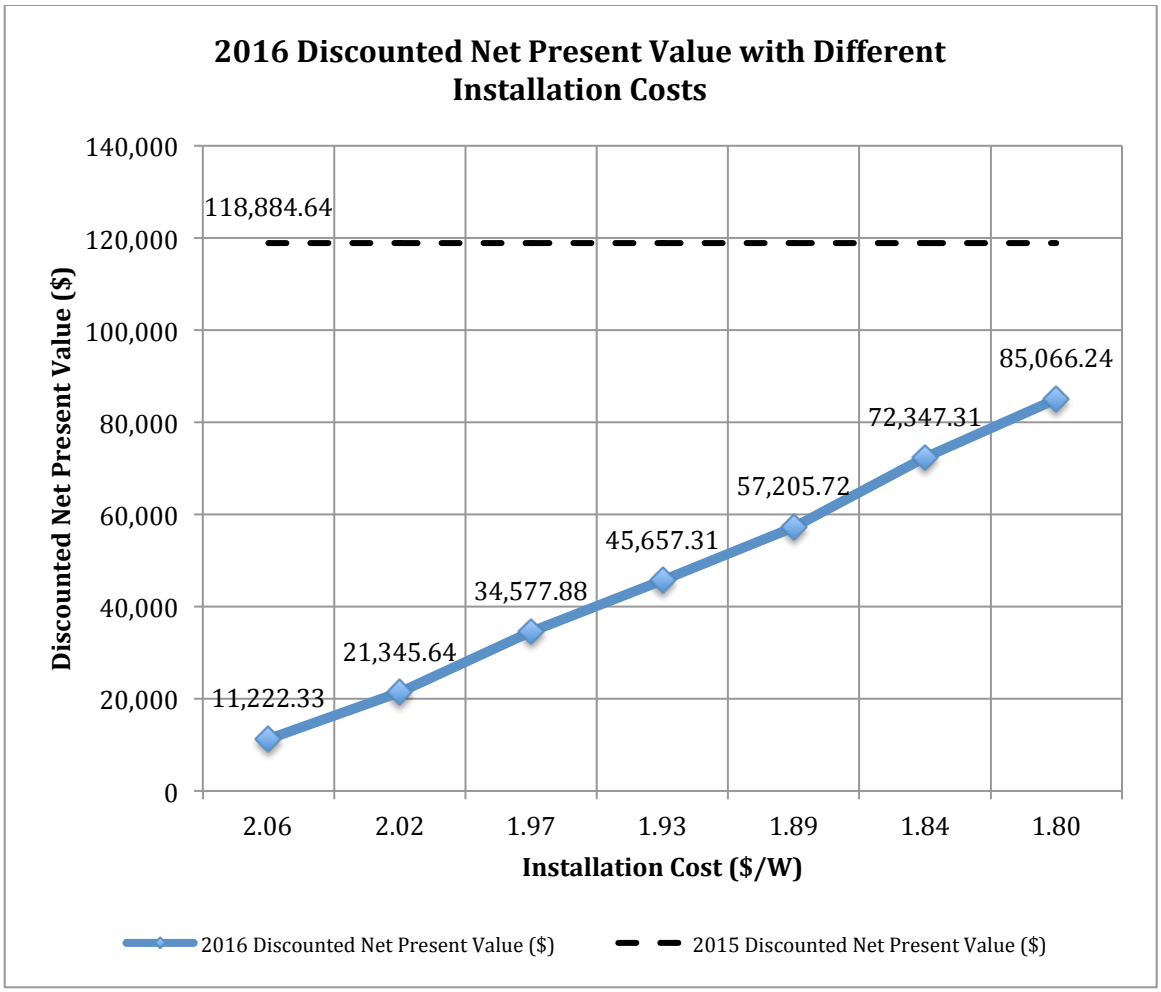


Figure 32. Possible discounted net present values in 2016 given the actual installation cost of $1.80/W and hypothetical installation costs greater than $1.80/W. All figures are in USD.

According to Figure 32, the $/W cost would have had to drop even lower than USD 1.80/W to maintain the trend of higher discounted net present values. Nonetheless, the $/W installation cost of USD 1.80 in 2016 was not low enough to offset the decreasing FIT price, and consequently the discounted net present values in Figure 30 decreased in this year as well as each subsequent year. For the "optimistic" costing scenario, the decrease in $/W system costs was enough to offset the decline in FIT prices for the years 2015 and 2016. However, discounted net present values decreased under this scenario in the years 2017 through 2020.

5.2.2 Energy Yield Variability Results

5.2.2.1 Photovoltaic Technology

Under the "pessimistic," "average," and "optimistic" pricing scenarios, 250 Monte Carlo simulations were performed and an average discounted net present value was calculated for each of the years 2014 through 2020. These simulations varied the amount of energy yield produced by the PV system, and key discounted NPV characteristics from the 250 simulations are shown in Table 40:

Scenario	Year	Standard Deviation	Minimum ($)	Average ($)	Maximum ($)	Range ($)
Pessimistic	2014	1,206.62	-114,637.17	-111,367.48	-107,866.91	6,770.26
	2015	1,008.67	-132,335.90	-129,904.62	-127,025.84	5,310.05
	2016	1,154.06	-156,380.17	-152,388.49	-149,129.47	7,250.70
	2017	1,077.83	-168,920.95	-166,252.73	-163,114.45	5,806.50
	2018	1,145.20	-177,526.87	-173,669.84	-170,788.59	6,738.28
	2019	1,159.55	-177,833.73	-174,965.90	-171,340.93	6,492.80
	2020	1,325.78	-162,782.14	-158,813.04	-154,455.76	8,326.38
Average	2014	1,680.81	54,618.22	58,226.09	63,491.07	8,872.85
	2015	1,539.02	24,282.20	28,345.58	32,480.83	8,198.63
	2016	1,449.45	-13,167.00	-9,498.14	-5,588.20	7,578.80
	2017	1,329.94	-44,194.31	-39,935.53	-36,795.13	7,399.18
	2018	1,340.83	-66,193.36	-62,369.85	-57,845.88	8,347.47
	2019	1,331.27	-85,481.34	-82,160.53	-78,653.41	6,827.93
	2020	1,272.65	-96,661.12	-92,929.21	-89,296.76	7,364.35
Optimistic	2014	2,339.51	389,834.71	395,678.78	402,658.42	12,823.71
	2015	2,331.88	320,327.83	326,508.50	333,467.68	13,139.85
	2016	1,937.90	241,067.34	245,414.21	250,226.29	9,158.94
	2017	1,973.82	160,877.37	165,990.28	172,364.67	11,487.30
	2018	1,729.06	91,486.15	96,647.79	101,561.19	10,075.04
	2019	1,646.75	31,534.36	36,114.21	40,969.89	9,435.53
	2020	1,376.66	-28,916.38	-25,073.10	-21,768.56	7,147.82

Table 40. PV discounted net present value, standard deviation, minimum, average, maximum, and range figures from the feed-in tariff Monte Carlo simulation results. All figures are in USD.

The standard deviations in Table 40 were rather small considering the values in the "Average ($)" column. As such, the 95% confidence intervals on either side of the means, which were calculated using Equation (24) from Section 5.1.2.1, were very narrow each and every year. Figure 33 illustrates this fact:

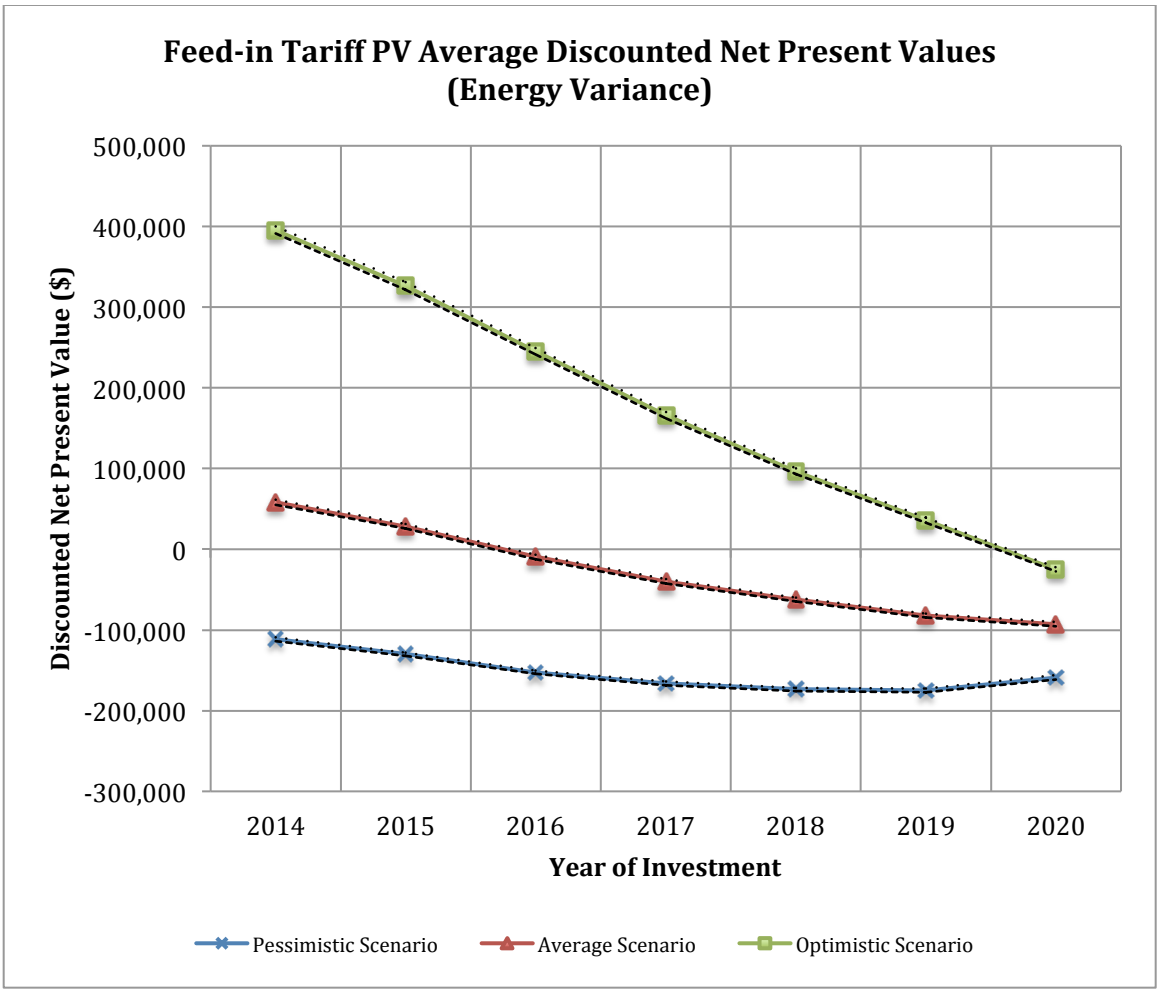


Figure 33. Average PV discounted net present values with energy variability 95% confidence intervals under the feed-in tariff scenario.

The dashed lines in Figure 33 represented the upper and lower 95% confidence intervals alongside the means of the 250 Monte Carlo simulations. As was the case with the 95% confidence intervals surrounding the means in the time-of-use tariff scenario in Section 5.1.2.1, a close-up was required in order to better see the width of the upper and lower limits in relation to the means. Figure 34 below provides this close-up for the FIT scenario for the years 2017 to 2020:

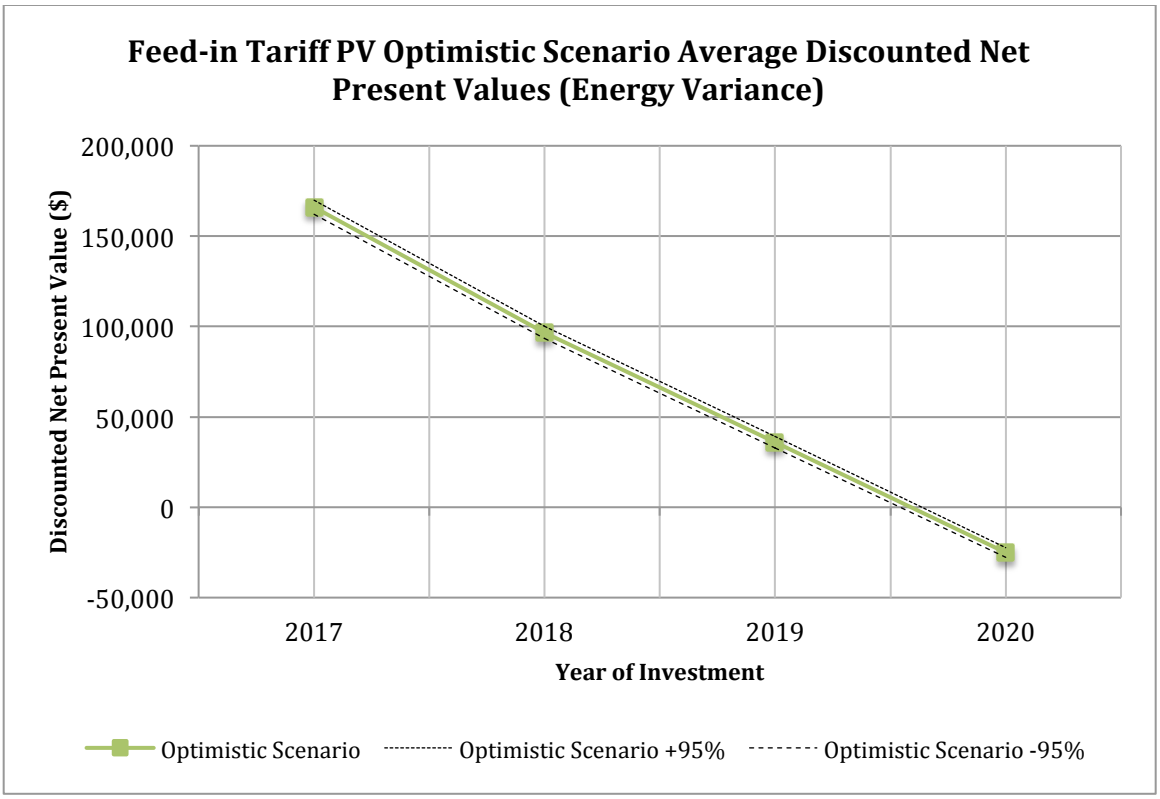


Figure 34. Close-up of the PV "optimistic" scenario's average discount net present values after 250 Monte Carlo simulations with the +95% and -95% confidence interval on each side of the mean for the years 2017 to 2020.

According to Figure 34, the 95% confidence intervals related to the discounted net present values were quite narrow even up-close. These dashed lines depicted a favourable situation from a risk management perspective, which will be further explored in the next section. The slim width of the 95% confidence intervals was somewhat expected for the FIT scenario because the fixed priced paid for solar electricity was designed to remove a lot of risk associated with operating a solar installation; this concept was discussed in Section 2.4.2.3.

Normality tests were performed on the simulated discounted net present values to ensure that these 250 data points followed a normal distribution. Below, Figure 35 shows an example normality test on the 250 discounted net present values from the "optimistic" scenario for 2014:

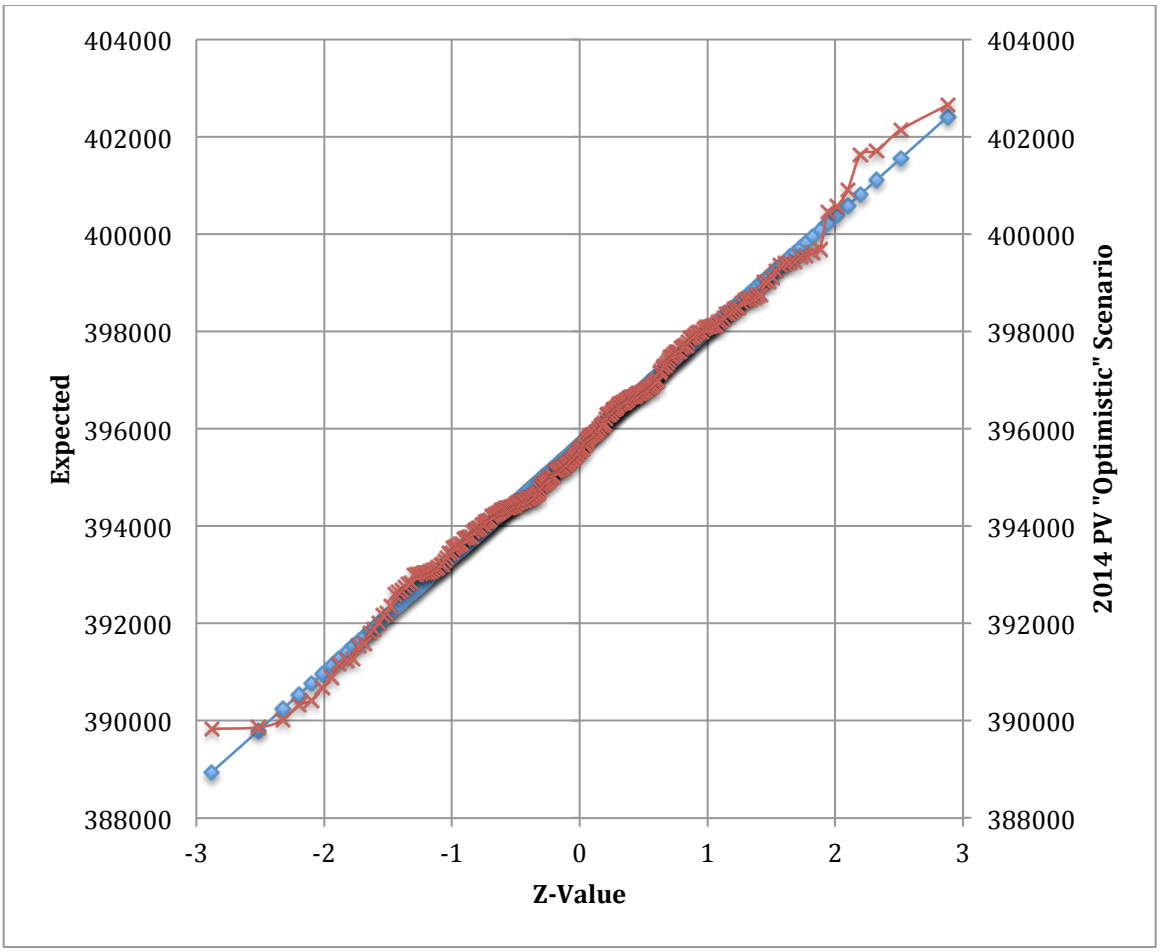


Figure 35. Normality test of the 250 discounted net present values generated by the Monte Carlo simulation for PV technology under the "optimistic" costing scenario for 2014.

In Figure 35, the red x's representing the values generated by the Monte Carlo simulation closely matched the blue squares of expected values. This meant that there was not enough evidence to indicate that the 250 discounted net present values generated by the Monte Carlo simulation were not normally distributed. Additional normality tests are provided in Appendix D.

5.2.2.2 Photovoltaic Technology Variability Analysis

The first part of the PV technology variability analysis will examine discounted net present value variability as a proportion of the mean. The following table summarizes the upper and lower bounds of where 95% of the discounted NPV data points fell in relation to the mean during the Monte Carlo simulation:

Discounted Net Present Value Variability due to Energy Yield				
Year	**% Above/Below Central Estimate**	**Pessimistic Scenario**	**Average Scenario**	**Optimistic Scenario**
2014	% above central estimate	2.12%	5.66%	1.16%
	% below central estimate	-2.12%	-5.66%	-1.16%
2015	% above central estimate	1.52%	10.64%	1.40%
	% below central estimate	-1.52%	-10.64%	-1.40%
2016	% above central estimate	1.48%	29.91%*	1.55%
	% below central estimate	-1.48%	-29.91%*	-1.55%
2017	% above central estimate	1.27%	6.53%	2.33%
	% below central estimate	-1.27%	-6.53%	-2.33%
2018	% above central estimate	1.29%	4.21%	3.51%
	% below central estimate	-1.29%	-4.21%	-3.51%
2019	% above central estimate	1.30%	3.18%	8.94%
	% below central estimate	-1.30%	-3.18%	-8.94%
2020	% above central estimate	1.64%	2.68%	10.76%
	% below central estimate	-1.64%	-2.68%	-10.76%

Table Notes:

- "Central estimate" is the mean discounted net present value from the Monte Carlo simulation
- The above figures represent variability as a proportion of the mean with 95% confidence
- *Values that are exceptional due to the central estimate being close to zero

Table 41. Percentage of discounted net present value variability due to energy yield for PV technology under the feed-in tariff scenario.

Between 2014 and 2020, 95% of the discounted NPV data points were at most plus or minus 10.76% on either side of the mean according to Table 41. However, this occurred in 2020 under the "optimistic" scenario when investment was not profitable. The highest discounted NPV according to Table 40 was observed in 2014 under the "optimistic" scenario, precisely when the spread discounted NPV variability due to energy yield was lowest at plus or minus 1.16% on either side of the mean. Thus, if a prospective investor was to secure a FIT contract in 2014, and if PV prices followed the "optimistic" scenario, then this investor would be investing under very ideal conditions. The upper and lower bounds in Table 41 were calculated using Equation (25) from Section 5.1.2.2.

From Table 42 below, discounted NPV variability was greatest in 2015. Between 2014 and 2020, the magnitude of variability due to system cost decreased while the size of variability due to O&M and degradation remained stable:

Discounted NPV Variability due to System Cost and O&M and Degradation			
Year	**% Above/Below Central Estimate**	**System Cost⊙**	**O&M and Degradation❖**
2014	% above central estimate	581.43%	52.93%
	% below central estimate	-292.03%	-50.55%
2015	% above central estimate	1057.87%	112.58%
	% below central estimate	-560.26%	-109.73%
2016	% above central estimate	2693.81%*	348.35%*
	% below central estimate	-1510.07%*	-347.45%*
2017	% above central estimate	517.20%	87.81%
	% below central estimate	-317.84%	-89.52%
2018	% above central estimate	255.08%	60.82%
	% below central estimate	-178.84%	-63.28%
2019	% above central estimate	143.81%	50.82%
	% below central estimate	-113.08%	-53.89%
2020	% above central estimate	73.09%	51.05%
	% below central estimate	-70.83%	-55.08%

Table Notes:

- ⊙Range from literature: Aanesen, Heck, and Pinner (2012), Ardani et al. (2013).
- ❖Range from literature: Branker et al. (2011), Di Francia (2013), Lowder et al. (2013), National Renewable Energy Laboratory (2013a), Zweibel (2010).
- "Central estimate" is the "average" discounted net present value with zero variability
- *Values that are exceptional due to the central estimate being close to zero

Table 42. Percentage of discounted net present value variability due to system cost, as well as O&M and degradation for PV technology under the feed-in tariff scenario.

According to the ratio figures in Table 43, discounted NPV variability due to varying system cost was consistently larger than variability due to energy yield:

Ratio of Variability due to System Cost to Variability due to O&M and Degradation		
Year	**Ratio Above/Below Central Estimate**	**Ratio**
2014	Ratio above central estimate	10.99
	Ratio below central estimate	5.78
2015	Ratio above central estimate	9.40
	Ratio below central estimate	5.11
2016	Ratio above central estimate	7.73
	Ratio below central estimate	4.35
2017	Ratio above central estimate	5.89
	Ratio below central estimate	3.55
2018	Ratio above central estimate	4.19
	Ratio below central estimate	2.83
2019	Ratio above central estimate	2.83
	Ratio below central estimate	2.10
2020	Ratio above central estimate	1.43
	Ratio below central estimate	1.29

Table Note:

- "Central estimate" is the "average" discounted net present value with zero variability

Table 43. Ratio of variability due to system cost to variability due to O&M and degradation for PV technology under the feed-in tariff scenario.

Given that installations commencing operations closer to 2014 were more profitable than those beginning towards 2020 under this tariff scenario, an investor choosing to take advantage of higher profitability would also be facing comparatively higher risks of greater potential discounted NPV variability in earlier years.

As per Table 44, discounted NPV variability due to O&M and degradation was 4.74 times greater than discounted NPV variability due to energy yield at the lowest point; at the highest point the former was 80.43 times greater than the latter:

Ratio of O&M and Degradation Variability to Energy Yield Variability				
Year	**Ratio Above/Below Central Estimate**	**Pessimistic Scenario**	**Average Scenario**	**Optimistic Scenario**
2014	Ratio above central estimate	24.92	9.35	45.67
	Ratio below central estimate	23.80	8.93	43.62
2015	Ratio above central estimate	73.98	10.58	80.43
	Ratio below central estimate	72.10	10.31	78.39
2016	Ratio above central estimate	234.69*	11.65*	225.08*
	Ratio below central estimate	234.08*	11.62*	224.50*
2017	Ratio above central estimate	69.10	13.45	37.67
	Ratio below central estimate	70.45	13.71	38.41
2018	Ratio above central estimate	47.06	14.43	17.34
	Ratio below central estimate	48.96	15.02	18.05
2019	Ratio above central estimate	39.12	16.00	5.69
	Ratio below central estimate	41.49	16.97	6.03
2020	Ratio above central estimate	31.20	19.02	4.74
	Ratio below central estimate	33.66	20.52	5.12

Table Note:

- "Central estimate" is the mean discounted net present value from the Monte Carlo simulation
- *Values that are exceptional due to the central estimate being close to zero

Table 44. A comparison of how much more discounted net present value variability is due to O&M and degradation compared with energy yield for PV technology under the feed-in tariff scenario.

The ratio values under the "average" scenario steadily progressed between 2014 and 2020, while those under the "pessimistic" and "optimistic" scenario had erratic movements, increasing from 2014 to 2015, and then decreasing between 2015 and 2020. The "optimistic" scenario ratios had the greatest range of movement, at times being higher than both those under the "average" and "pessimistic" scenarios and at other times being lower than those in the other two pricing scenarios.

5.2.2.3 Concentrated Photovoltaic Technology

The energy variability discounted NPV results for CPV technology and the feed-in tariff scenario are shown below in Table 45:

Scenario	Year	Standard Deviation	Minimum ($)	Average ($)	Maximum ($)	Range ($)
Pessimistic	2014	2,441.86	-84,847.64	-78,260.10	-69,676.36	15,171.28
	2015	2,461.50	-109,564.68	-101,825.59	-94,887.73	14,676.95
	2016	2,200.28	-151,605.22	-145,652.82	-139,185.06	12,420.16
	2017	2,051.58	-194,116.31	-188,323.69	-182,417.18	11,699.13
	2018	1,699.82	-235,525.83	-230,597.74	-226,036.46	9,489.36
	2019	1,619.26	-275,406.59	-271,003.55	-265,451.83	9,954.76
	2020	1,491.29	-313,580.58	-309,666.51	-305,839.24	7,741.35
Average	2014	3,133.23	101,351.32	112,207.58	119,815.48	18,464.16
	2015	3,517.23	109,970.20	119,241.00	129,250.75	19,280.55
	2016	3,722.24	74,295.94	85,302.88	94,486.69	20,190.74
	2017	3,371.88	32,073.82	40,939.61	49,813.98	17,740.16
	2018	2,747.11	-20,810.23	-12,710.45	-4,266.94	16,543.28
	2019	2,713.88	-71,217.65	-62,786.44	-55,269.22	15,948.43
	2020	2,546.29	-127,281.70	-119,901.68	-113,320.96	13,960.74
Optimistic	2014	4,578.67	386,511.79	398,479.45	409,251.21	22,739.42
	2015	4,609.58	459,189.65	472,207.11	485,311.81	26,122.17
	2016	5,391.53	465,501.86	481,265.07	494,456.81	28,954.95
	2017	5,249.46	428,434.17	444,817.88	459,920.17	31,486.01
	2018	4,761.13	375,960.85	391,605.70	404,025.55	28,064.70
	2019	4,294.22	303,082.31	313,807.12	328,285.02	25,202.71
	2020	4,086.76	245,262.35	257,421.66	267,101.25	21,838.90

Table 45. CPV discounted net present value, standard deviation, minimum, average, maximum, and range figures for the feed-in tariff Monte Carlo simulation results. All figures are in USD.

Table 45 indicated that the means from the "average" scenario increased in 2014 and 2015 but then decreased in the years afterwards, while the averages from the "optimistic" scenario increased until the year 2016 before decreasing afterwards as well. The increasing and decreasing discounted net present values matched the same pattern of increases and decreases from the no-variability scenario in Section 5.2.1.2.

Figure 36 below illustrates the plots of the average values and includes 95% confidence intervals on either side of the means:

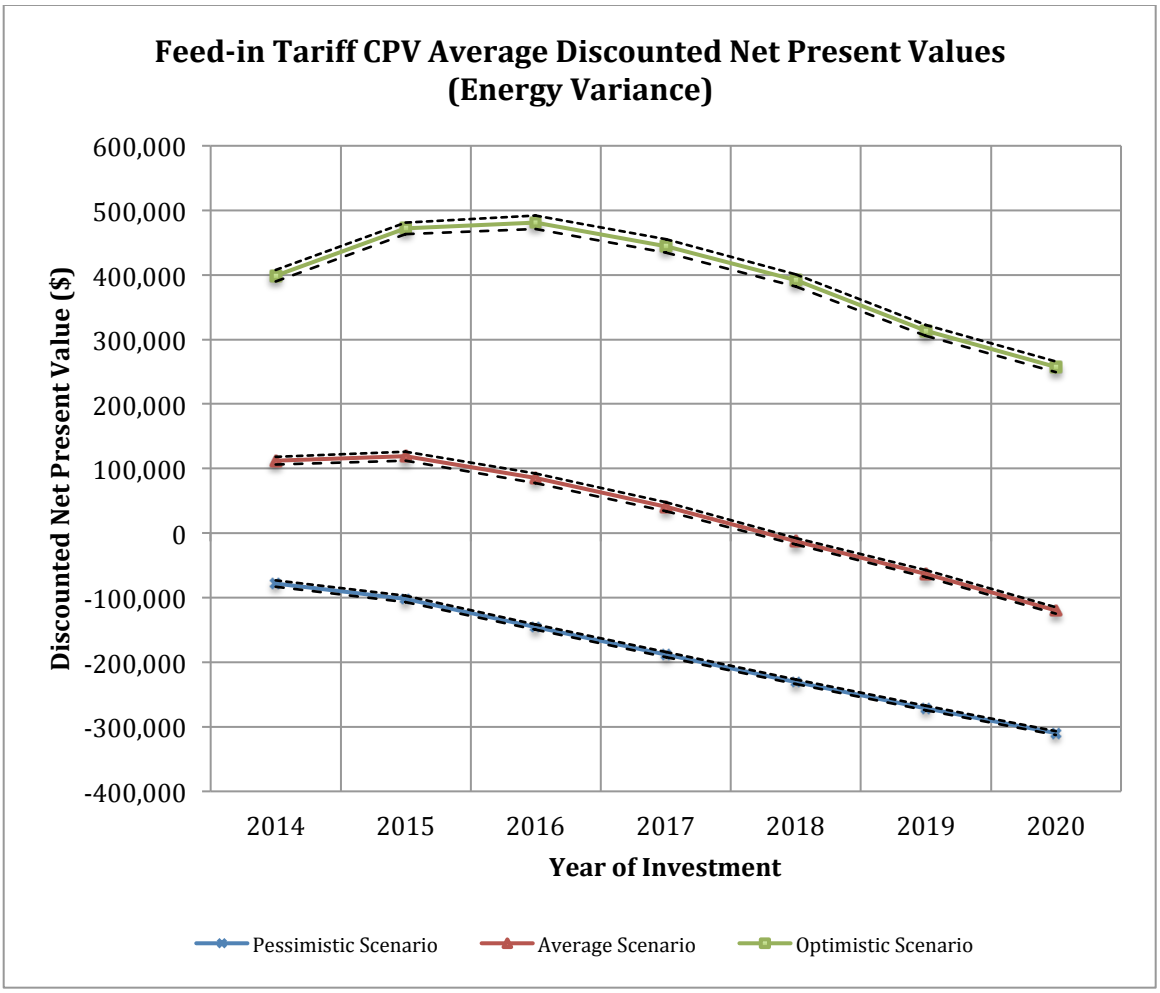


Figure 36. Average CPV discount net present values for energy variability with 95% confidence intervals under the feed-in tariff scenario.

The 95% confidence intervals were calculated using Equation (24) from Section 5.1.2.1. The curves shown by the "average" and "optimistic" scenarios in Figure 36 were in all likelihood due to the interaction between decreasing CPV system prices and declining feed-in tariff prices as was discussed in Section 5.2.1.2 using Figure 31 and Figure 32 to illustrate the effect.

In Figure 37 below, a close-up of the "average" scenario's discounted net present values is shown for the years 2014 through 2017 in order to illustrate the 95% confidence intervals on either side of the mean in greater detail:

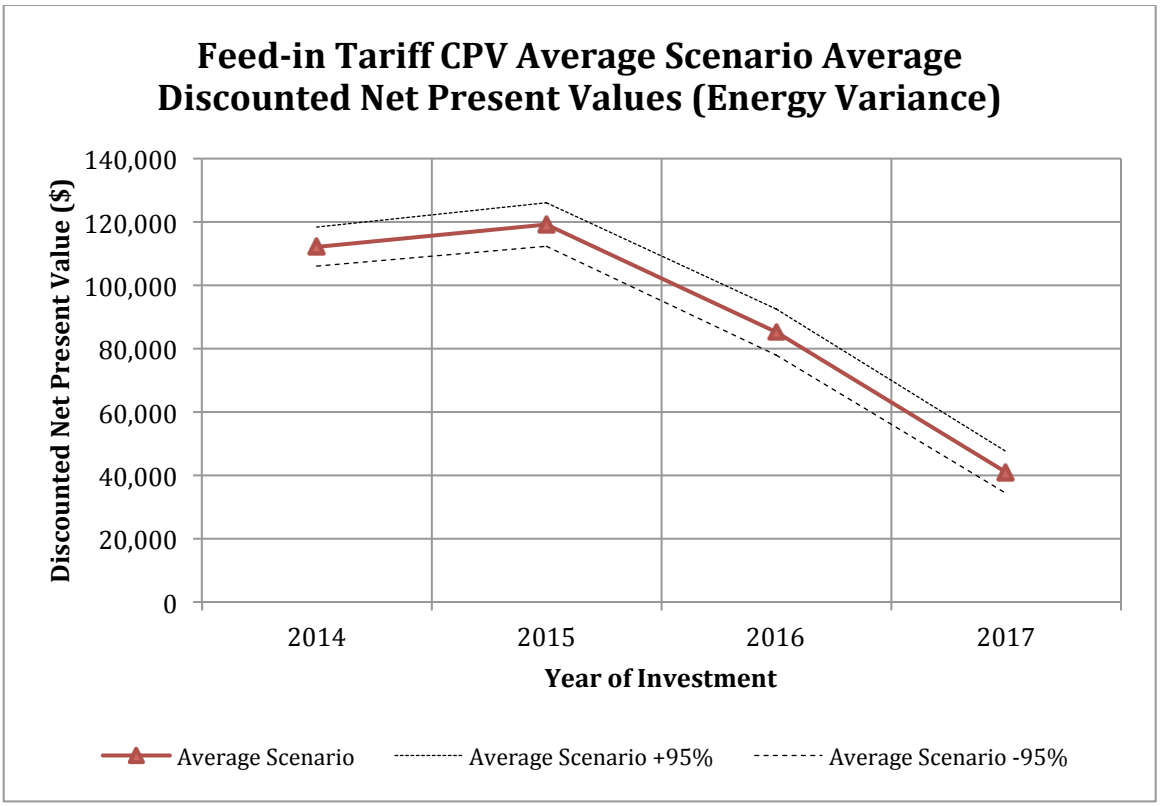


Figure 37. Close-up of the CPV "average" scenario's average discount net present values after 250 Monte Carlo simulations with the +95% and -95% confidence interval on each side of the mean for the years 2014 to 2017.

Figure 37 illustrated that although the *mean* discounted NPV peaked in 2015, a higher discounted net present value could have been observed in 2014 compared with 2015 according to the 95% confidence interval. Thus, an investment decision in either of the years 2014 or 2015 may have carried similar expectations given the range of possible discounted net present values provided by the 95% confidence intervals. Clearly, however, the discounted net present values expected in 2016 and 2017 were expected to be of a lesser value even taking the confidence intervals into account. Visually, the widths of the close-up CPV confidence intervals were wider than the close-up of the PV confidence intervals from Figure 34. Given that the CPV standard deviations shown in Table 45 were larger than the PV standard deviations from Table 40, this result was expected.

Normality tests were performed on the simulated discount net present values produced by the Monte Carlo simulation. In Figure 38, a normality test of the 250

discounted net present values generated by the Monte Carlo simulation for the 2014 "average" scenario is shown:

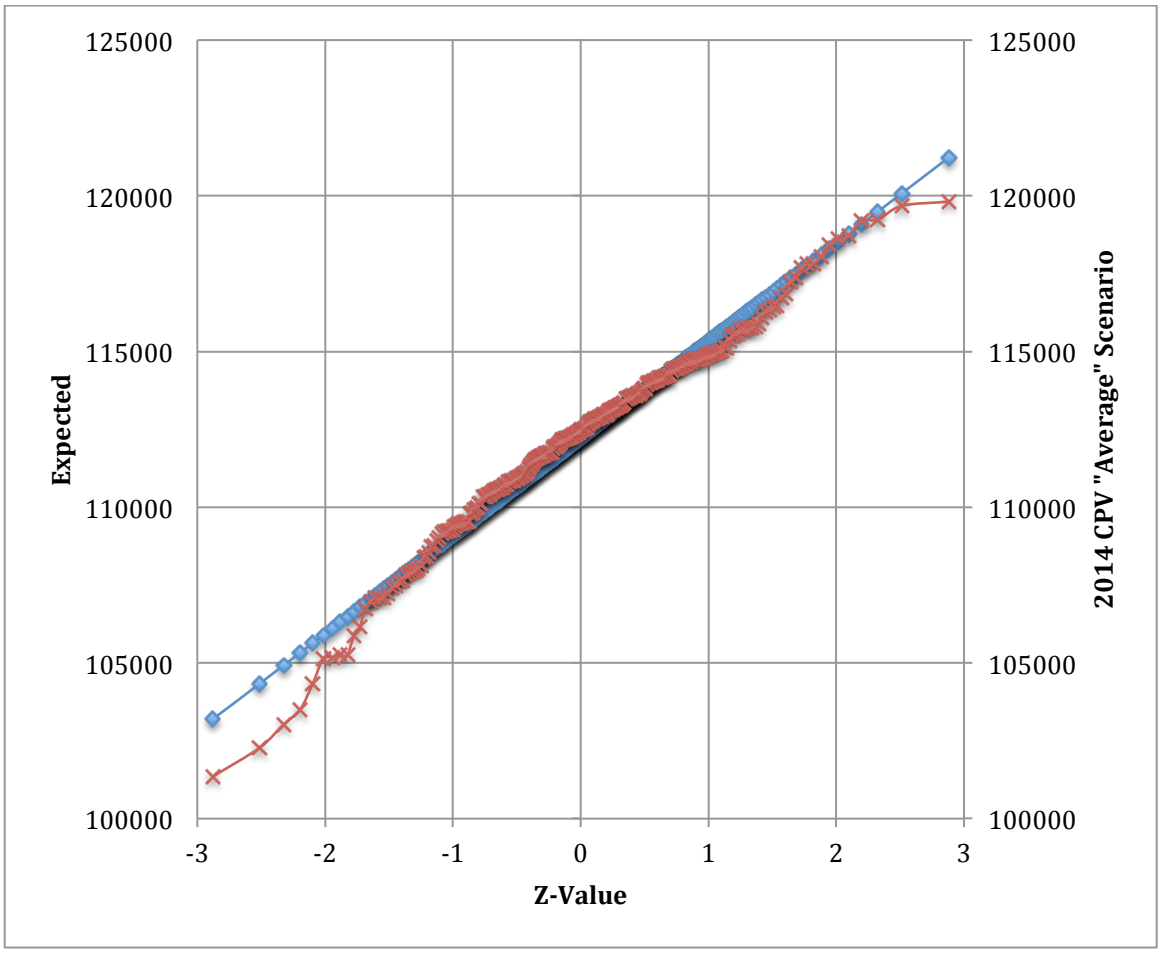


Figure 38. Normality test of the 250 discounted net present values generated by the Monte Carlo simulation for CPV technology under the "average" costing scenario for 2014.

The red x's of observed, simulated values roughly shadowed the blue squares of expected values. Figure 38 indicated that there was insufficient data to suggest that the 250 simulated discounted net present values were not normally distributed. Additional normality tests for the CPV feed-in tariff scenario are presented in Appendix D.

5.2.2.4 Concentrated Photovoltaic Technology Variability Analysis

Delving further into discounted NPV variability due to fluctuating system energy output, Table 46 indicates the upper and lower limits of how 95% of the discounted NPV data points fell around the mean between the years 2014 and 2020:

Discounted Net Present Value Variability due to Energy Yield				
Year	**% Above/Below Central Estimate**	**Pessimistic Scenario**	**Average Scenario**	**Optimistic Scenario**
2014	% above central estimate	6.12%	5.47%	2.25%
	% below central estimate	-6.12%	-5.47%	-2.25%
2015	% above central estimate	4.74%	5.78%	1.91%
	% below central estimate	-4.74%	-5.78%	-1.91%
2016	% above central estimate	2.96%	8.55%	2.20%
	% below central estimate	-2.96%	-8.55%	-2.20%
2017	% above central estimate	2.14%	16.14%	2.31%
	% below central estimate	-2.14%	-16.14%	-2.31%
2018	% above central estimate	1.44%	42.36%*	2.38%
	% below central estimate	-1.44%	-42.36%*	-2.38%
2019	% above central estimate	1.17%	8.47%	2.68%
	% below central estimate	-1.17%	-8.47%	-2.68%
2020	% above central estimate	0.94%	4.16%	3.11%
	% below central estimate	-0.94%	-4.16%	-3.11%

Table Notes:

- "Central estimate" is the mean discounted net present value from the Monte Carlo simulation
- The above figures represent variability as a proportion of the mean with 95% confidence
- *Values that are exceptional due to the central estimate being close to zero

Table 46. Percentage of discounted net present value variability due to energy yield for CPV technology under the feed-in tariff scenario.

Table 46 indicated that 95% of the discounted net present values were found plus or minus 16.14% on either side of the mean at most; the smallest was plus or minus 0.94%. These figures were calculated using Equation (25) from Section 5.1.2.2 As per Table 45, profitable investments were made in each of the years 2014-2020 under the "optimistic" scenario and the optimal year to invest was 2016. In that year, 95% of the discounted net present values were within plus or minus 2.20% of the mean. However, under the "optimistic" scenario, discounted NPV variability due to energy yield was not considerably large in any of the years 2014 through 2020. Thus, the decision to either invest or forego investment was likely not heavily impacted by energy yield variability.

Table 47 illustrated that discounted NPV variability due to system cost variability was greater than variability due to O&M and degradation:

Discounted NPV Variability due to System Cost and O&M and Degradation			
Year	**% Above/Below Central Estimate**	**System Cost⊙**	**O&M and Degradation❖**
2014	% above central estimate	254.12%	31.21%
	% below central estimate	-169.24%	-31.21%
2015	% above central estimate	297.19%	33.57%
	% below central estimate	-185.64%	-33.57%
2016	% above central estimate	465.07%	51.39%
	% below central estimate	-271.04%	-51.39%
2017	% above central estimate	986.84%	115.56%
	% below central estimate	-560.02%	-115.56%
2018	% above central estimate	3270.02%*	408.52%*
	% below central estimate	-1765.53%*	-408.52%*
2019	% above central estimate	601.57%	86.68%
	% below central estimate	-332.93%	-86.68%
2020	% above central estimate	314.36%	47.67%
	% below central estimate	-157.89%	-47.67%

Notes:

- ⊙Range from literature: Haysom et al. (2014).
- ❖Range from literature: Drury et al. (2013), Gerstmaier et al. (2014).
- "Central estimate" is the "average" discounted net present value with zero variability
- *Values that are exceptional due to the central estimate being close to zero

Table 47. Percentage of discounted net present value variability due to system cost, as well as O&M and degradation for CPV technology under the feed-in tariff scenario.

The size of system cost variability as well as O&M and degradation variability peaked in 2017 according to Table 47. Accordingly, discounted NPV variability risk stemming from these two sources of variability was greatest in this year and thus an investment in a CPV project commencing in 2017 may have been worthwhile to avoid due to this increased risk. Discounted NPV variability was affected more by system cost than O&M and degradation given that all ration figures in Table 48 are larger than 1:

Ratio of Variability due to System Cost to Variability due to O&M and Degradation		
Year	**Ratio Above/Below Central Estimate**	**Ratio**
2014	Ratio above central estimate	8.14
	Ratio below central estimate	5.42
2015	Ratio above central estimate	8.85
	Ratio below central estimate	5.53
2016	Ratio above central estimate	9.05
	Ratio below central estimate	5.27
2017	Ratio above central estimate	8.54
	Ratio below central estimate	4.85
2018	Ratio above central estimate	8.00
	Ratio below central estimate	4.32
2019	Ratio above central estimate	6.94
	Ratio below central estimate	3.84
2020	Ratio above central estimate	6.59
	Ratio below central estimate	3.31

Table Note:

- "Central estimate" is the "average" discounted net present value with zero variability

Table 48. Ratio of variability due to system cost to variability due to O&M and degradation for CPV technology under the feed-in tariff scenario.

With the exception of the values marked with a *, discounted net present value variability due to O&M and degradation was between 5.10 and 74.02 times greater than discounted net present value variability due to fluctuating energy yield as per Table 49:

Ratio of O&M and Degradation Variability to Energy Yield Variability				
Year	**Ratio Above/Below Central Estimate**	**Pessimistic Scenario**	**Average Scenario**	**Optimistic Scenario**
2014	Ratio above central estimate	5.10	5.70	13.86
	Ratio below central estimate	5.10	5.70	13.86
2015	Ratio above central estimate	7.09	5.81	17.55
	Ratio below central estimate	7.09	5.81	17.55
2016	Ratio above central estimate	17.36	6.01	23.40
	Ratio below central estimate	17.36	6.01	23.40
2017	Ratio above central estimate	54.12	7.16	49.96
	Ratio below central estimate	54.12	7.16	49.96
2018	Ratio above central estimate	282.75*	9.64*	171.43*
	Ratio below central estimate	282.75*	9.64*	171.43*
2019	Ratio above central estimate	74.02	10.23	32.32
	Ratio below central estimate	74.02	10.23	32.32
2020	Ratio above central estimate	50.50	11.45	15.32
	Ratio below central estimate	50.50	11.45	15.32

Table Note:

- "Central estimate" is the mean discounted net present value from the Monte Carlo simulation
- *Values that are exceptional due to the central estimate being close to zero

Table 49. A comparison of how much more discounted net present value variability is due to O&M and degradation compared with energy yield for CPV technology under the feed-in tariff scenario.

The ratio values under all three pricing scenarios shown in the table above increased over time. However, the "average" pricing scenario experienced a comparatively steadier increase compared with the "pessimistic" and "optimistic" scenarios, which experienced both up and down movements between 2014 and 2020.

5.2.3 Section 5.2 Summary

There were large differences between the PV and CPV results under the feed-in tariff scenario. Figure 29 and Figure 30, which illustrated the plots of discounted net present values under the "pessimistic," "average," and "optimistic" pricing scenarios with zero energy yield variability for PV and CPV technologies, respectively, demonstrated these differences. The plots in Figure 29 indicated that investment in PV technology should be made as soon as possible under the "optimistic" and "average" scenarios in order to secure the highest FIT prices and, consequently, the

best discounted net present values. Even when operation and maintenance costs, as well as degradation rates, were modified to reflect the "optimistic" scenario, the resulting dashed plot of discounted net present values did not show profitability after 2016. Conversely, the plots in Figure 30 suggested that under the "average" scenario the ideal time to invest in a CPV installation was 2015, while under the "optimistic" costing scenario the optimal time to invest was 2016. The interaction between decreasing system costs, declining FIT contract prices, and the impact of discounting likely caused the distinct discounted NPV curves shown in Figure 30. Depending upon the pricing scenario, the amount paid for the solar-produced electricity after 2015 or 2016 was not large enough to keep increasing yearly revenues enough to offset the effect of discounting even though system prices continued to decline. The price paid for electricity under FIT contracts was greater than the price paid under the time-of-use pricing scenario from Section 5.1. This was one reason why profitability was observed in the year 2014 under the "optimistic" pricing scenario for both PV and CPV technology in this section, for example, but why it took until later years to observe profitability until the time-of-use tariff scenario. The TOU prices were so low that system prices needed to decrease in order to realize positive discounted net present values.

The introduction of energy yield variability illustrated the range of possible discounted net present values according to 95% confidence intervals. Average PV and CPV discounted net present values were shown in Figure 33 and Figure 36, respectively, along with the corresponding confidence intervals. The confidence intervals for both technologies were not especially wide overall, even though the 95% CPV confidence interval was wider than the 95% PV confidence interval. From an investor's perspective, this implied that an investment in CPV technology carried more risk since the 95% confidence intervals indicated that the discounted net present value could deviate from the mean more so than compared with PV technology. However, given the mean and standard deviations provided by Table 40 for PV and Table 45 for CPV, an investor should be confident in the expected return since the standard deviation values were relatively small compared to the mean.

Calculations in Section 5.2.2.2 and 5.2.2.4 indicated that 95% of the discounted net present values were at most within plus or minus 10.76% on either side of the mean for PV technology and plus or minus 16.14% on either side of the mean for CPV technology. These results measured the accuracy of the simulations and produced additional confidence for prospective investors. In the following section, the discounted net present value results related to power purchase agreements will be presented.

5.3 Power Purchase Agreement Discounted Net Present Value Results

5.3.1 Deterministic Results

5.3.1.1 Photovoltaic Technology

The concept behind power purchase agreements was explained in Section 4.3.3. In brief, a power purchase agreement is an arrangement whereby a third party installs and operates a solar installation and an electricity customer purchases the power produced by the third party's system at a rate specified by a contractual agreement. In some cases, such as in this analysis, energy payment allocation factors are included in the agreement. These factors specify that the price paid for solar-produced electricity either increases above or decreases below the agreed upon contractual price depending upon the time of day. Based upon historical data, the electricity price fluctuations created by the energy payment allocation factors tended to correspond with typical electricity demand changes. When electricity demand was high, for example during midday Monday through Friday, the price paid for the solar-produced electricity increased as well via the energy payment allocation factors.

As described in Section 4.3.3, this analysis used ground mount FIT prices as baseline power purchase agreement rates. This followed the example of a power purchase agreement signed by the Ontario government with a Korean Consortium, where the

PPA price was equal to a FIT price in place at the time the agreement was signed. The baseline prices used as part of the power purchase agreement were provided in Table 26. These prices were multiplied by the energy payment allocation factors displayed in Table 28 during the time periods listed in Table 27. Future PPA prices were forecasted using a logarithmic regression and were charted in Figure 19 in Section 4.3.3. Figure 39 below demonstrates the discounted net present values under the PPA tariff scenario assuming zero energy yield variability:

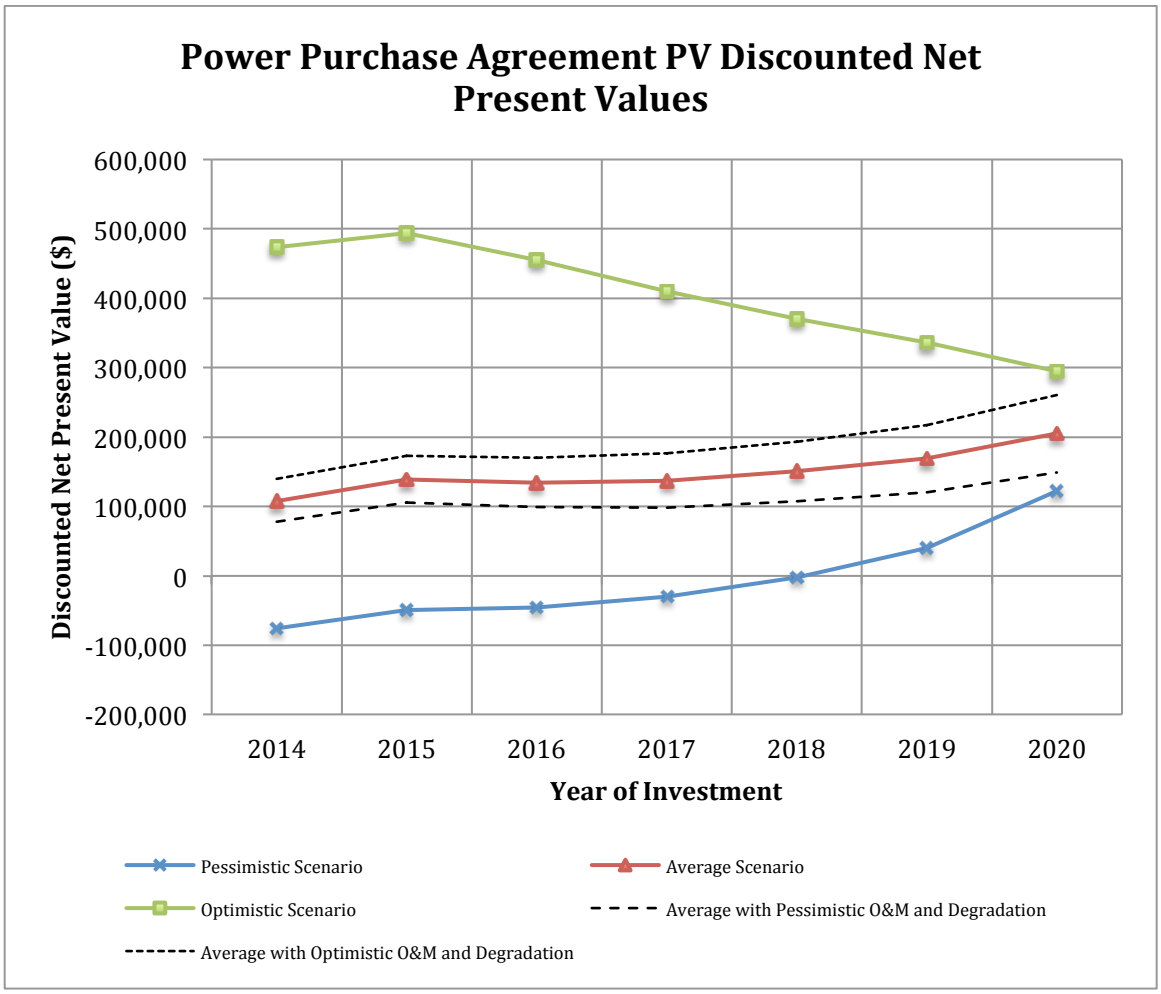


Figure 39. Discounted net present values for PV technology under the power purchase agreement tariff scenario. The values assume zero energy yield variability.

According to Figure 39, each of the "pessimistic", "average," and "optimistic" scenarios realized positive discounted net present values by the year 2019. This was the first instance where the discounted net present values from all three pricing scenarios were greater than zero. Figure 39 also illustrated plots of discounted net

present values that trended in different directions over time. The plot of the "optimistic" scenario discounted net present values decreased between 2014 and 2020, while the discounted net present values from the "pessimistic" scenario increased over the same timeframe. These results were similar to those from the CPV feed-in tariff scenario presented in Section 5.2.1.2 in that the curves in Figure 39 were a result of the relationship between declining $/W system costs and decreasing PPA baseline rates. For example, the PV "optimistic" pricing scenario under the PPA tariff scenario indicated a discounted net present value in 2014 of USD 473,208.19 given a system price of USD 1.82/W. In 2015, the discounted net present value increased to USD 493,851.91 as a result of a system cost of USD 1.70/W. Figure 40 below shows the relationship between the discounted net present value under several capital costs, which range from the actual 2014 value of USD 1.82/W down to the actual 2015 value of USD 1.70/W:

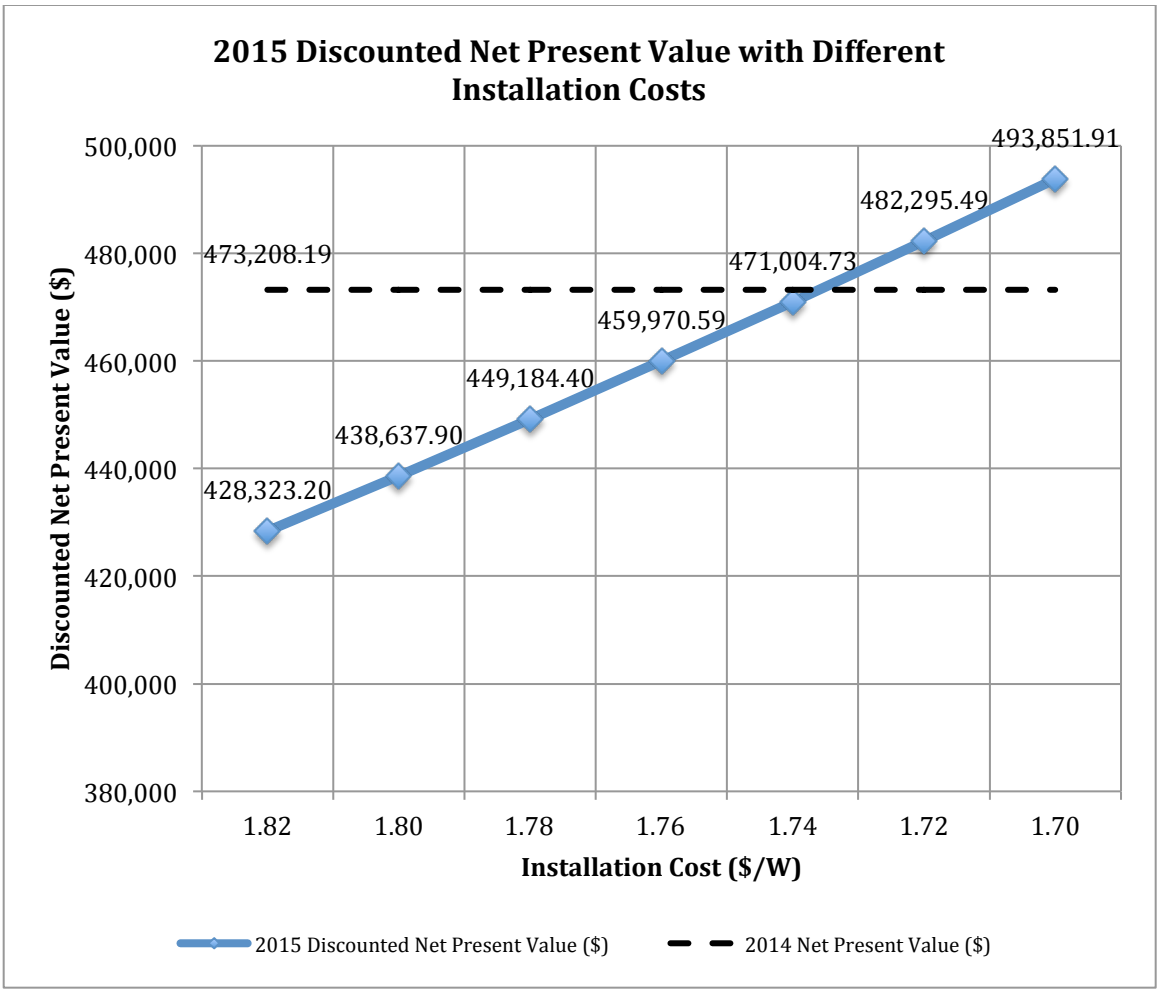


Figure 40. A comparison of 2014's net present value with the 2015 discounted net present value ($493,851.91 at an installation cost of $1.70/W). All values are in USD.

In the above figure, the discounted NPV in 2015 increased to USD 493,851.91 because the decrease in installation cost offset the decline in the PPA baseline price, which dropped from USD 0.259/kWh in 2014 to USD 0.247/kWh in 2015 as per Table 26 in Section 4.3.3. Even at an installation cost of USD 1.72/W, the discounted net present value under the "optimistic" scenario would have increased according to Figure 40. In 2016, however, the discounted net present value decreased because the reduction in installation cost was not large enough to offset the decline in the PPA baseline price:

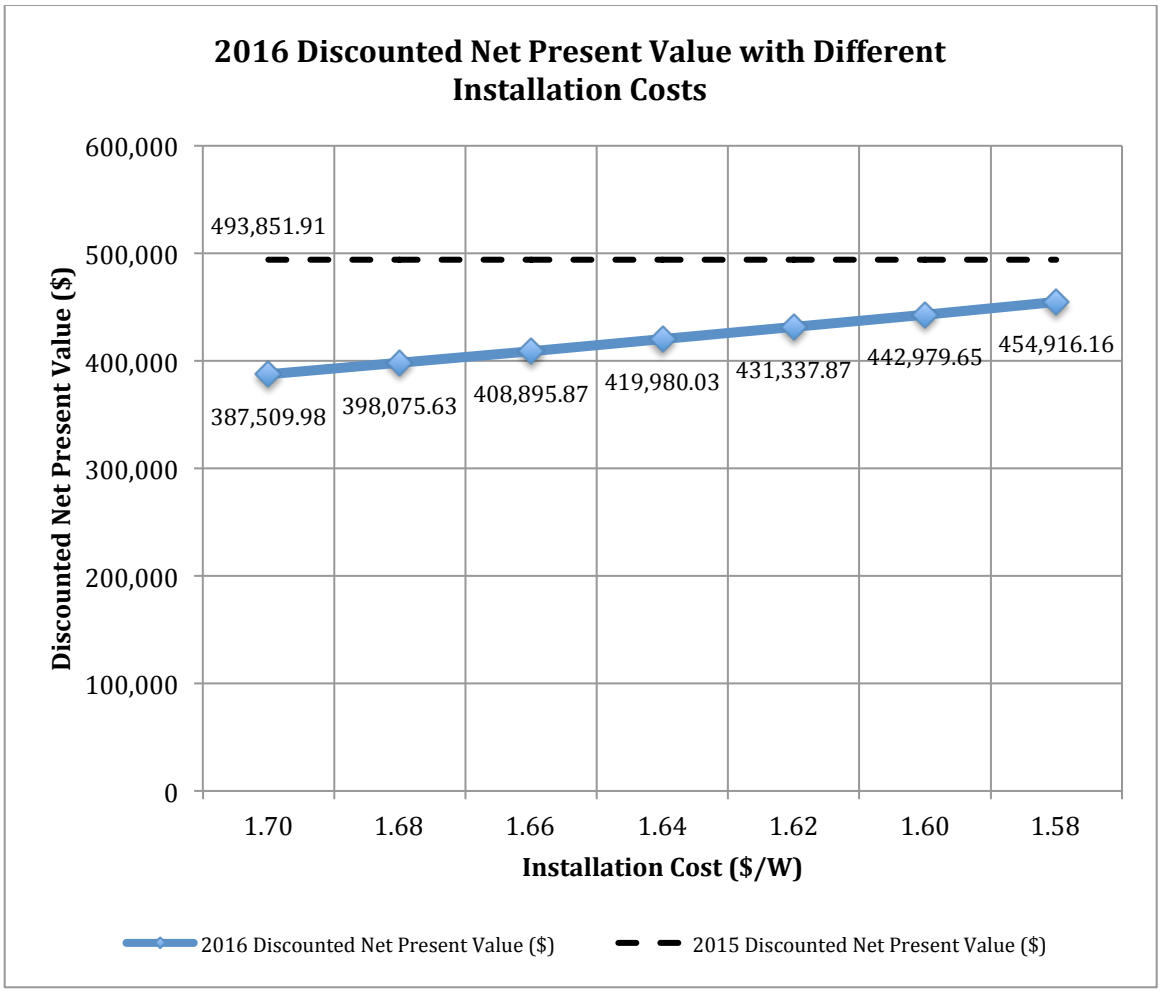


Figure 41. A comparison of 2015's discounted net present value with the 2016 discounted net present value. The 2016 value of $454,916.16 given an installation cost of $1.58/W is lower than the 2015 value of $493,851.91 given an installation cost of $1.70/W. All figures are in USD.

In Figure 41, the actual $/W installation cost of USD 1.58/W in 2016 was not low enough to increase the discounted NPV over the previous year's value of USD 493,851.91. From 2016 onwards, the declining system costs were not large enough to offset the reduction in PPA baseline costs, and discounted net present values declined as a result.

However, turning to the "pessimistic" scenario, the decreases in installation costs under this pricing scenario were in fact enough to offset the declining PPA baseline prices since discounted net present values increased between 2014 and 2020. Figure 42 below shows that if the 2019 system price was equal to the 2018 system price of USD 1.97/W, the 2019 discounted net present value would have been USD -

61,542.49. However, the actual 2019 system price was USD 1.60/W, which coincided with a discounted net present value of USD 39,889.31. This figure, in turn, was higher than the 2018 discounted NPV of USD -2,342.44.

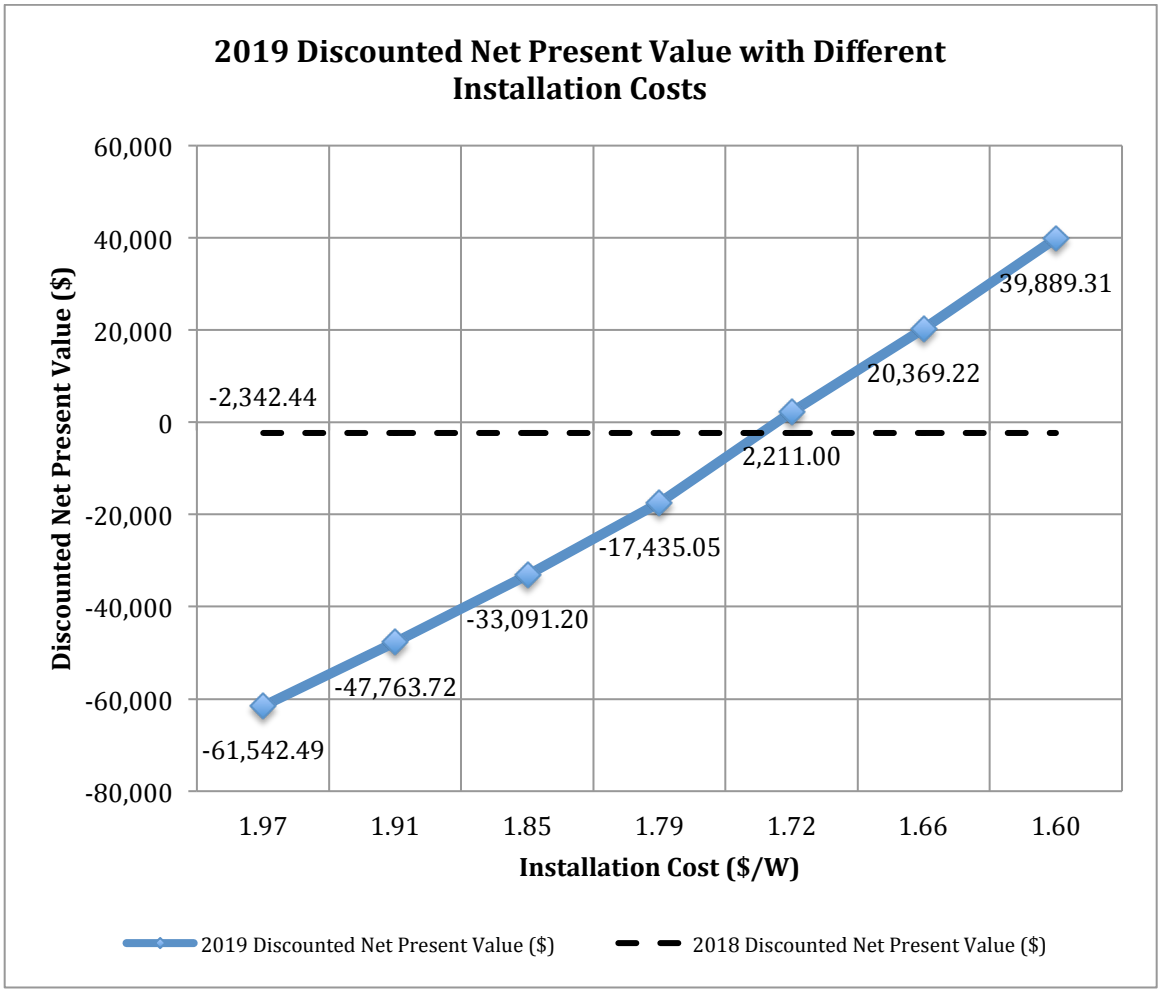


Figure 42. A comparison of 2018's discounted net present value with the 2019 discounted net present value. At an installation cost of $1.60/W in 2019, the discounted net present value of $39,889.31 is larger than the discounted NPV in 2018 of -$2,342.44 at an installation cost of $1.97/W. All figures are in USD.

According to Figure 42, the discounted NPV in 2019 would have increased given a system price lower than approximately USD 1.72/W. On the other hand, the discounted NPV would have declined if the system cost had been greater than USD 1.72/W. The trend of declining discounted net present values continued into the year 2020 for the "pessimistic" costing scenario:

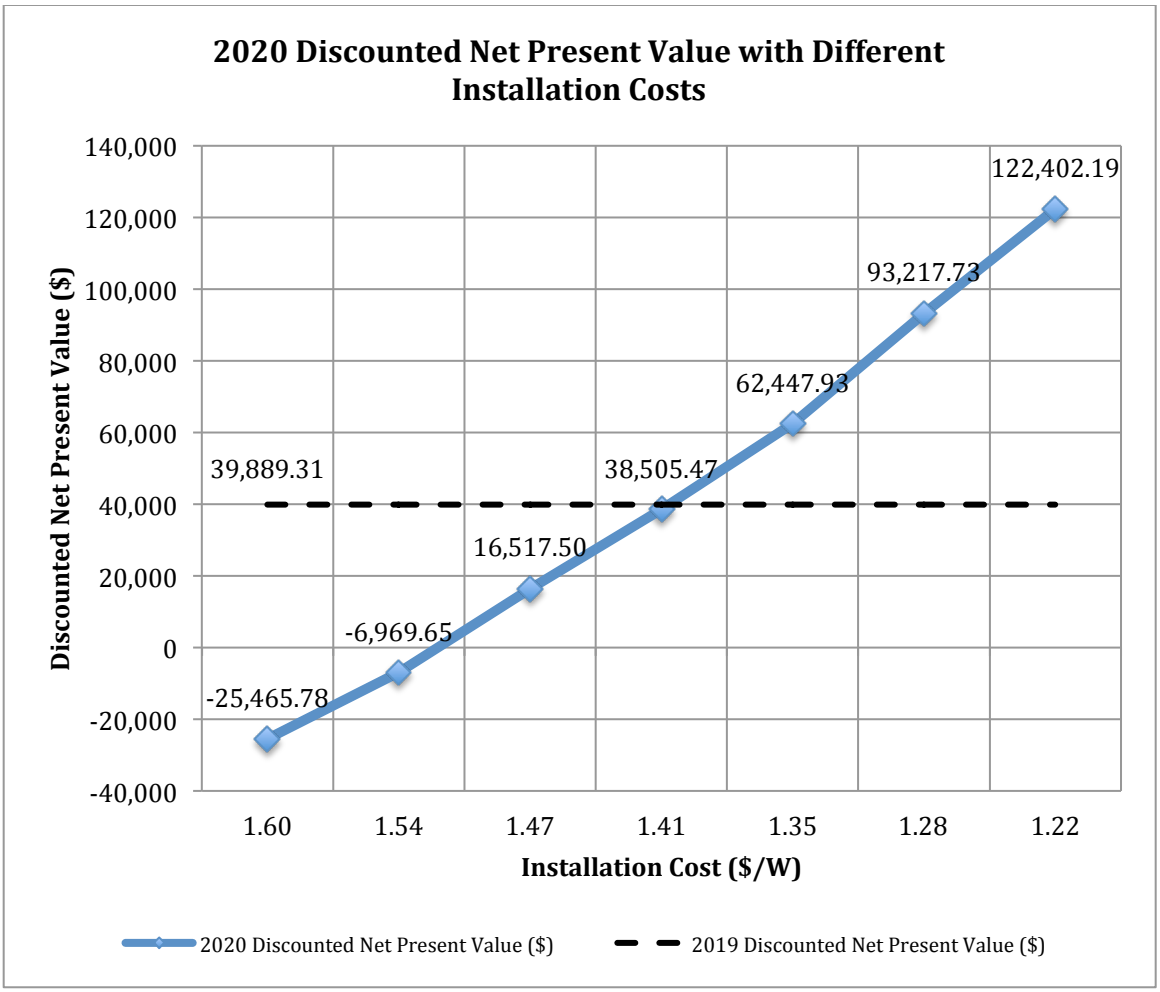


Figure 43. A comparison of 2019's discounted net present value with the 2020 discounted net present value. The actual installation cost in 2020 was $1.22/W under the "pessimistic" scenario. As such, the discounted net present value increased to $122,402.19 from the previous year's $39,889.31. All figures are in USD.

As per Figure 43, the discounted net present value in the year 2020 increased from the previous year due to the system price drop from USD 1.60 in 2019 to USD 1.22 in 2020. This change in price was large enough to offset the PPA baseline price drop from USD 0.160/kWh in 2019 to USD 0.143/kWh in 2020 as per Table 26 from Section 4.3.3. For an investor, the relationship between declining system costs and the price paid for electricity was important to understand, since it had a noticeable impact on the optimal time to invest.

5.3.1.2 Concentrated Photovoltaic Technology

Inputs from Table 19 and Table 20 in Section 4.2 were used to calculate discounted net present values for CPV technology. Figure 44 below shows the CPV discounted NPV results under the power purchase agreement tariff scenario:

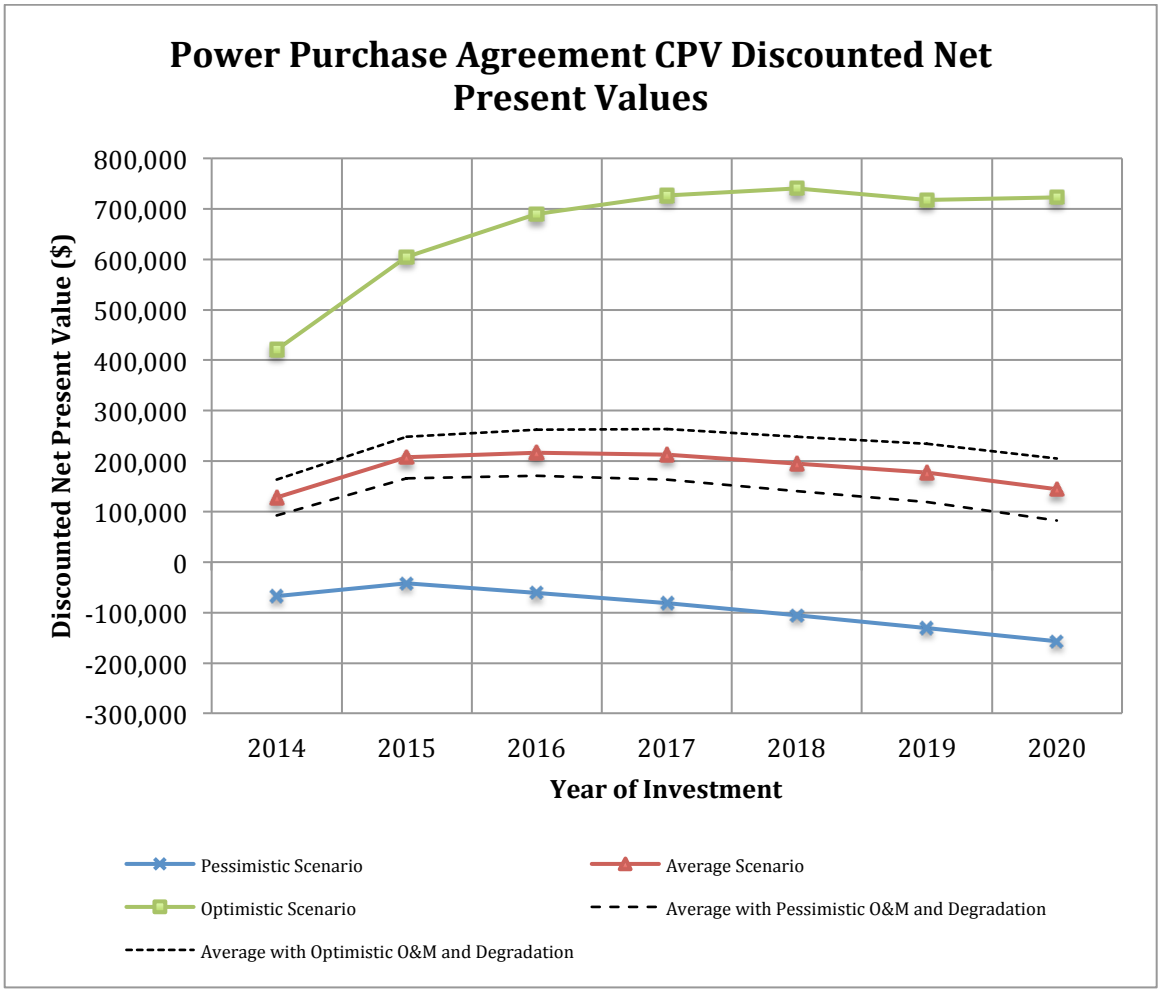


Figure 44. Discount net present values for a CPV installation selling the electricity it produces according to a power purchase agreement.

In Figure 44, the "optimistic" scenario yielded much larger discounted net present values compared with the "average" and "pessimistic" scenarios. As a rule, the lower the system price, the larger the CPV installation and, consequently, the more kilowatts of electricity produced. If system costs followed the "optimistic" pricing scenario, which was displayed in Table 19 in Section 4.2, the optimal year to invest in a CPV installation under the power purchase agreement scenario was 2018. In this year, the discounted net present value was USD 740,241.27. However, if the

system costs followed the "average" scenario then the ideal time to invest was in 2016 to yield a discounted net present value of USD 217,029.68. Even when accounting for both "pessimistic" and "optimistic" O&M costs as well as degradation rates, the "average" costing scenario illustrated by the dashed lines in Figure 44 did not compete with the discounted net present values from the "optimistic" costing scenario. Despite an increase in the discounted NPV between 2014 and 2015 under the "pessimistic" scenario, none of the discounted net present values were positive and thus did not represent a wise investment decision. Given the curves of the plots displayed in Figure 44, particularly for the "optimistic" and "average" scenarios, a potential CPV investor should understand the relationship between the system price, which had a significant impact on total profitability, and the price paid for electricity over the years in which the CPV system was operational. Furthermore, the investor should have knowledge of all other costs involved, since they also will have an impact to some degree on determining the optimal time to invest.

Comparing PV to CPV and using the "optimistic" pricing scenario as an example, the discounted net present values in 2014 were higher for PV technology compared with CPV technology. However, in 2015, a new trend began where CPV technology had higher discounted net present values than PV technology, and this continued through until the year 2020. From this information, a prospective investor was better off delaying investment until a future year and choosing CPV technology over PV technology. As per Figure 44, the optimal time to invest in CPV technology was in the year 2018.

5.3.2 Energy Yield Variability Results

5.3.2.1 Photovoltaic Technology

Using a Monte Carlo simulation, energy yield variability was introduced to the discounted net present value PV results under the power purchase agreement tariff scenario. The table below indicates the standard deviation, minimum, average, and

maximum values, as well as the range of discounted net present values for each year and each scenario:

Scenario	Year	Standard Deviation	Minimum ($)	Average ($)	Maximum ($)	Range ($)
Pessimistic	2014	1,276.04	-78,394.49	-75,494.47	-71,522.25	6,872.24
	2015	1,396.01	-52,505.94	-48,896.59	-44,894.19	7,611.74
	2016	1,299.83	-48,772.60	-45,252.16	-40,216.29	8,556.30
	2017	1,488.62	-33,665.72	-29,412.51	-24,844.71	8,821.01
	2018	1,515.13	-6,087.69	-2,474.27	2,572.50	8,660.19
	2019	1,619.77	35,370.19	39,841.02	44,664.91	9,294.72
	2020	1,802.52	117,051.42	122,282.25	129,274.79	12,223.37
Average	2014	1,653.57	102,972.73	107,597.56	111,885.17	8,912.43
	2015	1,972.88	133,747.44	138,907.09	143,810.26	10,062.83
	2016	1,717.97	128,897.03	134,120.14	138,797.85	9,900.83
	2017	1,824.31	132,997.55	137,028.80	141,341.02	8,343.47
	2018	1,901.92	144,193.19	150,381.28	156,263.61	12,070.42
	2019	1,936.85	164,023.97	169,286.46	175,439.01	11,415.04
	2020	1,988.00	199,032.66	205,645.95	210,769.46	11,736.80
Optimistic	2014	2,703.46	466,738.48	473,092.03	480,070.30	13,331.83
	2015	2,647.26	485,675.45	493,895.92	502,362.50	16,687.05
	2016	2,583.97	448,003.88	454,880.84	462,100.13	14,096.25
	2017	2,434.17	403,787.94	409,832.38	418,458.40	14,670.46
	2018	2,459.81	364,183.68	370,470.93	376,631.07	12,447.39
	2019	2,277.27	331,141.11	336,674.72	342,103.54	10,962.44
	2020	2,301.06	288,882.20	294,823.98	300,815.33	11,933.13

Table 50. PV discounted net present value, standard deviation, minimum, average, maximum, and range figures from the power purchase agreement Monte Carlo simulation results. All figures are in USD.

As expected in Table 50, the averaged figures closely followed the values from the static PV discounted NPV numbers in Figure 39 in Section 5.3.1.1. Above, the averages from the "pessimistic" scenario increased, while the averages from the "optimistic" scenario decreased. The standard deviations from each of the three pricing scenarios, however, followed a different pattern. The "pessimistic" scenario standard deviations tended to increase as time moved forward, while, the standard deviations from the "optimistic" scenario tended to decrease over the same period. The "average" standard deviations fluctuated without any discernable pattern.

In Figure 45 below, plots of the averages from the three pricing scenarios are shown with their associated 95% confidence intervals:

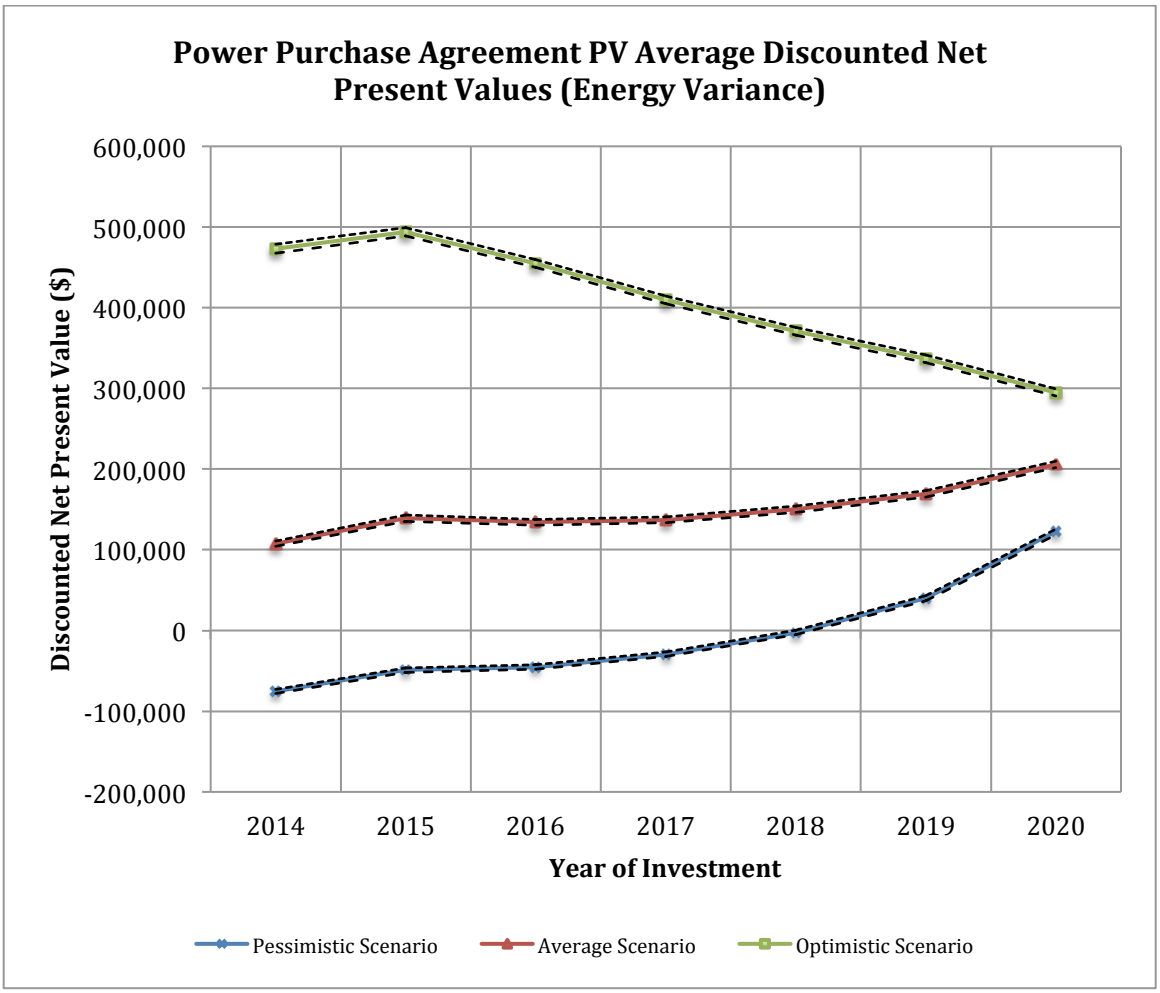


Figure 45. Plots of the PV discounted net present values under the power purchase agreement tariff scenario.

The shape of each plot of discounted net present values in Figure 45 closely matched the shape of the corresponding static plot from Figure 39 in Section 5.3.1.1. The 95% confidence intervals in Figure 45, represented by the dashed lines on either side of the mean plot and calculated using Equation (24) from Section 5.1.2.1, were narrow. From a risk management perspective, this meant that there was a 95% chance that a discounted NPV in any of the years 2014 though 2020 would fall within the confidence interval bounds. The closeness of the upper and lower 95% confidence interval limits to the mean meant there was a low risk that a discounted NPV would stray significantly from the mean. To better demonstrate the width of

one of the 95% confidence intervals, a close-up of the "pessimistic" plot from Figure 45 is shown below:

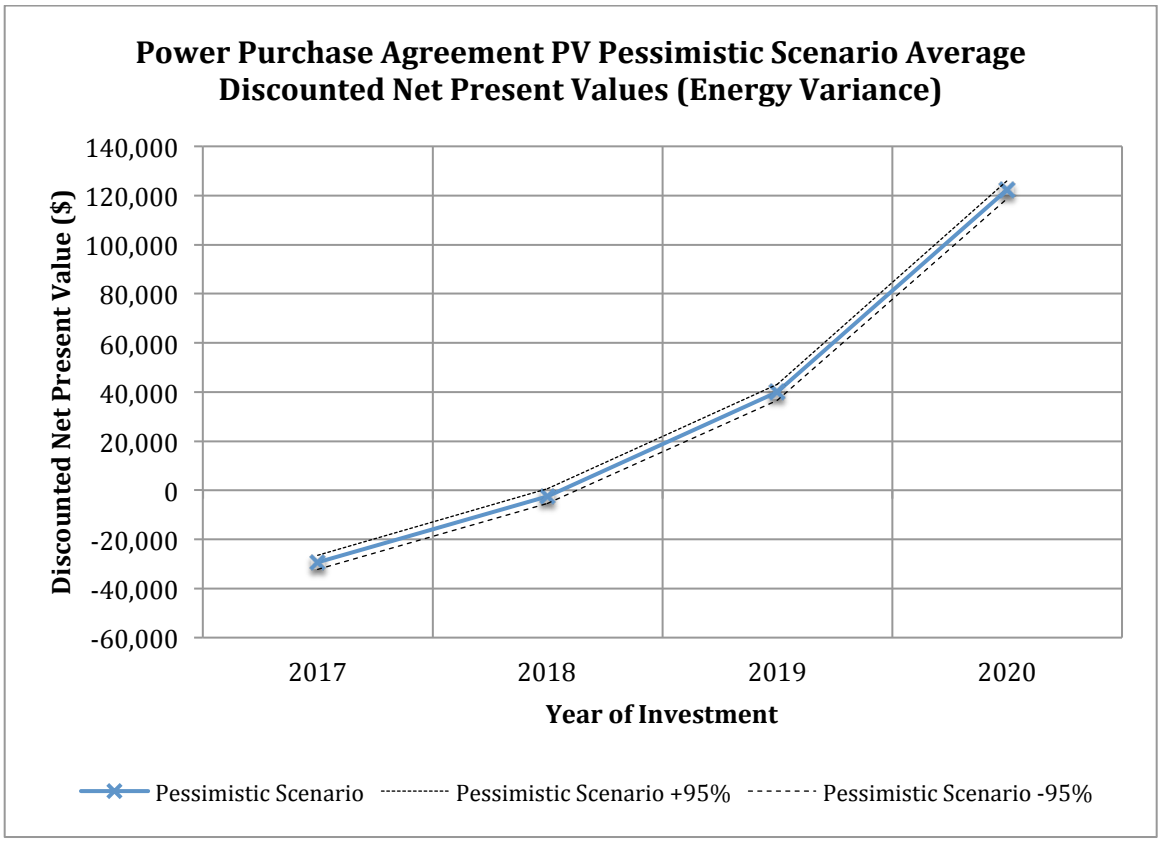


Figure 46. A close-up showing the mean discounted net present values from the "pessimistic" pricing scenario along with the 95% confidence interval on either side of the mean for the years 2017 through 2020.

Even with the close-up shown in Figure 46, the 95% confidence interval was positioned tight to the average value each year. The narrow 95% confidence interval for each of the "optimistic," "average," and "pessimistic" costing scenarios should provide confidence to a potential investor or lending firm involved in the setup and installation of a PV system that the value of the actual discounted NPV would be close to the value of the predicted NPV.

To confirm the validity of the analysis methodology in this section, normality tests were performed to ensure the 250 simulated data were normally distributed. Figure 47 below shows one such normality test for the 250 simulated values belonging to the 2014 "average" scenario:

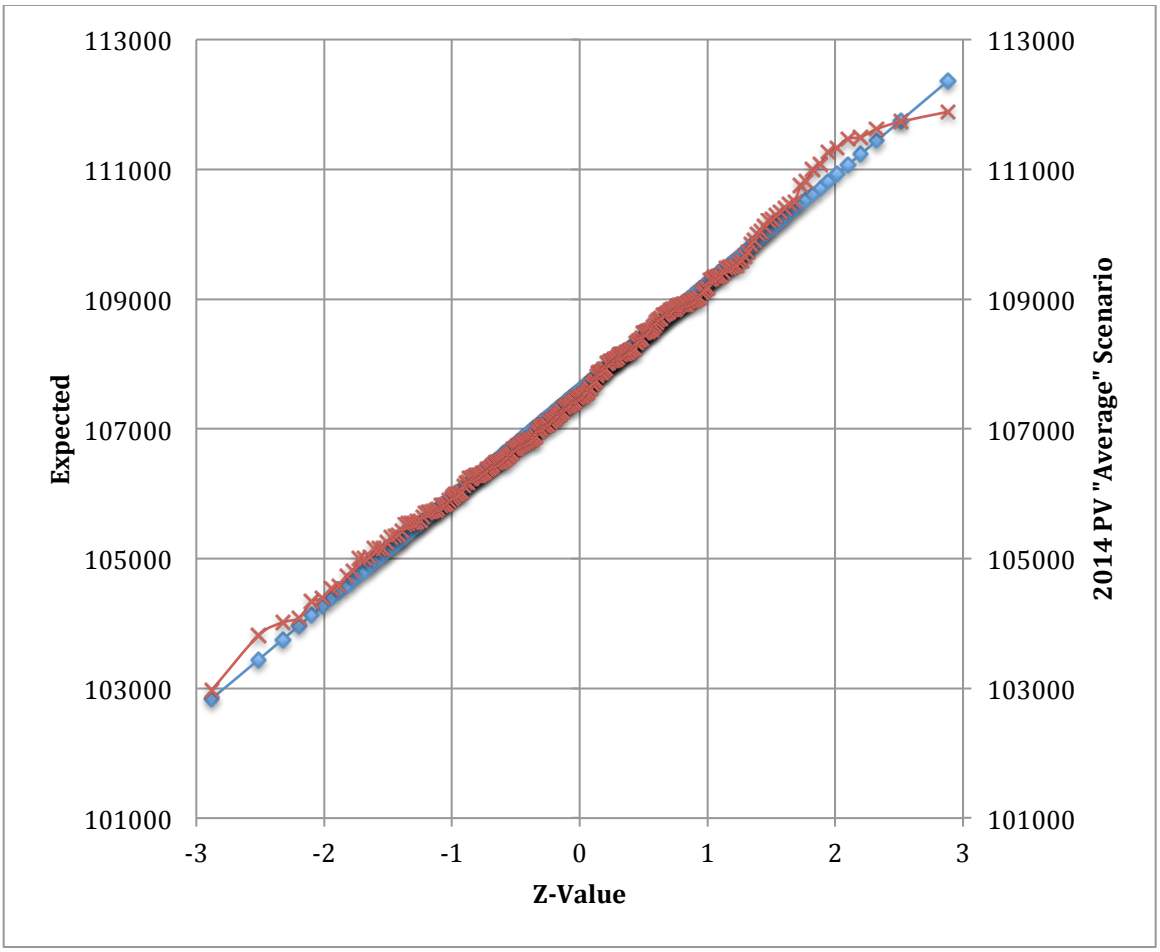


Figure 47. Normality test of the 250 simulated values for the 2014 PV "average" scenario.

The fact that the red x's of simulated values conformed to the blue squares of expected values meant that there was insufficient evidence to state that the 250 values generated by the Monte Carlo simulation were not normally distributed. This result was expected given that the Monte Carlo simulation inputs were normally distributed. Additional normality tests for the power purchase agreement tariff scenario are included in Appendix D. In the next section, additional PV variability analysis will be presented.

5.3.2.2 Photovoltaic Technology Variability Analysis

Table 51 provides a summary of discounted net present value variability due to energy yield:

Discounted Net Present Value Variability due to Energy Yield				
Year	**% Above/Below Central Estimate**	**Pessimistic Scenario**	**Average Scenario**	**Optimistic Scenario**
2014	% above central estimate	3.31%	3.01%	1.12%
	% below central estimate	-3.31%	-3.01%	-1.12%
2015	% above central estimate	5.60%	2.78%	1.05%
	% below central estimate	-5.60%	-2.78%	-1.05%
2016	% above central estimate	5.63%	2.51%	1.11%
	% below central estimate	-5.63%	-2.51%	-1.11%
2017	% above central estimate	9.92%	2.61%	1.16%
	% below central estimate	-9.92%	-2.61%	-1.16%
2018	% above central estimate	120.02%*	2.48%	1.30%
	% below central estimate	-120.02%*	-2.48%	-1.30%
2019	% above central estimate	7.97%	2.24%	1.33%
	% below central estimate	-7.97%	-2.24%	-1.33%
2020	% above central estimate	2.89%	1.89%	1.53%
	% below central estimate	-2.89%	-1.89%	-1.53%

Table Notes:

- "Central estimate" is the mean discounted net present value from the Monte Carlo simulation
- The above figures represent variability as a proportion of the mean with 95% confidence
- *Values that are exceptional due to the central estimate being close to zero

Table 51. Percentage of discounted net present value variability due to energy yield for PV technology under the power purchase agreement tariff scenario.

Excluding the values marked with a * in Table 51, 95% of the discounted net present value data points from the Monte Carlo simulation were no greater than plus or minus 9.92% on either side of the mean in any of the years 2014 to 2020. These values were calculated using Equation (25) from Section 5.1.2.2. The "pessimistic" scenario had the largest variability percentages, and these values grew from 2014 to 2017, but then diminished afterwards. As has been the case several times throughout Chapter 9, the "optimistic" percentage values in Table 51 were smaller than the "pessimistic" percentage values, but this was because these figures represented variability as a proportion of the mean instead of an absolute value.

In Table 52, the amount of discounted NPV variability due to system cost was considerably larger in 2014 compared with 2020:

Discounted NPV Variability due to System Cost and O&M and Degradation			
Year	**% Above/Below Central Estimate**	**System Cost⊙**	**O&M and Degradation❖**
2014	% above central estimate	338.94%	29.64%
	% below central estimate	-170.08%	-27.98%
2015	% above central estimate	255.71%	24.83%
	% below central estimate	-135.14%	-23.59%
2016	% above central estimate	239.37%	27.23%
	% below central estimate	-133.72%	-26.29%
2017	% above central estimate	198.94%	28.66%
	% below central estimate	-121.56%	-28.10%
2018	% above central estimate	146.00%	28.65%
	% below central estimate	-101.56%	-28.51%
2019	% above central estimate	98.82%	28.32%
	% below central estimate	-76.44%	-28.59%
2020	% above central estimate	43.45%	26.66%
	% below central estimate	-40.46%	-27.29%

Table Notes:

- ⊙Range from literature: Aanesen, Heck, and Pinner (2012), Ardani et al. (2013).
- ❖Range from literature: Branker et al. (2011), Di Francia (2013), Lowder et al. (2013), National Renewable Energy Laboratory (2013a), Zweibel (2010).
- "Central estimate" is the "average" discounted net present value with zero variability
- *Values that are exceptional due to the central estimate being close to zero

Table 52. Percentage of discounted net present value variability due to system cost, as well as O&M and degradation for PV technology under the power purchase agreement tariff scenario.

In 2014, the range of possible discounted net present values due to system cost variability was 338.94 percentage points above and 170.08 percentage points below the mean. In 2020, however, the range was only 43.45% above and 40.46% below the mean. Comparatively, discounted NPV variability from O&M and degradation was relatively the same in each of the years 2014 to 2020. Above the mean, O&M and degradation could have varied the discounted NPV at most by 29.64%; below the mean, this figures was 28.59%. In the years closer to 2020, the impact on discounted NPV from these two sources of variability was significantly more similar than in the years closer to 2014.

According to Table 53, variability due to system cost was always greater than variability due to O&M and degradation. However, these ratio figures decreased as time progressed towards the year 2020:

Ratio of Variability due to System Cost to Variability due to O&M and Degradation		
Year	**Ratio Above/Below Central Estimate**	**Ratio**
2014	Ratio above central estimate	11.43
	Ratio below central estimate	6.08
2015	Ratio above central estimate	10.30
	Ratio below central estimate	5.73
2016	Ratio above central estimate	8.79
	Ratio below central estimate	5.09
2017	Ratio above central estimate	6.94
	Ratio below central estimate	4.33
2018	Ratio above central estimate	5.10
	Ratio below central estimate	3.56
2019	Ratio above central estimate	3.49
	Ratio below central estimate	2.67
2020	Ratio above central estimate	1.63
	Ratio below central estimate	1.48

Table Note:

- "Central estimate" is the "average" discounted net present value with zero variability

Table 53. Ratio of variability due to system cost to variability due to O&M and degradation for PV technology under the power purchase agreement tariff scenario.

In 2020, system cost variability above the mean was about 1.63 times greater than O&M and degradation variability. This was considerably less than the 11.43 times difference between the two sources of variability in 2014. In each of the years 2014 to 2020, however, the ratio of variability due to system cost to variability due to O&M and degradation was higher above the central estimated compared with below the central estimate.

Also throughout each year between 2014 and 2020, discounted net present value variability due to O&M and degradation was greater than discounted NPV variability due to energy yield. To be precise, this variability ranged between 2.38 and 26.47 times greater depending upon the pricing scenario and the year:

Ratio of O&M and Degradation Variability to Energy Yield Variability				
Year	**Ratio Above/Below Central Estimate**	**Pessimistic Scenario**	**Average Scenario**	**Optimistic Scenario**
2014	Ratio above central estimate	8.95	9.84	26.47
	Ratio below central estimate	8.45	9.29	24.98
2015	Ratio above central estimate	4.44	8.92	23.64
	Ratio below central estimate	4.22	8.48	22.46
2016	Ratio above central estimate	4.84	10.85	24.46
	Ratio below central estimate	4.67	10.47	23.61
2017	Ratio above central estimate	2.89	10.98	24.62
	Ratio below central estimate	2.83	10.77	24.14
2018	Ratio above central estimate	0.24*	11.56	22.02
	Ratio below central estimate	0.24*	11.50	21.91
2019	Ratio above central estimate	3.55	12.63	21.36
	Ratio below central estimate	3.59	12.75	21.56
2020	Ratio above central estimate	9.23	14.07	17.43
	Ratio below central estimate	9.45	14.40	17.84

Table Note:

- "Central estimate" is the mean discounted net present value from the Monte Carlo simulation
- *Values that are exceptional due to the central estimate being close to zero

Table 54. A comparison of how much more discounted net present value variability is due to O&M and degradation compared with energy yield for PV technology under the power purchase agreement tariff scenario.

Interestingly, the ratio values from the "optimistic" scenario experienced an overall decline between 2014 and 2020, while the values from the "average" and "pessimistic" scenarios saw an increase over the same timeframe. The "average" scenario figures increased to a greater extent than those under the "pessimistic" scenario.

5.3.2.3 Concentrated Photovoltaic Technology

Turning to CPV technology, Table 55 below shows the standard deviation, minimum, average, maximum, and range of discounted net present values for the data generated by the Monte Carlo simulation under the power purchase agreement tariff scenario:

Scenario	Year	Standard Deviation	Minimum ($)	Average ($)	Maximum ($)	Range ($)
Pessimistic	2014	2,416.11	-73,089.57	-66,899.51	-60,293.57	12,796.00
	2015	2,909.56	-50,524.97	-41,788.72	-34,372.07	16,152.90
	2016	2,835.17	-67,868.37	-60,471.23	-52,681.05	15,187.32
	2017	2,745.00	-88,345.09	-81,433.25	-73,638.89	14,706.20
	2018	2,563.74	-111,284.09	-105,218.36	-98,526.57	12,757.51
	2019	2,661.91	-136,992.47	-130,013.32	-121,316.09	15,676.38
	2020	2,183.20	-163,500.37	-156,676.98	-150,685.33	12,815.03
Average	2014	3,357.73	118,373.34	128,287.82	140,256.49	21,883.15
	2015	4,122.75	197,392.65	207,437.09	219,535.16	22,142.51
	2016	3,873.51	204,710.90	216,924.71	227,473.31	22,762.42
	2017	4,656.01	201,173.66	212,699.94	224,787.33	23,613.67
	2018	4,271.81	178,464.04	194,493.30	208,321.92	29,857.87
	2019	4,314.91	163,367.23	177,447.52	190,127.34	26,760.12
	2020	3,720.03	132,315.19	143,872.81	155,738.84	23,423.66
Optimistic	2014	4,511.28	408,867.43	420,403.03	434,953.92	26,086.48
	2015	5,883.22	590,097.64	605,326.79	623,137.43	33,039.79
	2016	5,947.88	673,013.47	690,243.85	706,522.86	33,509.39
	2017	6,879.88	703,923.07	726,219.76	744,831.08	40,908.01
	2018	6,937.09	714,298.33	740,227.32	762,153.99	47,855.66
	2019	6,560.14	698,358.11	717,154.18	734,745.93	36,387.83
	2020	6,870.81	703,933.44	722,504.41	741,460.68	37,527.23

Table 55. CPV discounted net present value, standard deviation, minimum, average, maximum, and range figures from the power purchase agreement tariff scenario Monte Carlo simulation results. All figures are in USD.

Not surprisingly, the trend of the discounted NPV averages shown in Table 55 moved in parallel with the CPV discounted NPV averages without energy yield variability provided by Figure 44 in Section 5.3.1.2. The optimal time to invest in a CPV installation under the "average" scenario according to Table 55 was in 2016, while the ideal time to invest under the "optimistic" costing scenario was in 2018. These two most favourable investment years corresponded with the best times to invest under the no-variability CPV example from the same tariff scenario displayed in Figure 44. In Table 55, the ranges and standard deviations shown were larger than the ranges and standard deviations associated with the PV energy yield variability results from Section 5.3.2.1. Thus, the risk associated with energy variability was greater for CPV technology than PV technology.

Figure 48 below shows the mean values from the 250 Monte Carlo Simulations as well as the 95% confidence intervals on either side of the mean. The CPV confidence intervals were expected to be larger than the PV confidence intervals shown in the previous section given that the CPV standard deviations were larger compared with the PV standard deviations.

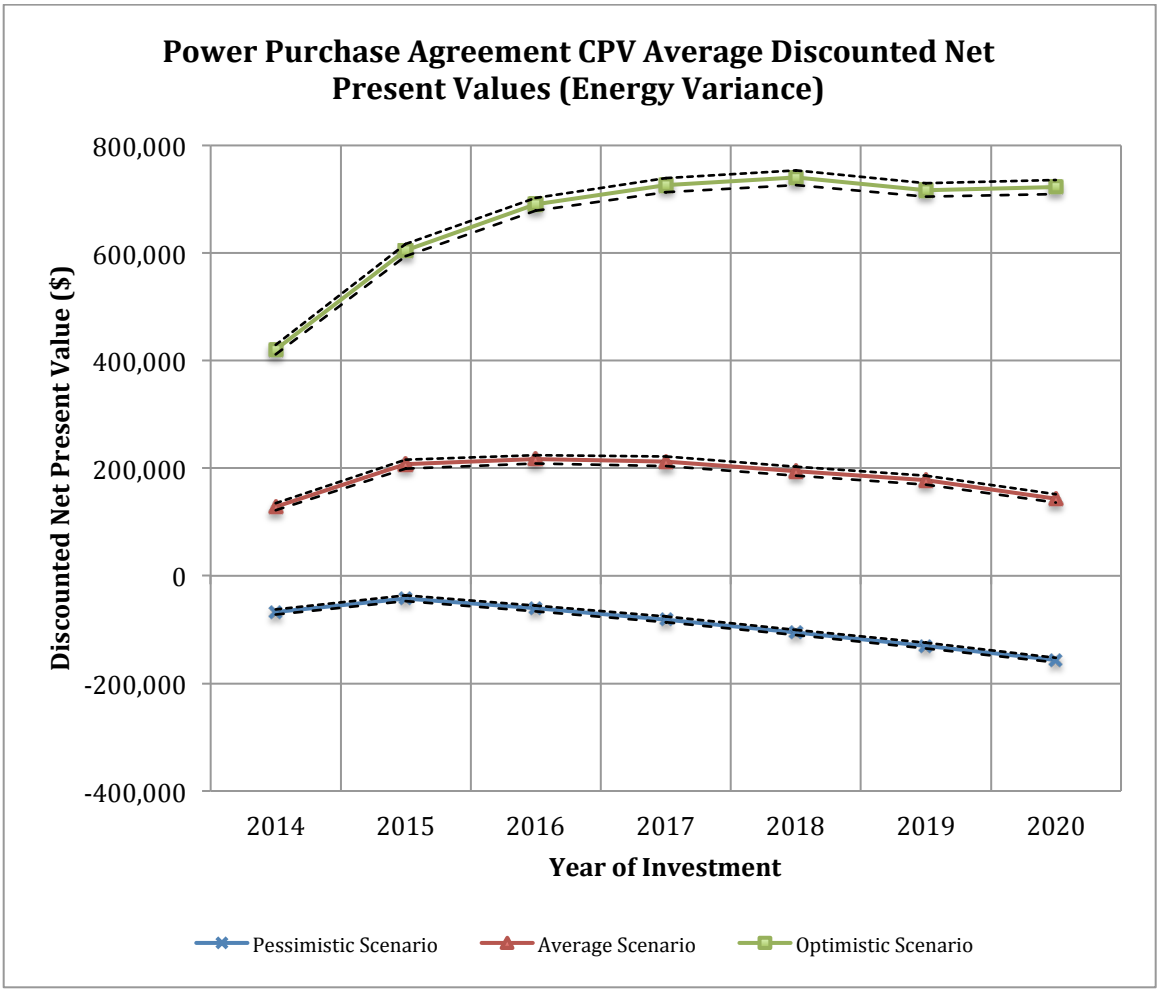


Figure 48. Average CPV discount net present values with energy variability 95% confidence intervals under the power purchase agreement tariff scenario.

In Figure 48, the 95% confidence intervals for the "optimistic" scenario were wider and thus easier to distinguish compared with the confidence intervals for the "pessimistic" scenario. This likely had to do with the fact that a larger CPV installation was constructed under the "optimistic" costing scenario compared with the "pessimistic" costing scenario in each of the years 2014 through 2020. The

confidence intervals were calculated using Equation (24) from Section 5.1.2.1. Given the same amount of investment capital in each year, a lower $/W installation cost meant that a greater amount of CPV installation could be built, which resulted in greater electricity output. Consequently, the larger the electricity output, the bigger the fluctuations in electricity production when energy yield was varied.

To better illustrate the width of the confidence intervals shown in Figure 48, a close-up of the "average" scenario plot line is shown below:

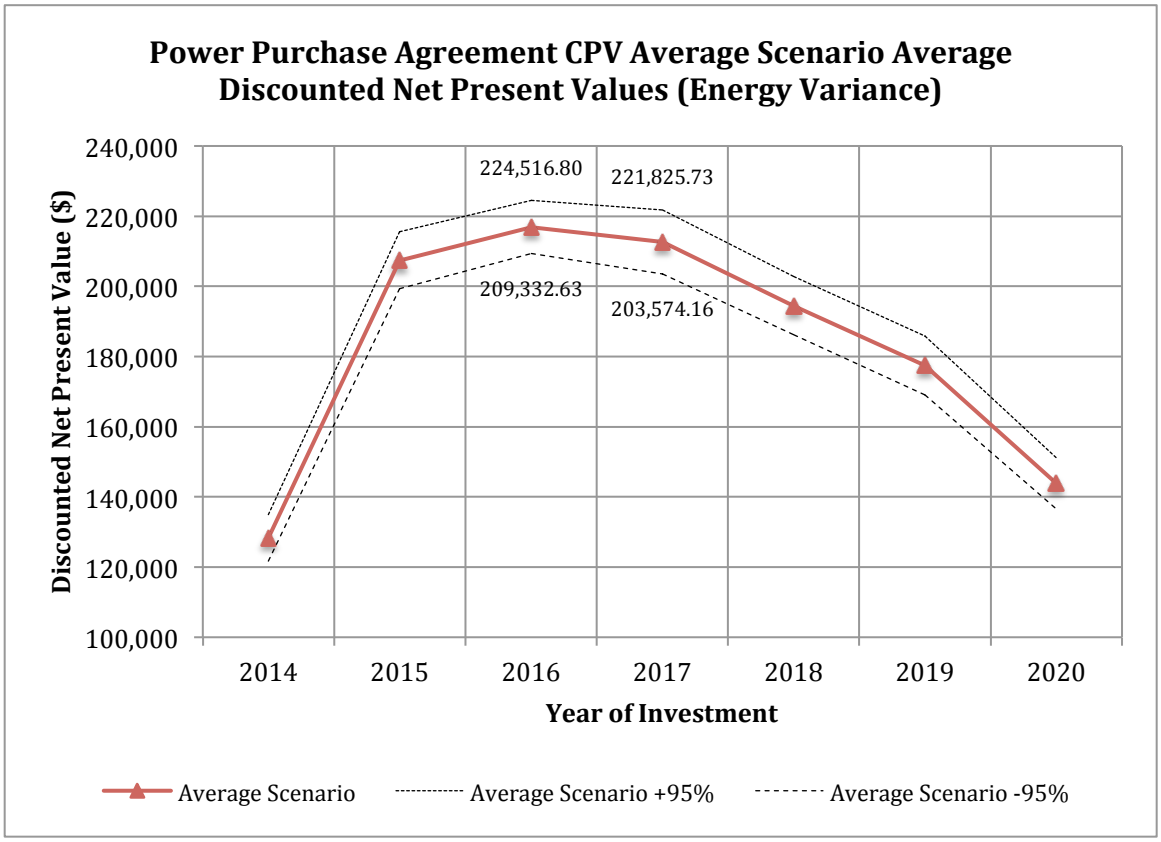


Figure 49. Close-up of the means and 95% confidence intervals each year from the "average" scenario after 250 Monte Carlo simulations.

Visually, the 95% confidence interval in Figure 49 appeared to be narrowest in the year 2014 and widest in 2017. Referring back to the CPV standard deviations from Table 55 in this section, the smallest standard deviation was recorded in 2014, while the largest was calculated in 2017. Thus, the width of the 95% confidence intervals in Figure 49 followed the size of the standard deviations as expected. For a potential investor, the widths of the confidence intervals indicated a certain amount

of risk associated with variability. In 2017, for example, there was a 95% probability that the discounted NPV would fall between USD 203,574.16 on the low side and USD 221,825.73 on the high side. If the investor required a minimum return of USD 200,000, then he or she could invest in 2017 and be confident that the minimum return would be realized. However, the probability would be even higher that the minimum return of USD 200,000 would be met in 2016 since the lower end of the 95% confidence was USD 209,332.63 in that year.

Normality tests were performed to confirm that the 250 discounted net present values generated by the Monte Carlo simulation were in fact normally distributed. Below, Figure 50 shows a normality test for the 2014 CPV "average" scenario:

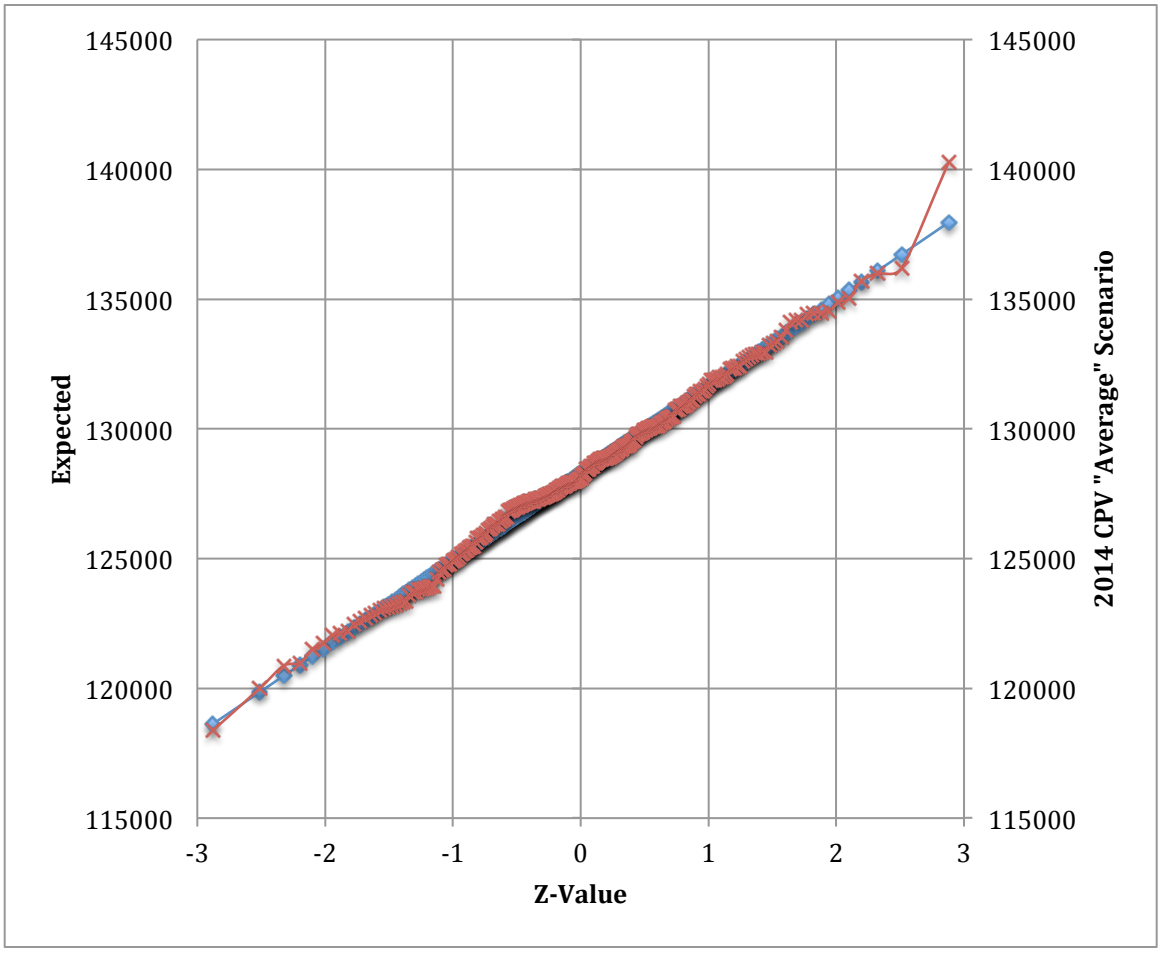


Figure 50. Normality test for the 2014 CPV "average" scenario under the power purchase agreement tariff scenario.

As shown by Figure 50, the simulated discounted net present values represented by the red x's closely matched the blue squares of expected values under a normal distribution. Thus, there was insufficient evidence to suggest that the discounted net present values from the CPV 2014 "average" scenario were not normally distributed. Additional normality tests for the discounted net present values simulated as part of the CPV power purchase agreement scenario are presented in Appendix D. In the next section, CPV energy yield variability under the PPA tariff scenario will be further analyzed.

5.3.2.4 Concentrated Photovoltaic Technology Variability Analysis

The following table summarizes discounted net present value variability due to energy yield as a proportion of the mean:

Discounted Net Present Value Variability due to Energy Yield				
Year	**% Above/Below Central Estimate**	**Pessimistic Scenario**	**Average Scenario**	**Optimistic Scenario**
2014	% above central estimate	7.08%	5.13%	2.10%
	% below central estimate	-7.08%	-5.13%	-2.10%
2015	% above central estimate	13.65%	3.90%	1.90%
	% below central estimate	-13.65%	-3.90%	-1.90%
2016	% above central estimate	9.19%	3.50%	1.69%
	% below central estimate	-9.19%	-3.50%	-1.69%
2017	% above central estimate	6.61%	4.29%	1.86%
	% below central estimate	-6.61%	-4.29%	-1.86%
2018	% above central estimate	4.78%	4.30%	1.84%
	% below central estimate	-4.78%	-4.30%	-1.84%
2019	% above central estimate	4.01%	4.77%	1.79%
	% below central estimate	-4.01%	-4.77%	-1.79%
2020	% above central estimate	2.73%	5.07%	1.86%
	% below central estimate	-2.73%	-5.07%	-1.86%

Table Notes:

- "Central estimate" is the mean discounted net present value from the Monte Carlo simulation
- The above figures represent variability as a proportion of the mean with 95% confidence
- *Values that are exceptional due to the central estimate being close to zero

Table 56. Percentage of discounted net present value variability due to energy yield for CPV technology under the power purchase agreement tariff scenario.

As illustrated by Table 56, 95% of discounted net present values varied at most plus or minus 13.65% on either side of the mean. This particular value was found under the "pessimistic" pricing scenario, where no profitability was realized according to Table 55. Where profitability was observed, between 2014 and 2020 under the "average" and "optimistic" scenarios, the highest value in Table 56 was plus or minus 5.13% on either side of the mean. Discounted NPV variability due to energy yield under the "average" and "optimistic" scenarios remained mostly constant over the years 2014 to 2020, while the "pessimistic" scenario saw a peak in 2015 followed by declining values. The values in Table 56 were calculated using Equation (25) from Section 5.1.2.2.

Discounted net present value variability due to system cost was greater above the mean than below the mean according to Table 57:

Discounted NPV Variability due to System Cost and O&M and Degradation			
Year	**% Above/Below Central Estimate**	**System Cost⊙**	**O&M and Degradation❖**
2014	% above central estimate	228.21%	27.61%
	% below central estimate	-152.08%	-27.61%
2015	% above central estimate	191.67%	19.92%
	% below central estimate	-120.22%	-19.92%
2016	% above central estimate	217.90%	21.11%
	% below central estimate	-127.90%	-21.11%
2017	% above central estimate	240.72%	23.48%
	% below central estimate	-138.23%	-23.48%
2018	% above central estimate	280.49%	27.63%
	% below central estimate	-154.04%	-27.63%
2019	% above central estimate	305.18%	32.80%
	% below central estimate	-173.56%	-32.80%
2020	% above central estimate	402.31%	42.71%
	% below central estimate	-209.03%	-42.71%

Notes:

- ⊙Range from literature: Haysom et al. (2014).
- ❖Range from literature: Drury et al. (2013), Gerstmaier et al. (2014).
- "Central estimate" is the "average" discounted net present value with zero variability
- *Values that are exceptional due to the central estimate being close to zero

Table 57. Percentage of discounted net present value variability due to system cost, as well as O&M and degradation for CPV technology under the power purchase agreement tariff scenario.

The size of the total interval spanning both above and below the mean in each year decreased between 2014 and 2015, but then increased in each of the remaining years until 2020. Thus, over all there was greater risk of discounted NPV variability due to installation cost in later years compared to earlier years. For O&M and degradation, the size of the total interval above and below the mean also decreased between 2014 and 2015 and increased in each of the years between 2015 and 2020. Thus, discounted NPV variability due to O&M and degradation was higher as time moved forwards towards 2020. An investor looking to avoid higher risks posed by these two sources of variability would be better off investing in 2015 compared with any of the other years between 2014 and 2020.

The ratio values in Table 58, however, confirmed that discounted NPV variability due to system costs was consistently greater than discounted NPV variability due to O&M and degradation variability:

Ratio of Variability due to System Cost to Variability due to O&M and Degradation		
Year	**Ratio Above/Below Central Estimate**	**Ratio**
2014	Ratio above central estimate	8.26
	Ratio below central estimate	5.51
2015	Ratio above central estimate	9.62
	Ratio below central estimate	6.04
2016	Ratio above central estimate	10.32
	Ratio below central estimate	6.06
2017	Ratio above central estimate	10.25
	Ratio below central estimate	5.89
2018	Ratio above central estimate	10.15
	Ratio below central estimate	5.57
2019	Ratio above central estimate	9.31
	Ratio below central estimate	5.29
2020	Ratio above central estimate	9.42
	Ratio below central estimate	4.89

Table Note:

- "Central estimate" is the "average" discounted net present value with zero variability

Table 58. Ratio of variability due to system cost to variability due to O&M and degradation for CPV technology under the power purchase agreement tariff scenario.

Interestingly, the above the central estimate ratio figures in the above table peaked in 2017, while the below the central estimate ratio figures peaked in 2016.

Turning to the comparison of discounted NPV variability from O&M and degradation to discounted NPV variability due to energy yield, the former was between 1.46 and 22.92 times greater than the latter according to Table 58:

Ratio of O&M and Degradation Variability to Energy Yield Variability				
Year	**Ratio Above/Below Central Estimate**	**Pessimistic Scenario**	**Average Scenario**	**Optimistic Scenario**
2014	Ratio above central estimate	3.90	5.38	13.13
	Ratio below central estimate	3.90	5.38	13.13
2015	Ratio above central estimate	1.46	5.11	10.46
	Ratio below central estimate	1.46	5.11	10.46
2016	Ratio above central estimate	2.30	6.03	12.50
	Ratio below central estimate	2.30	6.03	12.50
2017	Ratio above central estimate	3.55	5.47	12.65
	Ratio below central estimate	3.55	5.47	12.65
2018	Ratio above central estimate	5.79	6.42	15.04
	Ratio below central estimate	5.79	6.42	15.04
2019	Ratio above central estimate	8.17	6.88	18.29
	Ratio below central estimate	8.17	6.88	18.29
2020	Ratio above central estimate	15.64	8.43	22.92
	Ratio below central estimate	15.64	8.43	22.92

Table Note:

- "Central estimate" is the mean discounted net present value from the Monte Carlo simulation
- *Values that are exceptional due to the central estimate being close to zero

Table 59. A comparison of how much more discounted net present value variability is due to O&M and degradation compared with energy yield for CPV technology under the power purchase agreement tariff scenario.

The ratio figures increased as time progressed towards 2020 with the ratio values from the "pessimistic" scenario overtaking those from the "average" scenario in the year 2019. The ratio values under the "optimistic" scenario were consistently higher than those under the "average" and "pessimistic" scenarios in each of the years 2014 through 2020.

5.3.3 Section 5.3 Summary

In Section 5.3, the discounted NPV results for the power purchase agreement tariff scenario were presented. This was the first tariff scenario where discounted net present values from the "pessimistic", "average," and "optimistic" scenarios were all positive at the same time. This happened in the years 2019 and 2020 for PV technology. For CPV technology, only the "average" and "optimistic" pricing scenarios saw positive discounted net present values, but these values were observed from 2014 through 2020. Over all, the profitability observed under this particular tariff scenario was unparalleled, both in terms of when profitability was observed and the quantity of profitability as measured by the discounted net present values. Although the baseline PPA prices were comparable to the FIT prices from the tariff scenario in Section 5.2, the discounted net present values in this section were comparably higher. This was likely attributable to the energy payment allocation factors employed by the power purchase agreement, which scaled up the price paid for electricity during times of peak demand. Consequently, these times of peak demand were during midday when solar modules generally produced a significant proportion of their electricity output, and this was a factor in the higher profits realized compared with the FIT results.

The discounted net present values under the PPA tariff scenario from the "optimistic" pricing scenario decreased in value over time, while the discounted net present values from the "average" and "pessimistic" costing scenarios increased in value over time. The contrasting directions of the net present value plots were attributed to the relationship between falling system costs and diminishing baseline PPA prices over time. In some years, the decline in system prices made up for the downtrend in baseline power purchase agreement prices and as such the discounted net present values increased compared with the value in the previous year. In other years, the opposite was true and the drop in system costs did not offset the reduction in baseline PPA prices. In these particular years, the discounted net present value was lower than the previous year.

For PV technology, the best time to invest under the "optimistic" pricing scenario was 2015, while under both the "average" and "optimistic" scenarios it was 2020. For CPV technology, the optimal year to invest under the "optimistic" pricing scenario was 2018, while the best time to invest under the "average" scenario was in 2016. The 95% confidence intervals shown in Figure 45 and Figure 48 were fairly narrow, although the CPV confidence intervals were wider than the PV confidence intervals. This was attributed to larger fluctuations in energy output from comparatively larger CPV systems in terms of both energy rating (kW) and area (m^2). The risks to a prospective investor for investing in either PV or CPV technology under the power purchase agreement tariff scenario were not especially high as indicated by the narrow 95% confidence intervals in Figure 45 for PV technology and Figure 48 for CPV technology. At most, 95% of the discounted net present value data points from the Monte Carlo simulation were either plus or minus 9.92% of the mean for PV technology and plus or minus 13.65% for CPV technology.

In the next section, the analysis of the final tariff scenario, global adjustment tariff offsetting, will be presented.

5.4 Ontario Peak-Dependent Tariff Offsetting Discounted Net Present Value Results

Note: this section is herein referred to as the "global adjustment tariff offsetting scenario."

5.4.1 Deterministic Results

5.4.1.1 Photovoltaic Technology

Under this tariff scenario, value was generated by producing solar energy to offset the consumption of electricity from the electrical grid in a similar fashion as the

time-of-use pricing scenario presented in Section 5.1. This was distinct from the feed-in tariff and power purchase agreement tariff scenarios in Sections 5.2 and 5.3, respectively, where the solar produced electricity was sold at contractually set rates for a predetermined period of time, thus creating a revenue stream. The value created under this particular tariff scenario came from offsetting the three electricity charges faced by Class "A" electricity customers in Ontario, who were defined as those with peak energy demands exceeding three megawatts (Independent Electricity System Operator, n.d.b). The three electricity charges offset were the wholesale price of electricity, also known as the Hourly Ontario Energy Price, the global adjustment charge, and a distribution charge from the local electricity utility. A thorough discussion of each of these electricity charges, as well as the methodology and formulas used to calculate the value from offsetting, were provided in Section 3.3.1.3.

With zero variability in PV energy yield, Figure 51 below provides the discounted net present value figures for each of the "pessimistic," "average," and "optimistic" pricing scenarios. Values defining costs and other components for these three scenarios were provided in Table 15 and Table 16 in Section 4.1.

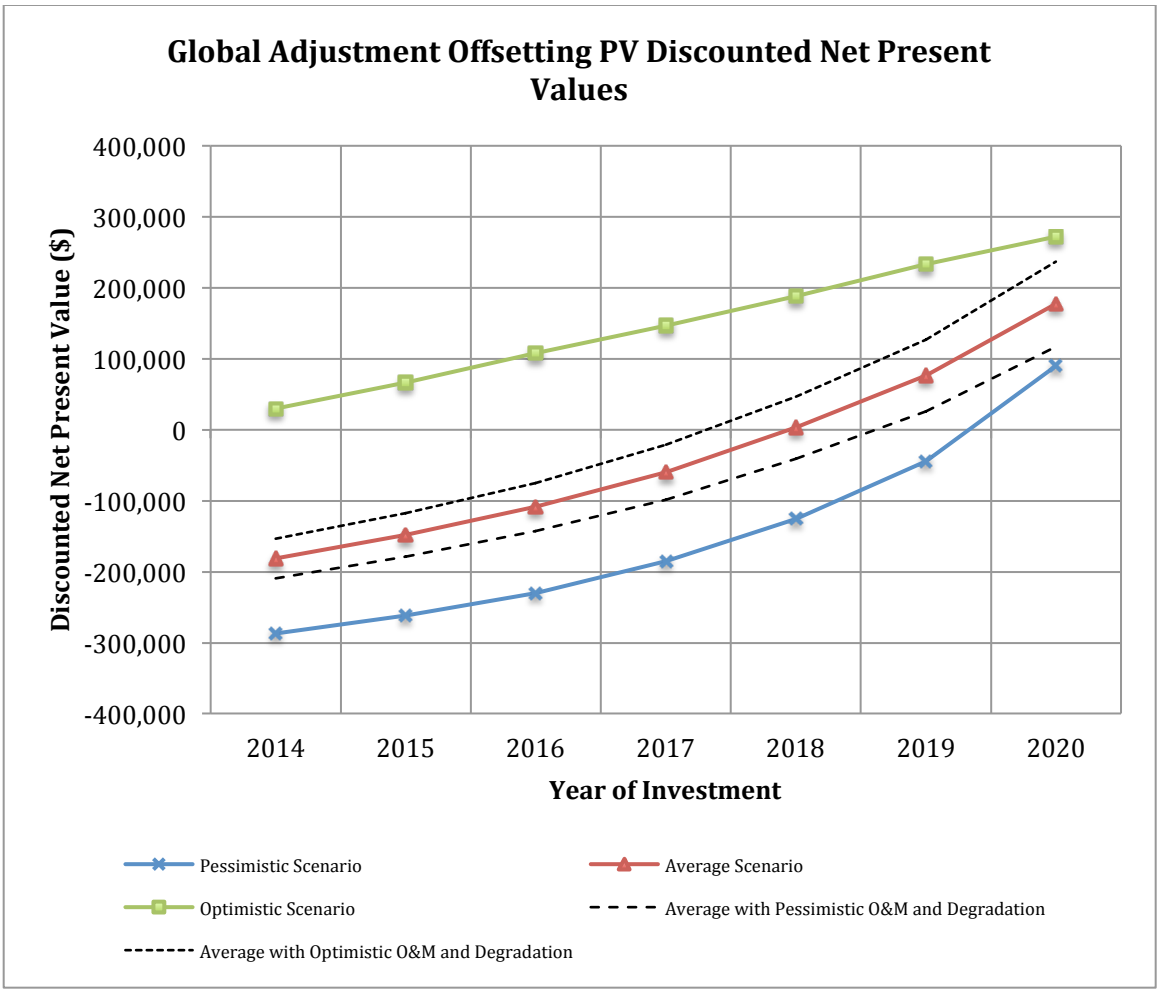


Figure 51. Discounted net present values under the global adjustment tariff offsetting scenario for PV technology.

According to Figure 51, discounted net present values increased as time moved towards 2020. Given that the average Hourly Ontario Energy Price was projected to increase over time as per Figure 11 in Section 3.3.1.3, this result was not completely unexpected since the higher the tariff, the more value there was from offsetting the charge. However, that same figure in Section 3.3.1.3 indicated the average global adjustment value was projected to decrease over the same timeframe, meaning the value from offsetting this particular fee would decrease. Interestingly, Figure 51 indicated that it was unnecessary to invest sooner rather than later to take advantage of the highest average global adjustment charge. In fact, it was worthwhile under each of the three tariff scenarios to wait until 2020 in order to realize the highest discounted net present values.

Although all three pricing scenarios had a positive discounted NPV in 2020, only the "optimistic" costing scenario saw positive discounted net present values in each of the years 2014 through 2020. Even when accounting for operation and maintenance costs, as well as degradation rates from either the "optimistic" or "pessimistic" pricing scenarios, the "average" costing scenario did not experience noteworthy positive discounted net present values until 2019. This was just one year before the "optimistic" costing scenario turned positive.

5.4.1.2 Concentrated Photovoltaic Technology

Turning to CPV, Figure 52 below provides the discounted net present values resulting from use of this relatively new technology to offset the electricity charges faced by Class "A" electricity customers in Ontario:

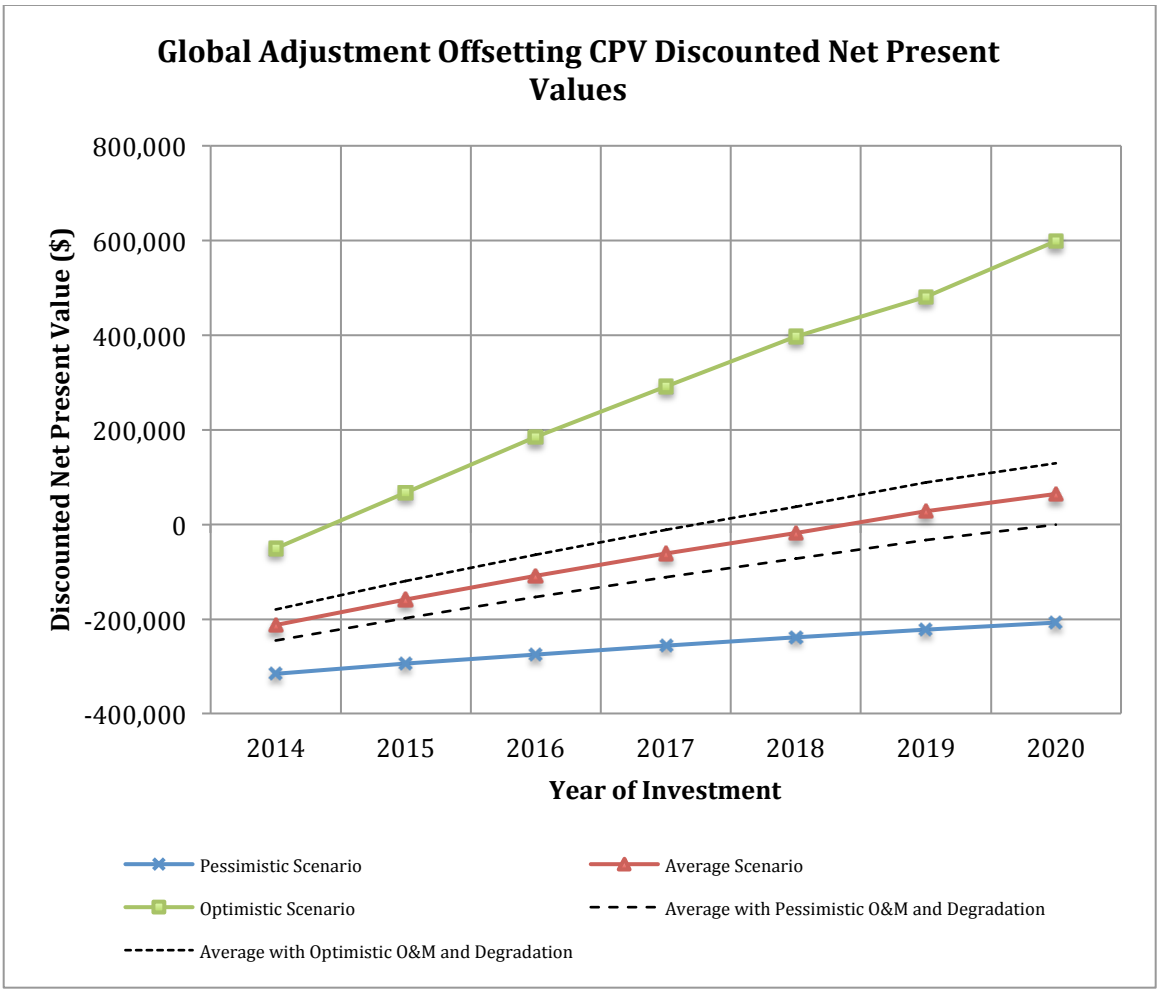


Figure 52. CPV discounted net present values for the "optimistic," "average," and "pessimistic" costing scenarios under the global adjustment tariff offsetting scenario.

The CPV results in Figure 52 indicated that the optimal time to invest in an installation was in 2020. In the previous section, the PV results also indicated that the optimal time to invest under the global adjustment tariff offsetting scenario was in 2020. Analogous to the PV results, investment was not necessary in the earlier years to take advantage of offsetting the higher average global adjustment charge, which was projected to decrease over time as per Figure 11 in Section 3.3.1.3. The range defined by the "Average with Pessimistic O&M and Degradation" and the "Average with Optimistic O&M and Degradation" widened as time progressed towards 2020. As was the case with the PV results in this and other tariff scenarios, the widening was likely caused by the fact that as CPV installation costs dropped

over time, larger installations were constructed and these installations outputted greater quantities of energy.

Unlike the PV results in Section 5.4.1.1, the "pessimistic" costing scenario in this section did not see any positive discounted net present values. Furthermore, the discounted net present values from the "optimistic" costing scenario were not always positive in this section. While the conditions existed under PV technology for the discounted net present values from all three pricing scenarios to become positive over time, the relationship between decreases in CPV system costs, operation and maintenance fees, and degradation rates was such that it kept the CPV discounted net present values under the "pessimistic" costing scenario always below zero. In fact, only the CPV discounted net present values of the "optimistic" and "average" scenarios eventually turned positive. Consequently, PV technology provided more investment opportunities than CPV technology.

5.4.2 Energy Yield Variability Results

5.4.2.1 Photovoltaic Technology

The introduction of energy yield variability via a Monte Carlo simulation produced a set of 250 discounted net present values. Note that for the results in this section, no Monte Carlo variability was included in the Hourly Ontario Energy Price. Table 60 below provides the standard deviation, minimum, average, maximum and range of discounted net present values stemming from the Monte Carlo simulation:

Scenario	Year	Standard Deviation	Minimum ($)	Average ($)	Maximum ($)	Range ($)
Pessimistic	2014	1,102.56	-290,966.16	-287,287.68	-284,767.42	6,198.74
	2015	1,223.09	-265,620.48	-262,022.62	-258,682.13	6,938.35
	2016	1,332.72	-233,388.66	-229,602.93	-226,079.13	7,309.53
	2017	1,580.33	-190,329.95	-185,129.12	-180,700.89	9,629.05
	2018	1,783.12	-130,220.64	-125,153.37	-120,303.71	9,916.93
	2019	2,241.76	-50,237.59	-43,982.97	-37,347.87	12,889.72
	2020	2,783.40	81,485.24	89,641.10	97,847.77	16,362.53
Average	2014	1,528.79	-186,822.53	-181,210.58	-176,712.68	10,109.85
	2015	1,670.27	-152,384.17	-148,194.33	-143,897.09	8,487.09
	2016	1,673.87	-114,702.07	-108,578.30	-103,155.59	11,546.48
	2017	2,089.14	-66,154.48	-59,389.15	-52,909.55	13,244.94
	2018	2,099.03	-2,009.66	3,272.50	8,992.78	11,002.43
	2019	2,429.22	70,382.50	76,797.76	83,679.99	13,297.48
	2020	2,992.99	170,447.23	177,215.12	184,699.42	14,252.19
Optimistic	2014	2,451.02	23,457.71	29,892.40	36,832.21	13,374.50
	2015	2,434.62	60,175.12	66,839.94	76,283.46	16,108.34
	2016	2,680.41	98,411.97	107,917.09	114,930.83	16,518.86
	2017	2,818.21	137,807.67	146,277.15	152,495.72	14,688.04
	2018	2,746.95	178,708.61	188,521.57	194,210.73	15,502.12
	2019	2,706.30	224,724.96	233,670.74	240,041.71	15,316.75
	2020	3,111.03	263,221.98	272,562.73	281,476.09	18,254.11

Table 60. Characteristics of the discounted net present values from the 250 Monte Carlo simulations performed for PV technology under the global adjustment tariff offsetting scenario with only energy variability.

With the exception of the "optimistic" scenario, as average discounted net present values in Table 60 increased the standard deviations grew larger in each year as well. Under the "optimistic" pricing scenario, the standard deviations increased in a non-linear fashion as time moved forward. Given that the standard deviation values were comparatively much smaller than the means in Table 60, the 95% confidence intervals surrounding the means were expected to be narrow. Figure 53 below illustrates the average discounted net present values for each of the years 2014 through 2020 under each of the three pricing scenarios along with the 95% confidence intervals on either side of the means:

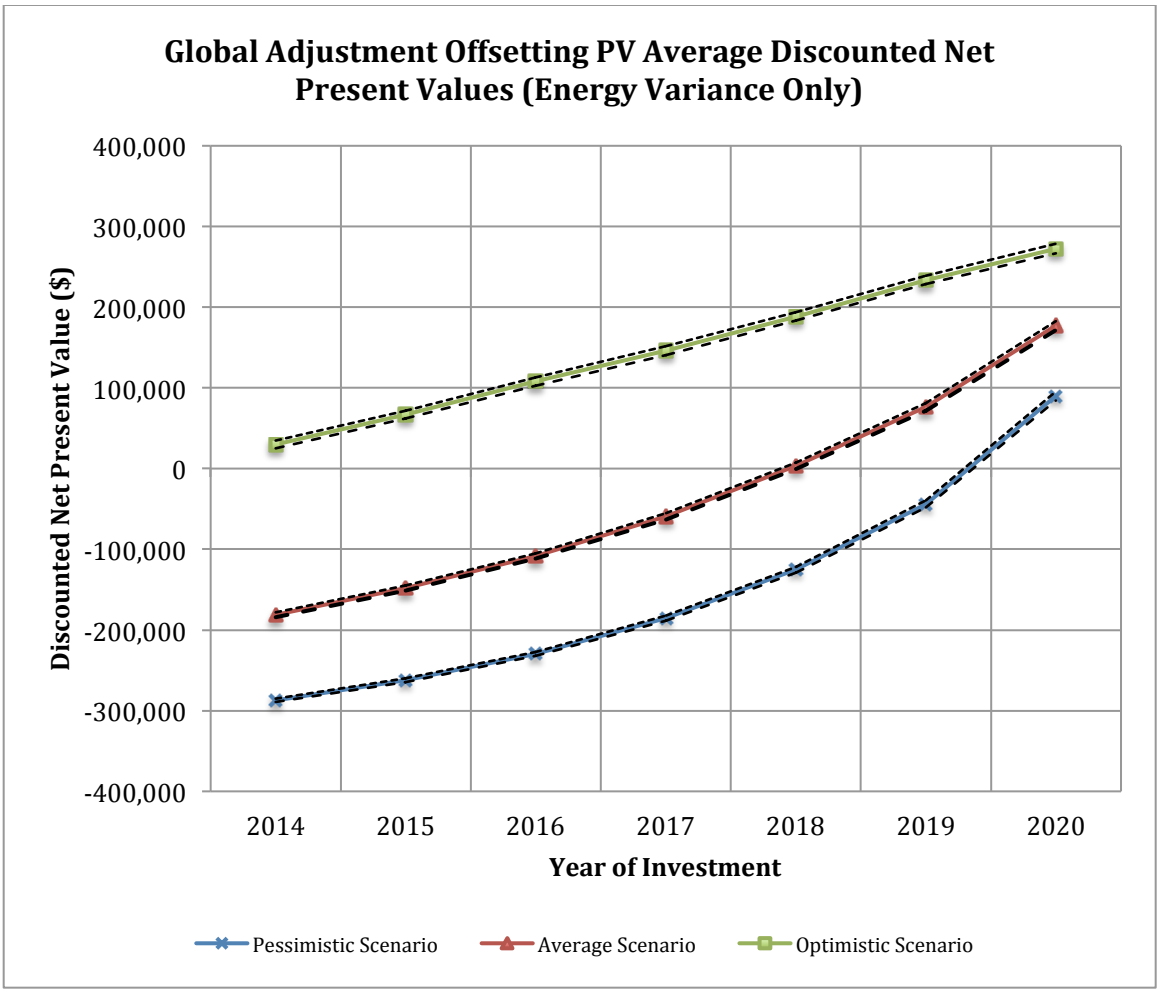


Figure 53. PV mean discounted net present values under the global adjustment tariff offsetting scenario with 95% confidence intervals on either side of the mean.

As was anticipated, the plots of the means in Figure 53 followed the plots from the PV no-variability results shown in Figure 51 in Section 5.4.1.1. The 95% confidence intervals, which were calculated using Equation (24) from Section 5.1.2.1, were tight against the means in each of the years 2014 through 2020. This has been the case throughout the energy yield variability analyses in this chapter. The restricted confidence intervals shown in Figure 53 were favourable from a risk management perspective because they provided visual confirmation as to where 95% of the discounted net present values could be expected to fall in any of the years under analysis. To highlight the narrowness of the range of the 95% confidence intervals, a close-up of the years 2017 to 2020 from the "optimistic" scenario in Figure 53 is shown below:

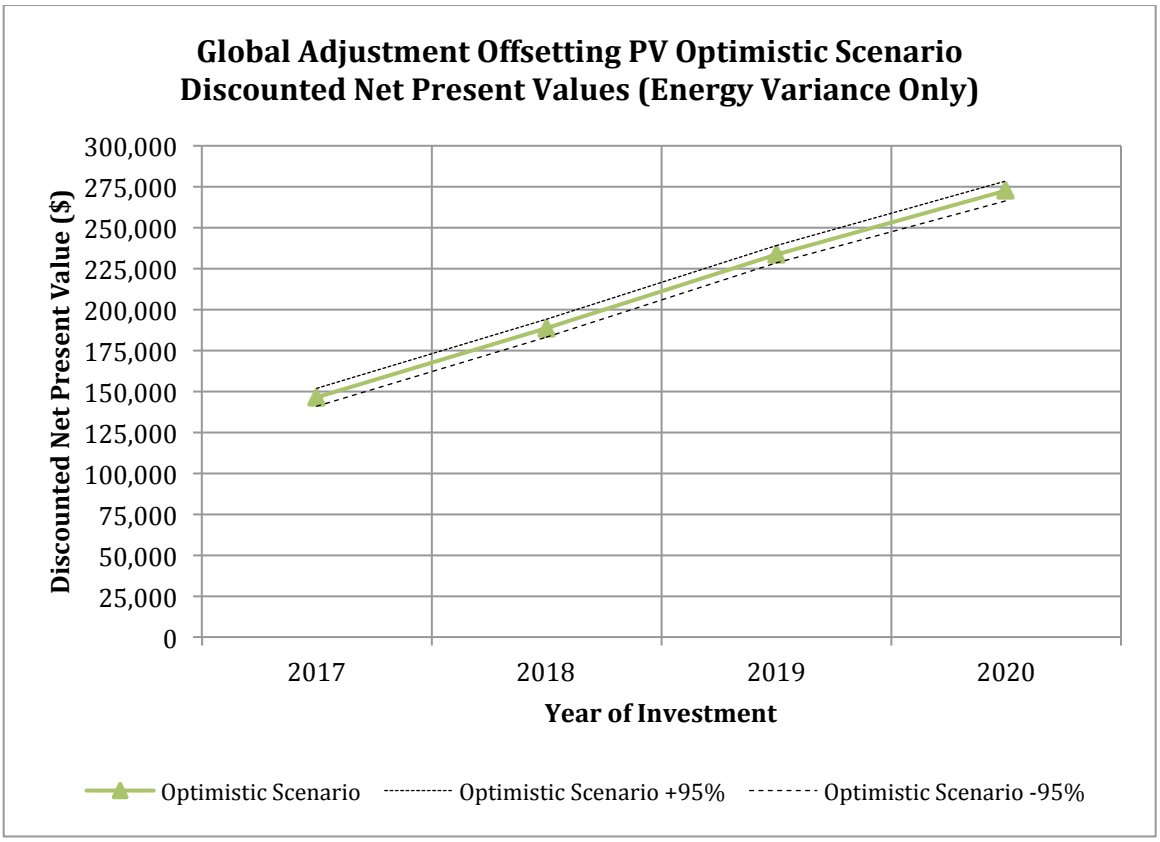


Figure 54. Close-up of the 95% confidence intervals for the "optimistic" scenario under the global adjustment tariff offsetting scenario for the years 2017 through 2020.

Even close-up in Figure 54, the 95% confidence interval was very close to the averages, meaning that 95% – the vast majority – of the simulated data fell within close proximity to the mean. For a potential investor, this was indicative of low risk of a future PV project's discounted net present value falling far away from the mean.

To close out Section 5.4.2.1, normality tests were performed on the 250 discounted net present values created by the Monte Carlo simulation to ensure they were normally distributed. Below, Figure 55 provides the results from one such test:

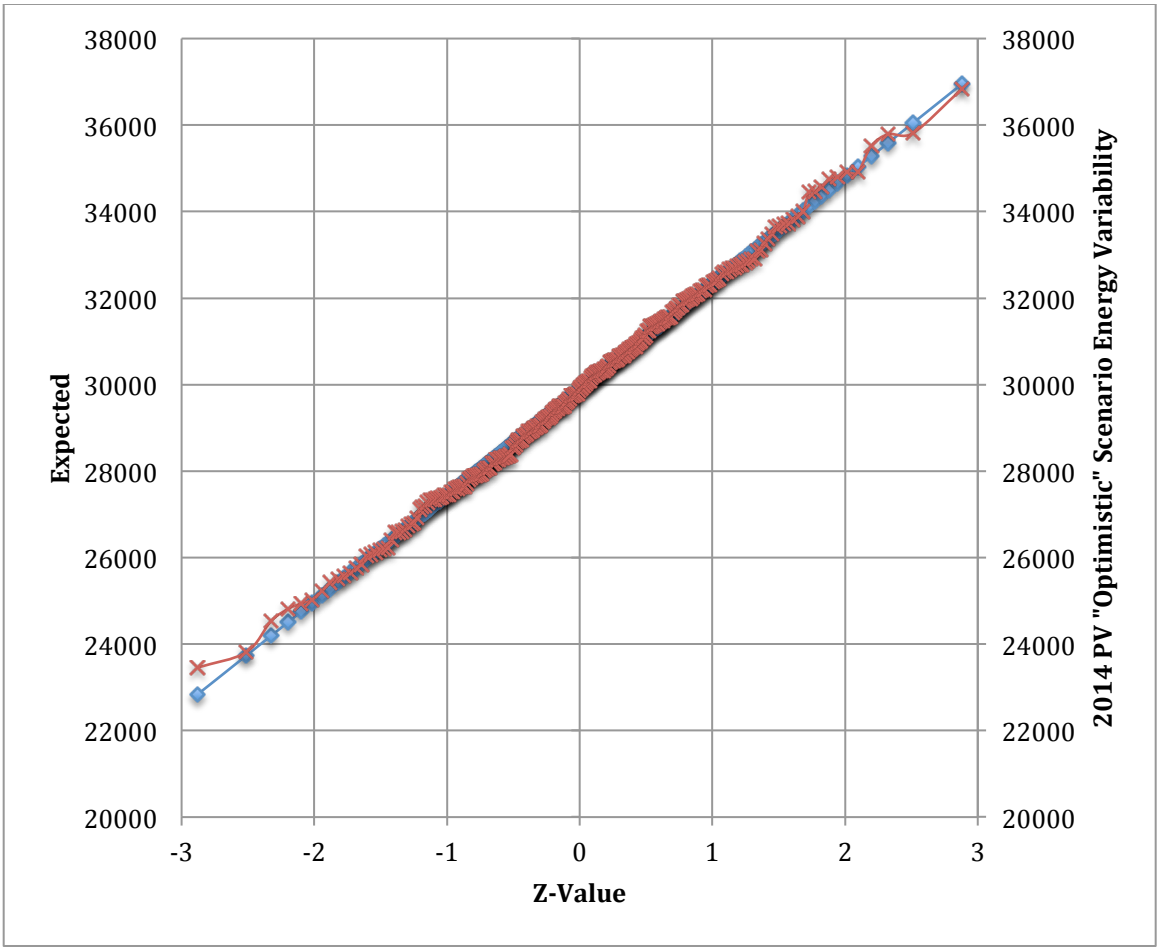


Figure 55. Normality test of the 250 discounted net present values created by the Monte Carlo simulation under the 2014 PV "optimistic" scenario.

Nearly all of the expected values, which were represented by the blue squares in Figure 55, were overlaid with red x's, which denoted the values generated by the Monte Carlo simulation. Consequently, Figure 55 indicated a lack of evidence to suggest that the discounted net present values from the 2014 PV "optimistic" scenario were not normally distributed. Additional normality tests from this tariff scenario for PV with only energy yield variability are provided in Appendix D.

5.4.2.2 Concentrated Photovoltaic Results

The discounted NPV characteristics of the 250 Monte Carlo simulation results for CPV technology under the global adjustment tariff offsetting scenario with energy yield variability are shown below in Table 61:

Scenario	Year	Standard Deviation	Minimum ($)	Average ($)	Maximum ($)	Range ($)
Pessimistic	2014	2,981.83	-325,994.07	-315,958.56	-308,065.08	17,928.99
	2015	3,737.32	-305,165.01	-293,969.88	-284,537.44	20,627.57
	2016	3,467.39	-283,757.68	-274,592.18	-265,147.44	18,610.24
	2017	4,048.50	-266,961.22	-256,366.02	-243,465.43	23,495.79
	2018	4,260.61	-254,329.93	-237,925.22	-226,823.41	27,506.52
	2019	4,194.54	-234,357.32	-222,399.66	-211,195.58	23,161.73
	2020	4,462.51	-220,993.19	-207,346.60	-193,356.77	27,636.42
Average	2014	4,296.78	-228,572.19	-212,411.67	-202,701.27	25,870.92
	2015	4,718.70	-171,207.53	-158,422.35	-146,481.65	24,725.88
	2016	5,828.57	-126,082.34	-108,914.58	-94,011.63	32,070.71
	2017	6,089.18	-76,813.23	-61,574.65	-45,444.34	31,368.89
	2018	6,279.31	-35,362.14	-18,152.44	-582.15	34,779.99
	2019	7,011.25	7,574.30	27,613.03	44,798.03	37,223.72
	2020	7,175.33	42,819.04	64,045.01	89,510.02	46,690.98
Optimistic	2014	6,289.51	-68,045.83	-50,267.10	-33,767.41	34,278.41
	2015	7,466.70	49,165.18	67,367.95	87,404.00	38,238.83
	2016	8,882.76	164,725.57	185,630.36	221,348.48	56,622.92
	2017	10,105.17	265,022.62	291,978.70	320,104.17	55,081.54
	2018	10,784.20	358,049.57	396,334.26	426,223.83	68,174.25
	2019	10,576.72	456,352.87	481,934.84	513,994.98	57,642.11
	2020	14,138.50	563,375.85	598,445.18	635,780.27	72,404.42

Table 61. Characteristics of the 250 CPV discounted net present values generated by the Monte Carlo simulation under the global adjustment tariff offsetting scenario and only energy yield variability.

Compared with the time-of-use CPV results, the only other tariff scenario with a 25-year timeframe, the standard deviations shown in Table 61 were higher under each of the three pricing scenarios in each of the years 2014 through 2020. This was likely due to the fact that the total amount of value created under the global adjustment tariff offsetting scenario was dependent upon offsetting three different electricity charges – the Hourly Ontario Energy Price, a global adjustment charge, and a distribution charge – while only electricity charges were offset under the time-of-use tariff scenario to create value. The larger CPV standard deviations under the global adjustment tariff offsetting scenario were expected to produce wider 95% confidence intervals compared with those associated with CPV technology under the time-of-use tariff scenario. Figure 56 below illustrates the global adjustment tariff offsetting scenario's 95% confidence intervals:

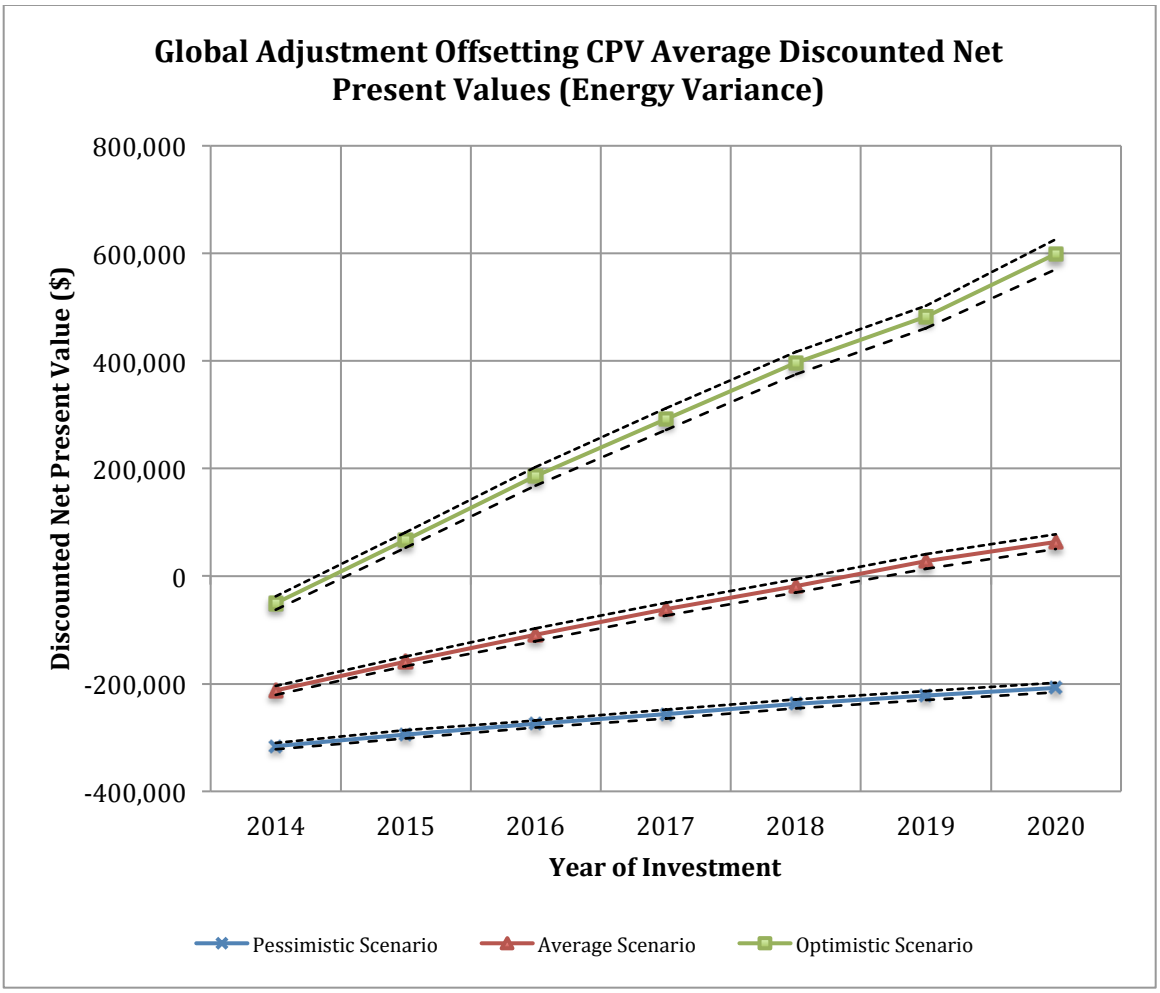


Figure 56. CPV average discounted net present values for the global adjustment tariff offsetting scenario with 95% confidence intervals on either side of the mean.

The 95% confidence intervals shown in Figure 56 were calculated using Equation (24) from Section 5.1.2.1. Without a close-up, the distinction between the plot of the mean values, as well as the plots of the dashed lines representing values two standard deviations above and below the mean are clearly distinguishable under the "optimistic" scenario in Figure 56. Also evident was the fact that the width of the 95% confidence interval increased as time progressed forward from 2014 to 2020. As was the case under previous tariff scenarios, this phenomenon was the result of greater energy variability from larger solar installations constructed in future years. Although variability increased, the 95% confidence interval provided proof that an investment in a CPV installation to offset global adjustment charges, wholesale electricity prices, and distribution charges would be quite profitable even with

variable energy yields under the "optimistic" pricing scenario. With the "average" costing scenario, positive discounted net present values were not observed until the year 2019, while no positive discounted net present values were realized under the "pessimistic," most expensive pricing scenario.

Using a close-up to better illustrate the widths of the 95% confidence intervals under the global adjustment tariff offsetting scenario, Figure 57 below shows a plot of mean discounted net present values under the "average" costing scenario with the associated upper and lower 95% confidence interval:

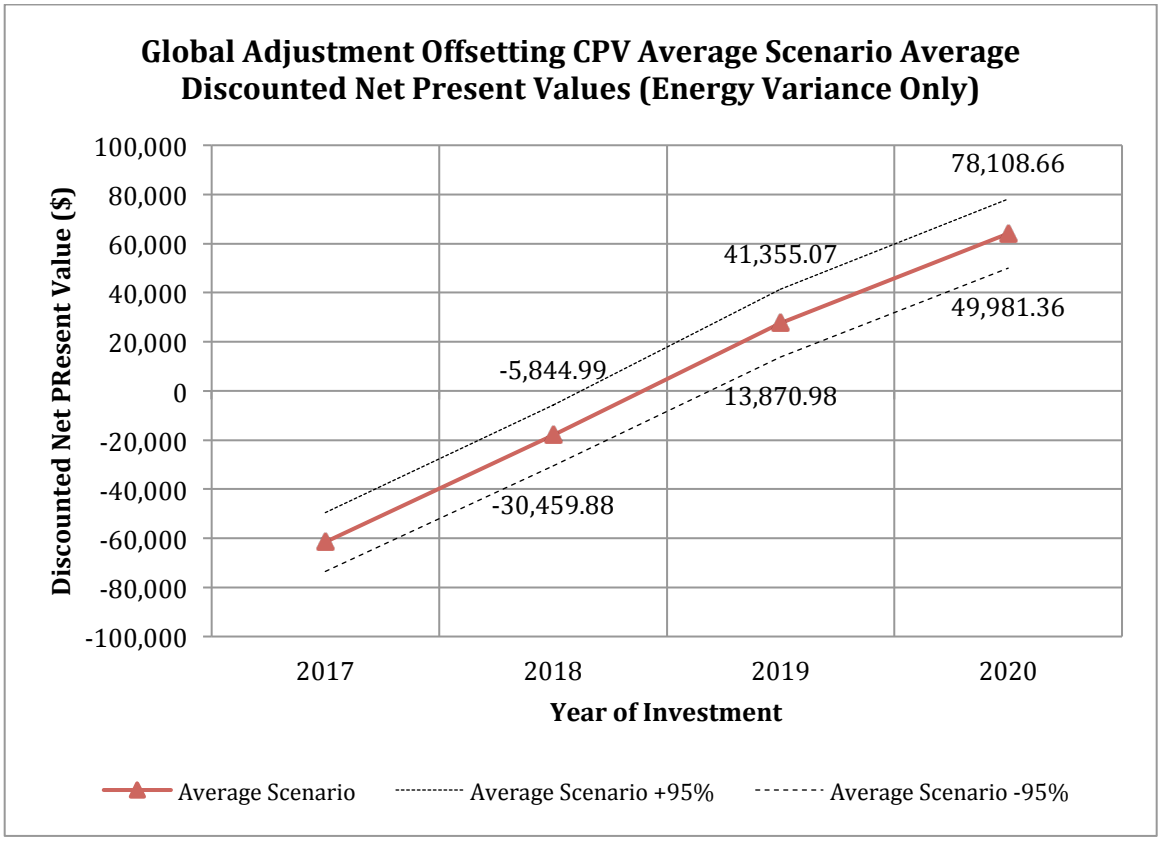


Figure 57. A plot of the mean discounted net present values from the "average" pricing scenario under the global adjustment tariff offsetting scenario with 95% confidence intervals.

Figure 57 highlighted the discounted net present values as they turned positive between the years 2018 and 2019. According to the 95% confidence intervals, an investment in a CPV installation to offset the global adjustment and other related electricity charges would more than likely be negative in 2018, but would probably be positive in 2019. Thus, a prospective investor was wiser to defer investment until

either the year 2019 or 2020 assuming costs and other system considerations followed the values provided by the "average" pricing scenario in Table 19 and Table 20 in Section 4.2.

While the confidence intervals were by no means large and they did not, for instance, straddle between positive and negative during a particular year, there was a certain degree of risk associated with investing in either of the years 2019 or 2020 given the width of the average scenario's 95% confidence interval. In 2019, the discounted net present value had a 95% chance of falling between USD 13,870.98 on the low side and USD 41,355.07 on the high side, which represented a fairly large difference in return on investment after 25 years. In 2020, the gap between USD 49,981.36 and USD 78,108.66 was also large, but the lower half of the 95% confidence interval represented a more attractive discounted net present value compared with the lower confidence interval from the year 2019. Knowing the minimal acceptable discounted net present value would help a prospective investor determine which year to invest.

To confirm that the 250 simulated results were normally distributed, normality tests were performed on the discounted net present values. Below, Figure 58 demonstrates one such normality test on the 250 discounted net present values from the year 2014 under the "pessimistic" costing scenario:

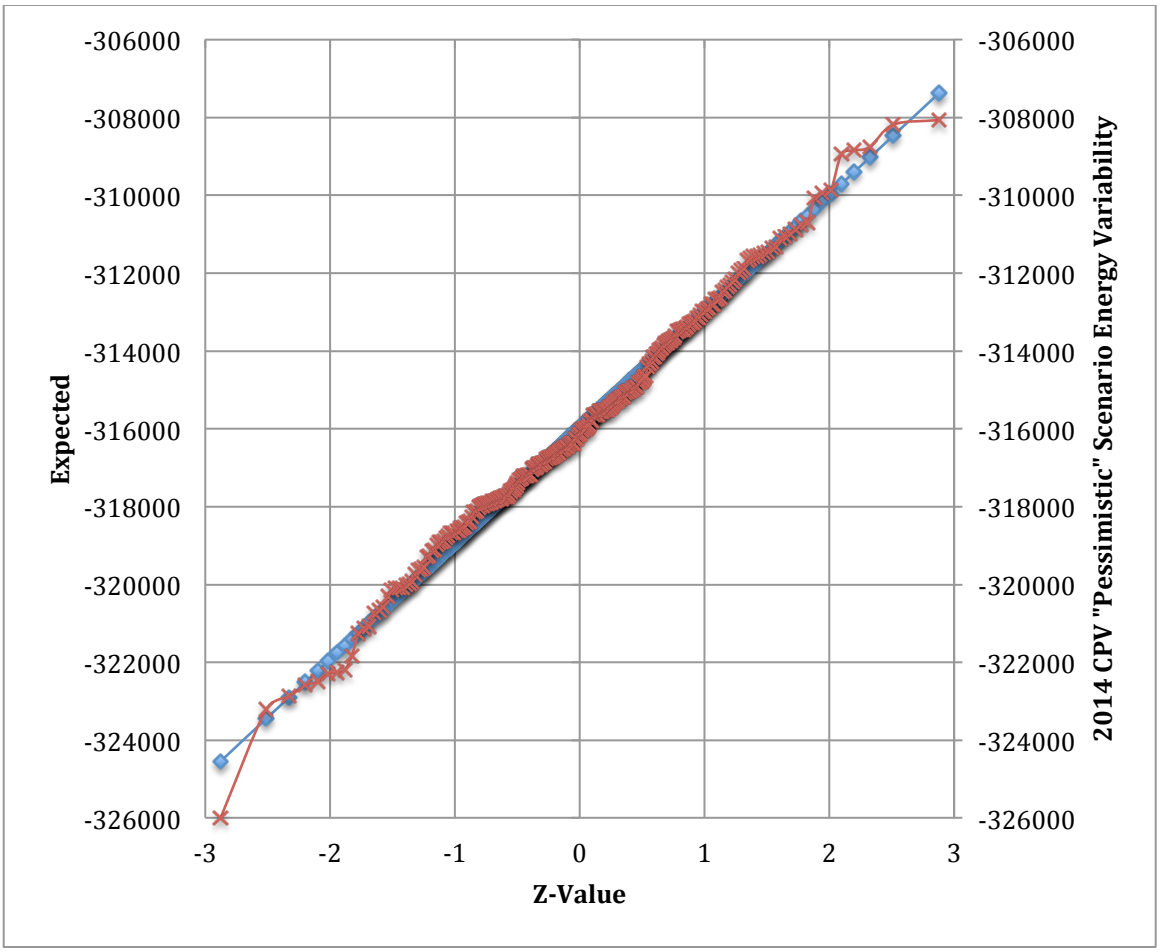


Figure 58. A normality test of the 250 discounted net present values generated by the Monte Carlo simulation under the 2014 CPV "pessimistic" pricing scenario.

In Figure 58, the simulated discounted net present values represented by the red x's did deviate somewhat from the blue squares of expected values. However, the deviation was in no way significant enough to conclude that there was sufficient evidence to indicate that the discounted net present values were not normally distributed. Additional normality tests for this scenario are presented in Appendix D. In the next section, the effect of tariff variability will be introduced and analyzed for the first time in Chapter 5.

5.4.3 Tariff Variability Results

5.4.3.1 Photovoltaic Technology

Tariff variability was unique to the global adjustment tariff offsetting scenario. As discussed in Section 3.3.1.3, the Hourly Ontario Energy Price, which was one of three electricity charges faced by Ontario energy customers with a peak demand exceeding 3 MW, was determined based upon market forces. Thus, the HOEP was subject to fluctuations each hour of each day, and the NPV analysis assumed that the distribution of the variable hourly HOEP values remained the same over all 25 years of solar installation operation. Note that the results in this section assumed no Monte Carlo variability in the solar installation's energy yield output. While unrealistic under real-world conditions, the point of maintaining a constant electricity output was to isolate and then analyze the amount of discounted net present value variability attributable to varying only the HOEP. Table 62 below provides figures from the analysis of the 250 discounted net present values generated by the Monte Carlo simulation under the conditions just described:

Scenario	Year	Standard Deviation	Minimum ($)	Average ($)	Maximum ($)	Range ($)
Pessimistic	2014	861.98	-290,421.57	-287,255.22	-285,228.76	5,192.81
	2015	933.54	-264,453.07	-262,055.57	-259,422.65	5,030.43
	2016	1,185.64	-232,502.44	-229,595.95	-226,093.52	6,408.91
	2017	1,403.09	-189,957.00	-184,844.26	-181,349.26	8,607.75
	2018	1,659.15	-129,350.07	-124,962.16	-120,240.67	9,109.40
	2019	2,264.10	-50,342.07	-43,836.24	-37,932.27	12,409.80
	2020	3,019.66	81,804.10	89,753.60	99,066.82	17,262.73
Average	2014	1,109.35	-185,013.36	-181,221.80	-178,243.70	6,769.66
	2015	1,239.32	-152,447.54	-148,302.95	-144,895.53	7,552.01
	2016	1,695.44	-113,419.30	-108,346.81	-104,634.29	8,785.01
	2017	1,765.77	-66,108.95	-59,396.88	-54,113.76	11,995.19
	2018	2,207.40	-3,283.21	3,477.01	9,730.99	13,014.20
	2019	2,545.42	69,348.89	76,940.48	84,815.84	15,466.95
	2020	2,829.80	168,795.01	177,487.10	185,459.78	16,664.77
Optimistic	2014	1,662.21	23,556.66	29,473.56	33,548.50	9,991.84
	2015	2,037.66	61,963.52	66,806.62	72,089.96	10,126.44
	2016	2,036.82	102,660.94	108,139.80	113,398.98	10,738.03
	2017	2,364.78	140,413.88	146,312.52	156,421.60	16,007.73
	2018	2,619.35	180,366.92	188,629.54	195,947.64	15,580.72
	2019	2,984.24	225,664.31	233,772.24	241,985.97	16,321.66
	2020	3,242.40	261,685.65	272,376.50	281,862.13	20,176.47

Table 62. The standard deviation, minimum, average, maximum, and range values for the 250 CPV discounted net present values generated by the Monte Carlo simulation under the global adjustment tariff offsetting scenario with only HOEP variability.

The standard deviations shown in Table 62 were approximately similar in value to the standard deviations shown in Table 60 under the PV energy variability scenario in Section 5.4.2.1. In some years, the standard deviations from Table 62 were larger than those in Table 60, while in other years the opposite was true. There was no distinct pattern defining the years in which the standard deviations were larger (or smaller) than in others. Similarly, the range values from the tariff variability only scenario were roughly about the same as the range values from the energy variability only scenario. In some years, the range values from the energy variability only scenario were larger than the tariff variability only and in other years the reverse was observed. No pattern was discernable as to when one year's range value would be larger than the range value from another year. The notable

takeaway from this comparison between PV tariff variability and PV energy yield variability was that the standard deviations from the discounted net present values from these two scenarios were mostly comparable.

Below, Figure 59 plots the average discounted net present values from Table 62 along with 95% confidence intervals on either side of the mean:

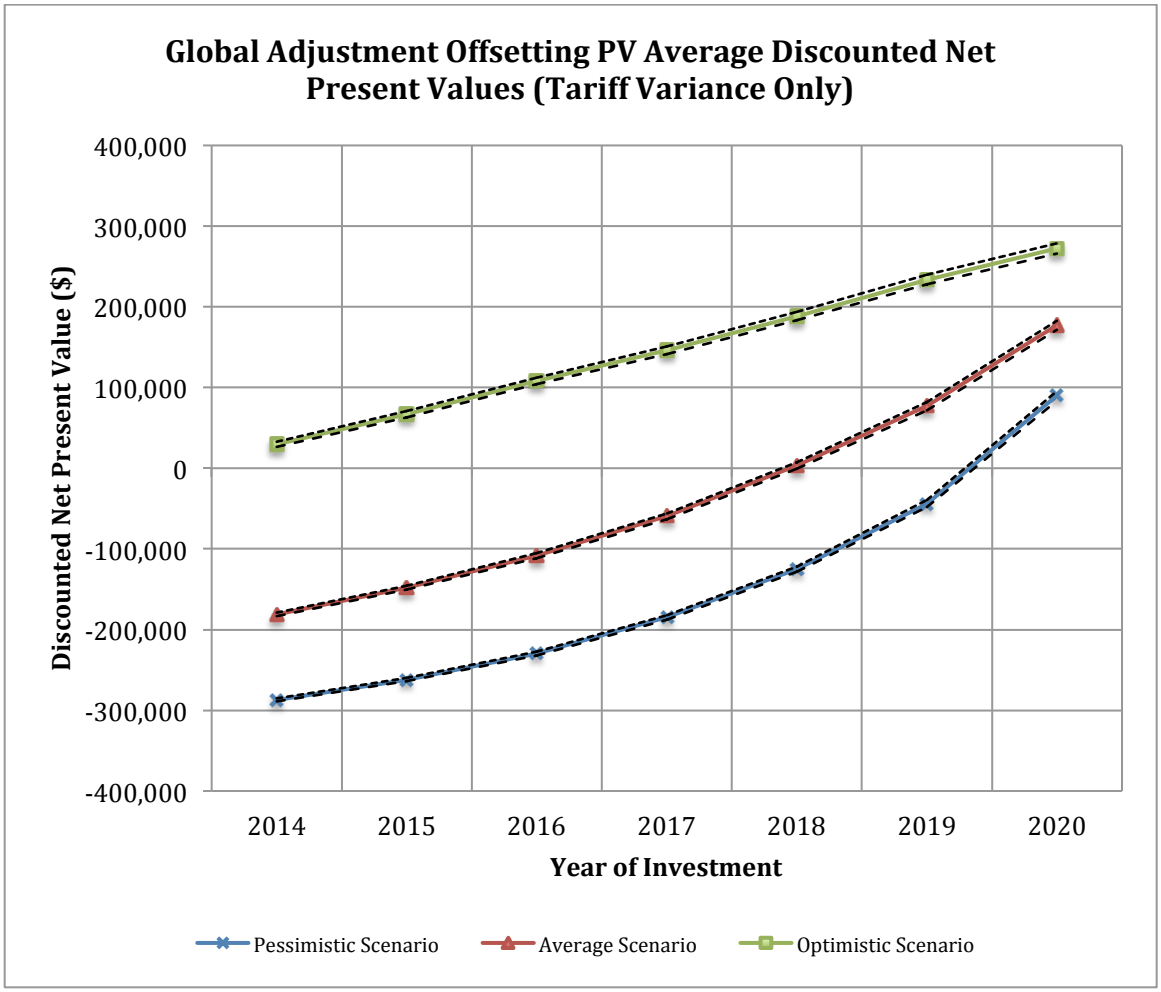


Figure 59. Plots of the "pessimistic," "average," and "optimistic" pricing scenarios under tariff only variability with 95% confidence intervals.

The shape of the discounted NPV plots in the above chart approximately followed the same shape of the discounted NPV plots from the energy yield variability scenario, which was shown by Figure 53 in Section 5.4.2.1. The 95% confidence intervals illustrated by Figure 59 were calculated using Equation (24) from Section 5.1.2.1. As was the case in Figure 53, the confidence intervals in the figure above

were very close to the plots of the means and were difficult to identify. Accordingly, Figure 60 below provides a close-up of the "pessimistic" pricing scenario between the years 2018 and 2020 as the discounted net present values cross over from negative to positive figures:

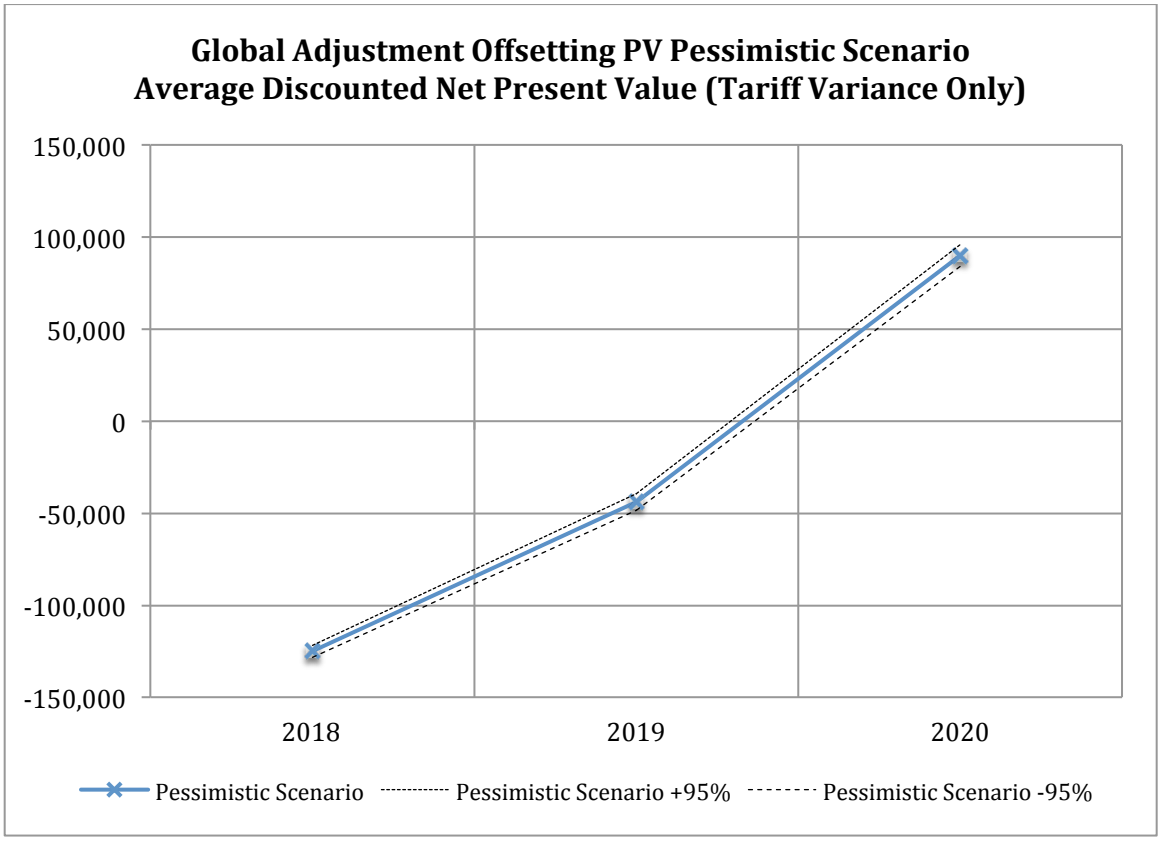


Figure 60. A close-up of the discounted net present values from the "pessimistic" scenario during the years 2018 to 2020 with 95% confidence intervals on either side of the means.

Even close-up, the confidence 95% confidence interval shown by Figure 60 was very close to the plot of the discounted NPV means. Thus, under a hypothetical scenario where energy variability was static during each year of PV system operation, the impact from a variable Hourly Ontario Energy Price on discounted net present value variability was minor. Of course, it was extremely unlikely that a PV system would produce a uniform amount of electricity during each of its assumed 25-years of operations.

To ensure the analysis performed on the data was appropriate, several normality tests were conducted. Below, Figure 61 provides the result of a normality test on the

250 discounted net present values generated via the Monte Carlo simulation under the "average" pricing scenario in 2014:

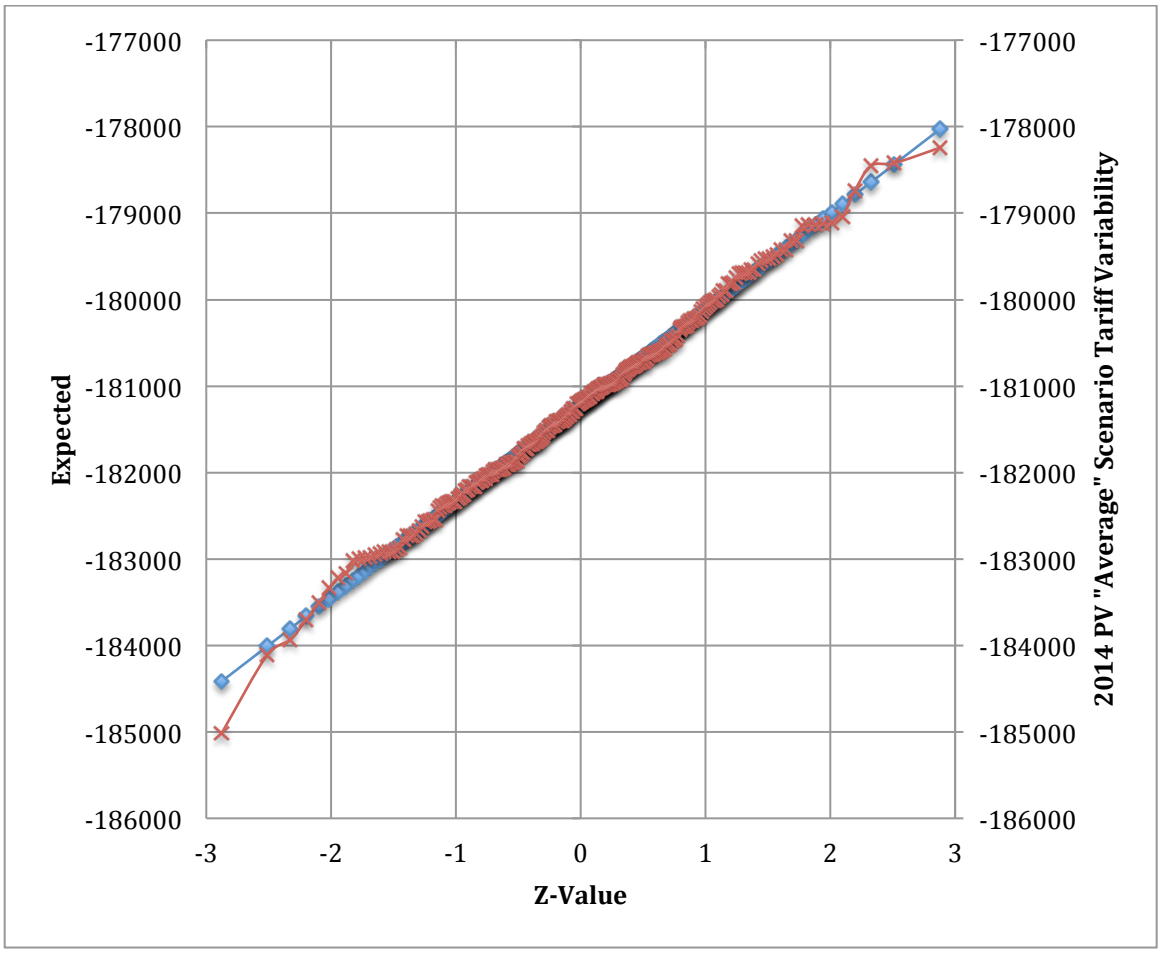


Figure 61. A normality test of the 250 discounted net present values generated by the Monte Carlo simulation under the "average" pricing scenario in 2014.

Although the red x's of observed values deviated from the expected values outside two standard deviations from the mean, over all, the normality test displayed in Figure 61 indicated that there was a lack of evidence to suggest that the discounted net present values generated by the Monte Carlo simulation were not normally distributed. Additional normality tests under the tariff only variability scenario for photovoltaic technology are available in Appendix D.

5.4.3.2 Concentrated Photovoltaic Technology

For CPV technology, the impact of tariff only variability on discounted net present values is illustrated by the figures in Table 63 below:

Scenario	Year	Standard Deviation	Minimum ($)	Average ($)	Maximum ($)	Range ($)
Pessimistic	2014	839.49	-317,651.81	-315,726.10	-313,289.98	4,361.82
	2015	865.37	-296,269.50	-293,675.07	-291,730.88	4,538.62
	2016	1,010.65	-277,995.57	-274,816.22	-272,345.68	5,649.89
	2017	1,200.09	-259,264.09	-256,012.28	-251,380.04	7,884.05
	2018	1,388.10	-241,474.52	-238,316.14	-235,188.09	6,286.44
	2019	1,394.38	-225,734.22	-222,159.46	-217,803.77	7,930.45
	2020	1,607.71	-211,538.62	-207,006.47	-202,691.98	8,846.64
Average	2014	1,104.22	-215,419.77	-212,538.36	-209,320.61	6,099.16
	2015	1,352.31	-162,059.38	-158,437.88	-153,834.82	8,224.56
	2016	1,630.82	-114,024.82	-108,845.06	-105,355.84	8,668.98
	2017	1,830.62	-66,192.86	-61,071.92	-55,589.00	10,603.87
	2018	2,128.45	-22,737.84	-17,714.02	-11,746.03	10,991.80
	2019	2,300.47	21,719.16	27,668.90	34,992.41	13,273.25
	2020	2,622.67	57,468.59	64,589.36	72,235.85	14,767.25
Optimistic	2014	1,466.65	-54,781.25	-50,644.66	-45,503.22	9,278.03
	2015	2,126.76	62,336.78	66,930.68	72,894.87	10,558.09
	2016	2,541.58	177,688.30	185,260.99	192,745.70	15,057.40
	2017	2,950.33	285,018.28	291,779.67	300,222.91	15,204.63
	2018	3,555.00	385,233.56	396,381.25	404,682.81	19,449.25
	2019	4,280.86	469,256.14	481,158.00	491,471.00	22,214.87
	2020	4,832.80	587,368.36	599,501.48	614,302.22	26,933.87

Table 63. CPV Discounted net present value standard deviation, minimum, average, maximum and range figures with only tariff variability under the global adjustment tariff offsetting scenario.

The standard deviations shown in Table 63 were comparable to the standard deviations from the PV tariff variability only scenario presented in Table 62 in the previous section. The standard deviations in Table 63 tended to increase over time. Interestingly, each year the "pessimistic" CPV standard deviations in Table 63 were smaller than the "pessimistic" PV standard deviations in Table 62. On the other hand, the "optimistic" CPV standard deviations were larger than the "optimistic" PV standard deviations in each of the years 2015 through 2020, the exact range of years where positive discounted net present values were observed under CPV technology. From a comparison of the two solar technologies, PV technology had positive discounted net present values for each of the years 2014 through 2020 under the "optimistic" costing scenario – one year more than CPV technology – and saw smaller amounts of variability. Thus, from a risk management point of view, PV

technology carried less risk than CPV technology because PV technology saw smaller discounted NPV fluctuations.

Even so, the overall risk associated with investing in CPV technology was not particularly significant. As illustrated by Figure 62, the 95% confidence intervals on either side of the mean for CPV technology are quite narrow, meaning there only a limited amount of risk associated discounted net present value variability:

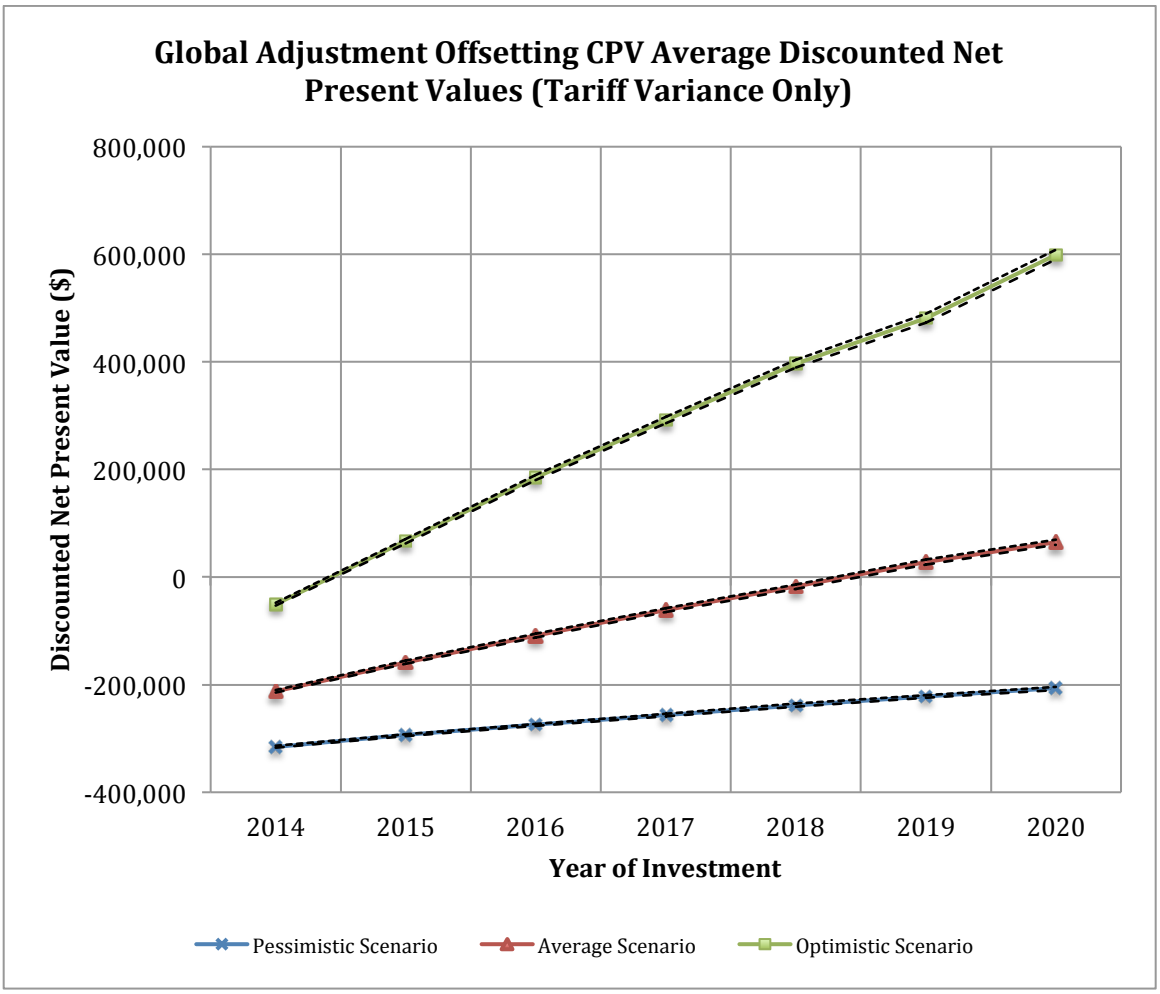


Figure 62. Discounted NPV averages for each of the three pricing scenarios with 95% confidence intervals surrounding the means each year.

In Figure 62, the 95% confidence intervals represented by the dashed lines were barely distinguishable for the "pessimistic" and "average" costing scenarios, as well as the earlier years of the "optimistic" scenario. The interval values were calculated using Equation (24) from Section 5.1.2.1. The 95% confidence intervals for CPV

technology in Figure 62 were quite narrow in some instances. To better illustrate the width of the 95% confidence interval under the "optimistic" pricing scenario, Figure 63 provides a close-up below:

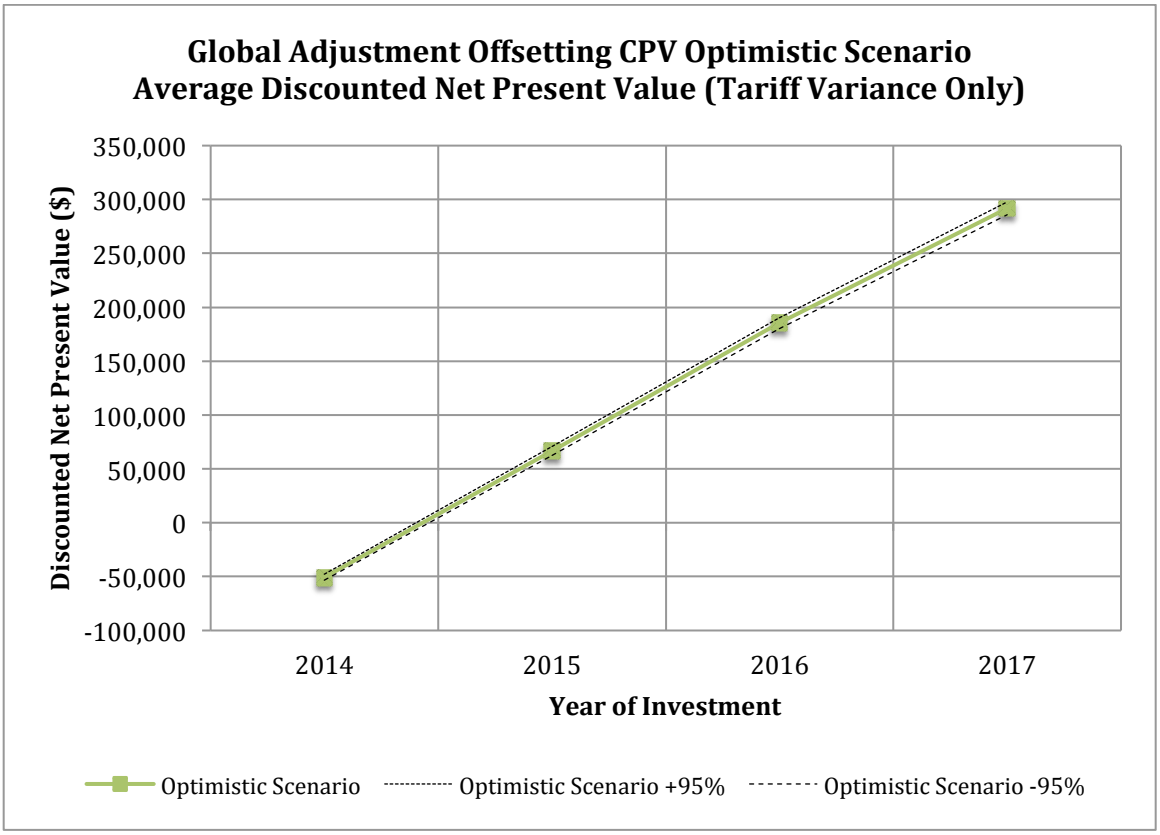


Figure 63. A close-up of "optimistic" scenario discounted net present values between 2014 and 2017 with 95% confidence intervals on either side of the means.

Figure 63 showed the discounted net present values turning positive in the year 2015. This close-up also displayed the narrowest segment of the 95% confidence interval, which became larger as time progressed towards the year 2020. In 2014 and even 2015, the confidence interval was so narrow that it was almost difficult to distinguish even close-up.

Analogous to the PV results from the previous section, variability of only the Hourly Ontario Energy Price under CPV technology had just a small impact on the discounted net present values. This was demonstrated by the slim 95% confidence intervals in Figure 59 in Section 5.4.2.1 and Figure 62 from this section. In 66.7% of the cases, the standard deviations from the PV *energy* variability scenario in Section

5.4.2.1 were larger than the standard deviations from the PV *tariff* variability scenario in 5.4.3.1. As well, 100% of the standard deviations from the CPV *energy* variability scenario, shown in Table 61 in Section 5.4.2.2, were larger than the CPV *tariff* variability standard deviations shown in Table 63 in this section. Thus, energy yield had a larger influence on discounted net present value variability compared with the Hourly Ontario Energy Price.

To conclude the analysis on tariff variability, the CPV discounted net present values generated by the Monte Carlo simulation with only tariff variability were checked for normality using a plot of observed values versus expected values:

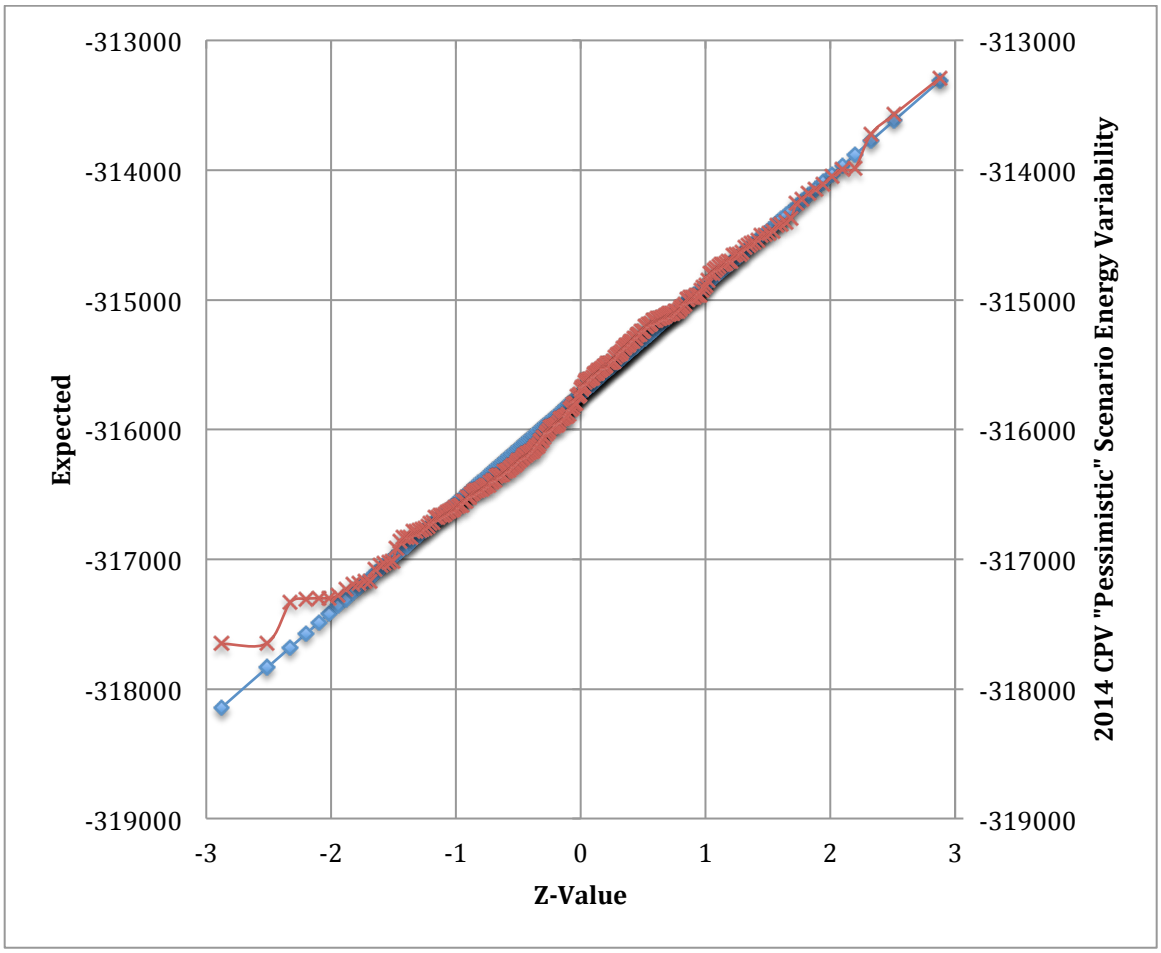


Figure 64. A normality test of the 250 discounted net present values generated by the Monte Carlo simulation under the 2014 CPV "pessimistic" pricing scenario.

In Figure 64, the red x's of generated values matched quite well with the blue squares of expected values with the exception of the Z values approximately two

and three standard deviations below the mean. However, this was not enough evidence to conclude that these generated values were not normally distributed. Additional normality tests are shown in Appendix D.

In the next section, the tariff variability from this section, as well as the energy yield variability from Section 5.4.2 will be combined and the quantity of resulting discounted NPV variability will be analyzed. This will represent the most realistic scenario under the global adjustment tariff offsetting scenario, since both the amount of energy produced by the solar modules and the Hourly Ontario Energy Price vary under real-world conditions.

5.4.4 Energy Yield and Tariff Variability

5.4.4.1 Photovoltaic Technology

Thus far in Chapter 5, the source of discounted NPV variability has been limited to either fluctuating solar installation energy yields or electricity tariffs. In this section, however, energy yield and tariff variability will be combined, and this is expected to increase the total amount of discounted net present value variability. Table 64 below provides discounted NPV characteristics of the results from both energy yield and tariff variability for PV technology:

Scenario	Year	Standard Deviation	Minimum ($)	Average ($)	Maximum ($)	Range ($)
Pessimistic	2014	1,265.49	-291,587.55	-287,274.97	-283,337.97	8,249.57
	2015	1,652.97	-266,131.44	-261,843.02	-254,977.24	11,154.20
	2016	1,755.93	-233,829.55	-229,637.53	-224,319.47	9,510.08
	2017	2,048.72	-190,704.30	-184,946.32	-179,673.91	11,030.39
	2018	2,604.39	-132,157.95	-125,077.36	-117,533.52	14,624.43
	2019	3,401.73	-55,574.82	-44,011.68	-33,716.58	21,858.24
	2020	4,270.29	76,281.26	89,416.31	100,623.48	24,342.22
Average	2014	1,844.66	-186,199.11	-181,310.34	-175,877.48	10,321.63
	2015	2,070.55	-152,945.15	-148,052.78	-142,107.77	10,837.38
	2016	2,313.18	-115,089.43	-108,609.63	-99,834.32	15,255.11
	2017	2,829.98	-67,252.63	-59,532.76	-50,946.00	16,306.63
	2018	3,070.85	-4,601.02	3,026.82	12,183.91	16,784.94
	2019	3,728.82	66,276.16	76,899.31	87,125.37	20,849.21
	2020	4,148.04	163,208.12	177,308.26	189,679.21	26,471.09
Optimistic	2014	3,086.32	21,447.62	30,069.65	39,419.78	17,972.16
	2015	3,035.21	56,148.34	66,858.81	78,035.40	21,887.06
	2016	3,467.58	99,596.26	108,374.89	116,753.05	17,156.79
	2017	3,680.79	135,150.21	146,217.97	156,621.49	21,471.28
	2018	3,896.98	177,691.33	188,316.05	198,252.63	20,561.30
	2019	4,056.05	223,188.56	233,266.60	244,310.21	21,121.65
	2020	4,524.80	259,715.80	272,307.32	287,482.15	27,766.35

Table 64. PV discounted net present value, standard deviation, minimum, average, maximum, and range figures with both energy yield and electricity tariff variability under the global adjustment tariff offsetting scenario.

As was anticipated, the standard deviations in Table 64 were larger than both the standard deviations from Table 60 in Section 5.4.2.1 under the energy variability only scenario and Table 62 in Section 5.4.3.1 under the tariff variability only scenario. This meant that the there was in fact greater variability observed in each year under each of the three pricing scenarios when both PV system energy yield and the Hourly Ontario Energy Price varied.

Using those standard deviations from Table 64 and Equation (24) from Section 5.1.2.1, 95% confidence intervals were calculated for the discounted net present value means in each of the years 2014 to 2020. Figure 65 below provides those means as well as associated 95% confidence intervals:

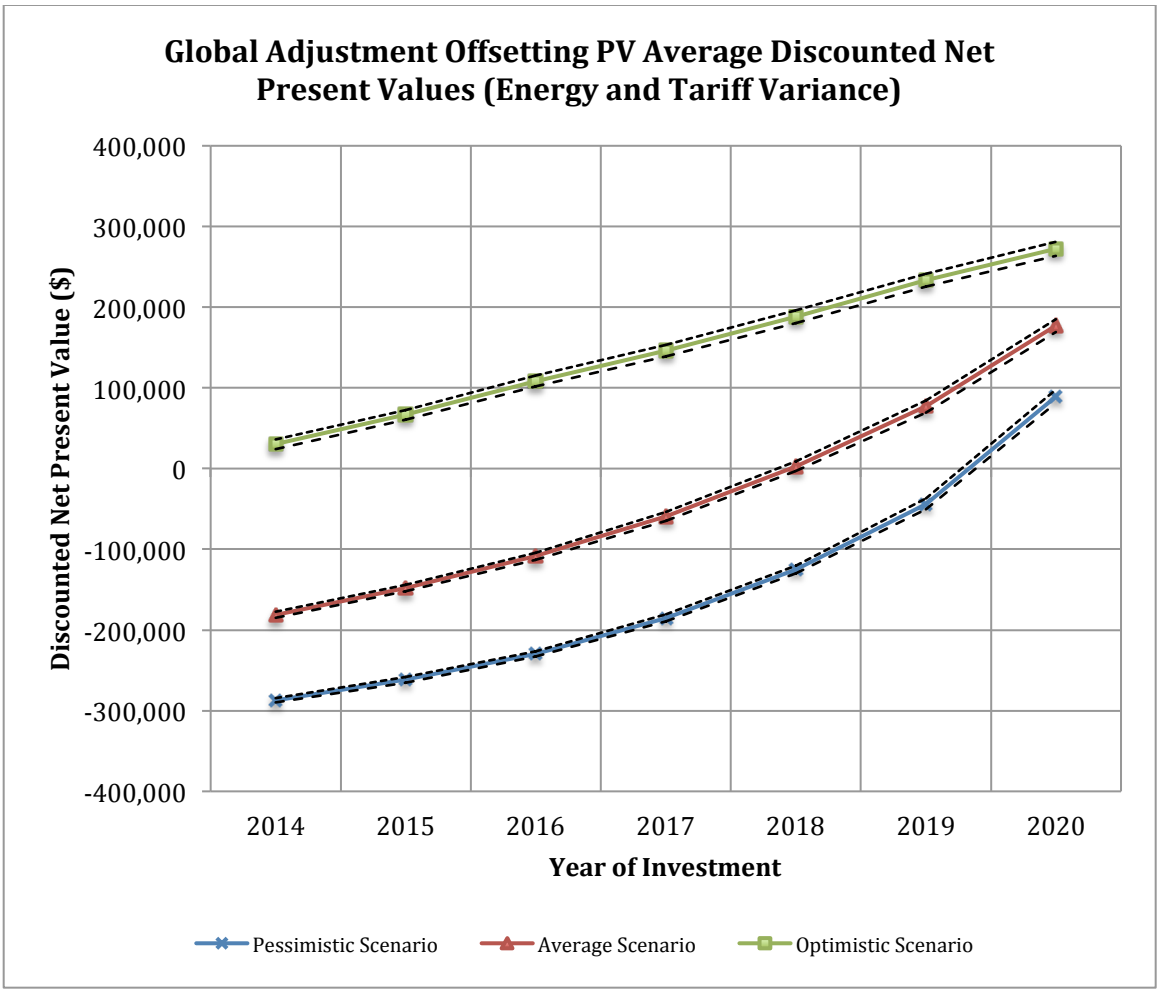


Figure 65. The average discounted net present values according to the "pessimistic," "average," and "optimistic" pricing scenarios with 95% confidence intervals.

The 95% confidence intervals in the above chart were represented by the dashed plot lines. Even with both energy and tariff variability, the widths of these confidence intervals were narrow, continuing the trend from the prior examples shown throughout Chapter 5. The confidence interval under the "optimistic" pricing scenario was clearly distinguishable from 2014 through 2020, but the same was not true during the earlier years under the "pessimistic" and "average" scenarios to a certain extent. While the widths of the confidence intervals did increase over time, the risk associated with the narrow 95% confidence intervals shown in Figure 65 was low over all, even in 2020. A prospective investor would be confident that in 95% of instances the actual discounted NPV would fall within very close proximity to the mean, regardless of the pricing scenario.

To illustrate how small the 95% confidence intervals were to the means, Figure 66 below shows a close-up of the discounted net present values under the "average" pricing scenario as they turned positive between the years 2017 through 2020:

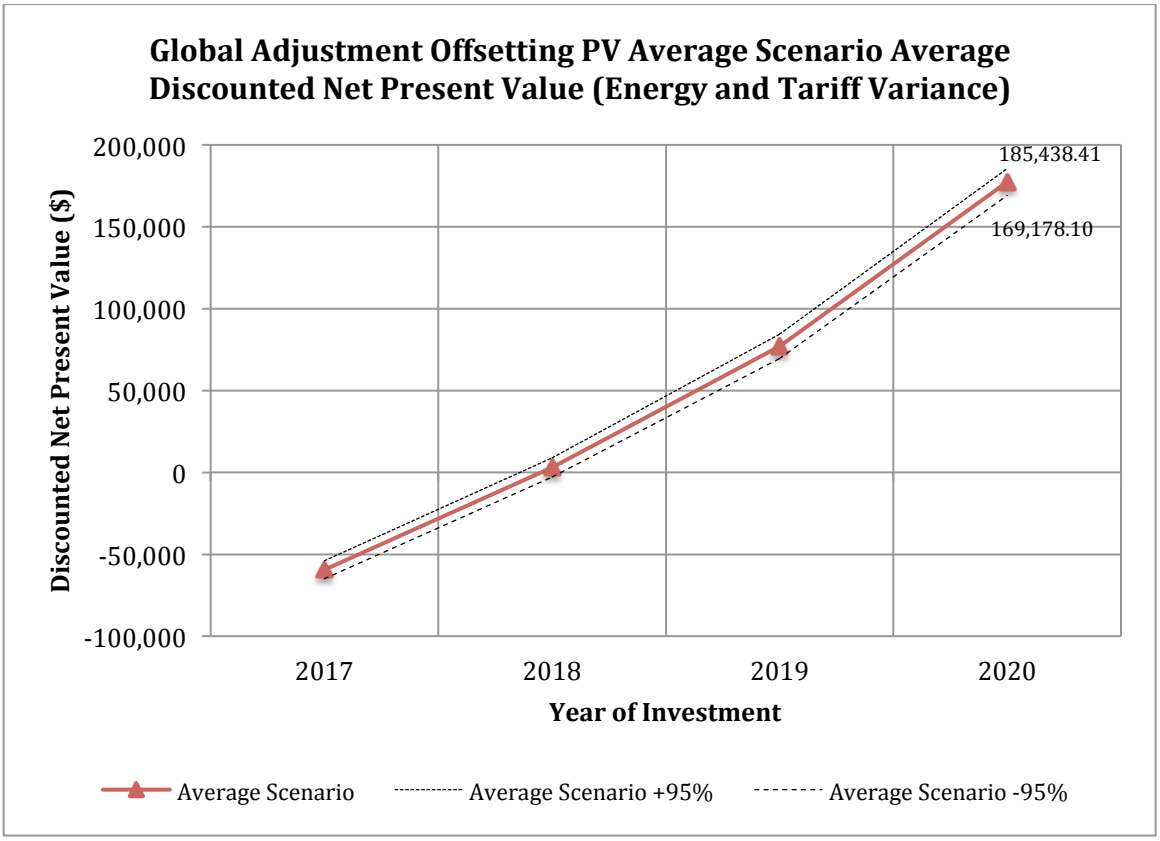


Figure 66. The discounted net present values under the "average" costing scenario with 95% confidence intervals on either side of the means between 2017 and 2020.

The values of both the upper and lower confidence interval in the year 2020 were included in Figure 66. The range of the 95% confidence interval in this year was USD 16,260.31. These values were calculated using Equation (24) from Section 5.1.2.1. All things considered, this was a small range provided that both energy yield and the Hourly Ontario Energy Price were variable. A prospective investor would be certain that the net present value would fall between USD 169,178.10 on the low side and USD 185,438.41 on the high side 95% of the time given an investment in PV technology under the average system costs in the year 2020. It was quite possible that this level of risk was small enough to be enticing to a large number of investors.

To confirm that the discounted net present values followed a normal distribution, several normality tests were performed. Below, Figure 67 shows one of the normality tests on the 250 discounted net present values from the 2014 "pessimistic" scenario:

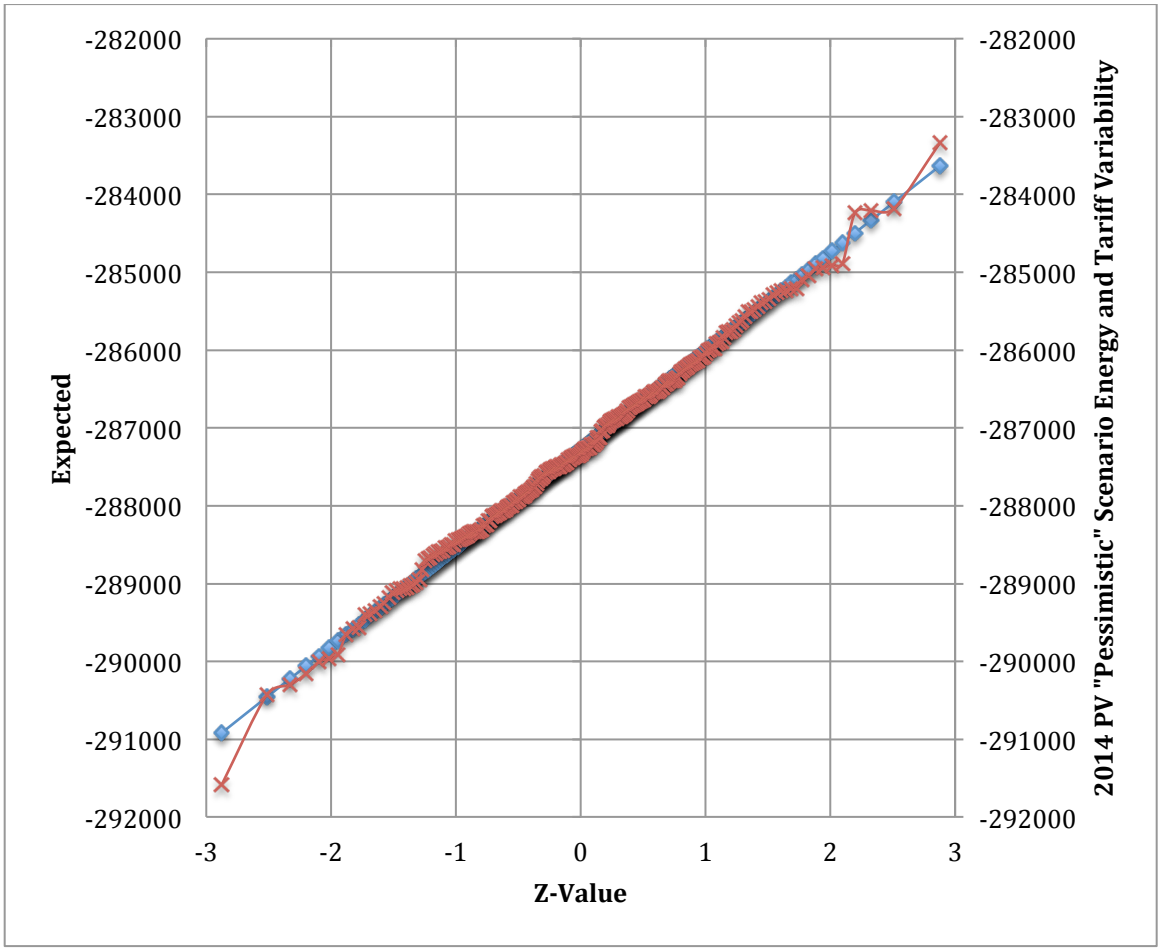


Figure 67. A normality test of the 250 discounted net present values created by the Monte Carlo simulation under the "pessimistic" costing scenario in the year 2014.

The red x's of generated values in Figure 67 closely followed the blue squares of expected values, and thus there was insufficient evidence to declare that the discounted net present values were not normally distributed. Additional normality tests for PV technology with both energy and HOEP variability are provided in Appendix D. Further analysis of discounted net present value follows in the next section.

5.4.4.2 Photovoltaic Technology Variability Analysis

The following table summarizes discounted net present value variability related to energy yield as a proportion of the mean:

Discounted Net Present Value Variability due to Energy Yield				
Year	**% Above/Below Central Estimate**	**Pessimistic Scenario**	**Average Scenario**	**Optimistic Scenario**
2014	% above central estimate	0.86%	1.99%	20.12%*
	% below central estimate	-0.86%	-1.99%	-20.12%*
2015	% above central estimate	1.24%	2.74%	8.90%
	% below central estimate	-1.24%	-2.74%	-8.90%
2016	% above central estimate	1.50%	4.17%	6.27%
	% below central estimate	-1.50%	-4.17%	-6.27%
2017	% above central estimate	2.17%	9.32%	4.93%
	% below central estimate	-2.17%	-9.32%	-4.93%
2018	% above central estimate	4.08%	198.85%*	4.06%
	% below central estimate	-4.08%	-198.85%*	-4.06%
2019	% above central estimate	15.15%*	9.50%	3.41%
	% below central estimate	-15.15%*	-9.50%	-3.41%
2020	% above central estimate	9.36%	4.59%	3.26%
	% below central estimate	-9.36%	-4.59%	-3.26%

Table Notes:

- "Central estimate" is the mean discounted net present value from the Monte Carlo simulation
- The above figures represent variability as a proportion of the mean with 95% confidence
- *Values that are exceptional due to the central estimate being close to zero

Table 65. Percentage of discounted net present value variability due to energy yield for PV technology under the global adjustment tariff offsetting scenario.

Between the "pessimistic," "average," and "optimistic" scenarios in Table 65, 95% of the discounted NPV variability due to energy yield was at most plus or minus 9.50% on either side of the mean. These figures were calculated using Equation (25) from Section 5.1.2.2. Under this tariff scenario, system profitability increased as time moved towards 2020. From the values in Table 65, discounted NPV variability due to energy yield increased as profitability increased. From an investment standpoint, this implied that higher degree of risk was associated with a higher reward.

According to Table 66, discounted NPV variability due to system cost grew between 2014 and 2017, but then declined afterwards. The same was true for discounted NPV variability due to O&M and degradation:

Discounted NPV Variability due to System Cost and O&M and Degradation			
Year	**% Above/Below Central Estimate**	**System Cost⊙**	**O&M and Degradation❖**
2014	% above central estimate	116.51%	15.32%
	% below central estimate	-58.59%	-15.51%
2015	% above central estimate	145.08%	20.57%
	% below central estimate	-76.78%	-20.85%
2016	% above central estimate	199.65%	31.18%
	% below central estimate	-111.61%	-31.65%
2017	% above central estimate	346.31%	64.08%
	% below central estimate	-211.61%	-65.16%
2018	% above central estimate	5644.60%*	1326.57%*
	% below central estimate	-3914.77%*	-1351.60%*
2019	% above central estimate	204.25%	65.33%
	% below central estimate	-157.43%	-66.70%
2020	% above central estimate	53.60%	33.45%
	% below central estimate	-49.44%	-34.24%

Table Notes:

- ⊙Range from literature: Aanesen, Heck, and Pinner (2012), Ardani et al. (2013).
- ❖Range from literature: Branker et al. (2011), Di Francia (2013), Lowder et al. (2013), National Renewable Energy Laboratory (2013a), Zweibel (2010).
- "Central estimate" is the "average" discounted net present value with zero variability
- *Values that are exceptional due to the central estimate being close to zero

Table 66. Percentage of discounted net present value variability due to system cost, as well as O&M and degradation for PV technology under the global adjustment tariff offsetting scenario.

Thus, an investor could expect the largest amount of discounted NPV variability in the year 2017 compared with other years between 2014 and 2020. Table 67 noted that, above the mean, discounted NPV variability due to system cost was at most 7.60 times greater than variability due to O&M and degradation; at a minimum, the former was 1.60 times greater than the latter. This meant that variability due to system cost was consistently larger than variability due to O&M and degradation:

Ratio of Variability due to System Cost to Variability due to O&M and Degradation		
Year	**Ratio Above/Below Central Estimate**	**Ratio**
2014	Ratio above central estimate	7.60
	Ratio below central estimate	3.78
2015	Ratio above central estimate	7.05
	Ratio below central estimate	3.68
2016	Ratio above central estimate	6.40
	Ratio below central estimate	3.53
2017	Ratio above central estimate	5.40
	Ratio below central estimate	3.25
2018	Ratio above central estimate	4.26
	Ratio below central estimate	2.90
2019	Ratio above central estimate	3.13
	Ratio below central estimate	2.36
2020	Ratio above central estimate	1.60
	Ratio below central estimate	1.44

Table Note:

- "Central estimate" is the "average" discounted net present value with zero variability

Table 67. Ratio of variability due to system cost to variability due to O&M and degradation for PV technology under the global adjustment tariff offsetting scenario.

Turning to a different comparison of variability sources, Table 68 indicated that discounted NPV variability due to O&M and degradation was between 2.31 times and 30.01 times greater than variability due to energy yield:

Ratio of O&M and Degradation Variability to Energy Yield Variability				
Year	**Ratio Above/Below Central Estimate**	**Pessimistic Scenario**	**Average Scenario**	**Optimistic Scenario**
2014	Ratio above central estimate	17.75	7.68	0.76*
	Ratio below central estimate	17.96	7.78	0.77*
2015	Ratio above central estimate	16.63	7.51	2.31
	Ratio below central estimate	16.85	7.61	2.34
2016	Ratio above central estimate	20.80	7.47	4.97
	Ratio below central estimate	21.12	7.58	5.05
2017	Ratio above central estimate	29.51	6.88	12.99
	Ratio below central estimate	30.01	6.99	13.21
2018	Ratio above central estimate	325.05*	6.67*	327.06*
	Ratio below central estimate	331.18*	6.80*	333.24*
2019	Ratio above central estimate	4.31*	6.87	19.17
	Ratio below central estimate	4.40*	7.02	19.57
2020	Ratio above central estimate	3.57	7.30	10.27
	Ratio below central estimate	3.66	7.47	10.51

Table Note:

- "Central estimate" is the mean discounted net present value from the Monte Carlo simulation
- *Values that are exceptional due to the central estimate being close to zero

Table 68. A comparison of how much more discounted net present value variability is due to O&M and degradation compared with energy yield for PV technology under the global adjustment tariff offsetting scenario.

Since all of the figures in the above table were greater than "1," discounted NPV variability due to O&M and degradation was greater than variability due to energy yield under each of the three pricing scenarios. The "average" ratio figures in the above table remained fairly constant between 2014 and 2020, while the "optimistic" ratios increased and the "pessimistic" ratios decreased over this timeframe.

PV technology has been tested, tried and proven on countless occasions. In contrast, CPV technology is relatively newer and has not been put through the same trials. In the next section, this analysis will turn to examine the discounted net present values observed under CPV technology with both energy yield variability and electricity tariff variability.

5.4.4.3 Concentrated Photovoltaic Technology

The expectations with both energy yield and tariff variability under CPV technology were the same as PV technology – a greater amount of variability was anticipated when compared with only energy yield variability or only tariff variability. Below, Table 69 provides details about the standard deviation, as well as the minimum, average, maximum, and range values for the 250 discounted net present values generated using a Monte Carlo simulation:

Scenario	Year	Standard Deviation	Minimum ($)	Average ($)	Maximum ($)	Range ($)
Pessimistic	2014	3,244.81	-323,859.03	-315,778.21	-306,513.06	17,345.97
	2015	3,764.77	-304,935.41	-293,759.37	-284,606.26	20,329.15
	2016	3,897.36	-284,777.62	-274,713.94	-264,509.04	20,268.58
	2017	4,053.32	-268,232.74	-256,050.66	-241,537.21	26,695.52
	2018	4,366.13	-250,293.61	-238,273.05	-225,898.04	24,395.57
	2019	4,625.08	-233,770.85	-222,159.71	-210,249.84	23,521.01
	2020	4,686.58	-222,272.61	-207,107.35	-195,688.14	26,584.47
Average	2014	4,482.98	-222,407.26	-212,560.02	-198,524.55	23,882.71
	2015	5,108.40	-175,177.00	-158,545.05	-146,081.25	29,095.75
	2016	6,046.28	-129,044.67	-109,724.34	-92,610.45	36,434.22
	2017	6,596.03	-78,655.19	-61,373.30	-43,844.51	34,810.68
	2018	7,133.58	-36,275.56	-17,983.78	1,468.94	37,744.50
	2019	7,754.39	6,975.75	27,759.85	47,375.78	40,400.03
	2020	7,741.28	42,013.15	64,526.18	87,463.93	45,450.78
Optimistic	2014	6,544.18	-67,639.82	-50,593.80	-32,624.18	35,015.64
	2015	7,684.75	44,235.34	67,018.03	87,775.87	43,540.52
	2016	9,038.85	157,651.20	185,253.91	214,387.50	56,736.30
	2017	10,578.21	258,007.97	292,190.13	321,374.77	63,366.80
	2018	11,420.84	366,505.49	395,250.42	423,714.40	57,208.91
	2019	13,045.04	441,018.42	481,225.58	514,085.59	73,067.17
	2020	14,564.64	559,941.65	596,868.50	638,201.63	78,259.98

Table 69. The characteristics of the 250 discounted net present values generated by the Monte Carlo simulations for the "pessimistic," "average," and "optimistic" pricing scenarios under the global adjustment tariff offsetting scenario and CPV technology.

The standard deviations shown in Table 69 were each larger than the energy yield variability only standard deviations shown in Table 61 in Section 5.4.2.2 and the tariff variability only standard deviations shown in Table 63 in Section 5.4.3.2. This was not unexpected, since it was probable that the energy yield and tariff variables

would produce more variability when combined as opposed to when each was on its own. When compared with the standard deviations from the PV energy and tariff variability in Table 64, the CPV standard deviations were larger than the PV standard deviations in each and every year under the three pricing scenarios. This was also anticipated, since the standard deviations associated with CPV technology were larger than those associated with PV technology throughout this analysis.

Using the standard deviations shown in Table 69, 95% confidence intervals were calculated using Equation (24) from Section 5.1.2.1. Below, Figure 68 shows the plots of the means from the three pricing scenarios with dashed lines representing the 95% confidence intervals:

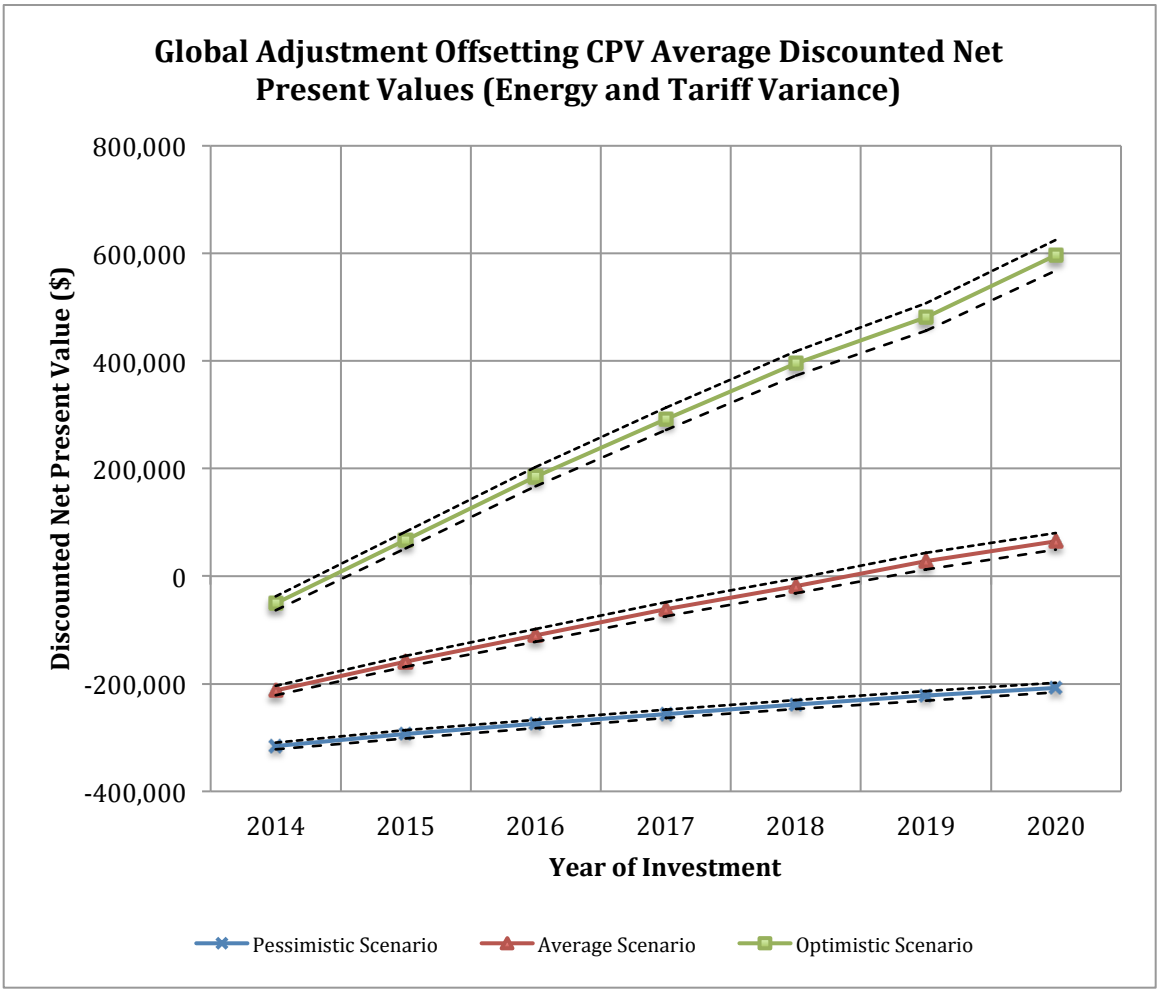


Figure 68. Plots of mean discounted net present values for the three costing scenarios using CPV technology under the global adjustment tariff offsetting scenario.

In Figure 68, the upper and lower boundaries of the 95% confidence intervals were clearly distinguishable under both the "optimistic" and "average" pricing scenarios from 2014 through until 2020. The 95% confidence intervals were also fairly discernable under the "pessimistic" scenario as well. The width of the confidence interval in the latter years under the "optimistic" scenario was the widest out of any tariff scenario presented in Chapter 5. However, even at the widest point in 2020, a prospective investor could be confident that the discounted net present value under the "optimistic" costing scenario would fall between USD 568,321.81 on the low side and USD 625,415.19 on the high side 19 times out of 20. Both visually and numerically, investment in CPV technology did not appear significantly riskier compared with PV technology. A close-up of the narrowest segment of the 95% confidence interval from the "optimistic" scenario is shown below in Figure 69:

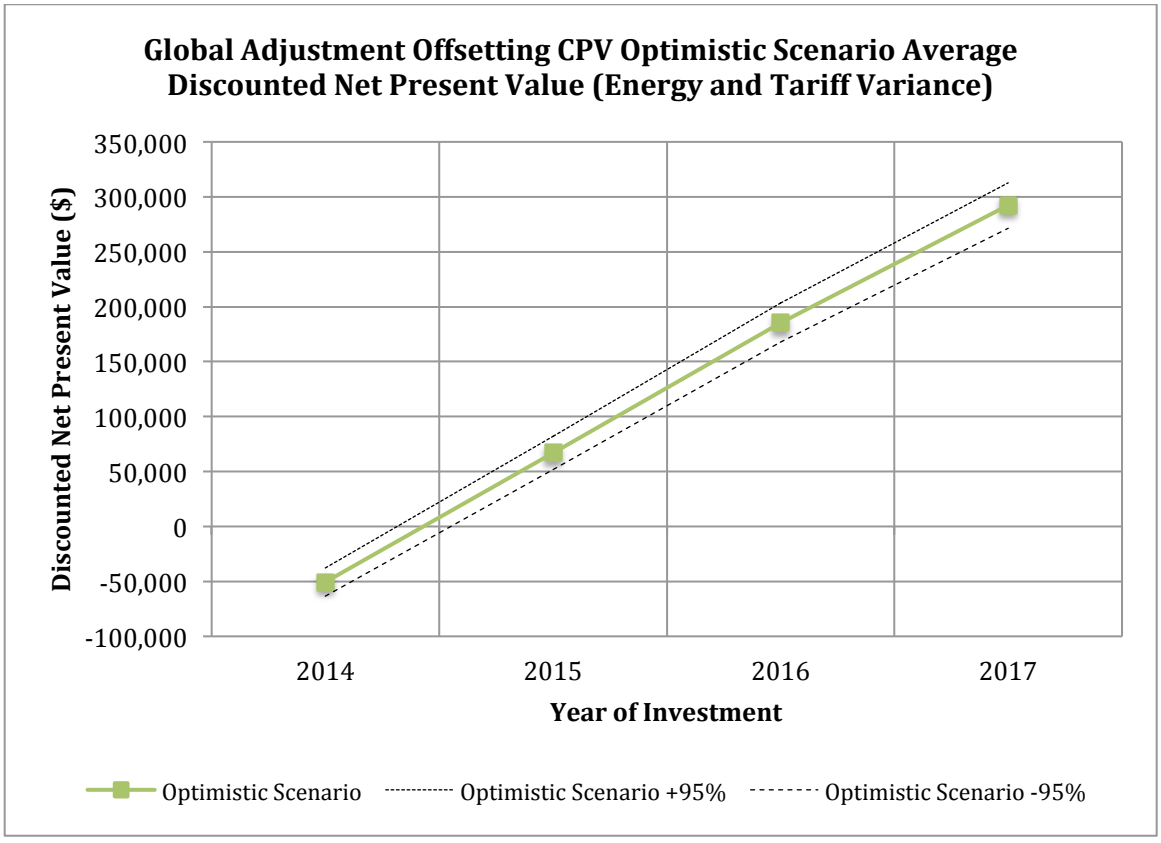


Figure 69. The 95% confidence intervals corresponding to the average discounted net present values for the years 2014 through 2017 under the "optimistic" scenario.

The detail shown in Figure 69 indicated that, under the "optimistic" scenario, once the mean discounted net present value turned positive the 95% confidence intervals

also turned positive. Although a prospective investor would be wise to wait until 2020 to invest in order to take advantage of the highest discounted NPV, an investment initiated in any of the years 2015 onwards had a high probability of realizing a positive discounted net present value. The same was true under the "average" scenario according to Figure 68, but the investor had to wait until 2019 or 2020 to invest in order to realize a positive discounted NPV.

Normality tests were performed on the 250 discounted net present values for the CPV scenario with both energy yield and tariff variability. Below, Figure 70 shows the result of one normality test on the discounted net present values from the "average" scenario in 2014:

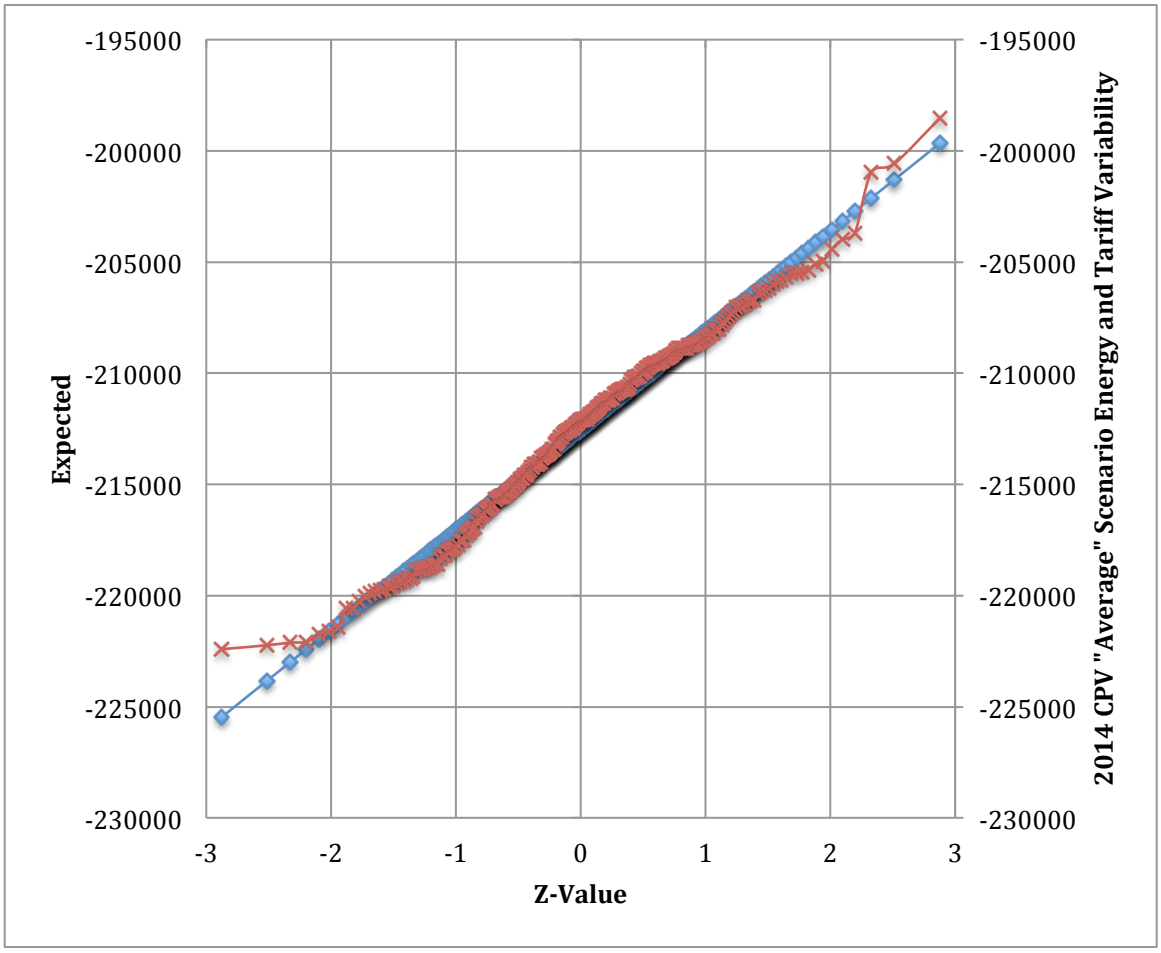


Figure 70. Results from a normality test on the 250 discounted net present values generated by the Monte Carlo simulation for the scenario with both energy yield and tariff variability under CPV technology in 2014.

According to Figure 70, the red x's of simulated values matched nicely with the blue squares of expected results, and thus this figure indicated that there was insufficient evidence to state that the discounted net present values were not normally distributed. Additional normality tests for this particular tariff and variability scenario are included in Appendix D.

5.4.4.4 Concentrated Photovoltaic Technology Variability Analysis

Turning to additional variability analysis on CPV technology, the following table summarizes discounted NPV variability due to energy yield as a proportion of the mean:

Discounted Net Present Value Variability due to Energy Yield				
Year	**% Above/Below Central Estimate**	**Pessimistic Scenario**	**Average Scenario**	**Optimistic Scenario**
2014	% above central estimate	2.01%	4.13%	25.35%
	% below central estimate	-2.01%	-4.13%	-25.35%
2015	% above central estimate	2.51%	6.32%	22.47%
	% below central estimate	-2.51%	-6.32%	-22.47%
2016	% above central estimate	2.78%	10.80%	9.56%
	% below central estimate	-2.78%	-10.80%	-9.56%
2017	% above central estimate	3.10%	21.06%	7.10%
	% below central estimate	-3.10%	-21.06%	-7.10%
2018	% above central estimate	3.59%	77.75%*	5.66%
	% below central estimate	-3.59%	-77.75%*	-5.66%
2019	% above central estimate	4.08%	54.75%*	5.31%
	% below central estimate	-4.08%	-54.75%*	-5.31%
2020	% above central estimate	4.44%	23.51%	4.78%
	% below central estimate	-4.44%	-23.51%	-4.78%

Table Notes:

- "Central estimate" is the mean discounted net present value from the Monte Carlo simulation
- The above figures represent variability as a proportion of the mean with 95% confidence
- *Values that are exceptional due to the central estimate being close to zero

Table 70. Percentage of discounted net present value variability due to energy yield for CPV technology under the global adjustment tariff offsetting scenario.

According to Table 70, 95% of the discounted NPV values generated by the Monte Carlo simulation were at most plus or minus 25.35% from the mean. Although this particular value was not marked with a *, its underlying mean of USD -50,598.80

was comparatively closer to zero than all but two other discounted NPV means. As an alternative measure, 95% of the discounted net present values were at most plus or minus 10.80% on either side of the mean *for all averages more than plus or minus USD 100,000 from zero*.

In Table 71, the size of discounted NPV variability due to system cost was consistently larger above the central estimate compared with below the central estimate:

Discounted NPV Variability due to System Cost and O&M and Degradation			
Year	**% Above/Below Central Estimate**	**System Cost⊙**	**O&M and Degradation❖**
2014	% above central estimate	76.19%	15.46%
	% below central estimate	-48.55%	-15.46%
2015	% above central estimate	142.21%	24.50%
	% below central estimate	-85.23%	-24.50%
2016	% above central estimate	269.96%	40.69%
	% below central estimate	-152.02%	-40.69%
2017	% above central estimate	577.87%	81.54%
	% below central estimate	-319.24%	-81.54%
2018	% above central estimate	2306.09%*	304.89%*
	% below central estimate	-1225.56%*	-304.89%*
2019	% above central estimate	1628.91%*	217.36%
	% below central estimate	-898.61%*	-217.36%
2020	% above central estimate	828.12%	101.17%
	% below central estimate	-421.05%	-101.17%

Notes:

- ⊙Range from literature: Haysom et al. (2014).
- ❖Range from literature: Drury et al. (2013), Gerstmaier et al. (2014).
- "Central estimate" is the "average" discounted net present value with zero variability
- *Values that are exceptional due to the central estimate being close to zero

Table 71. Percentage of discounted net present value variability due to system cost, as well as O&M and degradation for CPV technology under the global adjustment tariff offsetting scenario.

For O&M and degradation, the figures on either side of the central estimate were identical due to the evenness of the CPV operations and maintenance as well as degradation inputs that were defined in Table 19 in Section 4.2. Discounted NPV variability due to system costs increased year after year between 2014 and 2020,

while variability due to O&M and degradation increased until 2019, but then fell in 2020.

Nevertheless, the ratio figures in Table 72 indicated that discounted NPV variability due to system cost was consistently higher than variability due to O&M and degradation:

Ratio of Variability due to System Cost to Variability due to O&M and Degradation		
Year	**Ratio Above/Below Central Estimate**	**Ratio**
2014	Ratio above central estimate	4.93
	Ratio below central estimate	3.14
2015	Ratio above central estimate	5.80
	Ratio below central estimate	3.48
2016	Ratio above central estimate	6.63
	Ratio below central estimate	3.74
2017	Ratio above central estimate	7.09
	Ratio below central estimate	3.92
2018	Ratio above central estimate	7.56
	Ratio below central estimate	4.02
2019	Ratio above central estimate	7.49
	Ratio below central estimate	4.13
2020	Ratio above central estimate	8.19
	Ratio below central estimate	4.16

Table Note:

- "Central estimate" is the "average" discounted net present value with zero variability

Table 72. Ratio of discounted net present value variability due to system cost to variability due to O&M and degradation for CPV technology under the global adjustment tariff offsetting scenario.

The ratio numbers in the above table also increased each year. This could have meant that discounted NPV variability due to system cost increased at a greater rate than discounted NPV variability due to O&M and degradation. In this case, an investor may have wanted to invest in a CPV installation closer to 2014 than 2020 in order to take advantage of less overall discounted NPV variability risk from system costs and O&M plus degradation.

As a final part of the discounted NPV analysis, variability due to O&M and degradation was compared with variability due to energy yield. The finding was that the former was between 0.61 and 53.27 times greater than the latter:

Ratio of O&M and Degradation Variability to Energy Yield Variability				
Year	**% Above/Below Central Estimate**	**Pessimistic Scenario**	**Average Scenario**	**Optimistic Scenario**
2014	% above central estimate	7.68	3.74	0.61
	% below central estimate	7.68	3.74	0.61
2015	% above central estimate	9.75	3.88	1.09
	% below central estimate	9.75	3.88	1.09
2016	% above central estimate	14.63	3.77	4.25
	% below central estimate	14.63	3.77	4.25
2017	% above central estimate	26.28	3.87	11.49
	% below central estimate	26.28	3.87	11.49
2018	% above central estimate	84.89*	3.92*	53.83*
	% below central estimate	84.89*	3.92*	53.83*
2019	% above central estimate	53.27	3.97*	40.91
	% below central estimate	53.27	3.97*	40.91
2020	% above central estimate	22.81	4.30	21.15
	% below central estimate	22.81	4.30	21.15

Table Note:

- "Central estimate" is the mean discounted net present value from the Monte Carlo simulation
- *Values that are exceptional due to the central estimate being close to zero

Table 73. A comparison of how much more discounted net present value variability is due to O&M and degradation compared with energy yield for CPV technology under the global adjustment tariff offsetting scenario.

Note that the minimum value of 0.61 in Table 73 indicated that discounted NPV variability due to energy yield was greater than variability due to O&M and degradation. This value, however, was tied to the caveat in the paragraph at the start of this section discussing discounted NPV variability in relation to energy yields. Therefore, including only those years and scenarios where the mean discounted NPV was at least plus or minus USD 100,000 from zero, variability due to O&M and degradation was between 3.74 to 53.27 times greater than variability due to energy yield. Under this measure, discounted NPV variability due to O&M and degradation was always greater than discounted NPV variability due to fluctuating system output.

5.4.5 Section 5.4 Summary

Section 5.4 presented discounted net present value results under a variety of variability scenarios including zero variability, energy yield variability, tariff variability, and both energy yield and tariff variability. Variability from the latter scenario, as measured by the standard deviations calculated from the Monte Carlo simulation results, was higher compared with the variability observed under the three other tariff scenarios in Chapter 5. This was attributed to the fact that variability in the other tariff scenarios was at most attributable to only one source – energy yields – while the global adjustment tariff offsetting scenario included both energy yields and electricity prices as sources of variability in one analysis.

In this same section, the Hourly Ontario Energy Price, global adjustment fees, and distribution charges associated with grid electricity were offset using solar-produced electricity. This generated cost savings as opposed to a revenue stream. With electricity prices in the province of Ontario expected to increase over time, the value created by offsetting increased as time moved forwards towards the year 2020. Thus, a prospective investor was wise to delay investment until a later date if possible. Compared to the other tariff scenarios, the discounted net present values in this section were not the highest. However, given that there was no guaranteed price paid for electricity, the global adjustment tariff offsetting scenario still created significant value that would be beneficial to a Class "A" electricity customer in Ontario. This was especially true for CPV technology, which, under the "optimistic" scenario, yielded discounted net present values that were higher than those from the TOU scenario and competitive with those from the feed-in-tariff and power purchase agreement scenarios.

The risk profile of the investment in either a PV or CPV installation under the global adjustment tariff offsetting scenario with two sources of variability was not particularly different compared with the risk profiles from the tariff scenarios with only one source of variability. True, the standard deviations and 95% confidence

intervals under this tariff scenario were wider compared with the other scenarios. However, the widths were not wide enough to raise significant concerns over risk levels, and an investor looking at the discounted net present values that marked the 95% confidence interval on either side of the mean would not be likely to assess the risk of investing in either technology as "high." This was important for CPV technology, a relatively new technology compared with PV that does not have the same amount of fiscal study as its older counterpart. Proportionally, 95% of the discounted net present values for PV technology were at most within plus or minus 9.50% of the mean. For CPV technology, this figure was at most 25.35% given a mean less than USD 100,000 away from zero, or at most 10.80% given a mean more than plus or minus USD 100,000 away from zero. In the next section, this analysis will turn to the return on investment metric, which is related to the discounted net present value results.

Chapter 6: Return on Investment Results

The plots of the return on investment results for both PV and CPV technologies followed approximately the same pattern as the plots of the discounted net present value results. This was expected since the inputs used to calculate return on investment and discounted net present value overlap, and return on investment is simply the ratio of the discounted net present value to the total amount of capital invested. This was shown in Equation (10) in Section 3.3.1.4. For PV technology, the total amount of capital invested in each of the years 2014 through 2020 was presented in Table 18 in Section 4.1, while the same information for CPV technology was shown in Table 21 in Section 4.2. Since the return on investment plots mirrored the discounted net present value plot, ROI charts will not be included in Chapter 6. Instead, tables will provide details about the return on investment values. It should also be noted that the time-of-use and global adjustment tariff offsetting scenarios assumed a 25-year return on investment, while the feed-in tariff and power purchase agreement tariff scenarios assumed a 20-year return on investment.

6.1 Time-of-Use Tariff Scenario Return on Investment Figures

Below, Table 74 shows the return on investment figures for PV technology under the time-of-use tariff scenario. When the no-variability results were compared with the energy variability results, the ROI values from the static energy yield analysis and the average ROI values calculated from the 250 Monte Carlo simulations were the same to three decimal places.

Scenario	Year	Return on Investment
Pessimistic	2014	-0.715
	2015	-0.674
	2016	-0.621
	2017	-0.547
	2018	-0.456
	2019	-0.324
	2020	-0.137
Average	2014	-0.559
	2015	-0.504
	2016	-0.439
	2017	-0.359
	2018	-0.263
	2019	-0.145
	2020	0.000
Optimistic	2014	-0.250
	2015	-0.185
	2016	-0.116
	2017	-0.055
	2018	0.014
	2019	0.084
	2020	0.146

Table 74. PV technology return on investment figures under the time-of-use tariff scenario.

For each of the three scenarios in Table 74, the return on investment numbers increased over time. However, only the ROI values under the "optimistic" pricing scenario were able to cross into positive territory. The "average" scenario came close to accomplishing the same feat in the year 2020 with a return on investment of 0%.

Turning to CPV technology, return on investment figures for both no-variability and energy variability scenarios are shown in Table 75. Recall that, under the energy variability scenario, average return on investment was calculated from 250 Monte Carlo simulations for each of the years 2014 to 2020.

Scenario	Year	Return on Investment
Pessimistic	2014	-0.727
	2015	-0.688
	2016	-0.650
	2017	-0.610
	2018	-0.574
	2019	-0.521
	2020	-0.487
Average	2014	-0.562
	2015	-0.470
	2016	-0.384
	2017	-0.301
	2018	-0.227
	2019	-0.143
	2020	-0.079
Optimistic	2014	-0.298
	2015	-0.101
	2016	0.095
	2017	0.265
	2018	0.436
	2019	0.554
	2020	0.733

Table 75. Return on investment values for CPV technology under the time-of-use tariff scenario.

In Table 75, the ROI values increased each year. However, as was the case with the PV return on investment numbers, only the "optimistic" scenario was able to turn positive before the year 2020. With time-of-use pricing, a reasonable return on investment for both CPV and PV technologies was achievable only under the "optimistic" scenario. For this particular scenario, CPV technology provided higher positive returns on investment than PV technology. Thus, a prospective investor would be wise to examine the merits of using CPV technology instead of PV technology and to defer investment until the year 2020 if possible to maximize the potential return on investment.

6.2 Feed-in Tariff Scenario Return on Investment Figures

The feed-in tariff scenario photovoltaic ROI values are shown in Table 76:

Scenario	Year	Return on Investment
Pessimistic	2014	-0.223
	2015	-0.259
	2016	-0.302
	2017	-0.324
	2018	-0.336
	2019	-0.322
	2020	-0.288
Average	2014	0.116
	2015	0.056
	2016	-0.019
	2017	-0.078
	2018	-0.120
	2019	-0.151
	2020	-0.168
Optimistic	2014	0.791
	2015	0.652
	2016	0.487
	2017	0.323
	2018	0.187
	2019	0.066
	2020	-0.045

Table 76. PV return on investment numbers under the feed-in tariff scenario.

The return on investment figures in Table 76 indicated that prospective solar investors were better off securing a FIT contract at a time closer to 2014 rather than 2020, since feed-in tariff rates were projected to decrease as per Figure 18 in Section 4.3.2. As expected, the "optimistic" scenario, with the lowest associated costs and degradation rates, provided the highest return on investment. Even as ROI figures decreased as time progressed under this scenario, the values remained positive until the year 2019. In comparison, the returns on investment under the "average" scenario were positive only during the years 2014 and 2015.

For CPV technology under the feed-in tariff scenario, the average return on investment figures stemming from the 250 Monte Carlo simulations matched the corresponding no-variability ROI figures. A table of these values is shown below:

Scenario	Year	Return on Investment
Pessimistic	2014	-0.156
	2015	-0.203
	2016	-0.288
	2017	-0.367
	2018	-0.445
	2019	-0.499
	2020	-0.561
Average	2014	0.225
	2015	0.238
	2016	0.169
	2017	0.080
	2018	-0.024
	2019	-0.115
	2020	-0.218
Optimistic	2014	0.797
	2015	0.943
	2016	0.953
	2017	0.867
	2018	0.756
	2019	0.578
	2020	0.467

Table 77. CPV return on investment values under the feed-in tariff scenario.

The positive ROI values in Table 77 under the "average" and "optimistic" costing scenarios indicated that the optimal year to invest fell between 2014 and 2020. According the "average" scenario, the highest return on investment of 23.8% was observed in 2015, while the greatest ROI of 95.3% was observed in 2016 under the "optimistic" pricing scenario. As anticipated, this exactly followed the maximum discounted net present value results for CPV technology shown in Section 5.2.2.2. Consequently, someone interested in investing in CPV technology would likely realize a higher return on investment by funding a CPV project that commenced operations in 2016 if costs followed the "optimistic" scenario. The same was true for

the year 2015 if costs were subject to those found under the "average" scenario. Once again, the ROI values were greater for CPV technology compared with PV technology. Although Chapter 5 indicated that CPV technology was found to have more risk compared with PV technology, these higher risks also came with higher rewards according to the ROI figures in this section.

6.3 Power Purchase Agreement Tariff Scenario Return on Investment Figures

The PV return on investment figures obtained under the power purchase agreement tariff scenario are shown below in Table 78:

Scenario	Year	Return on Investment
Pessimistic	2014	-0.151
	2015	-0.097
	2016	-0.090
	2017	-0.058
	2018	-0.005
	2019	0.074
	2020	0.222
Average	2014	0.216
	2015	0.277
	2016	0.266
	2017	0.267
	2018	0.291
	2019	0.312
	2020	0.373
Optimistic	2014	0.946
	2015	0.987
	2016	0.902
	2017	0.798
	2018	0.715
	2019	0.620
	2020	0.535

Table 78. Return on investment figures for PV technology under the power purchase agreement tariff scenario.

In Section 5.3.1.1, it was noted that the power purchase agreement tariff scenario was the first instance where all three pricing scenarios were positive at the same time under PV technology. As such, the ROI values in Table 78 reflected this

phenomenon: the return on investment values were all positive for each of the years 2014 through 2020 under the "average" and "optimistic" scenarios, while the ROI numbers turned positive in the year 2019 under the "pessimistic" costing scenario. The PPA tariff scenario included declining baseline PPA prices shown in Table 26 in Section 4.3.3. Interestingly, unlike the FIT scenario from the previous section that also included declining electricity prices, the optimal time to invest according to Table 78 was not when the baseline PPA price was highest in 2014. Instead, the optimal time to invest according to the "pessimistic" and "average" scenarios was 2020, and under the "optimistic" scenario the best time to invest was in 2015. A prospective investor should understand the relationship between associated system costs and energy prices in order to determine when to invest in order to take advantage of the highest return on investment amounts.

CPV technology's return on investment figures, are shown in Table 79 below:

Scenario	Year	Return on Investment
Pessimistic	2014	-0.133
	2015	-0.084
	2016	-0.120
	2017	-0.159
	2018	-0.203
	2019	-0.240
	2020	-0.284
Average	2014	0.256
	2015	0.414
	2016	0.430
	2017	0.415
	2018	0.376
	2019	0.326
	2020	0.261
Optimistic	2014	0.841
	2015	1.209
	2016	1.368
	2017	1.415
	2018	1.430
	2019	1.322
	2020	1.310

Table 79. CPV return on investment values for the power purchase agreement tariff scenario.

As per Table 79, the returns on investment were positive for each of the years 2014 to 2020 under the "average" and "optimistic" scenarios. Under the "pessimistic" pricing scenario, the returns on investment were negative in each of the years covering the same timeframe. CPV technology exhibited the first instance of returns on investment exceeding 100% under this tariff scenario. This occurred between the years 2015 to 2020 under the "optimistic" costing scenario. Analogous to PV, the optimal time to invest was a point in time between 2014 and 2020. For the "average" scenario, this year was 2016, while for the "optimistic" scenario this year was 2018. Someone with an interest in securing a power purchase agreement and investing in either PV or CPV technology would be wise to study which year represented the highest return on investment depending upon which technology was selected. Notably, CPV technology provided higher returns on investment

compared with PV technology in this and each of the other tariff scenarios presented thus far.

6.4 Global Adjustment Tariff Offsetting Scenario Return on Investment Figures

The return on investment figures for PV technology under the global adjustment tariff offsetting scenario are shown below in Table 80:

Scenario	Year	Return on Investment
Pessimistic	2014	-0.575
	2015	-0.524
	2016	-0.455
	2017	-0.361
	2018	-0.242
	2019	-0.081
	2020	0.162
Average	2014	-0.362
	2015	-0.296
	2016	-0.215
	2017	-0.116
	2018	0.006
	2019	0.141
	2020	0.321
Optimistic	2014	0.060
	2015	0.134
	2016	0.214
	2017	0.285
	2018	0.364
	2019	0.430
	2020	0.494

Table 80. Return on investment figures for PV under the global adjustment tariff offsetting scenario.

The global adjustment tariff offsetting scenario encompassed four distinct variability options: zero variability, energy yield variability, tariff variability, and energy yield as well as tariff variability. The figures in Table 80 represented the return on investment figures from all four variability options. In some instances across the four variability scenarios, the ROI values differed by one one-thousandth of the value shown in Table 80. However, this amount was likely not enough to change a potential investor's decision to make or defer an investment, and so the

values in Table 80 were understood as expected values of return on investment. Over all, the ROI values grew as time progressed towards 2020. In parallel to the power purchase agreement scenario, positive returns on investment were observed for PV technology under all three costing scenarios. In the above table, positive returns on investment were observed under all three scenarios in the year 2020.

For CPV technology, the ROI values are shown in Table 81 below:

Scenario	Year	Return on Investment
Pessimistic	2014	-0.631
	2015	-0.587
	2016	-0.545
	2017	-0.499
	2018	-0.460
	2019	-0.409
	2020	-0.375
Average	2014	-0.425
	2015	-0.317
	2016	-0.216
	2017	-0.119
	2018	-0.035
	2019	0.051
	2020	0.117
Optimistic	2014	-0.101
	2015	0.134
	2016	0.367
	2017	0.568
	2018	0.766
	2019	0.886
	2020	1.085

Table 81. CPV return on investment figures under the global adjustment tariff offsetting scenario.

Analogous to the PV results in Table 80, the CPV return on investment figures in Table 81 increased and improved as time progressed towards 2020. No positive ROI values were observed in 2014. However, positive ROI values were observed under the "optimistic" scenario in 2015, while the same was observed in 2019 under the "average" scenario. The CPV results revealed a return on investment exceeding 100% under the "optimistic" scenario in the year 2020. The only other tariff

scenario that observed ROI values greater than 100% was the power purchase agreement tariff scenario under, also under CPV technology. Interestingly, both CPV and PV technologies had the same ROI in 2015 of 13.4% under the "optimistic" scenario. In future years, the CPV returns on investment outpaced the PV returns. A person or company looking to invest in PV or CPV technology to offset their Class "A" electricity charges would be better of choosing CPV technology over PV technology and delaying investment until 2020.

6.5. Summary

In Chapter 6, ROI figures were provided for the time-of-use, feed-in tariff, power purchase agreement, and global adjustment tariff offsetting scenarios. With a few minor exceptions, the returns on investment from the no-variability scenarios were equal to the average of the returns on investment calculated from the 250 simulated values up to three decimal places. For those exceptions, the ROI value varied by only one one-thousandth of the value displayed within this section. The results shown in Chapter 6 mirrored the discounted net present value results from Chapter 5. For instance, if the discounted net present values increased from the year 2014 to 2020, then the return on investment figures also increased during that same timeframe. If the discounted net present values increased and then decreased, the ROI values would follow the exact trend. This was because return on investment, which was calculated by Equation (10) in Section 3.3.1.4, was equal to the ratio of the discounted net present value to the total amount invested in the PV or CPV installation.

Over all, it was more favourable to invest in CPV technology under each of the four tariff scenarios because CPV technology created mostly higher returns on investment compared with PV technology. The exception to this rule, however, was when CPV technology did not yield positive returns on investment but PV technology did, such as under the "pessimistic" scenario of the power purchase agreement tariff scenario in the years 2019 and 2020 and under the "pessimistic"

scenario of the global adjustment tariff offsetting scenario in the year 2020. CPV technology was able to achieve returns on investment in excess of 100% under the power purchase agreement scenario and global adjustment tariff offsetting scenario. Although PV technology did not cross the 100% return mark one, it came very close in 2015 under power purchase agreement's "optimistic" costing scenario when its return on investment was 98.7%. In the next section, the results for internal rate of return, the third financial metric, will be presented and discussed.

Chapter 7: Internal Rate of Return Results

Internal rate of return was defined in Section 2.4.2.1 as the discount rate that would yield a net present value of exactly zero (Ayyub, 2003). Details about the manner in which internal rate of return was calculated were provided in Section 3.3.1.4. In concise terms, a project is profitable when the IRR exceeds the discount rate, but when the IRR is less than the discount rate the project is unprofitable. As per Table 4 in Section 2.4.2.1, discount rates uncovered during the literature review ranged between 2-12% in previous PV and CPV studies. This thesis employed discount rates between 8-9% for PV and 8-10% of CPV technology for the analysis. To illustrate the relationship between internal rate of return and profitability, consider the example of the IRR for the "optimistic" costing scenario under the time-of-use tariff. Figure 71 below shows the internal rates of return for projects commencing in each of the years 2014 through 2020 under the "optimistic" PV costing scenario and the TOU tariff:

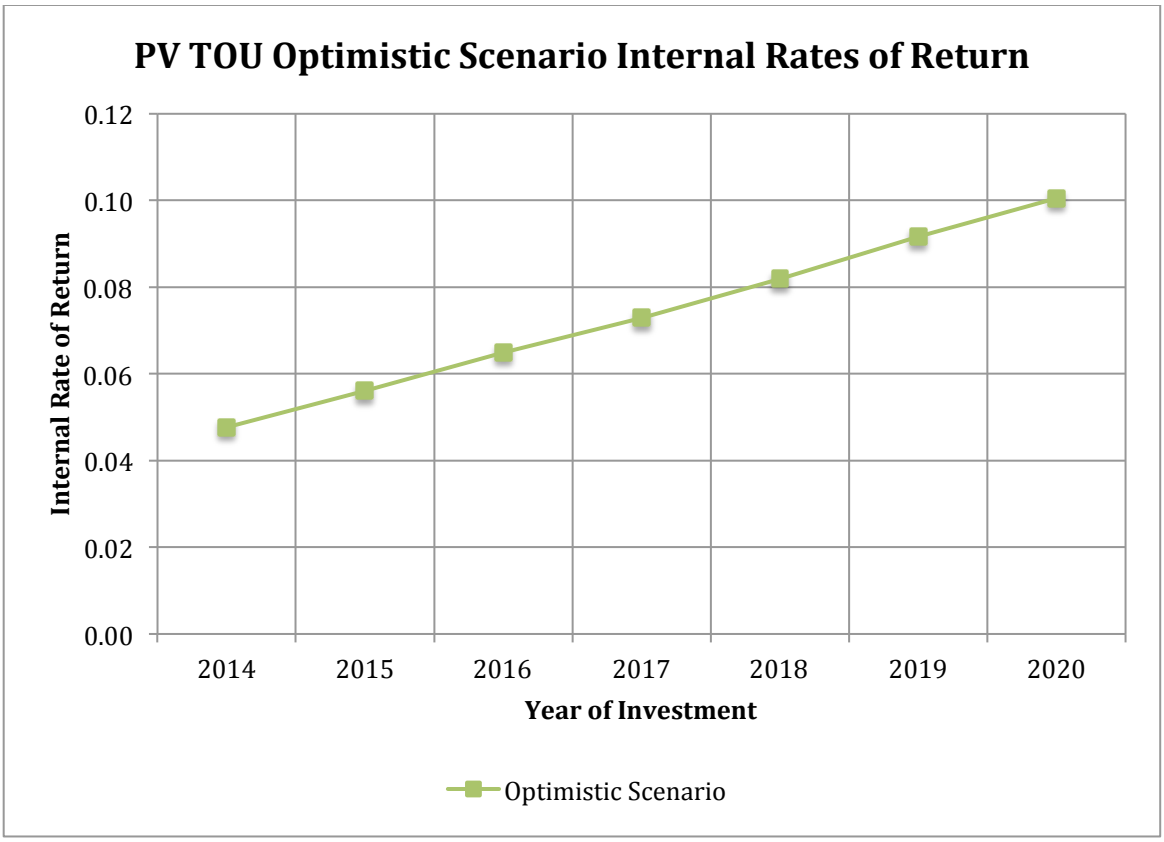


Figure 71. The internal rates of return for PV projects commencing in each of the years 2014 through 2020 under the time-of-use tariff scenario.

In Figure 71, the internal rate of return increased from approximately 4.7% in 2014 to about 10% in 2020. According to Figure 20 from Section 5.1.1.1, the discounted net present values turned positive in 2018. This was the same year in which the internal rate of return in Figure 71 exceeded 8%, which was the discount rate for PV technology under the "optimistic" pricing scenario according to Table 15 in Section 4.2. Thus, 2018 was the first year in which the PV project was profitable, and since the internal rates of return in 2019 and 2020 were also in excess of 8%, those two years also saw profitable PV investments. Looking at the return on investment results from Chapter 6, the negative ROI figures turned positive also in the year 2018 under the "optimistic" pricing scenario and TOU tariff. Thus, there was a definite relationship between internal rate of return and the discounted net present value as well as return on investment financial metrics that were presented in Chapters 5 and 6, respectively.

The nature of the IRR metric allows for this chapter to include analysis and discussion pertaining to what internal rate of return would be required to realize a profit if a PV or CPV solar investment is unprofitable. The content in this chapter will compensate for the 8-10% discount rate chosen as part of the discounted NPV analysis in Chapter 5, since some prospective solar investors may have a discount rate outside of that range. The following subsections will present the internal rate of return results for both PV and CPV technology under the four tariff scenarios. Since the plots of the averaged internal rates of return from the 250 Monte Carlo simulations nearly exactly matched the IRR results from the scenarios with zero variability, the internal rate of return plots shown by the charts within this section will be constructed using the simulated data that included energy variability. This will be more realistic than using data that did not account for energy variability. For the global adjustment tariff offsetting scenario, internal rates of return from the simulations that included both energy yield and tariff variability will be presented.

7.1 Time-of-Use Tariff Scenario

7.1.1 Photovoltaic Technology

Under the time-of-use tariff scenario, the internal rates of return associated with PV technology increased as time moved forward. This was expected, since the discounted net present values, which were shown in Figure 23 in Section 5.1.2.1 also became larger as time progressed towards the year 2020. Below, Figure 72 illustrates the increasing internal rates of return:

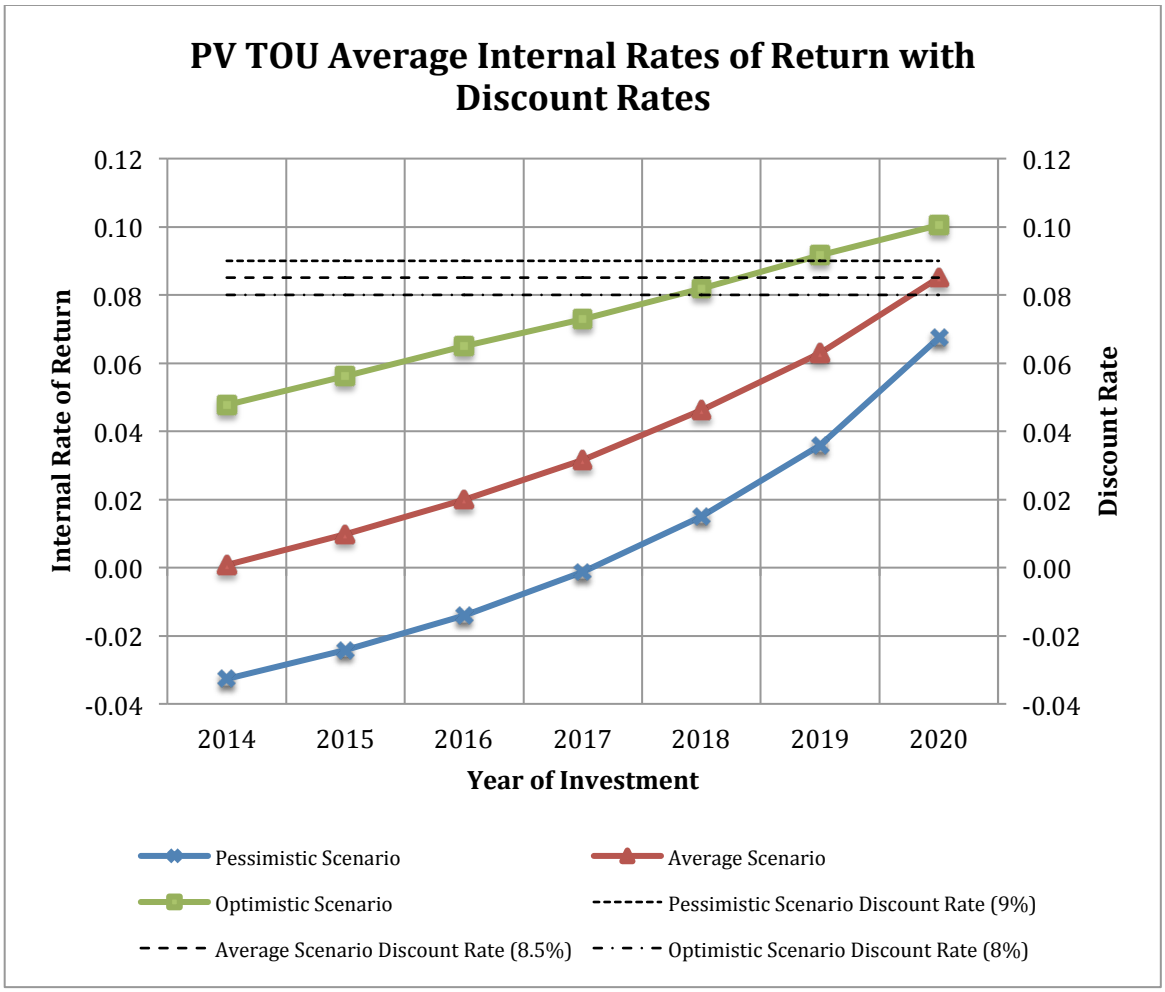


Figure 72. PV time-of-use internal rates of return under the three pricing scenarios during each of the years 2014 to 2020. The discount rates from the three pricing scenarios have been included as well.

In Figure 72, the discount rates associated with the "pessimistic," "average," and "optimistic" pricing scenarios were included since, as mentioned in the opening section of this chapter, a relationship exists between the internal rate of return and the discount rate. In order for a project to be profitable, the internal rate of return must exceed the discount rate. Thus, according to Figure 72, PV projects under the "optimistic" scenario became profitable after 2018, the year in which the internal rate of return crossed above the 8% discount rate associated with that particular scenario. Under the "average" scenario, the internal rate of return equalled the discount rate of 8.5%, which was represented by the middle dashed line in Figure 72, in the year 2020. The "pessimistic" scenario did not meet or exceed the 9%

discount rate in any of the years between 2014 and 2020 according to Figure 72 and thus did not experience any profitable investments.

Figure 72 also indicated the discount rate required for a profitable project in each of the years 2014 through 2020. This was one piece of information that the discounted NPV analysis could not provide. For example, under the "average" scenario, a discount rate of 4% on PV a project commencing in 2018 would have meant that the installation would have been profitable. In order for a PV project to be profitable in 2014 under the "optimistic" costing scenario, the discount rate would have needed to be lower than 4.8%. Each of the plots in Figure 72 had a positive slope over the years 2014 to 2020, although the "optimistic" plot was more linear compared with the curved "average" and "pessimistic" IRR plots.

A PV project's internal rate of return is a particularly important metric for a prospective investor, since it will have to exceed the investor's risk adjusted cost of capital in order for the project to be considered attractive. Generally speaking, projects with higher internal rates of return are more appealing to potential investors than projects with lower internal rates of return. Thus, an investor assessing the internal rates of return in Figure 72 may conclude that investment in a PV installation under the time-of-use tariff scenario was attractive only under the "optimistic" pricing scenario and only during the years 2019 or 2020, assuming the investor's cost of capital was 8%. The decision whether or not to invest can be simplified according to just two pieces of information – the IRR and cost of capital, and the usefulness of the internal rate of return is why it has been included as part of this analysis. The internal rates of return in Figure 72 increased over time, so an investor with a higher discount rate may have needed to wait longer to invest compared with an investor with a lower discount rate.

7.1.2 Photovoltaic Technology Variability Analysis

This section will explore the impact of energy yield variability on the internal rate of return metric. Included will be analyses of 95% confidence intervals, variability as a proportion of the mean, and ratio calculations. Beginning with 95% confidence intervals, Equation (26) below was used to compute the values comprising the intervals for each of the "pessimistic," "average," and "optimistic" scenarios:

$$IRR_{95\%CI}(t) = IRR_{\mu}(t) \pm 1.96\ (IRR_{\sigma}(t)) \tag{26}$$

In (26), $IRR_{95\%CI}(t)$ stands for the internal rate of return 95% confidence interval at time t, $IRR_{\mu}(t)$ denotes the mean internal rate of return from the 250 Monte Carlo simulations at time t, while $IRR_{\sigma}(t)$ represents the standard deviation of the 250 simulated internal rates of return at time t.

Using Equation (26), Table 82 provides 95% IRR confidence intervals accounting for variability due to fluctuating system energy yields:

Year	Pessimistic Scenario		Average Scenario		Optimistic Scenario	
	95% Lower CI Value	95% Upper CI Value	95% Lower CI Value	95% Upper CI Value	95% Lower CI Value	95% Upper CI Value
2014	-0.0332	-0.0322	0.0003	0.0012	0.0472	0.0482
2015	-0.0247	-0.0238	0.0093	0.0102	0.0556	0.0567
2016	-0.0147	-0.0136	0.0194	0.0203	0.0644	0.0656
2017	-0.0019	-0.0008	0.0310	0.0321	0.0722	0.0735
2018	0.0145	0.0157	0.0457	0.0469	0.0812	0.0826
2019	0.0352	0.0365	0.0623	0.0636	0.0909	0.0924
2020	0.0666	0.0682	0.0842	0.0859	0.0996	0.1013

Table 82. Internal rate of return 95% confidence intervals for PV technology under the time-of-use tariff scenario.

According to Table 82, the largest 95% confidence interval was observed under the "average" scenario in 2020 where the mean IRR was 0.0850. In this case, the 95% confidence interval extended 0.09% above the mean, and 0.08% below the mean. These values were rather minute. Given that all other 95% confidence intervals

were even smaller, there did not exist a significant risk of the IRR deviating significantly from the mean.

The coefficient of variation calculation, defined in Section 5.1.2.2, was also used in this section to determine how close 95% of the internal rate of return values generated by the Monte Carlo simulation were to the mean IRR in each of the years 2014 to 2020. As noted in Section 5.1.2.2, the coefficient of variation is equal to the ratio of the standard deviation to the mean. Given that the 250 Monte Carlo simulations were normally distributed as per the normality tests shown throughout Chapter 5 and Appendix D, a 95% confidence interval of proportionality was calculated by multiplying the coefficient of variation by 1.96, which represents the z-value for 95% of the area under a normal distribution. Below, Equation (26) defines the calculation of the 95% proportional confidence interval:

$$IRR_{95\%}(t) = \pm 1.96\left(\frac{IRR_{\sigma}(t)}{IRR_{\mu}(t)}\right) \tag{27}$$

In Equation (27), $\%IRR_{95\%}(t)$ stands for the percent of IRR values at time t that are within 95% of the mean, $IRR_{\sigma}(t)$ represents the standard deviation of the 250 internal rates of return from the Monte Carlo simulation at time t, while $IRR_{\mu}(t)$ denotes the mean of the 250 internal rates of return from the Monte Carlo simulation at time t.

Table 83 below provides internal rate of return variability as a proportion of the mean. The figures were calculated using Equation (27), and those marked with a * were ignored because they included a mean value close to zero as part of the calculation. This practice will continue throughout this chapter, in the same manner as Chapter 5.

Internal Rate of Return Variability due to Energy Yield				
Year	**% Above/Below Central Estimate**	**Pessimistic Scenario**	**Average Scenario**	**Optimistic Scenario**
2014	% above central estimate	1.39%	55.15%*	1.07%
	% below central estimate	-1.39%	-55.15%*	-1.07%
2015	% above central estimate	2.04%	4.69%	0.98%
	% below central estimate	-2.04%	-4.69%	-0.98%
2016	% above central estimate	3.76%	2.40%	0.92%
	% below central estimate	-3.76%	-2.40%	-0.92%
2017	% above central estimate	41.17%*	1.71%	0.86%
	% below central estimate	-41.17%*	-1.71%	-0.86%
2018	% above central estimate	4.05%	1.31%	0.84%
	% below central estimate	-4.05%	-1.31%	-0.84%
2019	% above central estimate	1.78%	1.07%	0.82%
	% below central estimate	-1.78%	-1.07%	-0.82%
2020	% above central estimate	1.17%	1.03%	0.86%
	% below central estimate	-1.17%	-1.03%	-0.86%

Table Notes:

- "Central estimate" is the mean internal rate of return value from the Monte Carlo simulation
- The above figures represent variability as a proportion of the mean with 95% confidence
- *Values that are exceptional due to the central estimate being close to zero

Table 83. Percentage of internal rate of return variability due to energy yield for PV technology under the time-of-use tariff scenario.

According to the above table, the internal rate of return was not significantly affected by energy yield variability. The figures indicated that 95% of the IRR data points generated by the Monte Carlo simulation fell within plus or minus 4.69% of the mean at most between 2014 and 2020. For an investor looking to minimize the risk of IRR variability, the most ideal time to invest in a profitable PV installation according to Table 83 was in 2019 under the "optimistic" scenario where IRR variability due to energy yield was plus or minus 0.82%. Besides the two exceptions, the values in Table 83 supported the finding from Chapter 5 that energy yield variability did not have a significant impact on the financial attractiveness of PV projects under the TOU tariff scenario. In Chapter 5, this fact was put forward by the narrowness of the 95% discounted net present value confidence intervals presented in Figure 23 in Section 5.1.2.1.

In Table 84, the internal rate of return could fluctuate to a greater extent above the mean due to system costs between 2014 and 2019. In 2020, however, the opposite was true:

IRR Variability due to System Cost and O&M and Degradation			
Year	**% Above/Below Central Estimate**	**System Cost⊙**	**O&M and Degradation❖**
2014	% above central estimate	5948.31%*	1355.26%*
	% below central estimate	-4249.25%*	-1561.42%*
2015	% above central estimate	477.27%	113.15%
	% below central estimate	-349.57%	-130.58%
2016	% above central estimate	227.69%	57.34%
	% below central estimate	-171.40%	-66.27%
2017	% above central estimate	130.72%	37.49%
	% below central estimate	-104.11%	-43.41%
2018	% above central estimate	77.08%	26.89%
	% below central estimate	-67.40%	-31.18%
2019	% above central estimate	45.57%	20.95%
	% below central estimate	-43.14%	-24.32%
2020	% above central estimate	18.16%	16.76%
	% below central estimate	-20.73%	-19.47%

Table Notes:

- ⊙Range from literature: Aanesen, Heck, and Pinner (2012), Ardani et al. (2013).
- ❖Range from literature: Branker et al. (2011), Di Francia (2013), Lowder et al. (2013), National Renewable Energy Laboratory (2013a), Zweibel (2010).
- "Central estimate" is the "average" internal rate of return value with zero variability
- *Values that are exceptional due to the central estimate being close to zero

Table 84. Percentage of internal rate of return variability due to system cost, as well as O&M and degradation for PV technology under the time-of-use tariff scenario.

IRR variability due to operations and maintenance costs, as well as degradation rates, was greater below the mean in each of the years 2014 through 2020. Over that same timeframe, IRR variability due to systems cost decreased in a more significant manner than variability due to O&M and degradation. Thus, an investor was faced with the prospect of higher IRR variability due to system costs in the years closer to 2014. If the investor deferred investment until a later year, they could expect less IRR variability due to systems cost and, consequently, less risk of the IRR fluctuating from the mean.

The ratio figures in Table 85 indicated that there was more variability due to system cost compared with O&M and degradation in each of the years 2014 to 2020. This ratio was largest at 4.39 above the mean in 2014, but by 2020 system cost variability was only 1.08 times greater than O&M and degradation variability above the mean:

Ratio of Variability due to System Cost to Variability due to O&M and Degradation		
Year	**Ratio Above/Below Central Estimate**	**Ratio**
2014	Ratio above central estimate	4.39
	Ratio below central estimate	2.72
2015	Ratio above central estimate	4.22
	Ratio below central estimate	2.68
2016	Ratio above central estimate	3.97
	Ratio below central estimate	2.59
2017	Ratio above central estimate	3.49
	Ratio below central estimate	2.40
2018	Ratio above central estimate	2.87
	Ratio below central estimate	2.16
2019	Ratio above central estimate	2.18
	Ratio below central estimate	1.77
2020	Ratio above central estimate	1.08
	Ratio below central estimate	1.06

Table Note:

- "Central estimate" is the "average" internal rate of return value with zero variability

Table 85. Ratio of variability due to system cost to variability due to O&M and degradation for PV technology under the time-of-use tariff scenario.

Accordingly, an investor could expect system cost and O&M plus degradation variability to have less of an impact on the internal rate of return for a project commencing operations in 2020 compared with a project beginning in 2014.

As per Table 86, IRR variability due to O&M and degradation ranged between 6.64 and 133.02 times greater than IRR variability due to energy yield:

Ratio of O&M and Degradation Variability to Energy Yield Variability				
Year	**Ratio Above/Below Central Estimate**	**Pessimistic Scenario**	**Average Scenario**	**Optimistic Scenario**
2014	Ratio above central estimate	975.04*	24.58	1267.63*
	Ratio below central estimate	1123.36*	28.31	1460.45*
2015	Ratio above central estimate	55.55	24.12	115.27
	Ratio below central estimate	64.11	27.84	133.02
2016	Ratio above central estimate	15.23	23.91	62.00
	Ratio below central estimate	17.61	27.64	71.67
2017	Ratio above central estimate	0.91*	21.94	43.38
	Ratio below central estimate	1.05*	25.40	50.23
2018	Ratio above central estimate	6.64	20.54	31.98
	Ratio below central estimate	7.70	23.82	37.07
2019	Ratio Above central estimate	11.76	19.52	25.51
	Ratio below central estimate	13.65	22.66	29.61
2020	Ratio above central estimate	14.35	16.22	19.60
	Ratio below central estimate	16.67	18.84	22.77

Table Note:

- "Central estimate" is the mean internal rate of return value from the Monte Carlo simulation
- *Values that are exceptional due to the central estimate being close to zero

Table 86. A comparison of how much more internal rate of return variability is due to O&M and degradation compared with energy yield for PV technology under the time-of-use tariff scenario.

Although the ratio values under the three pricing scenarios were widely different from one another in 2014, by 2020 they were all comparatively closer together indicating that the ratio of O&M and degradation variability to energy yield variability was much more similar regardless of pricing scenario in 2020 compared with 2014.

7.1.3 Concentrated Photovoltaic Technology

Turning to CPV, Figure 73 below shows the internal rates of return as well as the discount rates for concentrated photovoltaic technology under the three pricing scenarios. The three discount rates were defined in Table 19 in Section 4.2.

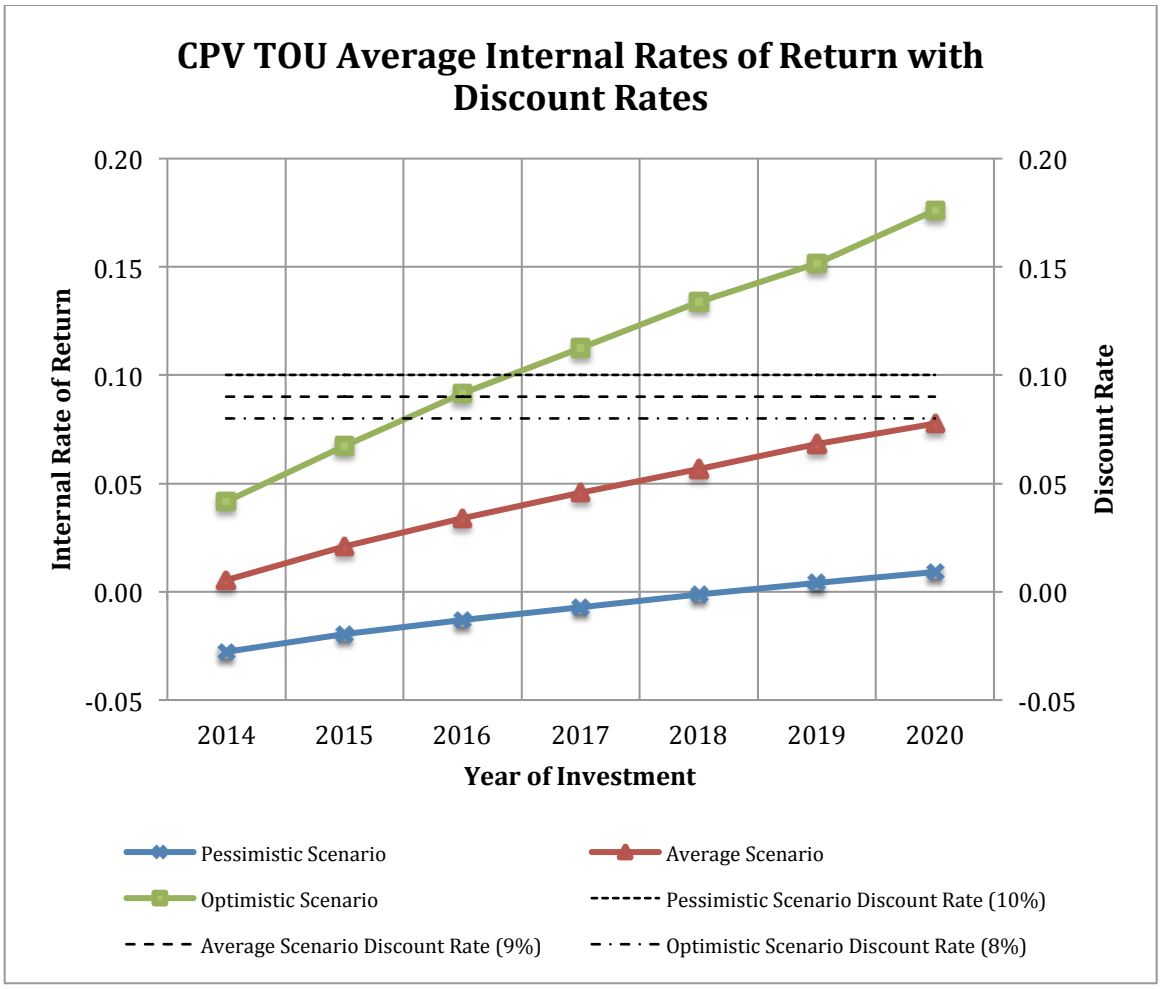


Figure 73. Average internal rates of return from the 250 Monte Carlo simulations under the time-of-use tariff scenario for CPV technology.

Figure 73 illustrated that, as expected, the CPV projects with the "optimistic" scenario costs had higher internal rates of return compared with CPV projects that had costs following the "average" and "pessimistic" pricing scenarios. The "optimistic" scenario in Figure 73, which was associated with a discount rate of 8%, crossed the 8% threshold in 2016. Referring back to the discounted NPV results from Figure 26 in Section 5.1.2.2, 2016 was also the year in which discounted net present values turned positive under the "optimistic" scenario. Thus, as anticipated, the IRR results for the "optimistic" scenario in this section were synched with the results from Section 5.1. This was also the case for the relationship between the "average" and "pessimistic" internal rates of return and discounted net present values.

Figure 73 also indicated that only CPV projects following the "optimistic" pricing scenario would become profitable. The "average" scenario came close to reaching the 9% discount rate in 2020, but ultimately was short. In order for a CPV project to realize profitability at the present time in 2014, the discount rate would have needed to be lower than 4.2% and this would have been possible only according to the "optimistic" costing scenario. At that same discount rate, the "average" scenario could have experienced profitability beginning in 2017. The "pessimistic" costing scenario was not a candidate for profitability during any of the years 2014 through 2020.

All three plots of internal rates of return in Figure 73 increased as time moved forward. However, the plot of internal rates of return under the "optimistic" pricing scenario increased at a steeper rate than the plots under the "average" and "pessimistic" pricing scenarios. To illustrate what this could mean to a prospective investor, consider, for example, an investor with a discount rate of 6%. If costs followed the "optimistic" pricing scenario then the internal rate of return on the CPV investment would exceed the discount rate in 2015. However, the same investor would need to wait until 2019 for the IRR to exceed the discount rate if CPV system costs followed the "average" pricing scenario.

7.1.4 Concentrated Photovoltaic Technology Variability Analysis

Using Equation (26) from Section 7.1.2, the following 95% internal rate of return confidence intervals were calculated:

Year	Pessimistic Scenario		Average Scenario		Optimistic Scenario	
	95% Lower CI Value	95% Upper CI Value	95% Lower CI Value	95% Upper CI Value	95% Lower CI Value	95% Upper CI Value
2014	-0.0286	-0.0268	0.0045	0.0063	0.0407	0.0425
2015	-0.0204	-0.0186	0.0199	0.0217	0.0663	0.0685
2016	-0.0140	-0.0120	0.0328	0.0349	0.0903	0.0931
2017	-0.0081	-0.0059	0.0446	0.0468	0.1110	0.1142
2018	-0.0023	-0.0001	0.0553	0.0579	0.1317	0.1359
2019	0.0030	0.0053	0.0667	0.0696	0.1490	0.1538
2020	0.0081	0.0104	0.0762	0.0792	0.1732	0.1790

Table 87. Internal rate of return 95% confidence intervals for CPV technology under the time-of-use tariff scenario.

The figures in Table 87 indicated that none of the 95% confidence intervals straddled into both negative and positive territory. The largest distance between a lower and upper value was 0.0057 under the "optimistic" scenario in 2020. This translated into the year in which there was the highest risk of the internal rate of return varying on account of energy yield variability. However, the value of 0.0057 was rather small, and given that all other 95% confidence interval ranges were less than this amount, the overall risk to IRR variability posed by fluctuating system output was minor.

Equation (27) from Section 7.1.2 was used to determine how close 95% of the internal rate of return data points generated by the Monte Carlo simulation were to the mean in each of the years 2014 to 2020. Those results are displayed in Table 88 below:

Internal Rate of Return Variability due to Energy Yield				
Year	**% Above/Below Central Estimate**	**Pessimistic Scenario**	**Average Scenario**	**Optimistic Scenario**
2014	% above central estimate	3.19%	16.47%*	2.18%
	% below central estimate	-3.19%	-16.47%*	-2.18%
2015	% above central estimate	4.66%	4.39%	1.64%
	% below central estimate	-4.66%	-4.39%	-1.64%
2016	% above central estimate	7.84%	3.09%	1.50%
	% below central estimate	-7.84%	-3.09%	-1.50%
2017	% above central estimate	15.82%	2.50%	1.39%
	% below central estimate	-15.82%	-2.50%	-1.39%
2018	% above central estimate	88.18%*	2.30%	1.59%
	% below central estimate	-88.18%*	-2.30%	-1.59%
2019	% above central estimate	27.97%	2.15%	1.56%
	% below central estimate	-27.97%	-2.15%	-1.56%
2020	% above central estimate	12.62%	1.97%	1.63%
	% below central estimate	-12.62%	-1.97%	-1.63%

Table Notes:

- "Central estimate" is the mean internal rate of return value from the Monte Carlo simulation
- The above figures represent variability as a proportion of the mean with 95% confidence
- *Values that are exceptional due to the central estimate being close to zero

Table 88. Percentage of internal rate of return variability due to energy yield for CPV technology under the time-of-use tariff scenario.

According to Table 88, 95% of the IRR data points were at most plus or minus 27.97% away from the mean. During years of profitable investment, 2016 to 2020 under the "optimistic" scenario, this same variability was at most plus or minus 1.63% on either side of the mean in the year 2020. Over all, however, the differences between variability as a proportion of the mean between 2016 and 2020 under the "optimistic" scenario in Table 88 were not large, meaning this may not have had a significant impact on the decision whether or not to invest in any of those years.

Table 89 illustrated IRR variability due to system cost as well as O&M and degradation variability under CPV technology:

IRR Variability due to Variability in System Cost and O&M and Degradation			
Year	**% Above/Below Central Estimate**	**System Cost⊙**	**O&M and Degradation❖**
2014	% above central estimate	669.50%*	232.14%*
	% below central estimate	-611.41%*	-265.89%*
2015	% above central estimate	224.89%	64.59%
	% below central estimate	-194.22%	-73.48%
2016	% above central estimate	170.95%	41.96%
	% below central estimate	-138.62%	-47.46%
2017	% above central estimate	146.02%	32.78%
	% below central estimate	-115.36%	-36.90%
2018	% above central estimate	136.18%	27.88%
	% below central estimate	-102.14%	-31.24%
2019	% above central estimate	122.10%	24.49%
	% below central estimate	-93.88%	-27.31%
2020	% above central estimate	126.56%	22.56%
	% below central estimate	-88.10%	-25.06%

Notes:

- ⊙Range from literature: Haysom et al. (2014).
- ❖Range from literature: Drury et al. (2013), Gerstmaier et al. (2014).
- "Central estimate" is the "average" internal rate of return value with zero variability
- *Values that are exceptional due to the central estimate being close to zero

Table 89. Percentage of internal rate of return variability due to system cost, as well as O&M and degradation for CPV technology under the time-of-use tariff scenario.

According to the figures in Table 89, the IRR could vary to a greater extent above the mean compared with below the mean on account of system cost variability. On the other hand, the IRR could vary more so below the mean than above due to variable O&M and degradation. For both system cost, and O&M and degradation, the magnitude of IRR variability was greater in 2014 than in 2020. This meant that a CPV project commencing operations in a year closer to 2014 could experience greater IRR variability compared with a CPV project beginning in a year closer to 2020 as a result of these two sources of variability.

The ratio figures in Table 90 indicated that IRR variability due to system cost was consistently greater than IRR variability due to O&M and degradation, since all of the values in the table were greater than "1:"

Ratio of Variability due to System Cost to Variability due to O&M and Degradation		
Year	**Ratio Above/Below Central Estimate**	**Ratio**
2014	Ratio above central estimate	2.88
	Ratio below central estimate	2.30
2015	Ratio above central estimate	3.48
	Ratio below central estimate	2.64
2016	Ratio above central estimate	4.07
	Ratio below central estimate	2.92
2017	Ratio above central estimate	4.45
	Ratio below central estimate	3.13
2018	Ratio above central estimate	4.88
	Ratio below central estimate	3.27
2019	Ratio above central estimate	4.99
	Ratio below central estimate	3.44
2020	Ratio above central estimate	5.61
	Ratio below central estimate	3.52

Table Note:

- "Central estimate" is the "average" internal rate of return value with zero variability

Table 90. Ratio of variability due to system cost to variability due to O&M and degradation for CPV technology under the time-of-use tariff scenario.

According to Table 91 and excluding any values marked with a *, IRR variability due to O&M and degradation was between 0.88 and 44.89 times greater than IRR variability due to energy yield:

Ratio of O&M and Degradation Variability to Energy Yield Variability				
Year	**Ratio Above/Below Central Estimate**	**Pessimistic Scenario**	**Average Scenario**	**Optimistic Scenario**
2014	Ratio above central estimate	72.74*	14.09*	106.54*
	Ratio below central estimate	83.31*	16.14*	122.02*
2015	Ratio above central estimate	13.86	14.73	39.46
	Ratio below central estimate	15.76	16.76	44.89
2016	Ratio above central estimate	5.35	13.58	28.05
	Ratio below central estimate	6.05	15.36	31.73
2017	Ratio above central estimate	2.07	13.13	23.64
	Ratio below central estimate	2.33	14.78	26.61
2018	Ratio above central estimate	0.32*	12.11	17.57
	Ratio below central estimate	0.35*	13.56	19.69
2019	Ratio above central estimate	0.88	11.41	15.68
	Ratio below central estimate	0.98	12.72	17.48
2020	Ratio above central estimate	1.79	11.43	13.84
	Ratio below central estimate	1.99	12.70	15.37

Table Note:

- "Central estimate" is the mean internal rate of return value from the Monte Carlo simulation
- *Values that are exceptional due to the central estimate being close to zero

Table 91. A comparison of the percentages of how much more internal rate of return variability is due to O&M and degradation compared with energy yield for CPV technology under the time-of-use tariff scenario.

The range of values in Table 91 included at least one value less than "1," meaning there was one point where IRR variability due to energy yield was greater than variability due to O&M and degradation. However, this was under the "pessimistic" scenario in 2019 where investment was not profitable. Had investment been possible in this year, extra scrutiny should have been applied before making a decision to invest since an uncontrollable source of variability, energy yield, had a greater impact on varying the internal rate of return than a partially controllable source of variability, O&M and degradation. In the next section, the IRR results from the feed-in tariff scenario will be analyzed.

7.2 Feed-in Tariff Scenario

7.2.1 Photovoltaic Technology

Under the feed-in tariff scenario, which saw the contracted rate paid for solar-produced electricity decrease as time moved forward, the plots of the average internal rates of return decreased between 2014 and 2020. This was in contrast to the time-of-use tariff scenario from Section 7.1, where electricity prices were projected to increase over time. Below, Figure 74 shows these declining IRR plots under PV technology:

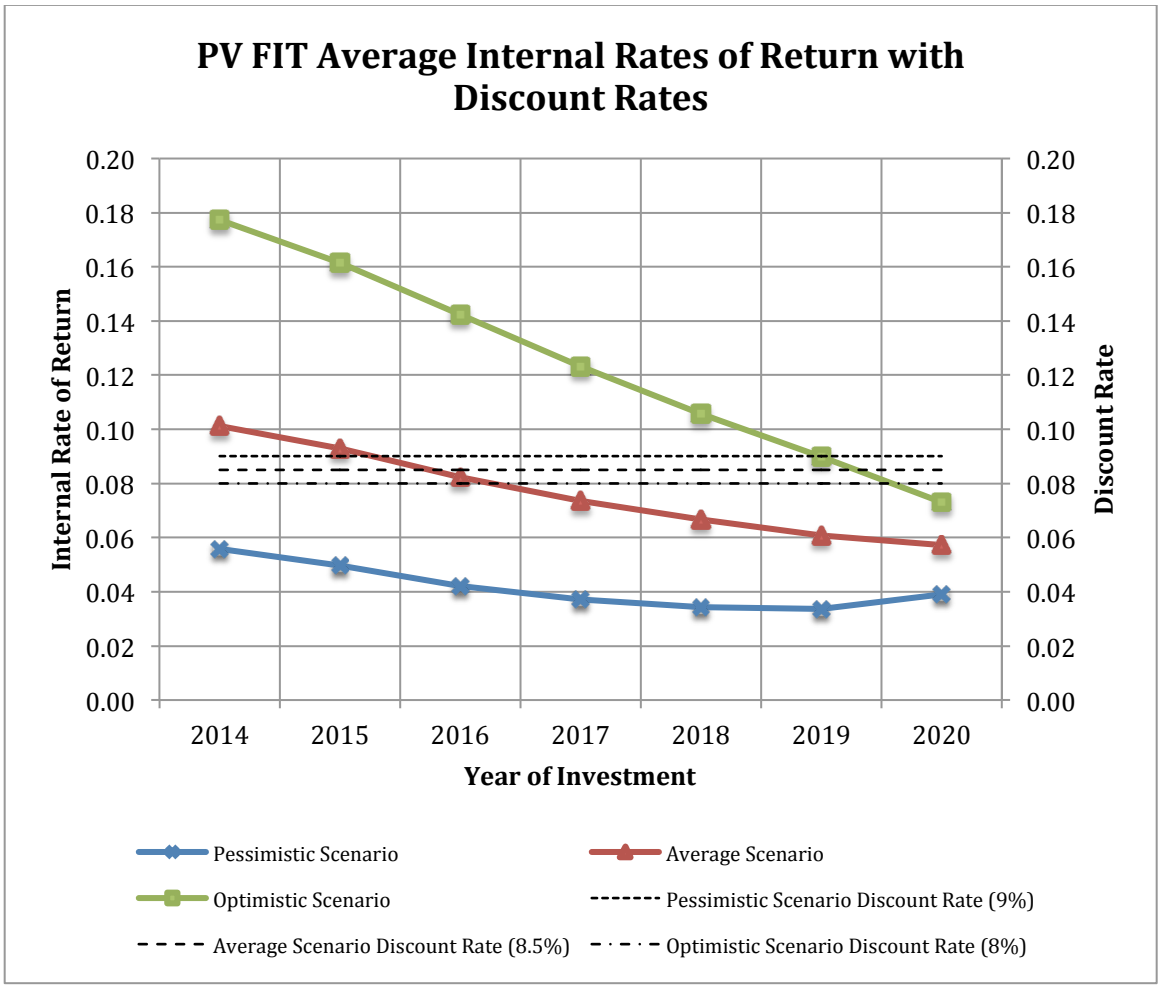


Figure 74. Average internal rates of return for PV projects under the feed-in tariff scenario for the years 2014 to 2020. The discount rates have been included as well.

Unlike the PV results from the time-of-use scenario, the internal rates of return in Figure 74 were all greater than zero. However, this did not mean that all PV projects

with a FIT contract were profitable. According to Figure 74, only PV projects following the "optimistic" and "average" pricing scenarios experienced profitability. Under the "average" scenario, the internal rate of return crossed below the 8.5% discount rate in the year 2016. This meant that if PV systems were subject to this scenario's costs a prospective investor should secure a FIT contract prior to 2016. For the "optimistic" costing scenario, the plot of internal rates of return did not cross the 8% discount rate threshold until 2020. Under this scenario, an investor had more years to choose from where an investment in a PV system would be profitable. Generally speaking, the internal rates of return in Figure 74 indicated that an investor should secure a FIT contract and commence PV system operations sooner rather than later in order to benefit from the highest internal rate of return possible.

Although Figure 74 indicated that the "pessimistic" pricing scenario did not realize any IRR values in excess of the 9% discount rate, a hypothetical discount rate of 4% would have meant that the "pessimistic" scenario was profitable in the years 2014 through 2016. Both the "average" and "optimistic" pricing scenarios would have been profitable for each of the years 2014 through 2020 with a discount rate of 4%. In Figure 74, the three IRR plots had a negative slope over time. The "optimistic" plot was more linear in nature compared with the "average" and "pessimistic" IRR plots, which had a slight curve to them in later years.

Compared with the time-of-use results, the feed-in tariff results showed overall better internal rates of return. For instance, the highest IRR under the TOU tariff scenario was 10% under the "optimistic" costing scenario. Under the FIT scenario, the highest internal rate of return was 17.7% under the "optimistic" pricing scenario. Of course, a PV system operator could always choose to generate value from offsetting under the TOU tariff scenario as opposed to generating revenue under the FIT scenario. In the years 2019 and 2020, for instance, the internal rate of return was higher under the TOU tariff scenario compared with the FIT scenario. For PV projects commencing in those two particular years, offsetting time-of-use

tariffs provided a higher internal rate of return. However, if a company was required to initiate a solar installation project at some point prior to 2019, a feed-in tariff provided a higher internal rate of return.

7.2.2 Photovoltaic Technology Variability Analysis

The 95% IRR confidence intervals, which define IRR variability due to fluctuating energy yields, are shown below in Table 92. The values were calculated using Equation (26) from Section 7.1.2.

Year	Pessimistic Scenario		Average Scenario		Optimistic Scenario	
	95% Lower CI Value	95% Upper CI Value	95% Lower CI Value	95% Upper CI Value	95% Lower CI Value	95% Upper CI Value
2014	0.0551	0.0566	0.1002	0.1021	0.1759	0.1785
2015	0.0491	0.0504	0.0921	0.0938	0.1601	0.1627
2016	0.0415	0.0427	0.0814	0.0831	0.1411	0.1436
2017	0.0365	0.0378	0.0726	0.0743	0.1219	0.1244
2018	0.0337	0.0350	0.0659	0.0676	0.1044	0.1069
2019	0.0330	0.0343	0.0598	0.0615	0.0886	0.0911
2020	0.0384	0.0397	0.0564	0.0581	0.0717	0.0743

Table 92. Internal rate of return 95% confidence intervals for PV technology under the feed-in tariff scenario.

According to the figures in the above table, the 95% confidence interval above and below the mean in 2014 under the "optimistic" scenario was the widest. Taking into account that the mean IRR in that year was 17.72%, the upper 95% CI value of 17.85% and the lower 95% CI value of 17.59% in 2014 under the "optimistic" pricing scenario do not seem especially far off from the mean. Thus, even though the internal rate of return could have varied above or below the mean more so in this particular year than under any other pricing scenario and any other year, the magnitude of variability defined by the 95% confidence interval indicated that IRR variability risk was low over all.

The values in Table 93 below, which were calculated using Equation (27) from Section 7.1.2, indicate the spread of 95% of the IRR data points generated by the Monte Carlo simulation in relation to the mean:

Internal Rate of Return Variability due to Energy Yield				
Year	**% Above/Below Central Estimate**	**Pessimistic Scenario**	**Average Scenario**	**Optimistic Scenario**
2014	% above central estimate	1.31%	0.91%	0.74%
	% below central estimate	-1.31%	-0.91%	-0.74%
2015	% above central estimate	1.23%	0.91%	0.78%
	% below central estimate	-1.23%	-0.91%	-0.78%
2016	% above central estimate	1.45%	1.03%	0.89%
	% below central estimate	-1.45%	-1.03%	-0.89%
2017	% above central estimate	1.65%	1.16%	1.03%
	% below central estimate	-1.65%	-1.16%	-1.03%
2018	% above central estimate	1.78%	1.27%	1.20%
	% below central estimate	-1.78%	-1.27%	-1.20%
2019	% above central estimate	1.82%	1.40%	1.41%
	% below central estimate	-1.82%	-1.40%	-1.41%
2020	% above central estimate	1.57%	1.48%	1.73%
	% below central estimate	-1.57%	-1.48%	-1.73%

Table Notes:

- "Central estimate" is the mean internal rate of return value from the Monte Carlo simulation
- The above figures represent variability as a proportion of the mean with 95% confidence
- *Values that are exceptional due to the central estimate being close to zero

Table 93. Percentage of internal rate of return variability due to energy yield for PV technology under the feed-in tariff scenario.

As per Table 93, 95% of the simulated IRR values were within plus or minus 1.82% of the mean at most. This percentage value meant that energy yield did not have a significant impact on IRR variability. Table 93 also indicated that IRR variability due to energy yield generally increased as time progressed towards 2020.

In Table 94, the magnitude of IRR variability due to system cost generally decreased between 2014 and 2020. For O&M and degradation, the magnitude increased over the same timeframe:

IRR Variability due to System Cost and O&M and Degradation			
Year	**% Above/Below Central Estimate**	**System Cost⊙**	**O&M and Degradation❖**
2014	% above central estimate	75.27%	7.84%
	% below central estimate	-44.77%	-7.88%
2015	% above central estimate	73.68%	9.13%
	% below central estimate	-46.41%	-9.36%
2016	% above central estimate	72.97%	11.19%
	% below central estimate	-48.86%	-11.75%
2017	% above central estimate	67.49%	13.79%
	% below central estimate	-49.44%	-14.84%
2018	% above central estimate	58.27%	16.94%
	% below central estimate	-48.57%	-18.71%
2019	% above central estimate	47.98%	21.05%
	% below central estimate	-44.53%	-23.89%
2020	% above central estimate	27.62%	25.68%
	% below central estimate	-31.72%	-30.01%

Table Notes:

- ⊙Range from literature: Aanesen, Heck, and Pinner (2012), Ardani et al. (2013).
- ❖Range from literature: Branker et al. (2011), Di Francia (2013), Lowder et al. (2013), National Renewable Energy Laboratory (2013a), Zweibel (2010).
- "Central estimate" is the "average" internal rate of return value with zero variability
- *Values that are exceptional due to the central estimate being close to zero

Table 94. Percentage of internal rate of return variability due to system cost, as well as O&M and degradation for PV technology under the feed-in tariff scenario.

The percentages from these two distinct sources of variability were remarkably similar in 2020 despite the different directions in trend over time. According to the ratio figures in Table 95, variability due to system cost was always greater than variability due to O&M and degradation in each of the years 2014 through 2020:

Ratio of Variability due to System Cost to Variability due to O&M and Degradation		
Year	**Ratio Above/Below Central Estimate**	**Ratio**
2014	Ratio above central estimate	9.60
	Ratio below central estimate	5.68
2015	Ratio above central estimate	8.07
	Ratio below central estimate	4.96
2016	Ratio above central estimate	6.52
	Ratio below central estimate	4.16
2017	Ratio above central estimate	4.89
	Ratio below central estimate	3.33
2018	Ratio above central estimate	3.44
	Ratio below central estimate	2.60
2019	Ratio above central estimate	2.28
	Ratio below central estimate	1.86
2020	Ratio above central estimate	1.08
	Ratio below central estimate	1.06

Table Note:

- "Central estimate" is the "average" internal rate of return value with zero variability

Table 95. Ratio of variability due to system cost to variability due to O&M and degradation for PV technology under the feed-in tariff scenario.

However, this ratio of variability decreased over time to the point where the ratio values were both nearly one in 2020 meaning that these two sources of variability had approximately the same affect on IRR variability in later years. Although higher profitability was associated with projects commencing operations in earlier years, an investor would have to assess the higher IRR risks found in 2014 compared with 2020 as part of a decision whether or not to invest.

In Table 96, IRR variability due to O&M and degradation was between 5.98 times and 20.21 times greater than IRR variability due to energy yield fluctuations:

Ratio of O&M and Degradation Variability to Energy Yield Variability				
Year	**Ratio Above/Below Central Estimate**	**Pessimistic Scenario**	**Average Scenario**	**Optimistic Scenario**
2014	Ratio above central estimate	5.98	8.61	10.65
	Ratio below central estimate	6.01	8.65	10.70
2015	Ratio above central estimate	7.43	9.99	11.66
	Ratio below central estimate	7.61	10.24	11.95
2016	Ratio above central estimate	7.71	10.84	12.61
	Ratio below central estimate	8.09	11.38	13.24
2017	Ratio above central estimate	8.38	11.92	13.44
	Ratio below central estimate	9.02	12.83	14.46
2018	Ratio above central estimate	9.52	13.31	14.17
	Ratio below central estimate	10.52	14.70	15.65
2019	Ratio above central estimate	11.59	15.03	14.96
	Ratio below central estimate	13.15	17.06	16.98
2020	Ratio above central estimate	16.41	17.30	14.84
	Ratio below central estimate	19.17	20.21	17.34

Table Note:

- "Central estimate" is the mean internal rate of return value from the Monte Carlo simulation
- *Values that are exceptional due to the central estimate being close to zero

Table 96. A comparison of how much more internal rate of return variability is due to O&M and degradation compared with energy yield for PV technology under the feed-in tariff scenario.

This meant that operations and maintenance costs, as well as degradation rates, had a larger impact on the internal rate of return than energy yield variability regardless of when an investment was made. Over time, the ratio values under each of the three pricing scenarios increased, with the figures from the "average" scenario eventually overtaking those from the "optimistic" and "pessimistic" scenarios.

7.2.3 Concentrated Photovoltaic Technology

Over all, the internal rates of return figures under CPV technology followed the trend of the PV IRR values from Section 7.2.1. In 2014, the CPV internal rate of return values were higher compared with those in 2020 under each of the "pessimistic," "average," and "optimistic" pricing scenarios. Below, Figure 75 provides a look at the plots of these internal rates of return:

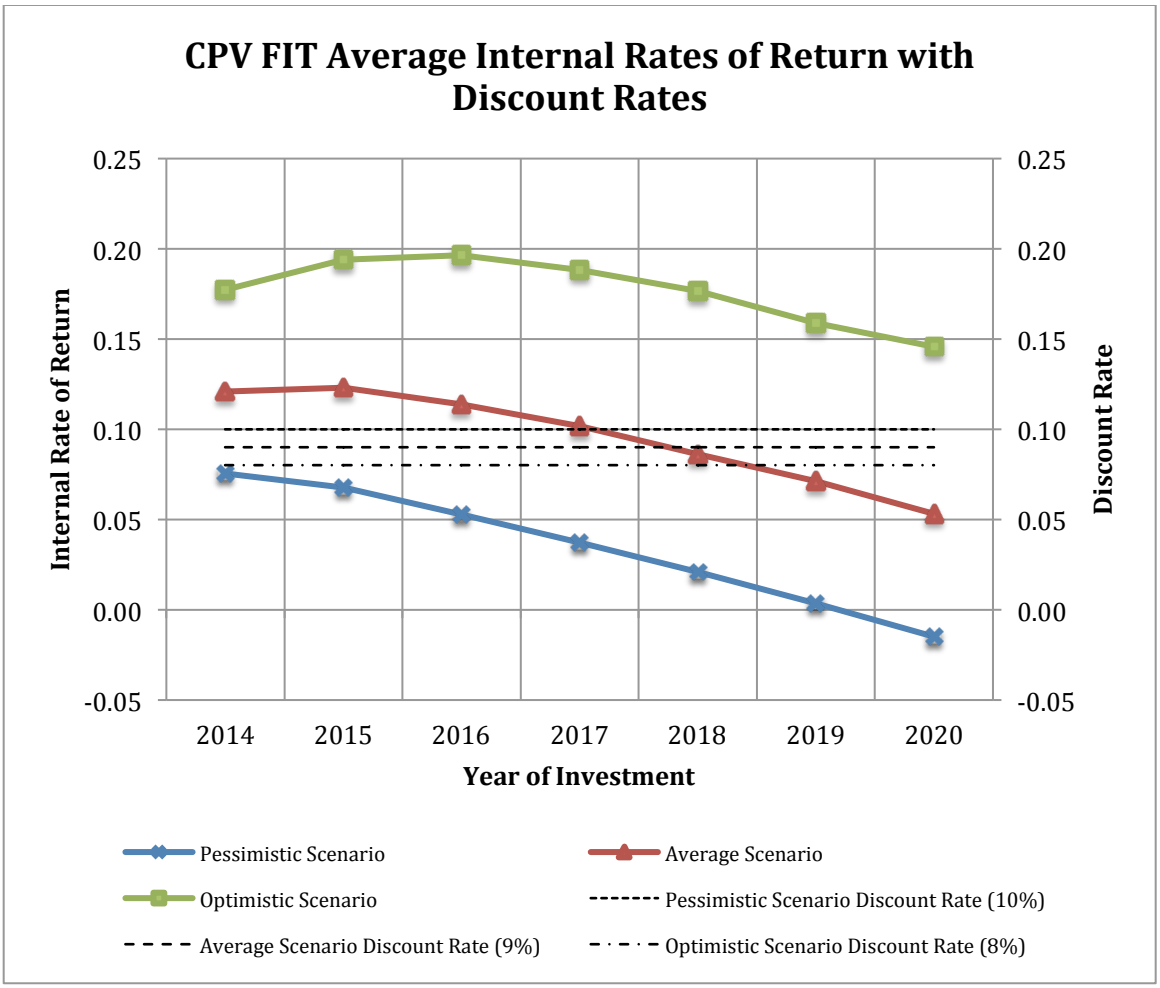


Figure 75. The average internal rate of return values for PV technology under the feed-in tariff scenario with discount rates for comparison.

In Figure 75, the internal rates of return under the "average" and "optimistic" scenarios actually increased before decreasing to their lowest values in 2020. The "optimistic" IRR plot had a distinct uptrend until 2016, and the "average" IRR plot had a slight uptrend between 2014 and 2015. Thus, these two plots could be considered as "peaked." The highest IRR under the "optimistic" scenario was 19.6% in 2016, while the highest IRR under the "average" scenario was 12.3% in 2015. As expected, these peaks exactly matched the uppermost values from the discounted NPV results in Figure 36 in Section 5.2.2.3. This was the first instance where a scenario – in Figure 75 it was the "optimistic" scenario – had internal rates of return that exceeded the associated discount rate in each of the years 2014 through 2020.

The highest CPV internal rate of return value under each of the three scenarios shown in Figure 75 was greater than the highest CPV IRR from the "pessimistic," "average," and "optimistic" pricing scenarios under the time-of-use pricing scenario. Thus, with concentrated photovoltaic technology, higher internal rates of return were achievable by selling solar-produced electricity under a FIT contract compared with using solar electricity to offset time-of-use electricity charges.

The lowest discount rate in Figure 75 was 8% under the "optimistic" pricing scenario. At that particular rate, nearly all three costing scenarios were profitable in 2014. However, the 7.6% internal rate of return associated with the "pessimistic" scenario in that year was 0.4% below the lowest 8% discount rate. Had the lowest discount rate been 5%, for example, then the "optimistic" scenario would have still been profitable in each of the years 2014 through 2020, the "average" scenario would have gained the distinction of being profitable from 2014 to 2020, and the "pessimistic" scenario would have seen profitability in the years 2014, 2015, and 2016.

7.2.4 Concentrated Photovoltaic Technology Variability Analysis

The 95% IRR confidence intervals for CPV technology are shown in Table 97 below:

Year	Pessimistic Scenario		Average Scenario		Optimistic Scenario	
	95% Lower CI Value	95% Upper CI Value	95% Lower CI Value	95% Upper CI Value	95% Lower CI Value	95% Upper CI Value
2014	0.0741	0.0771	0.1192	0.1228	0.1748	0.1798
2015	0.0663	0.0694	0.1210	0.1249	0.1916	0.1967
2016	0.0515	0.0543	0.1118	0.1159	0.1934	0.1994
2017	0.0360	0.0387	0.0997	0.1035	0.1857	0.1913
2018	0.0196	0.0221	0.0847	0.0879	0.1740	0.1792
2019	0.0023	0.0049	0.0697	0.0729	0.1565	0.1611
2020	-0.0161	-0.0136	0.0516	0.0547	0.1435	0.1479

Table 97. Internal rate of return 95% confidence intervals on either side of the mean for CPV technology under the feed-in tariff scenario.

The figures in the above table were calculated using Equation (27) from Section 7.1.2. According to Table 97, the widest 95% confidence interval was found in 2016 under the "optimistic" scenario. This was of interest to a prospective CPV investor, since the internal rates of return found under the "optimistic" scenario were the highest. However, even under this widest confidence interval an investor could expect an internal rate of return between 19.34% and 19.94% 19 times out of 20. In a sense, the highest risk of IRR variability in 2016 under the "optimistic" pricing scenario was not exactly a significant amount of risk.

Continuing with the variability analysis, Equation (27) in Section 7.1.2 was used to calculate the lower and upper limit, percentage-wise, of where 95% of the data points generated during the Monte Carlo simulation fell with respect to the mean for each of the years 2014 to 2020:

Internal Rate of Return Variability due to Energy Yield				
Year	**% Above/Below Central Estimate**	**Pessimistic Scenario**	**Average Scenario**	**Optimistic Scenario**
2014	% above central estimate	1.95%	1.45%	1.42%
	% below central estimate	-1.95%	-1.45%	-1.42%
2015	% above central estimate	2.22%	1.60%	1.31%
	% below central estimate	-2.22%	-1.60%	-1.31%
2016	% above central estimate	2.65%	1.81%	1.53%
	% below central estimate	-2.65%	-1.81%	-1.53%
2017	% above central estimate	3.61%	1.86%	1.49%
	% below central estimate	-3.61%	-1.86%	-1.49%
2018	% above central estimate	5.88%	1.81%	1.48%
	% below central estimate	-5.88%	-1.81%	-1.48%
2019	% above central estimate	35.77%*	2.21%	1.45%
	% below central estimate	-35.77%*	-2.21%	-1.45%
2020	% above central estimate	8.44%	2.89%	1.51%
	% below central estimate	-8.44%	-2.89%	-1.51%

Table Notes:

- "Central estimate" is the mean internal rate of return value from the Monte Carlo simulation
- The above figures represent variability as a proportion of the mean with 95% confidence
- *Values that are exceptional due to the central estimate being close to zero

Table 98. Percentage of internal rate of return variability due to energy yield for CPV technology under the feed-in tariff scenario.

Excluding the two outliers in Table 98, 95% of the internal rates of return values were within plus or minus 8.44% of the mean at the most. This particular value of 8.44% occurred in 2020 under the "pessimistic" scenario. Generally speaking, IRR variability due to energy yield increased as time progressed from 2014 to 2020, implying that there was greater risk from this source of variability for project commencing in later years compared with those beginning operations in earlier years.

Comparatively, system cost, as well as O&M and degradation, had a larger impact on the internal rate of return. In Table 99, the internal rate of return could have varied by at most 174.27% away from the mean as a result of system cost variability:

IRR Variability due to System Cost and O&M and Degradation			
Year	**% Above/Below Central Estimate**	**System Cost[⊙]**	**O&M and Degradation[✣]**
2014	% above central estimate	46.45%	7.36%
	% below central estimate	-37.49%	-7.63%
2015	% above central estimate	58.01%	8.23%
	% below central estimate	-44.76%	-8.56%
2016	% above central estimate	72.48%	10.01%
	% below central estimate	-53.48%	-10.47%
2017	% above central estimate	85.46%	12.60%
	% below central estimate	-63.23%	-13.29%
2018	% above central estimate	104.40%	16.60%
	% below central estimate	-75.80%	-17.71%
2019	% above central estimate	122.54%	22.74%
	% below central estimate	-94.91%	-24.63%
2020	% above central estimate	174.27%	34.53%
	% below central estimate	-127.93%	-38.22%

Notes:

- [⊙]Range from literature: Haysom et al. (2014).
- [✣]Range from literature: Drury et al. (2013), Gerstmaier et al. (2014).
- "Central estimate" is the "average" internal rate of return value with zero variability
- *Values that are exceptional due to the central estimate being close to zero

Table 99. Percentage of internal rate of return variability due to system cost, as well as O&M and degradation for CPV technology under the feed-in tariff scenario.

For O&M and degradation, IRR was at most 38.22% away from the mean value. The magnitude of variability in Table 99 above and below the mean increased between

2014 and 2020, although system cost variability was consistently larger than O&M and degradation variability. The ratios in Table 100 proved this point and indicated that there was greater IRR variability potential above the mean compared with below the mean:

Ratio of Variability due to System Cost to Variability due to O&M and Degradation		
Year	**Ratio Above/Below Central Estimate**	**Ratio**
2014	Ratio above central estimate	6.31
	Ratio below central estimate	4.91
2015	Ratio above central estimate	7.05
	Ratio below central estimate	5.23
2016	Ratio above central estimate	7.24
	Ratio below central estimate	5.11
2017	Ratio above central estimate	6.78
	Ratio below central estimate	4.76
2018	Ratio above central estimate	6.29
	Ratio below central estimate	4.28
2019	Ratio above central estimate	5.39
	Ratio below central estimate	3.85
2020	Ratio above central estimate	5.05
	Ratio below central estimate	3.35

Table Note:

- "Central estimate" is the "average" internal rate of return value with zero variability

Table 100. Ratio of variability due to system cost compared with variability due to O&M and degradation for CPV technology under the feed-in tariff scenario.

In terms of quantifying how much greater IRR variability due to O&M and degradation was compared with variability due to energy yield, Table 101 provided this data. Excluding the values in 2019 under the "pessimistic" scenario because they were calculated using outlier values from Table 98, variability due to O&M and degradation was between 2.82 and 25.24 times greater than variability due to energy yield:

Ratio of O&M and Degradation Variability to Energy Yield Variability				
Year	**Ratio Above/Below Central Estimate**	**Pessimistic Scenario**	**Average Scenario**	**Optimistic Scenario**
2014	Ratio above central estimate	3.78	5.08	5.20
	Ratio below central estimate	3.92	5.27	5.39
2015	Ratio above central estimate	3.71	5.15	6.27
	Ratio below central estimate	3.86	5.36	6.53
2016	Ratio above central estimate	3.77	5.52	6.54
	Ratio below central estimate	3.95	5.78	6.84
2017	Ratio above central estimate	3.48	6.76	8.48
	Ratio below central estimate	3.68	7.13	8.94
2018	Ratio above central estimate	2.82	9.18	11.24
	Ratio below central estimate	3.01	9.79	12.00
2019	Ratio above central estimate	0.64*	10.30	15.64
	Ratio below central estimate	0.69*	11.16	16.95
2020	Ratio above central estimate	4.09	11.96	22.80
	Ratio below central estimate	4.53	13.24	25.24

Table Note:

- "Central estimate" is the mean internal rate of return value from the Monte Carlo simulation
- *Values that are exceptional due to the central estimate being close to zero

Table 101. A comparison of how much more internal rate of return variability is due to O&M and degradation compared with energy yield for CPV technology under the feed-in tariff scenario.

Between 2014 and 2020, the ratio values under the "optimistic" pricing scenario saw the steepest increase, followed by the ratio values under the "average" pricing scenario. The "pessimistic" scenario ratio values were fairly stable over this timeframe, experiencing only a slight overall increase between 2014 and 2020. In the next section, the IRR analysis will shift to the power purchase agreement tariff scenario.

7.3 Power Purchase Agreement Tariff Scenario

7.3.1 Photovoltaic Technology

According to the results in Section 5.3, the power purchase agreement tariff scenario was the first instance where all three costing scenarios yielded positive discounted net present values in the same year. This happened in the years 2019 and 2020 according to Figure 45 in Section 5.3.2.1. As such, the plots of internal

rates of return for each of the "pessimistic," "average," and "optimistic" pricing scenarios were expected to exceed the three dashed lines representing discount rates in 2019 and 2020. Below, Figure 76 provides confirmation that all three plots are greater than their associated discount rates during those two particular years:

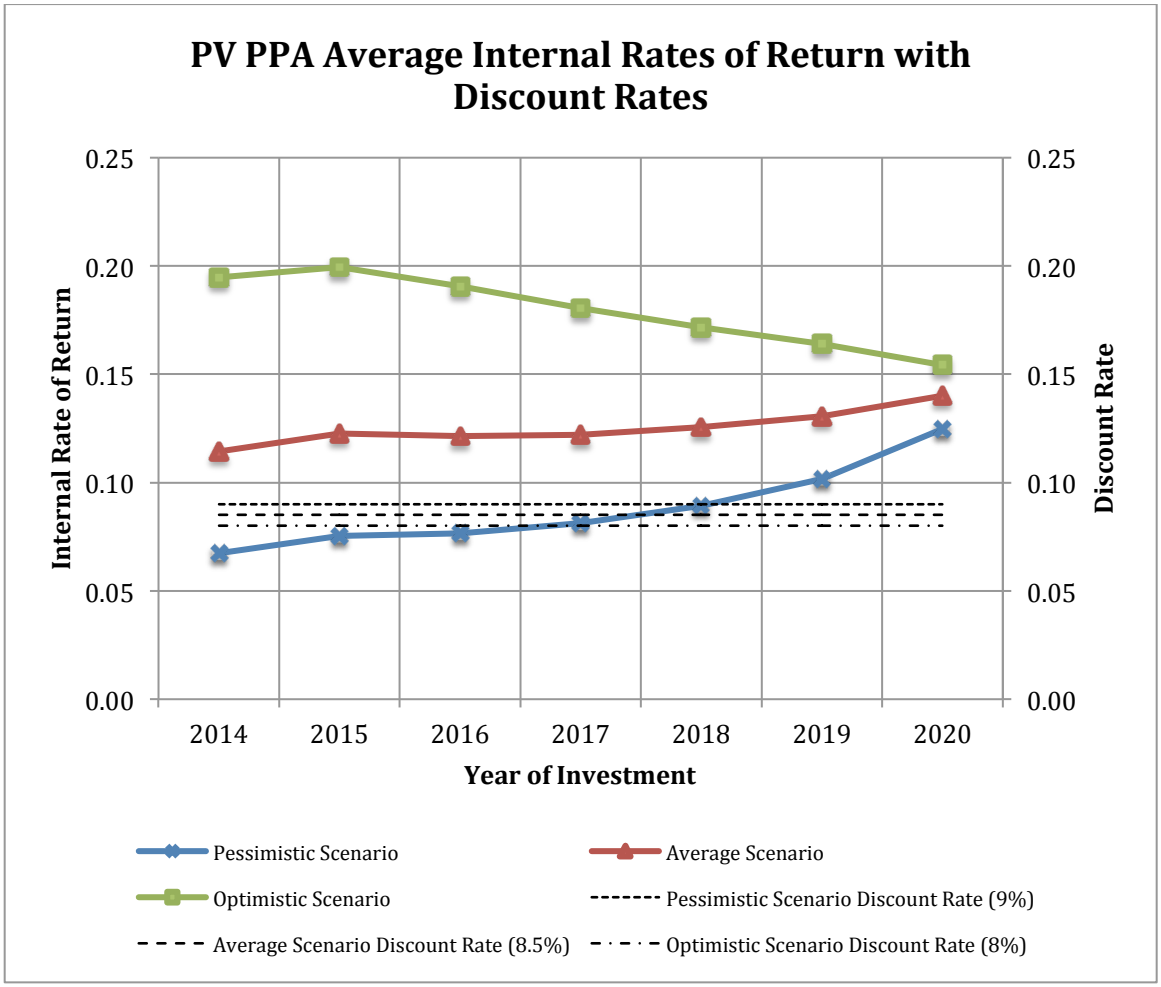


Figure 76. Internal rate of return plots for the "pessimistic," "average," and "optimistic" pricing scenarios for PV technology under the power purchase agreement tariff scenario.

As anticipated, all three IRR plots exceeded their associated discount rate in the years 2019 and 2020 according to Figure 76. The shapes of the IRR plots in Figure 76 were different for each of the three pricing scenarios: the "optimistic" IRR plot increased between 2014 and 2015, but then decreased afterwards; the "average" plot rose between 2014 and 2015, declined between 2015 and 2016, and then increased afterwards; and the "pessimistic" plot increased between 2014 and 2020. The "optimistic" IRR plot was favourable towards projects with higher discount

rates in the years closer to 2014 compared with 2020, while the opposite was true for the "pessimistic" costing scenario's IRR plot. Had the discount rate been set below 6.7%, all three scenarios would have experienced profitability during each of the years 2014 through 2020. However, under current discount rate values, only the internal rates of return from the "average" and "optimistic" scenarios were above their respective discount rates for the entire seven-year period.

Compared with the time-of-use and feed-in tariff scenarios, the power purchase agreement tariff scenario had the highest observed IRR thus far. This value, 19.9%, was recorded in the year 2015 under the "optimistic" pricing scenario. In contrast, the highest IRR value from FIT section was 17.7% in 2014 under the "optimistic" scenario, while the highest value from the TOU section was 10.0% in the year 2020 under the PV "optimistic" scenario. This indicated that the power purchase agreement was, thus far, the best way to generate value from solar-produced electricity.

7.3.2 Photovoltaic Technology Variability Analysis

According to Figure 76, the internal rates of return from the three pricing scenarios somewhat converged in the year 2020. In that year, the "pessimistic" IRR was 12.5%, the "average" IRR was 14.0%, and the "optimistic" IRR was 15.4%. Given that PV system energy output was variable, these internal rates of return may have been able to fluctuate enough so that the "optimistic" scenario did not have the highest IRR, or the "pessimistic" scenario did not have the lowest IRR, for example. To investigate this further, 95% IRR confidence intervals were calculated using Equation (26) from Section 7.1.2. Table 102 below provides the confidence interval figures:

Year	Pessimistic Scenario		Average Scenario		Optimistic Scenario	
	95% Lower CI Value	95% Upper CI Value	95% Lower CI Value	95% Upper CI Value	95% Lower CI Value	95% Upper CI Value
2014	0.0665	0.0680	0.1134	0.1153	0.1931	0.1961
2015	0.0746	0.0763	0.1215	0.1236	0.1979	0.2008
2016	0.0758	0.0773	0.1204	0.1223	0.1893	0.1920
2017	0.0804	0.0822	0.1211	0.1231	0.1792	0.1819
2018	0.0884	0.0901	0.1246	0.1267	0.1703	0.1730
2019	0.1006	0.1025	0.1295	0.1317	0.1627	0.1652
2020	0.1236	0.1257	0.1389	0.1411	0.1530	0.1554

Table 102. Internal rate of return 95% confidence intervals for PV technology under the power purchase agreement tariff scenario.

Focusing on the year 2020, Table 102 indicated that the 95% confidence intervals were not close to overlapping. Thus, it was unlikely that the "optimistic" scenario would not have the highest IRR, or the "pessimistic" scenario would not have the lowest IRR in that year. Table 102 also indicated that the 95% confidence interval was widest in 2014 under the "optimistic" scenario compared with all other years and pricing scenarios. However, 95 times out of 100 the internal rate of return in that year would be between 19.31% and 19.61%, which in all likelihood represented a narrow range of possible values to most potential investors.

In the next table, a measure of how close 95% of the internal rate of return values generated by the Monte Carlo simulation is to the mean is presented:

Internal Rate of Return Variability due to Energy Yield				
Year	**% Above/Below Central Estimate**	**Pessimistic Scenario**	**Average Scenario**	**Optimistic Scenario**
2014	% above central estimate	1.12%	0.82%	0.77%
	% below central estimate	-1.12%	-0.82%	-0.77%
2015	% above central estimate	1.07%	0.88%	0.74%
	% below central estimate	-1.07%	-0.88%	-0.74%
2016	% above central estimate	0.98%	0.78%	0.72%
	% below central estimate	-0.98%	-0.78%	-0.72%
2017	% above central estimate	1.06%	0.82%	0.74%
	% below central estimate	-1.06%	-0.82%	-0.74%
2018	% above central estimate	0.98%	0.84%	0.78%
	% below central estimate	-0.98%	-0.84%	-0.78%
2019	% above central estimate	0.92%	0.82%	0.76%
	% below central estimate	-0.92%	-0.82%	-0.76%
2020	% above central estimate	0.84%	0.79%	0.80%
	% below central estimate	-0.84%	-0.79%	-0.80%

Table Notes:

- "Central estimate" is the mean internal rate of return value from the Monte Carlo simulation
- The above figures represent variability as a proportion of the mean with 95% confidence
- *Values that are exceptional due to the central estimate being close to zero

Table 103. Percentage of internal rate of return variability due to energy yield for PV technology under the power purchase agreement tariff scenario.

Table 103 illustrated that with energy yield variability 95% of the IRR values were at most plus or minus 1.12% on either side of the mean. This was the smallest proportional variability value calculated thus far in this analysis, and looking at all of the values in Table 103 indicated that IRR variability due to energy yield under PV technology and the power purchase agreement tariff scenario was consistently miniscule. In all likelihood, the figures in the above table alone were too similar to differentiate one year and one pricing scenario as a particularly better investment opportunity than the others.

Turning to other sources that impacted the internal rate of return, variability due to system cost diminished between 2014 and 2020, while IRR variability due to O&M and degradation increased overall during that same timeframe:

IRR Variability due to System Cost and O&M and Degradation			
Year	**% Above/Below Central Estimate**	**System Cost⊙**	**O&M and Degradation❖**
2014	% above central estimate	70.17%	6.84%
	% below central estimate	-41.20%	-6.81%
2015	% above central estimate	62.68%	6.70%
	% below central estimate	-38.40%	-6.74%
2016	% above central estimate	57.17%	7.22%
	% below central estimate	-36.90%	-7.39%
2017	% above central estimate	47.81%	7.72%
	% below central estimate	-33.49%	-8.04%
2018	% above central estimate	36.52%	8.18%
	% below central estimate	-28.96%	-8.66%
2019	% above central estimate	25.47%	8.66%
	% below central estimate	-22.25%	-9.33%
2020	% above central estimate	10.15%	9.04%
	% below central estimate	-10.92%	-9.91%

Table Notes:

- ⊙Range from literature: Aanesen, Heck, and Pinner (2012), Ardani et al. (2013).
- ❖Range from literature: Branker et al. (2011), Di Francia (2013), Lowder et al. (2013), National Renewable Energy Laboratory (2013a), Zweibel (2010).
- "Central estimate" is the "average" internal rate of return value with zero variability
- *Values that are exceptional due to the central estimate being close to zero

Table 104. Percentage of internal rate of return variability due to system cost, as well as O&M and degradation for PV technology under the power purchase agreement tariff scenario.

The magnitude of the change in the values shown in Table 104 between 2014 and 2020 was much larger for system cost compared with O&M and degradation. Nevertheless, by 2020 the amount of IRR variability due to system cost was similar to the amount of IRR variability due to O&M and degradation. An investor looking to avoid higher IRR variability would be wise to defer investment until closer to 2020, when system cost had less of an impact on the variability of internal rate of return. However, this would have to be balanced against rising variability due to O&M and degradation, which was highest in 2020. Since profitability was observed in different years under the three different pricing scenarios according to Figure 76, investors had several different attractive investment options to choose from under the PPA tariff scenario.

The ratios of system cost variability to O&M and degradation variability in Table 105 indicated that IRR variability due to system cost was consistently larger than that from O&M and degradation:

Ratio of Variability due to System Cost to Variability due to O&M and Degradation		
Year	**Ratio Above/Below Central Estimate**	**Ratio**
2014	Ratio above central estimate	10.26
	Ratio below central estimate	6.05
2015	Ratio above central estimate	9.36
	Ratio below central estimate	5.70
2016	Ratio above central estimate	7.92
	Ratio below central estimate	5.00
2017	Ratio above central estimate	6.19
	Ratio below central estimate	4.17
2018	Ratio above central estimate	4.47
	Ratio below central estimate	3.34
2019	Ratio above central estimate	2.94
	Ratio below central estimate	2.39
2020	Ratio above central estimate	1.12
	Ratio below central estimate	1.10

Table Note:

- "Central estimate" is the "average" internal rate of return value with zero variability

Table 105. Ratio of variability due to system cost to variability due to O&M and degradation for PV technology under the power purchase agreement tariff scenario.

Moreover, the ratio of system cost variability to variability from O&M and degradation was consistently higher above the central estimate than below the central estimate.

In terms of quantifying how much more IRR variability was attributable to O&M and degradation instead of energy yield, Table 106 showed that this quantity ranged between 6.10 and 12.49 times greater:

Ratio of O&M and Degradation Variability to Energy Yield Variability				
Year	**Ratio Above/Below Central Estimate**	**Pessimistic Scenario**	**Average Scenario**	**Optimistic Scenario**
2014	Ratio above central estimate	6.12	8.35	8.92
	Ratio below central estimate	6.10	8.32	8.89
2015	Ratio above central estimate	6.26	7.65	9.03
	Ratio below central estimate	6.30	7.70	9.09
2016	Ratio above central estimate	7.36	9.28	9.97
	Ratio below central estimate	7.53	9.49	10.20
2017	Ratio above central estimate	7.30	9.37	10.47
	Ratio below central estimate	7.59	9.75	10.90
2018	Ratio above central estimate	8.38	9.75	10.51
	Ratio below central estimate	8.87	10.32	11.13
2019	Ratio above central estimate	9.45	10.51	11.32
	Ratio below central estimate	10.18	11.33	12.19
2020	Ratio above central estimate	10.82	11.39	11.33
	Ratio below central estimate	11.87	12.49	12.43

Table Note:

- "Central estimate" is the mean internal rate of return value from the Monte Carlo simulation
- *Values that are exceptional due to the central estimate being close to zero

Table 106. A comparison of how much more internal rate of return variability is due to O&M and degradation compared with energy yield for PV technology under the power purchase agreement tariff scenario.

According to these range values, IRR variability due to O&M and degradation was always greater than IRR variability caused by fluctuating energy yields. The ratio values under all three of the pricing scenarios from this table increased as time progressed from 2014 to 2020. The ratio values were much more similar in the year 2020 compared with the year 2014.

7.3.3 Concentrated Photovoltaic Technology

Unlike the PV results in Section 7.3.1, the CPV results did not include an instance where internal rates of return from all three of the "pessimistic," "average," and "optimistic" scenarios exceeded their associated discount rates. According to Figure 77 below, only the "optimistic" and "average" pricing scenarios experienced profitability:

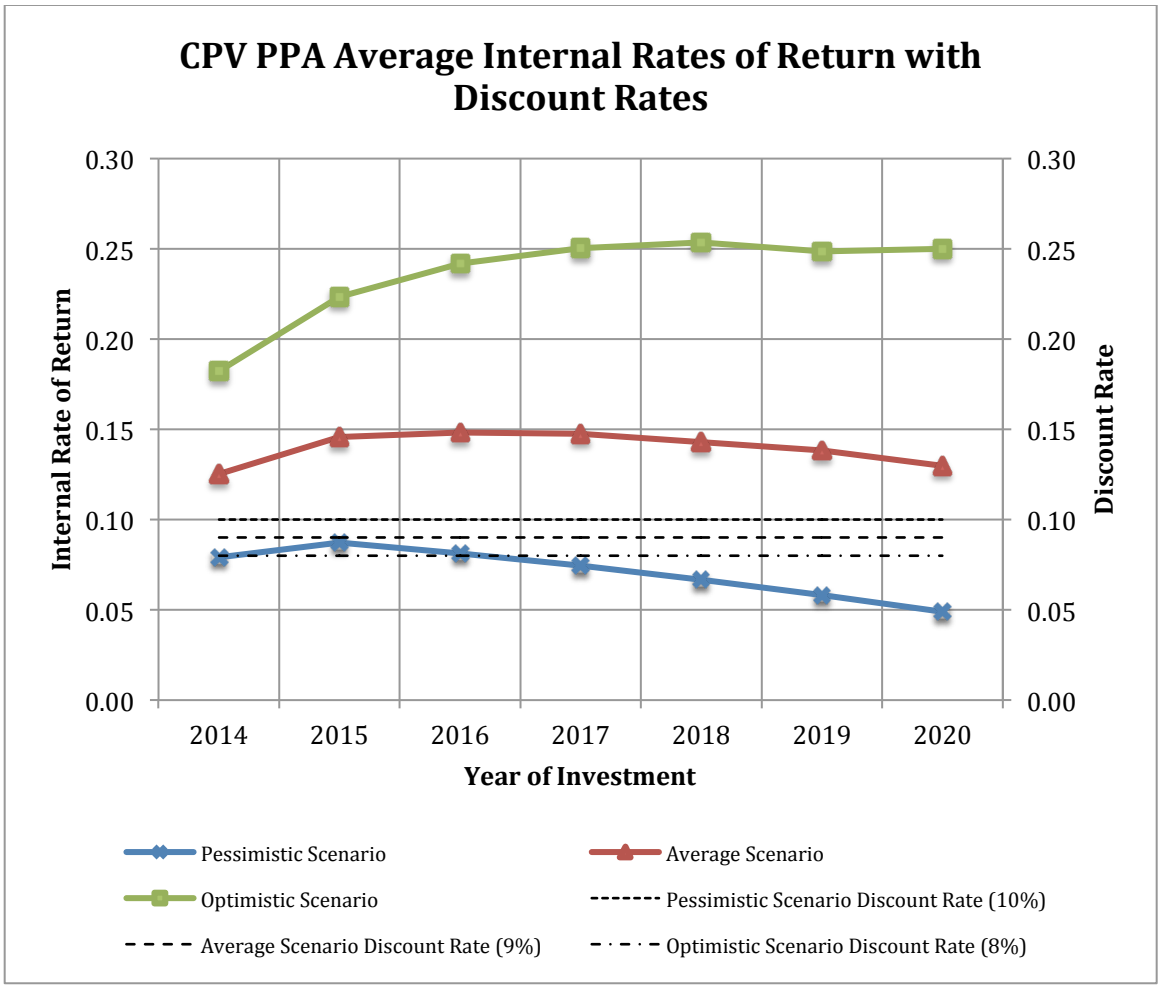


Figure 77. Plots of the internal rates of return under the power purchase agreement tariff scenario for CPV technology compared with associated discount rates.

Figure 77 indicated that the internal rate of return under the "optimistic" scenario quickly increased as time moved forward, but then stabilized between the years 2017 and 2020. The "average" scenario saw internal rates of return briefly rise, but then decrease from 2016 until 2020. The "pessimistic" scenario also saw an increase in IRR between 2014 and 2015, but then it too experienced decreasing internal rates of return afterwards. All three plots had a distinctive curve, with some of them decreasing more so than others in the later years in Figure 77.

The "pessimistic" scenario was almost slightly profitable in 2014. If the discount rate had been below 7.9% in that year, then all three scenarios would have seen internal rates of return in excess of the discount rate. Thus far, Figure 77 displayed

the highest internal rate of return from either CPV or PV technology. Under the "optimistic" scenario in 2018, an internal rate of return of 25.3% was observed. As anticipated, this corresponded with the highest discounted net present value of USD 740,227.32 in Figure 48 in Section 5.3.2.3. For a solar investor seeking to find the highest value for a project, selling CPV produced solar electricity with a power purchase agreement for a project commencing in the year 2018 was the solution. Perhaps most interesting was that this highest IRR was accomplished over only a 20-year timeframe.

7.3.4 Concentrated Photovoltaic Technology Variability Analysis

To analyze the impact of energy yield variability on the internal rate of return, 95% confidence intervals were calculated using Equation (26) from Section 7.1.2. Below, Table 107 provides the 95% confidence interval values:

Year	Pessimistic Scenario		Average Scenario		Optimistic Scenario	
	95% Lower CI Value	95% Upper CI Value	95% Lower CI Value	95% Upper CI Value	95% Lower CI Value	95% Upper CI Value
2014	0.0778	0.0807	0.1234	0.1272	0.1798	0.1847
2015	0.0854	0.0889	0.1436	0.1482	0.2202	0.2266
2016	0.0795	0.0830	0.1462	0.1506	0.2386	0.2454
2017	0.0728	0.0762	0.1449	0.1500	0.2463	0.2541
2018	0.0651	0.0682	0.1405	0.1452	0.2493	0.2574
2019	0.0566	0.0599	0.1360	0.1409	0.2450	0.2522
2020	0.0474	0.0502	0.1276	0.1318	0.2461	0.2542

Table 107. The values of the 95% IRR confidence intervals for CPV technology under the power purchase agreement tariff scenario.

According to Table 107, the largest 95% confidence interval width was found in the year 2020 under the "optimistic" pricing scenario with a width of 0.0081. This represented the year in which there was the greatest risk of IRR variability due to fluctuating energy yield. However, the risk was relatively small. The 95% CI did not, for example, include and negative values or drop below the "average" or "pessimistic" pricing scenario 95% confidence intervals in that year. Instead, in 2020 under the "optimistic" scenario a prospective investor could expect an internal

rate of return between 24.61% and 25.42% 19 times out of 20. Given that all other confidence intervals were narrower than those values, the impact of energy yield variability on the internal rate of return can be considered minimal.

Turning to variability as a proportion of the mean, the following table indicates where 95% of the observed internal rate of return data points from the Monte Carlo simulation were located above and below the mean value:

Internal Rate of Return Variability due to Energy Yield				
Year	**% Above/Below Central Estimate**	**Pessimistic Scenario**	**Average Scenario**	**Optimistic Scenario**
2014	% above central estimate	1.84%	1.48%	1.35%
	% below central estimate	-1.84%	-1.48%	-1.35%
2015	% above central estimate	1.99%	1.58%	1.44%
	% below central estimate	-1.99%	-1.58%	-1.44%
2016	% above central estimate	2.11%	1.48%	1.41%
	% below central estimate	-2.11%	-1.48%	-1.41%
2017	% above central estimate	2.22%	1.75%	1.56%
	% below central estimate	-2.22%	-1.75%	-1.56%
2018	% above central estimate	2.34%	1.64%	1.60%
	% below central estimate	-2.34%	-1.64%	-1.60%
2019	% above central estimate	2.84%	1.75%	1.45%
	% below central estimate	-2.84%	-1.75%	-1.45%
2020	% above central estimate	2.91%	1.62%	1.61%
	% below central estimate	-2.91%	-1.62%	-1.61%

Table Notes:

- "Central estimate" is the mean internal rate of return value from the Monte Carlo simulation
- The above figures represent variability as a proportion of the mean with 95% confidence
- *Values that are exceptional due to the central estimate being close to zero

Table 108. Percentage of internal rate of return variability due to energy yield for CPV technology under the power purchase agreement tariff scenario.

As per Table 108, internal rate of return variability due to energy yield was at most 2.91% on either side of the mean. During the years of profitable investment, 2014 to 2020 under the "average" and "optimistic" scenarios, IRR variability was plus or minus 1.75% on either side of the mean at most due to fluctuating energy yield. For a prospective investor looking to minimize the impact of energy yield variability on the project's internal rate of return, the best time to invest was in 2014 under the "optimistic" pricing scenario since IRR variability due to energy yield increased as

time progressed towards 2020. Profitability was not highest in 2014 according to Figure 77, but was still very respectable at USD 420,403.03 on average.

According to Table 109, the percentage point width of possible IRR values above and below the mean due to system cost variability increased from 82.84 percentage points in 2014 to 155.20 percentage points in 2020:

IRR Variability due to System Cost and O&M and Degradation			
Year	**% Above/Below Central Estimate**	**System Cost⊙**	**O&M and Degradation❖**
2014	% above central estimate	45.56%	7.08%
	% below central estimate	-36.68%	-7.33%
2015	% above central estimate	53.01%	6.73%
	% below central estimate	-40.31%	-6.97%
2016	% above central estimate	62.98%	7.33%
	% below central estimate	-45.29%	-7.59%
2017	% above central estimate	69.49%	8.11%
	% below central estimate	-49.53%	-8.42%
2018	% above central estimate	77.37%	9.12%
	% below central estimate	-53.33%	-9.50%
2019	% above central estimate	79.68%	10.30%
	% below central estimate	-57.97%	-10.78%
2020	% above central estimate	92.80%	11.89%
	% below central estimate	-62.40%	-12.51%

Notes:

- ⊙Range from literature: Haysom et al. (2014).
- ❖Range from literature: Drury et al. (2013), Gerstmaier et al. (2014).
- "Central estimate" is the "average" internal rate of return value with zero variability
- *Values that are exceptional due to the central estimate being close to zero

Table 109. Percentage of internal rate of return variability due to system cost, as well as O&M and degradation for CPV technology under the power purchase agreement tariff scenario.

The quantity of variability above the central estimate was larger than the amount of variability below the central estimate. Generally speaking, an investor who was sensitive to IRR variability risk would be better to invest in an earlier year, where the effect of system cost variability on IRR variability was generally smaller.

Turning to O&M and degradation, the width of the total interval above and below the mean decreased between 2014 and 2015 but then increased from 2015

onwards. The difference between the O&M and degradation variability percentages in 2014 and 2020 was not especially great, however, meaning that IRR variability due to O&M and degradation was of a somewhat similar magnitude during each of the seven years under analysis. The ratio values in Table 110 indicate that IRR variability from system costs is always greater than IRR variability from O&M and degradation:

Ratio of Variability due to System Cost to Variability due to O&M and Degradation		
Year	**Ratio Above/Below Central Estimate**	**Ratio**
2014	Ratio above central estimate	6.44
	Ratio below central estimate	5.00
2015	Ratio above central estimate	7.87
	Ratio below central estimate	5.79
2016	Ratio above central estimate	8.59
	Ratio below central estimate	5.96
2017	Ratio above central estimate	8.57
	Ratio below central estimate	5.88
2018	Ratio above central estimate	8.48
	Ratio below central estimate	5.61
2019	Ratio above central estimate	7.73
	Ratio below central estimate	5.38
2020	Ratio above central estimate	7.80
	Ratio below central estimate	4.99

Table Note:

- "Central estimate" is the "average" internal rate of return value with zero variability

Table 110. Ratio of variability due to system cost to variability due to O&M and degradation for CPV technology under the power purchase agreement tariff scenario.

Finally, compared with the other IRR results in Chapter 7, Table 111 below contained some of the smallest values of the ratio of IRR variability due to O&M and degradation to variability due to energy yield:

Ratio of O&M and Degradation Variability to Energy Yield Variability				
Year	**Ratio Above/Below Central Estimate**	**Pessimistic Scenario**	**Average Scenario**	**Optimistic Scenario**
2014	Ratio above central estimate	3.85	4.77	5.26
	Ratio below central estimate	3.99	4.94	5.45
2015	Ratio above central estimate	3.39	4.25	4.67
	Ratio below central estimate	3.51	4.40	4.83
2016	Ratio above central estimate	3.47	4.97	5.18
	Ratio below central estimate	3.60	5.15	5.37
2017	Ratio above central estimate	3.65	4.63	5.20
	Ratio below central estimate	3.79	4.81	5.40
2018	Ratio above central estimate	3.91	5.56	5.70
	Ratio below central estimate	4.07	5.80	5.94
2019	Ratio above central estimate	3.63	5.89	7.08
	Ratio below central estimate	3.80	6.16	7.41
2020	Ratio above central estimate	4.09	7.35	7.39
	Ratio below central estimate	4.30	7.73	7.77

Table Note:

- "Central estimate" is the mean internal rate of return value from the Monte Carlo simulation
- *Values that are exceptional due to the central estimate being close to zero

Table 111. A comparison of how much more internal rate of return variability is due to O&M and degradation compared with energy yield for CPV technology under the power purchase agreement tariff scenario.

Under CPV technology, internal rate of return variability due to O&M and degradation was between 3.39 and 7.77 times greater than variability due to energy yield. This range indicated that variability due to O&M and degradation was consistently larger than variability due to fluctuating system output, but the difference was not as large as other scenarios presented throughout Chapter 7. The ratio values under the "average" and "optimistic" scenario in Table 111 kept close together between 2014 and 2020, while the "pessimistic" values maintained distinctive, lower values. In the next section, the IRR results from the fourth and final tariff scenario will be presented.

7.4 Global Adjustment Tariff Offsetting Scenario

7.4.1 Photovoltaic Technology

The photovoltaic technology results in this section incorporated both energy yield variability and tariff variability, since this was the most realistic scenario. The average internal rates of return from 250 Monte Carlo simulations performed for each of the years 2014 through 2020 and for the "pessimistic," "average," and "optimistic" pricing scenarios are shown below in Figure 78:

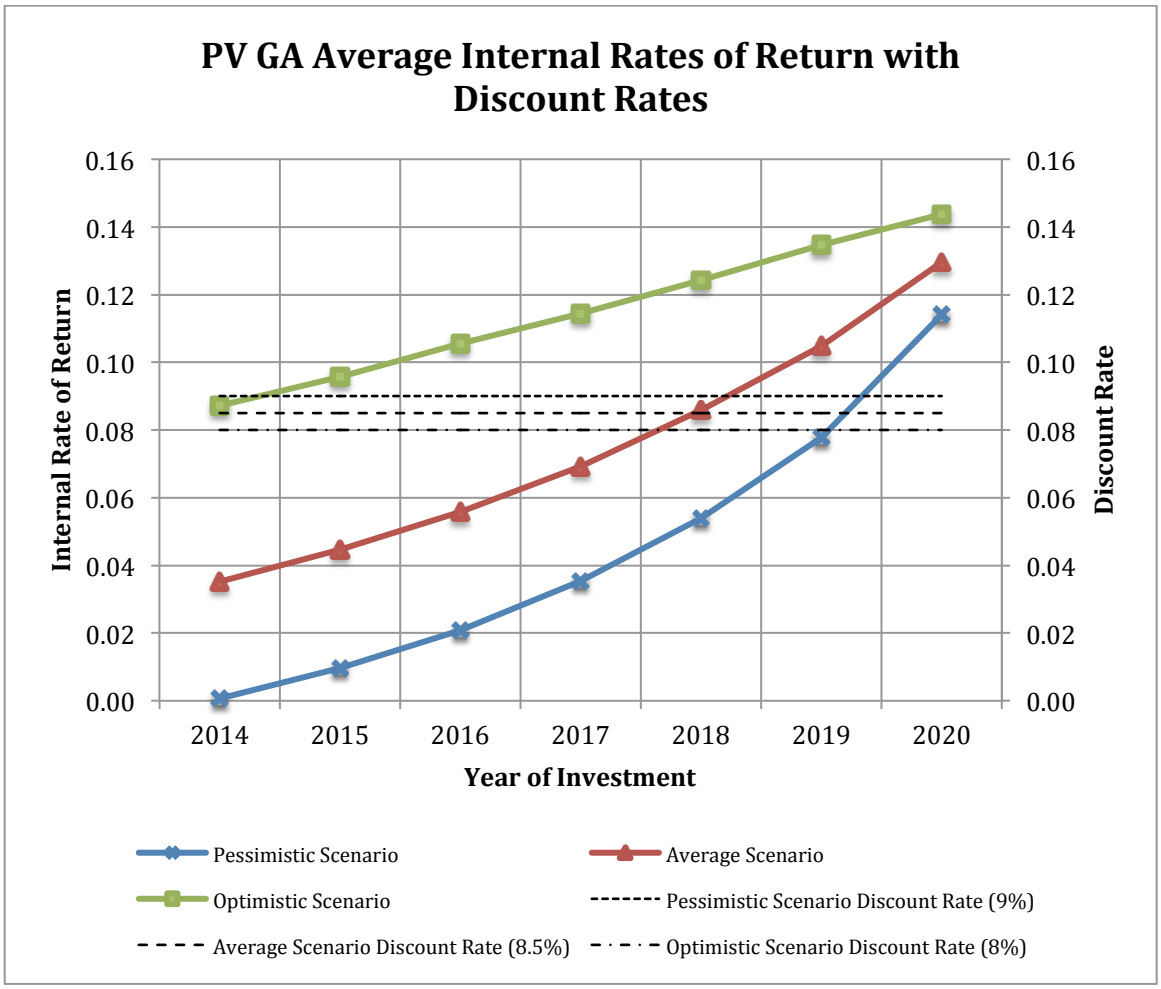


Figure 78. Plots showing the internal rates of return for PV technology and the "pessimistic," "average," and "optimistic" pricing scenarios under the global adjustment tariff offsetting scenario.

The plots shown in Figure 78 were comparable to the plots shown by Figure 72 from the PV time-of-use tariff scenario in that the internal rates of return increased as time progressed towards the year 2020. All three plots in both cases had a

positive slope, with the "optimistic" IRR plot being more linear in nature than the "average" and "pessimistic" plots. Both the TOU and global adjustment tariff offsetting scenario assumed 25-year timeframes, and value was generated from offsetting grid-produced electricity demand and associated charges instead of selling solar-produced electricity to create a revenue stream. However, the internal rates of return under the global adjustment tariff offsetting scenario were comparatively larger, over all, than the IRR values from the TOU tariff scenario shown by Figure 72. This was logical, since only electricity prices were offset under the TOU scenario, whereas wholesale electricity prices, global adjustment charges, and distribution fees were offset under the present tariff scenario. According to Figure 78, the highest IRR was 14.4% and this was observed in 2020 under the "optimistic" costing scenario. While this was not the highest IRR observed out of all four of the tariff scenarios, it exceeded the highest IRR under the TOU scenario, which was 10.0% and also observed in the year 2020.

In Figure 78 above, only the internal rates of return under the "optimistic" scenario exceeded the associated discount rate in each of the years 2014 to 2020. In order for all three scenarios to be profitable in 2014, a discount rate of 0% was necessary due to the "pessimistic" scenario's IRR of 0.001 in that year. However, this exceptionally low discount rate was not realistic. Despite the "pessimistic" scenario's low IRR in 2014, the plot of "pessimistic" internal rates of return significantly improved over time, eventually crossing above the 9% associated discount rate after 2019. Thus, all three costing scenarios exhibited profitability in 2020, which was indicated by their internal rates of return exceeding their associated discount rates.

7.4.2 Photovoltaic Technology Variability Analysis

To assess the impact of energy yield variability on the internal rate of return, 95% confidence intervals were calculated using Equation (26) from Section 7.1.2. Below, Table 112 provides these values:

Year	Pessimistic Scenario		Average Scenario		Optimistic Scenario	
	95% Lower CI Value	95% Upper CI Value	95% Lower CI Value	95% Upper CI Value	95% Lower CI Value	95% Upper CI Value
2014	-0.0002	0.0015	0.0341	0.0362	0.0857	0.0885
2015	0.0086	0.0108	0.0436	0.0459	0.0943	0.0972
2016	0.0196	0.0219	0.0546	0.0570	0.1039	0.1071
2017	0.0342	0.0366	0.0678	0.0707	0.1127	0.1161
2018	0.0525	0.0554	0.0842	0.0874	0.1223	0.1261
2019	0.0758	0.0795	0.1028	0.1066	0.1326	0.1366
2020	0.1118	0.1164	0.1274	0.1317	0.1415	0.1459

Table 112. 95% IRR confidence intervals for PV technology under the global adjustment tariff offsetting scenario.

According to the figures in Table 112, the largest 95% confidence interval was found in the year 2020 under the "pessimistic" scenario. Not only was this the only year under the "pessimistic" pricing scenario where investment in a PV project was profitable, but also it was the year with the most IRR variability risk according to the 95% confidence intervals. Perhaps investment under the "pessimistic" costing scenario should be avoided because of the higher IRR risk involved compared with the other pricing scenarios and the long time required to wait until an investment is profitable.

The "optimistic" and "average" pricing scenarios became attractive to potential investors in the years 2014 and 2019, respectively. Although the "average" scenario's mean IRR and upper 95% confidence interval in 2018 did exceed the 8.5% discount rate, the lower bound of the 95% CI was below the discount rate. There was therefore a chance that a project commencing in that year would not be a profitable investment, which is why 2019 was considered an attractive year for investment under the "average" pricing scenario. For the "optimistic" pricing scenario, the bottommost bound of the 95% confidence interval of 0.0857 was comfortably above the associated discount rate of 8%.

Using Equation (27) from Section 7.2.1, the following values were calculated to determine IRR variability as a proportion of the mean:

Internal Rate of Return Variability due to Energy Yield				
Year	**% Above/Below Central Estimate**	**Pessimistic Scenario**	**Average Scenario**	**Optimistic Scenario**
2014	% above central estimate	130.81%*	2.89%	1.65%
	% below central estimate	-130.81%*	-2.89%	-1.65%
2015	% above central estimate	11.15%	2.53%	1.49%
	% below central estimate	-11.15%	-2.53%	-1.49%
2016	% above central estimate	5.39%	2.21%	1.53%
	% below central estimate	-5.39%	-2.21%	-1.53%
2017	% above central estimate	3.40%	2.11%	1.51%
	% below central estimate	-3.40%	-2.11%	-1.51%
2018	% above central estimate	2.67%	1.83%	1.53%
	% below central estimate	-2.67%	-1.83%	-1.53%
2019	% above central estimate	2.39%	1.83%	1.49%
	% below central estimate	-2.39%	-1.83%	-1.49%
2020	% above central estimate	2.02%	1.68%	1.55%
	% below central estimate	-2.02%	-1.68%	-1.55%

Table Notes:

- "Central estimate" is the mean internal rate of return value from the Monte Carlo simulation
- The above figures represent variability as a proportion of the mean with 95% confidence
- *Values that are exceptional due to the central estimate being close to zero

Table 113. Percentage of internal rate of return variability due to energy yield for PV technology under the global adjustment tariff offsetting scenario.

Table 113 indicated that 95% of the internal rates of return generated by the Monte Carlo simulation were at most plus or minus 11.15% on either side of the mean due to energy yield variability. Comparing the years 2014 to 2020, there was a higher amount of variability between the figures under the three pricing scenarios in earlier years compared with later years. Thus, an investor could expect energy yield to vary the IRR more so for a PV project commencing in 2014 compared with one starting in 2020.

In Table 114, the magnitude of IRR variability due to system cost was significantly larger than IRR variability due to O&M and degradation in 2014:

IRR Variability due to System Cost and O&M and Degradation			
Year	**% Above/Below Central Estimate**	**System Cost⊙**	**O&M and Degradation❖**
2014	% above central estimate	147.41%	25.85%
	% below central estimate	-98.06%	-27.86%
2015	% above central estimate	114.33%	21.08%
	% below central estimate	-78.40%	-22.82%
2016	% above central estimate	88.86%	17.57%
	% below central estimate	-62.86%	-19.10%
2017	% above central estimate	65.18%	14.86%
	% below central estimate	-48.94%	-16.24%
2018	% above central estimate	44.73%	12.71%
	% below central estimate	-37.16%	-13.95%
2019	% above central estimate	28.65%	11.15%
	% below central estimate	-25.81%	-12.30%
2020	% above central estimate	10.90%	9.82%
	% below central estimate	-11.88%	-10.90%

Table Notes:

- ⊙Range from literature: Aanesen, Heck, and Pinner (2012), Ardani et al. (2013).
- ❖Range from literature: Branker et al. (2011), Di Francia (2013), Lowder et al. (2013), National Renewable Energy Laboratory (2013a), Zweibel (2010).
- "Central estimate" is the "average" internal rate of return value with zero variability
- *Values that are exceptional due to the central estimate being close to zero

Table 114. Percentage of internal rate of return variability due to system cost, as well as O&M and degradation for PV technology under the global adjustment tariff offsetting scenario.

The width of the system cost interval both above and below the central estimate in that year was 245.47 percentage points, compared with 53.71 percentage points for O&M and degradation. However, by 2020 the values in the above table related to system cost above and below the mean were nearly on par with those associated with O&M and degradation. In 2020, the width of the system cost interval was 22.79 percentage points, while the width of the O&M and degradation interval was 20.72 percentage points. In order for the percentage variability figures due to both system cost as well as O&M and degradation to be close to one another in 2020, the system cost figures had decrease further between 2014 and 2020 compared with the O&M and degradation figures over the same timeframe.

The ratio figures in Table 115 indicated that IRR variability due to system cost was always greater than IRR variability due to O&M and degradation:

Ratio of Variability due to System Cost to Variability due to O&M and Degradation		
Year	**Ratio Above/Below Central Estimate**	**Ratio**
2014	Ratio above central estimate	5.70
	Ratio below central estimate	3.52
2015	Ratio above central estimate	5.42
	Ratio below central estimate	3.44
2016	Ratio above central estimate	5.06
	Ratio below central estimate	3.29
2017	Ratio above central estimate	4.39
	Ratio below central estimate	3.01
2018	Ratio above central estimate	3.52
	Ratio below central estimate	2.66
2019	Ratio above central estimate	2.57
	Ratio below central estimate	2.10
2020	Ratio above central estimate	1.11
	Ratio below central estimate	1.09

Table Note:

- "Central estimate" is the "average" internal rate of return value with zero variability

Table 115. Ratio of variability due to system cost to variability due to O&M and degradation for PV technology under the global adjustment tariff offsetting scenario.

This ratio was always larger above the mean than below the mean. Finally, between 2014 and 2020, Table 116 showed that variability due to O&M and degradation ranged between 1.89 and 16.94 times greater than variability due to system output:

Ratio of O&M and Degradation Variability to Energy Yield Variability				
Year	**Ratio Above/Below Central Estimate**	**Pessimistic Scenario**	**Average Scenario**	**Optimistic Scenario**
2014	Ratio above central estimate	0.20*	8.93	15.71
	Ratio below central estimate	0.21*	9.63	16.94
2015	Ratio above central estimate	1.89	8.35	14.19
	Ratio below central estimate	2.05	9.04	15.36
2016	Ratio above central estimate	3.26	7.96	11.45
	Ratio below central estimate	3.54	8.66	12.45
2017	Ratio above central estimate	4.37	7.03	9.86
	Ratio below central estimate	4.78	7.68	10.77
2018	Ratio above central estimate	4.77	6.94	8.33
	Ratio below central estimate	5.23	7.61	9.14
2019	Ratio above central estimate	4.67	6.08	7.49
	Ratio below central estimate	5.15	6.71	8.26
2020	Ratio above central estimate	4.87	5.86	6.32
	Ratio below central estimate	5.40	6.50	7.01

Table Note:

- "Central estimate" is the mean internal rate of return value from the Monte Carlo simulation
- *Values that are exceptional due to the central estimate being close to zero

Table 116. A comparison of how much more internal rate of return variability is due to O&M and degradation compared with energy yield for PV technology under the global adjustment tariff offsetting scenario.

The values in the above table signalled to a prospective investor that, regardless of when an investment was made, variability due to O&M and degradation was larger than variability due to fluctuating energy yield and thus had a bigger impact on the internal rate of return. The ratio values between the three costing scenarios in Table 116 were widely spaced out in 2014, but as time moved forward towards 2020 the ratio values converged towards comparatively similar figures.

7.4.3 Concentrated Photovoltaic Technology

The CPV average internal rate of return results under the global adjustment tariff offsetting scenario are shown in Figure 79 below:

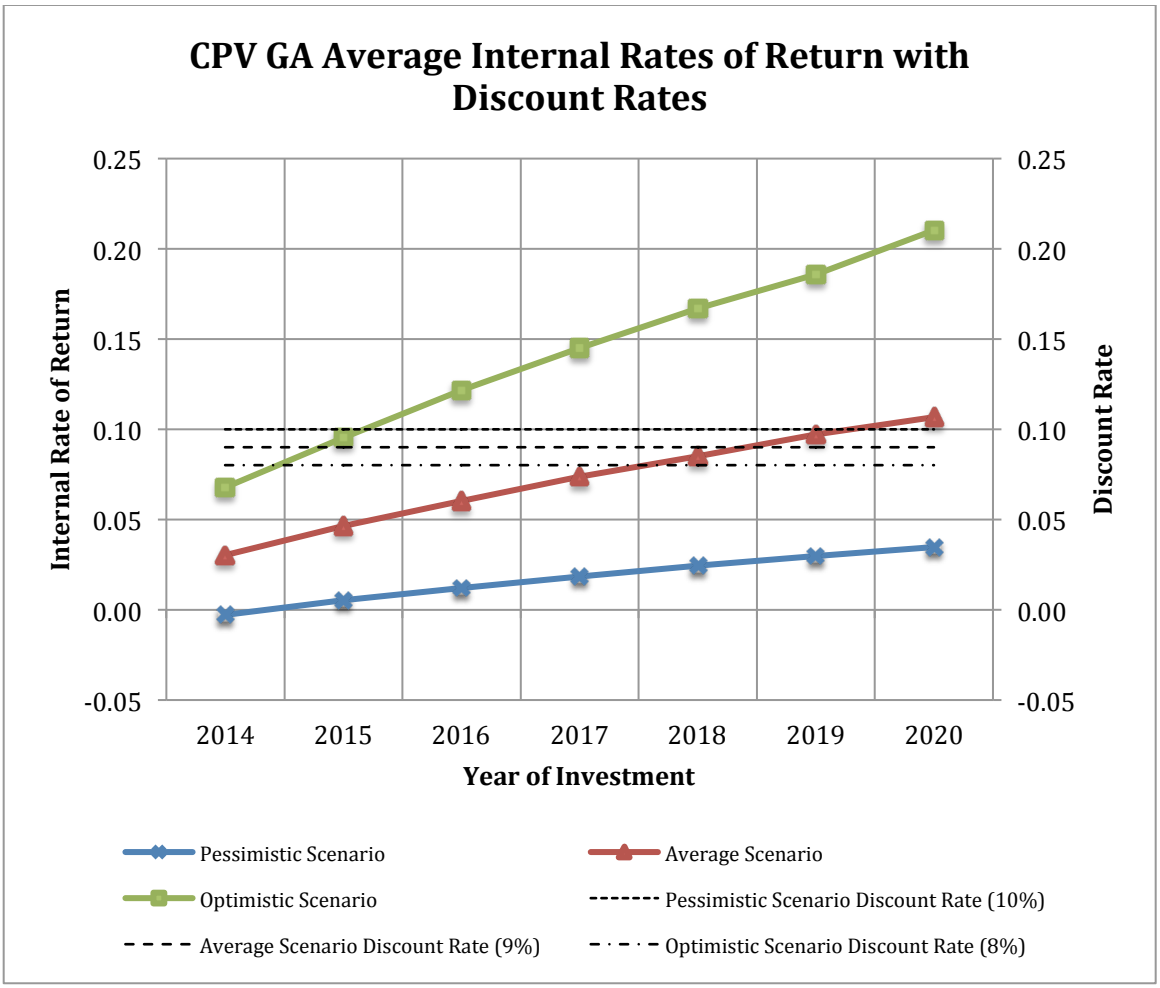


Figure 79. Plots of the "pessimistic," "average," and "optimistic" average internal rates of return for CPV technology under the global adjustment tariff offsetting scenario.

According to Figure 79, only the "optimistic" and "average" internal rates of return crossed above their corresponding discount rates of 8% and 9%, respectively. This occurred in 2015 under the "optimistic" scenario, and 2019 under the "average" scenario. Unlike the PV results under the same tariff scenario, the CPV "pessimistic" pricing scenario did not exceed its corresponding discount rate at any point. However, despite the lower internal rates of return under the "pessimistic" pricing scenario, the "optimistic" scenario reached an IRR of 21.0% in 2020, which was greater than the highest IRR of 14.4% for PV technology under the same tariff scenario. Thus, CPV technology provided greater value compared with PV technology when offsetting the global adjustment charge and other peak dependent tariffs in Ontario.

Figure 79 also indicated that profitability would have been possible in 2014 through 2020 under the "optimistic" scenario had the discount rate been reduced to less than 6.8%. For the "average" scenario, the same would have been true with a discount rate under 3.0%. The IRR plots in the above figure have positive slopes, but the "optimistic" IRR plot was much steeper than the comparatively flatter "average" and "pessimistic" IRR plots.

In contrast with the CPV results from the time-of-use scenario in Section 7.1, which offset only electricity charges, the internal rates of return from the global adjustment tariff offsetting scenario were higher. This was anticipated, since three electricity charges were offset under the present tariff scenario, compared with only one under the TOU tariff scenario. Compared with the CPV results from the other three tariff scenarios, the internal rates of return realized from offsetting global adjustment charges, wholesale electricity prices, and distribution fees were second only to the internal rates of return observed under the power purchase agreement tariff scenario.

7.4.4 Concentrated Photovoltaic Technology Variability Analysis

The 95% internal rate of return confidence intervals for CPV technology under the global adjustment tariff offsetting scenario are shown in Table 117 below:

Year	Pessimistic Scenario		Average Scenario		Optimistic Scenario	
	95% Lower CI Value	95% Upper CI Value	95% Lower CI Value	95% Upper CI Value	95% Lower CI Value	95% Upper CI Value
2014	-0.0052	-0.0007	0.0279	0.0327	0.0648	0.0709
2015	0.0031	0.0078	0.0439	0.0493	0.0920	0.0991
2016	0.0097	0.0147	0.0573	0.0636	0.1176	0.1260
2017	0.0161	0.0211	0.0703	0.0771	0.1401	0.1500
2018	0.0219	0.0272	0.0816	0.0889	0.1615	0.1729
2019	0.0272	0.0327	0.0933	0.1013	0.1791	0.1922
2020	0.0321	0.0376	0.1028	0.1109	0.2028	0.2174

Table 117. Internal rate of return 95% confidence intervals for the three pricing scenarios under CPV technology and the global adjustment tariff offsetting scenario.

Table 117 indicated that the widest 95% confidence interval was located in the year 2020 under the "optimistic" scenario, and the width of this 95% CI was 0.0146. Although comparatively wider than the other confidence intervals in the above table, a CPV project commencing operations in the year 2020 under the "optimistic" pricing scenario could expect an internal rate of return between 20.28% and 21.74% 19 times out of 20. In all likelihood, this span of values represented a low level of internal rate of return risk to prospective investors.

For a different perspective on accuracy, Table 118 below looks at the upper and lower bounds of where 95% of the IRR values from the Monte Carlo simulation fell with respect to the mean:

Internal Rate of Return Variability due to Energy Yield				
Year	**% Above/Below Central Estimate**	**Pessimistic Scenario**	**Average Scenario**	**Optimistic Scenario**
2014	% above central estimate	77.25%*	8.00%	4.51%
	% below central estimate	-77.25%*	-8.00%	-4.51%
2015	% above central estimate	43.74%*	5.85%	3.72%
	% below central estimate	-43.74%*	-5.85%	-3.72%
2016	% above central estimate	20.41%	5.20%	3.44%
	% below central estimate	-20.41%	-5.20%	-3.44%
2017	% above central estimate	13.25%	4.59%	3.42%
	% below central estimate	-13.25%	-4.59%	-3.42%
2018	% above central estimate	10.77%	4.32%	3.42%
	% below central estimate	-10.77%	-4.32%	-3.42%
2019	% above central estimate	9.05%	4.13%	3.52%
	% below central estimate	-9.05%	-4.13%	-3.52%
2020	% above central estimate	7.90%	3.78%	3.48%
	% below central estimate	-7.90%	-3.78%	-3.48%

Table Notes:

- "Central estimate" is the mean internal rate of return value from the Monte Carlo simulation
- The above figures represent variability as a proportion of the mean with 95% confidence
- *Values that are exceptional due to the central estimate being close to zero

Table 118. Percentage of internal rate of return variability due to energy yield for CPV technology under the global adjustment tariff offsetting scenario.

The above figures were calculated using Equation (27) from Section 7.1.2. According to the percentages in Table 118, 95% of the IRR values generated by the Monte Carlo simulation were at most plus or minus 20.41% on either side of the mean on account of fluctuating energy yields. This figure was higher than many of the energy yield variability values observed throughout Chapter 9. However, it occurred under the "pessimistic" scenario, where CPV investment was not profitable during any of the years 2014 to 2020 according to Figure 79. Focusing on the specific years where investments were profitable under the "average" and "optimistic" scenarios according to the same table, 95% of the IRR values were at most 4.13% on either side of the mean due to fluctuating system energy output.

In Table 119, system cost variability above the central estimate was greater than variability below the central estimate:

IRR Variability due to System Cost and O&M and Degradation			
Year	**% Above/Below Central Estimate**	**System Cost⊙**	**O&M and Degradation❖**
2014	% above central estimate	123.85%	36.20%
	% below central estimate	-109.52%	-40.00%
2015	% above central estimate	105.06%	25.29%
	% below central estimate	-88.27%	-27.79%
2016	% above central estimate	100.97%	20.72%
	% below central estimate	-79.92%	-22.66%
2017	% above central estimate	96.59%	18.13%
	% below central estimate	-74.76%	-19.74%
2018	% above central estimate	96.48%	16.59%
	% below central estimate	-71.20%	-18.01%
2019	% above central estimate	90.76%	15.44%
	% below central estimate	-69.25%	-16.70%
2020	% above central estimate	97.07%	14.81%
	% below central estimate	-67.41%	-15.98%

Notes:

- ⊙Range from literature: Haysom et al. (2014).
- ❖Range from literature: Drury et al. (2013), Gerstmaier et al. (2014).
- "Central estimate" is the "average" internal rate of return value with zero variability
- *Values that are exceptional due to the central estimate being close to zero

Table 119. Percentage of internal rate of return variability due to system cost, as well as O&M and degradation for CPV technology under the global adjustment tariff offsetting scenario.

Although system cost variability decreased over all between 2014 and 2020, Table 119 indicated that above the mean there was a somewhat sharp decline in the percentage values between 2014 and 2015 and then smaller decreases until 2019. A rise in system cost variability occurred between 2019 and 2020 above the mean. Below the central estimate, the size of system cost variability consistently decreased each year as time progressed towards 2020. For O&M and degradation, the values in Table 119 decreased both above and below the mean each year.

System cost had a larger potential impact on the IRR compared with O&M and degradation. The ratio figures in Table 120 support this sentiment, and also illustrate that the ratio values above the central estimate are always larger than the ratio values below the central estimate:

Ratio of Variability due to System Cost to Variability due to O&M and Degradation		
Year	**Ratio Above/Below Central Estimate**	**Ratio**
2014	Ratio above central estimate	3.42
	Ratio below central estimate	2.74
2015	Ratio above central estimate	4.15
	Ratio below central estimate	3.18
2016	Ratio above central estimate	4.87
	Ratio below central estimate	3.53
2017	Ratio above central estimate	5.33
	Ratio below central estimate	3.79
2018	Ratio above central estimate	5.82
	Ratio below central estimate	3.95
2019	Ratio above central estimate	5.88
	Ratio below central estimate	4.15
2020	Ratio above central estimate	6.56
	Ratio below central estimate	4.22

Table Note:

- "Central estimate" is the "average" internal rate of return value with zero variability

Table 120. Ratio of variability due to system cost to variability due to O&M and degradation for CPV technology under the global adjustment tariff offsetting scenario.

Finally, O&M and degradation variability was between 1.02 and 8.87 times greater than energy yield variability according to Table 121:

Ratio of O&M and Degradation Variability to Energy Yield Variability				
Year	**Ratio Above/Below Central Estimate**	**Pessimistic Scenario**	**Average Scenario**	**Optimistic Scenario**
2014	Ratio above central estimate	0.47*	4.52	8.03
	Ratio below central estimate	0.52*	5.00	8.87
2015	Ratio above central estimate	0.58*	4.32	6.81
	Ratio below central estimate	0.64*	4.75	7.48
2016	Ratio above central estimate	1.02	3.98	6.03
	Ratio below central estimate	1.11	4.36	6.60
2017	Ratio above central estimate	1.37	3.95	5.29
	Ratio below central estimate	1.49	4.30	5.77
2018	Ratio above central estimate	1.54	3.84	4.85
	Ratio below central estimate	1.67	4.17	5.26
2019	Ratio above central estimate	1.71	3.74	4.38
	Ratio below central estimate	1.85	4.05	4.74
2020	Ratio above central estimate	1.87	3.92	4.26
	Ratio below central estimate	2.02	4.23	4.60

Table Note:

- "Central estimate" is the mean internal rate of return value from the Monte Carlo simulation
- *Values that are exceptional due to the central estimate being close to zero

Table 121. A comparison of how much more internal rate of return variability is due to O&M and degradation compared with energy yield for CPV technology under the global adjustment tariff offsetting scenario.

Between 2014 and 2020, the ratio values under the "pessimistic" scenario increased, while those under the "optimistic" scenario decreased. The ratios under the "average" scenario decreased as well, but not to the same extent as those found under the "optimistic" scenario.

7.5 Summary

In Chapter 7, internal rate of return results were presented. This particular metric was useful to prospective solar investors because it provided an alternative way in which to choose when to invest separate from discounted net present value and return on investment analyses. Specifically, the IRR metric determined the discount rate that would set the solar investment project's net present value equal to zero. Over all, the 95% internal rate of return confidence intervals were quite narrow. The largest 95% CI was found under CPV technology and the global adjustment

tariff offsetting scenario, although the width of this confidence interval was only 0.0146. This was by no means exceptionally wide, and would likely not cause worry that the IRR would fluctuate below the associated discount rate. The IRR metric also indicated what discount rate was necessary in each of the years 2014 through 2020 in order for a project to be profitable. This was valuable information, since different prospective investors would likely have different discount rates.

The highest internal rates of return were found under the "optimistic" pricing scenario, followed by those under the "average" and then "pessimistic" scenarios. This was logical, since the lower PV and CPV costs meant that more installation could be constructed, which in turn produced more electricity to either be sold or used to offset existing electricity costs. The PPA tariff scenario in Section 7.3 recorded the highest PV or CPV IRR value, which was 25.3%. The next highest was 21.0% under the global adjustment tariff offsetting scenario in Section 7.4, followed by 19.6% under the feed-in tariff scenario in Section 7.2, and then 17.6% under the time-of-use tariff scenario in Section 7.1. Energy yield variability did not have a significant impact on the internal rate of return. Systems cost had the greatest impact, followed in the vast majority of cases by O&M and degradation, and then energy yield.

PV technology was the only solar technology that saw internal rates of return in excess of the associated discount rates under the "pessimistic" pricing scenario. This occurred under the power purchase agreement and global adjustment tariff offsetting scenarios. Thus, if system costs followed the "pessimistic" scenario, PV technology had an advantage over CPV technology as it provided more value as indicated by the internal rates of return. Any of the charts in Section 7 that plotted internal rates of return could have been used to determine what discount rate would be required in order for an investment to be profitable. This was true for both PV and CPV technologies, and required that the IRR exceed the discount rate in the year in which the project commenced. In the next section, the final metric from the financial analysis, levelized cost of electricity, will be presented.

Chapter 8: Levelized Cost of Electricity Results

The LCOE was previously defined as "the average cost of production per kWh over the technology investment life" (Davis & Owens, 2003, p. 1593) or, in other terms, the price at which solar-produced electricity must be sold over the system's operational lifetime in order to break even. In Section 2.4.2.2, the controversy surrounding applying this metric to solar installations was discussed, which is why this thesis will propose a new metric, levelized *profitability* of electricity, in Section 11.1.

The levelized cost of electricity metric did not rely upon a particular tariff scenario for calculation. Instead, it depended solely upon the solar installation's costs, cash flows, quantity of energy produced, as well as discount and degradation rates. As such, the LCOE results in this chapter will be presented according to the operational lifespan of the solar installation, since discounting over different periods of time produced different LCOE values. The results will also be categorized according to solar technology. Note that the discount rates used for the LCOE calculations were the same as those used in the analysis throughout Chapters 5 to 7. These discount rates were defined in Figure 15 for PV technology and Figure 19 for CPV technology.

8.1 Time-of-Use and Global Adjustment Tariff Offsetting Scenarios

8.1.1 Photovoltaic Technology

Under both the time-of-use and global adjustment tariff offsetting scenarios, which had 25-year timeframes, the LCOE values were identical under each of the "pessimistic," "average," and "optimistic" pricing scenarios. The inputs used to calculate LCOE under these two tariff scenarios were presented in Table 15 and Table 16 Section 4.1. Equation (5) in Section 3.3.1.4 was used to perform the levelized cost of electricity calculation. As expected, the average LCOE value calculated from the 250 Monte Carlo simulations under each of the three pricing

scenarios was nearly the same as the LCOE found under the no-variability scenarios. Figure 80 below shows the levelized cost of electricity values calculated under the time-of-use and global adjustment tariff offsetting scenario:

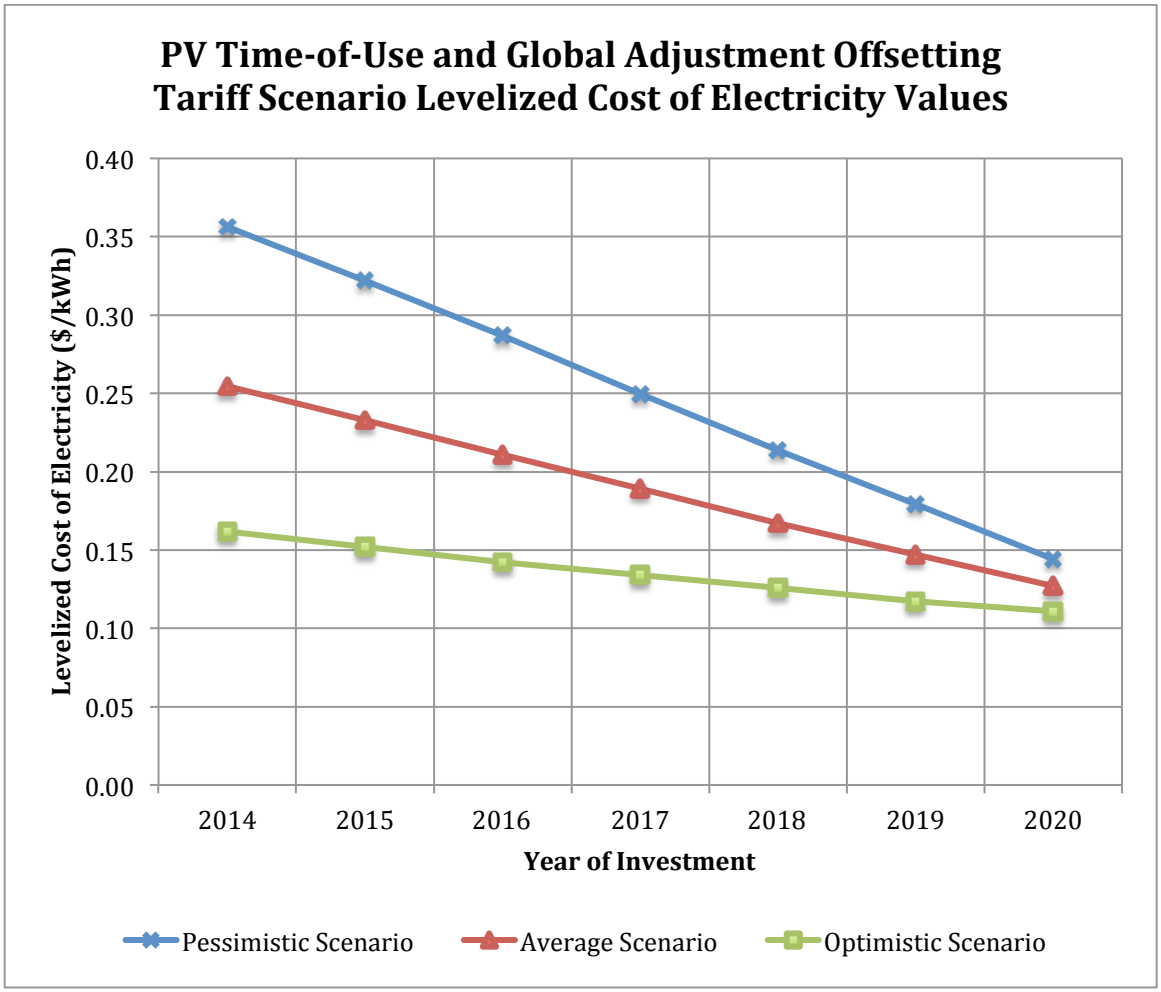


Figure 80. Levelized cost of electricity figures for the time-of-use and global adjustment tariff offsetting scenarios for PV technology.

According to Figure 80, the levelized cost of electricity decreased as time progressed towards 2020. This was expected, given the decrease in PV system costs illustrated by Table 15 in Section 4.1 between 2014 and 2020. Also as anticipated, the "optimistic" costing scenario had the lowest LCOE values and the "pessimistic" pricing scenario had the highest LCOE values. Interestingly, the LCOE figures for 2020 under the "pessimistic," "average," and "optimistic" scenarios were USD 0.144/kWh, USD 0.127/kWh, and USD 0.111/kWh, respectively. These three values were relatively close together, despite differences in discount rate, operation and

maintenance cost, and solar panel degradation rates between the three scenarios. Likely, the similar system costs in 2020 of USD 1.22/W, USD 1.21/W, and USD 1.20/W according to the "pessimistic," "average," and "optimistic" scenarios, respectively, had an impact on the convergence of the three LCOE plots shown by Figure 80 in that year.

On their own, the LCOE values in Figure 80 provided limited insight into the financial attractiveness afforded by the TOU and global adjustment tariff offsetting scenarios. Consider, for example, the time-of-use discounted net present value results for PV technology in Section 5.1.1.1. According to these figures, investment in a PV installation was not profitable until the year 2018. This was confirmed by the IRR results in Section 7.1.1. The LCOE results in Figure 80, however, indicated a value of USD 0.126/kWh in 2018 under the "optimistic" scenario, but looking at the time-of-use rates from Table 22 in Section 4.3.1, the PV installation offset electricity valued above that price *only* during peak hours throughout the year. These hours were 11:00 to 17:00 between May 1st and October 31, and 07:00 to 11:00 as well as 17:00 to 19:00 between November 1st and April 30th.

Time-of-use electricity prices were either scaled up or down each year according to a scaling factor that was defined by Equation (22) in Section 4.3.1. As such, some years contained more instances than others where the price of the electricity being offset was higher than the LCOE. The highest scale-up figure, 1.297 in the year 2021 according to Figure 17 in Section 4.3.1, meant that the value of grid-produced electricity offset by solar-produced electricity in the year 2021 exceeded the LCOE of USD 0.126/kWh only during select times. These times were between 11:00 to 17:00 during the summer months, and from 07:00 to 11:00 and 17:00 to 19:00 during every other month of the year 2021. On the other hand, the lowest scaling figure, 1.005 for a project commencing in 2018, meant that only the power produced during peak times between 11:00 to 17:00 over the summer months would be higher than the LCOE. The rest of the time, the value of electricity offset was less than the LCOE of USD 0.126/kWh.

Nevertheless, the solar installation was still profitable over all despite the fluctuations as to when the value of offsetting exceeded the LCOE value. This conclusion bolstered the argument that the levelized cost of electricity was not necessarily the optimal metric to define the financial attractiveness of an intermittent source of electricity. After all, the system was profitable even though it did not always offset electricity that was priced higher than the LCOE.

8.1.2 Photovoltaic Technology Variability Analysis

Below, Table 122 shows the 95% confidence intervals for the LCOE metric. The variability in the levelized cost of electricity was caused by fluctuating PV system energy output:

Year	Pessimistic Scenario		Average Scenario		Optimistic Scenario	
	95% Lower CI Value	95% Upper CI Value	95% Lower CI Value	95% Upper CI Value	95% Lower CI Value	95% Upper CI Value
2014	0.3545	0.3580	0.2534	0.2560	0.1610	0.1625
2015	0.3202	0.3237	0.2317	0.2339	0.1512	0.1527
2016	0.2853	0.2882	0.2099	0.2119	0.1414	0.1428
2017	0.2485	0.2510	0.1881	0.1899	0.1333	0.1345
2018	0.2125	0.2148	0.1663	0.1679	0.1250	0.1262
2019	0.1785	0.1802	0.1463	0.1477	0.1169	0.1180
2020	0.1435	0.1449	0.1262	0.1275	0.1103	0.1114

Table 122. Levelized cost of electricity 95% confidence intervals for PV technology under the time-of-use and global adjustment tariff offsetting scenarios.

The figures in Table 122 were calculated using a modified version of Equation (26) from Section 7.1.2, where LCOE means and standard deviations were used in place of IRR means and standard deviations. The values in Table 122 indicated that the largest 95% confidence interval was found in the year 2014 under the "pessimistic" pricing scenario. However, the difference between USD 0.3580/kWh and USD 0.3545/kWh was not exactly large by any means.

Looking at LCOE variability as a proportion of the average, the following table indicates the upper and lower limits of where 95% of the LCOE data points generated by the Monte Carlo simulation fell in relation to the mean:

Levelized Cost of Electricity Variability due to Energy Yield				
Year	**% Above/Below Central Estimate**	**Pessimistic Scenario**	**Average Scenario**	**Optimistic Scenario**
2014	% above central estimate	0.502%	0.504%	0.464%
	% below central estimate	-0.502%	-0.504%	-0.464%
2015	% above central estimate	0.538%	0.484%	0.479%
	% below central estimate	-0.538%	-0.484%	-0.479%
2016	% above central estimate	0.517%	0.496%	0.477%
	% below central estimate	-0.517%	-0.496%	-0.477%
2017	% above central estimate	0.503%	0.487%	0.469%
	% below central estimate	-0.503%	-0.487%	-0.469%
2018	% above central estimate	0.545%	0.471%	0.478%
	% below central estimate	-0.545%	-0.471%	-0.478%
2019	% above central estimate	0.482%	0.480%	0.480%
	% below central estimate	-0.482%	-0.480%	-0.480%
2020	% above central estimate	0.472%	0.523%	0.493%
	% below central estimate	-0.472%	-0.523%	-0.493%

Table Notes:

- "Central estimate" is the mean LCOE value from the Monte Carlo simulation
- The above figures represent variability as a proportion of the mean with 95% confidence
- *Values that are exceptional due to the central estimate being close to zero

Table 123. Levelized cost of electricity variability due to energy yield for PV technology and a 25-year project lifespan.

According to Table 123, 95% of the LCOE values fell within plus or minus 1% of the mean. The maximum value was plus or minus 0.545%, the smallest value seen thus far in the analysis in terms of variability as a proportion of the mean. The low figures in the above table indicated that energy yield variability had only a very minute impact on the value of the LCOE. The values in Table 123 were calculated using a variation of Equation (27) from Section 7.1.2 that substituted IRR means and standard deviations for LCOE means and standard deviations.

To investigate what impact other sources of variability had on the levelized cost of electricity, Table 124 looked at the impact from system cost as well as O&M and degradation:

Levelized Cost of Electricity Variability due to System Cost and O&M and Degradation			
Year	**% Above/Below Central Estimate**	**System Cost⊙**	**O&M and Degradation❖**
2014	% above central estimate	39.87%	5.71%
	% below central estimate	-36.48%	-5.71%
2015	% above central estimate	38.30%	6.07%
	% below central estimate	-34.73%	-6.00%
2016	% above central estimate	35.97%	6.52%
	% below central estimate	-32.63%	-6.35%
2017	% above central estimate	32.12%	7.07%
	% below central estimate	-29.18%	-6.78%
2018	% above central estimate	27.82%	7.76%
	% below central estimate	-24.83%	-7.32%
2019	% above central estimate	22.03%	8.58%
	% below central estimate	-20.12%	-7.96%
2020	% above central estimate	13.66%	9.66%
	% below central estimate	-12.63%	-8.80%

Table Notes:

- ⊙Range from literature: Aanesen, Heck, and Pinner (2012), Ardani et al. (2013).
- ❖Range from literature: Branker et al. (2011), Di Francia (2013), Lowder et al. (2013), National Renewable Energy Laboratory (2013a), Zweibel (2010).
- "Central estimate" is the "average" LCOE value with zero variability
- *Values that are exceptional due to the central estimate being close to zero

Table 124. Percentage of levelized cost of electricity variability due to system cost, as well as O&M and degradation for PV technology and a 25-year project lifespan.

Above and below the central estimate, the mean LCOE value in each of the years 2014 to 2020, LCOE variability due to system cost was similar in each year. There was, however, a slightly greater size of variability above the central estimate compared with below. This meant that higher LCOE values could fall further away from the mean than lower LCOE values below the average. For O&M and degradation, the maximum magnitude of variability was equidistant above and below the central estimate in 2014, but larger above the mean in all years afterwards. Table 124 also indicated that between 2014 and 2020 the maximum size of LCOE variability due to system cost decreased significantly by 26.21% above the mean and 23.84% below the mean. This was greater than the change in LCOE variability due to O&M and degradation, which increased by 3.05% and 3.09% above and below the mean, respectively, over the same timeframe. Thus, there was

higher risk that the LCOE would fluctuate for projects commencing closer to 2014 compared with those starting closer to 2020.

A direct comparison each year of the figures from the two columns in Table 124 indicated that LCOE variability due to system cost was greater than LCOE variability due to O&M and degradation. This was confirmed by the ratio figures in Table 125, which were all greater than 1:

Ratio of Variability due to System Cost to Variability due to O&M and Degradation		
Year	**Ratio Above/Below Central Estimate**	**Ratio**
2014	Ratio above central estimate	6.99
	Ratio below central estimate	6.39
2015	Ratio above central estimate	6.30
	Ratio below central estimate	5.79
2016	Ratio above central estimate	5.52
	Ratio below central estimate	5.14
2017	Ratio above central estimate	4.54
	Ratio below central estimate	4.31
2018	Ratio above central estimate	3.58
	Ratio below central estimate	3.39
2019	Ratio above central estimate	2.57
	Ratio below central estimate	2.53
2020	Ratio above central estimate	1.41
	Ratio below central estimate	1.43

Table Note:

- "Central estimate" is the "average" LCOE value with zero variability

Table 125. Ratio of variability due to system cost to variability due to O&M and degradation for PV technology and a 25-year project lifespan.

In terms of risk due to variable O&M and degradation compared with varying energy yield, Table 126 indicated that the former was between 11.16 and 20.46 times larger than the latter:

Ratio of O&M and Degradation Variability to Energy Yield Variability				
Year	**Ratio Above/Below Central Estimate**	**Pessimistic Scenario**	**Average Scenario**	**Optimistic Scenario**
2014	Ratio above central estimate	11.38	11.32	12.31
	Ratio below central estimate	11.38	11.32	12.31
2015	Ratio above central estimate	11.30	12.56	12.69
	Ratio below central estimate	11.16	12.40	12.53
2016	Ratio above central estimate	12.62	13.15	13.66
	Ratio below central estimate	12.28	12.80	13.29
2017	Ratio above central estimate	14.05	14.50	15.09
	Ratio below central estimate	13.47	13.90	14.46
2018	Ratio above central estimate	14.25	16.47	16.25
	Ratio below central estimate	13.44	15.53	15.32
2019	Ratio above central estimate	17.81	17.87	17.88
	Ratio below central estimate	16.52	16.58	16.59
2020	Ratio above central estimate	20.46	18.47	19.58
	Ratio below central estimate	18.64	16.83	17.85

Table Note:

- "Central estimate" is the mean LCOE value from the Monte Carlo simulation
- *Values that are exceptional due to the central estimate being close to zero

Table 126. A comparison of how much more levelized cost of electricity variability is due to O&M and degradation compared with energy yield for PV technology and a 25-year project lifespan.

Between 2014 and 2020, the ratio values in Table 126 increased under all three of the costing scenarios. The values across the three pricing scenarios were somewhat similar in 2014, and this was also true in the year 2020. Thus, the ratios appeared to increase at a fairly similar rate.

8.1.3 Concentrated Photovoltaic Technology

For CPV technology under the same two tariff scenarios, the levelized cost of electricity values are displayed below in Figure 81. All of the CPV inputs that went into the LCOE calculations were shown in Table 19 and Table 20 in Section 4.2. The levelized cost of electricity formula was defined by Equation (5) in Section 3.3.1.4.

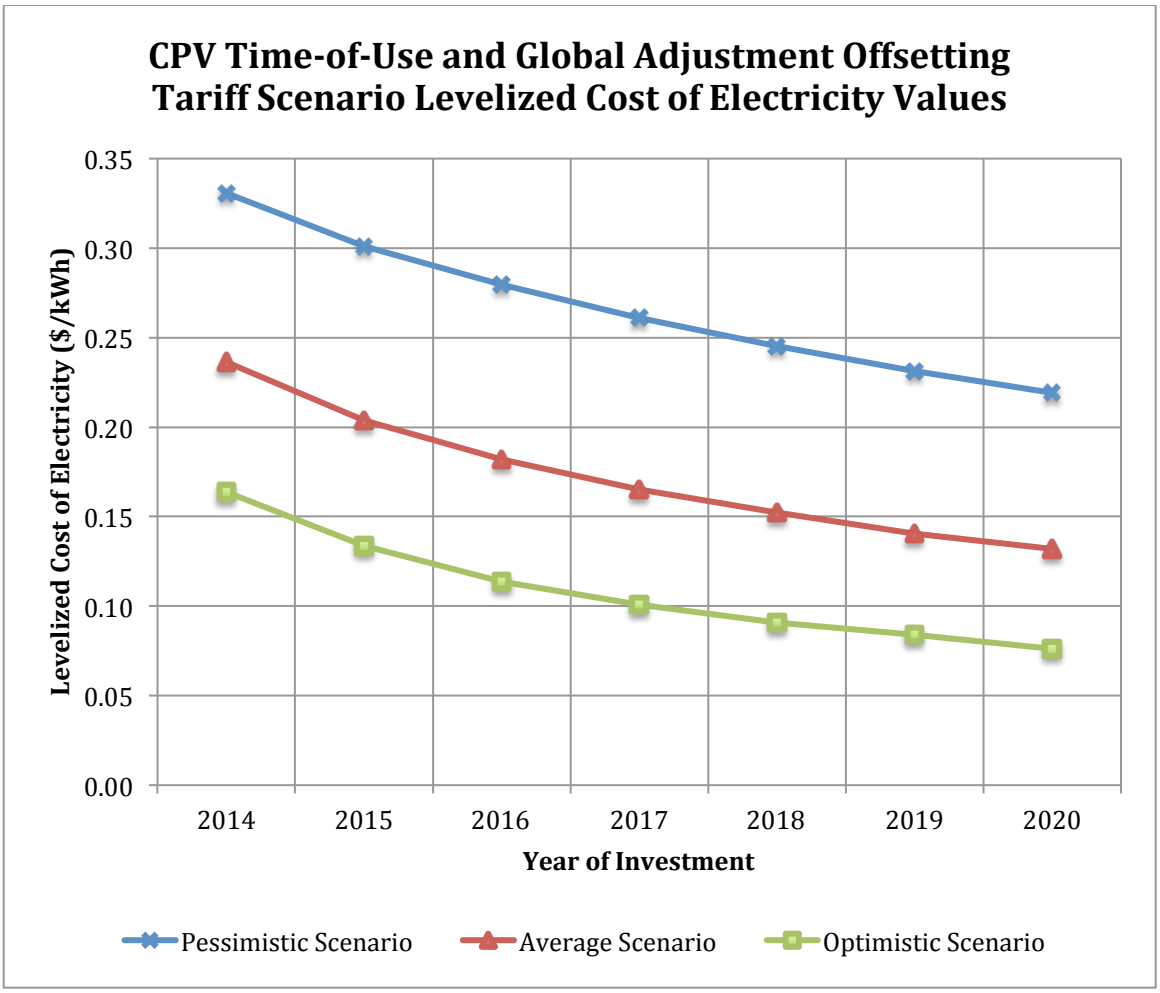


Figure 81. Levelized cost of electricity figures for the time-of-use and global adjustment tariff offsetting scenarios for CPV technology.

Above, Figure 81 paralleled Figure 80 from the Section 8.1.1 in that it displayed LCOE values that declined over time. To illustrate, once again, that the LCOE was not the most appropriate metric to assess the financial attractiveness of a solar installation, consider once again the time-of-use tariff scenario. The discounted net present value results from Figure 26 in Section 5.1.2.2 indicated that investment in a CPV installation became profitable in the year 2016 under the "optimistic" pricing scenario. As indicated by Figure 81 above, the "optimistic" scenario LCOE value in 2016 was USD 0.114/kWh. However, the instances when the solar installation offset electricity that was worth more than USD 0.114/kWh varied since time-of-use rates were increased and decreased over the 25-year operational lifetime of the CPV installation according to Equation (22) in Section 4.3.1. During some of the time the

value offset by solar-produced electricity was grater than USD 0.114/kWh, and other times it was less. This reinforced the idea that the value derived from solar-produced electricity depended strongly upon *when* the power was produced. If the electricity was produced at a time when the price of grid-produced electricity exceeded the levelized cost of electricity, this was more valuable compared to when the cost of electricity was less than the LCOE.

Conveniently, the highest solar irradiance readings were observed in Ottawa during the summer months and during midday, which corresponded with the most expensive electricity price of CAD 0.161/kWh (USD 0.147 at the time of writing). In concert with the highest solar irradiance readings, solar installations also outputted their greatest amount of energy during the summer months, particularly during midday. This was one reason why CPV installation profitability was observed even though the value of the electricity being offset was not always above the LCOE value. For reference, Table 127 below provides CPV system output figures assuming no energy yield variability under the "optimistic" pricing scenario in the year 2016:

Month	System Output (kWh)
January	28,746.46
February	36,204.64
March	48,739.60
April	48,754.61
May	55,135.60
June	56,785.71
July	58,723.31
August	53,511.72
September	43,161.17
October	33,224.04
November	18,949.56
December	21,828.81

Table 127. "Optimistic" pricing scenario CPV system output in 2016 under the time-of-use tariff scenario.

As per the above table, the greatest amounts of CPV system output were observed during the summer months.

8.1.4 Concentrated Photovoltaic Technology Variability Analysis

Recall that LCOE variability was the result of fluctuating system energy output. Below, Table 128 shows the 95% confidence LCOE intervals for CPV technology and a 25-year operational timeframe:

Year	Pessimistic Scenario		Average Scenario		Optimistic Scenario	
	95% Lower CI Value	95% Upper CI Value	95% Lower CI Value	95% Upper CI Value	95% Lower CI Value	95% Upper CI Value
2014	0.3277	0.3338	0.2340	0.2383	0.1623	0.1650
2015	0.2983	0.3038	0.2022	0.2056	0.1327	0.1349
2016	0.2771	0.2822	0.1803	0.1836	0.1129	0.1148
2017	0.2586	0.2636	0.1637	0.1666	0.1000	0.1016
2018	0.2430	0.2475	0.1509	0.1537	0.0900	0.0916
2019	0.2292	0.2336	0.1392	0.1418	0.0831	0.0846
2020	0.2171	0.2213	0.1308	0.1331	0.0755	0.0768

Table 128. Levelized cost of electricity 95% confidence intervals for CPV technology under the time-of-use and global adjustment tariff offsetting scenarios.

According to the values in the above table, the largest 95% confidence interval was located in the year 2014 under the "pessimistic" scenario. This was the same year and pricing scenario where the largest 95% confidence interval was found under PV technology in Section 8.1.2. In Table 128, this largest confidence interval was not large from a risk perspective, since the difference between the upper and lower bound was 0.0061, or less than USD 0.01.

Continuing with LCOE variability related to system output, the following table provides figures for levelized cost of electricity variability as a proportion of the mean:

Levelized Cost of Electricity Variability due to Energy Yield				
Year	**% Above/Below Central Estimate**	**Pessimistic Scenario**	**Average Scenario**	**Optimistic Scenario**
2014	% above central estimate	0.915%	0.904%	0.833%
	% below central estimate	-0.915%	-0.904%	-0.833%
2015	% above central estimate	0.906%	0.846%	0.830%
	% below central estimate	-0.906%	-0.846%	-0.830%
2016	% above central estimate	0.914%	0.886%	0.839%
	% below central estimate	-0.914%	-0.886%	-0.839%
2017	% above central estimate	0.942%	0.878%	0.807%
	% below central estimate	-0.942%	-0.878%	-0.807%
2018	% above central estimate	0.921%	0.909%	0.916%
	% below central estimate	-0.921%	-0.909%	-0.916%
2019	% above central estimate	0.961%	0.924%	0.899%
	% below central estimate	-0.961%	-0.924%	-0.899%
2020	% above central estimate	0.949%	0.875%	0.862%
	% below central estimate	-0.949%	-0.875%	-0.862%

Table Notes:

- "Central estimate" is the mean LCOE value from the Monte Carlo simulation
- The above figures represent variability as a proportion of the mean with 95% confidence
- *Values that are exceptional due to the central estimate being close to zero

Table 129. Levelized cost of electricity variability due to energy yield for CPV technology and a 25-year project lifespan.

According to Table 129, 95% of the LCOE values generated by the Monte Carlo simulation were at most plus or minus 0.961% on either side of the mean. Analogous to the PV results in Section 8.1.2, all values were less than 1%. However, in each year and under each pricing scenario, LCOE variability due to energy yield was larger for CPV technology compared with PV technology. This supported the results from earlier in this thesis that indicated CPV systems outputted greater amounts of energy than PV installations, and thus were subject to wider fluctuations in output when energy variability was introduced. Nevertheless, the risk posed by energy yield variability on the LCOE was minimal over all regardless of the solar technology.

In Table 130, LCOE variability due to system costs as well as O&M and degradation are displayed:

Levelized Cost of Electricity Variability due to System Cost and O&M and Degradation			
Year	**% Above/Below Central Estimate**	**System Cost⊙**	**O&M and Degradation❖**
2014	% above central estimate	40.10%	6.40%
	% below central estimate	-30.72%	-6.22%
2015	% above central estimate	47.59%	7.13%
	% below central estimate	-34.43%	-6.93%
2016	% above central estimate	53.68%	7.78%
	% below central estimate	-37.45%	-7.56%
2017	% above central estimate	58.18%	8.40%
	% below central estimate	-38.93%	-8.15%
2018	% above central estimate	61.01%	8.96%
	% below central estimate	-40.39%	-8.69%
2019	% above central estimate	64.67%	9.56%
	% below central estimate	-40.29%	-9.28%
2020	% above central estimate	66.09%	10.07%
	% below central estimate	-42.27%	-9.76%

Notes:

- ⊙Range from literature: Haysom et al. (2014).
- ❖Range from literature: Drury et al. (2013), Gerstmaier et al. (2014).
- "Central estimate" is the "average" LCOE value with zero variability
- *Values that are exceptional due to the central estimate being close to zero

Table 130. Percentage of levelized cost of electricity variability due to system cost, as well as O&M and degradation for CPV technology and a 25-year project lifespan.

In each of the years 2014 to 2020, the system cost percentages were larger than their counterparts under the O&M and degradation heading. Thus, once again, variability due to system cost was greater than variability due to O&M and degradation. In Table 130, system cost variability above the central estimate was noticeably greater than variability below the central estimate. The same was true for O&M and degradation. The magnitude of LCOE variability due to system cost increased as time progressed from 2014 to 2020. There was also an increase for O&M and degradation over the same timeframe, but the magnitude was comparatively smaller. Thus, the LCOE attached to projects commencing in 2020 could have varied more so than the LCOE of a project beginning in 2014.

Table 131 provided precise ratios of how much larger variability due to system cost was compared to O&M and degradation:

Ratio of Variability due to System Cost to Variability due to O&M and Degradation		
Year	**Ratio Above/Below Central Estimate**	**Ratio**
2014	Ratio above central estimate	6.27
	Ratio below central estimate	4.94
2015	Ratio above central estimate	6.67
	Ratio below central estimate	4.97
2016	Ratio above central estimate	6.90
	Ratio below central estimate	4.96
2017	Ratio above central estimate	6.93
	Ratio below central estimate	4.77
2018	Ratio above central estimate	6.81
	Ratio below central estimate	4.65
2019	Ratio above central estimate	6.76
	Ratio below central estimate	4.34
2020	Ratio above central estimate	6.57
	Ratio below central estimate	4.33

Table Note:

- "Central estimate" is the "average" LCOE value with zero variability

Table 131. Ratio of variability due to system cost to variability due to O&M and degradation for CPV technology and a 25-year project lifespan.

In each case according to the table above, LCOE variability due to system cost was greater than LCOE variability due to O&M and degradation since all of the figures were greater than 1.

Comparing the impact of O&M and degradation to energy yield on the variability of the LCOE, the former ranged between 6.80 times and 11.68 times greater than the later according to Table 132:

Ratio of O&M and Degradation Variability to Energy Yield Variability				
Year	**Ratio Above/Below Central Estimate**	**Pessimistic Scenario**	**Average Scenario**	**Optimistic Scenario**
2014	Ratio above central estimate	7.00	7.08	7.69
	Ratio below central estimate	6.80	6.88	7.47
2015	Ratio above central estimate	7.87	8.43	8.59
	Ratio below central estimate	7.64	8.19	8.35
2016	Ratio above central estimate	8.51	8.78	9.28
	Ratio below central estimate	8.27	8.53	9.01
2017	Ratio above central estimate	8.92	9.56	10.41
	Ratio below central estimate	8.66	9.28	10.10
2018	Ratio above central estimate	9.73	9.86	9.77
	Ratio below central estimate	9.44	9.57	9.48
2019	Ratio above central estimate	9.96	10.35	10.63
	Ratio below central estimate	9.66	10.04	10.32
2020	Ratio above central estimate	10.61	11.51	11.68
	Ratio below central estimate	10.29	11.16	11.33

Table Note:

- "Central estimate" is the mean LCOE value from the Monte Carlo simulation
- *Values that are exceptional due to the central estimate being close to zero

Table 132. A comparison of how much more levelized cost of electricity variability is due to O&M and degradation compared with energy yield for CPV technology and a 25-year project lifespan.

Since the values in Table 132 were all greater than "1," O&M and degradation consistently had a larger impact on the LCOE than energy yield. These same figures steadily increased as time progressed towards 2020 under each of the three costing scenarios. The three pricing scenarios had similar values in 2014, and they also had similar values in 2020 meaning the ratios increased at similar rates.

8.2 Feed-in Tariff and Power Purchase Agreement Tariff Scenarios

8.2.1 Photovoltaic Technology

Unlike the two tariff scenarios from Section 8.1, which assumed 25-year timeframes, the feed-in tariff and power purchase agreement tariff scenarios in this section will assume 20-year timeframes. The levelized cost of electricity values for these two tariff scenarios are shown below in Figure 82:

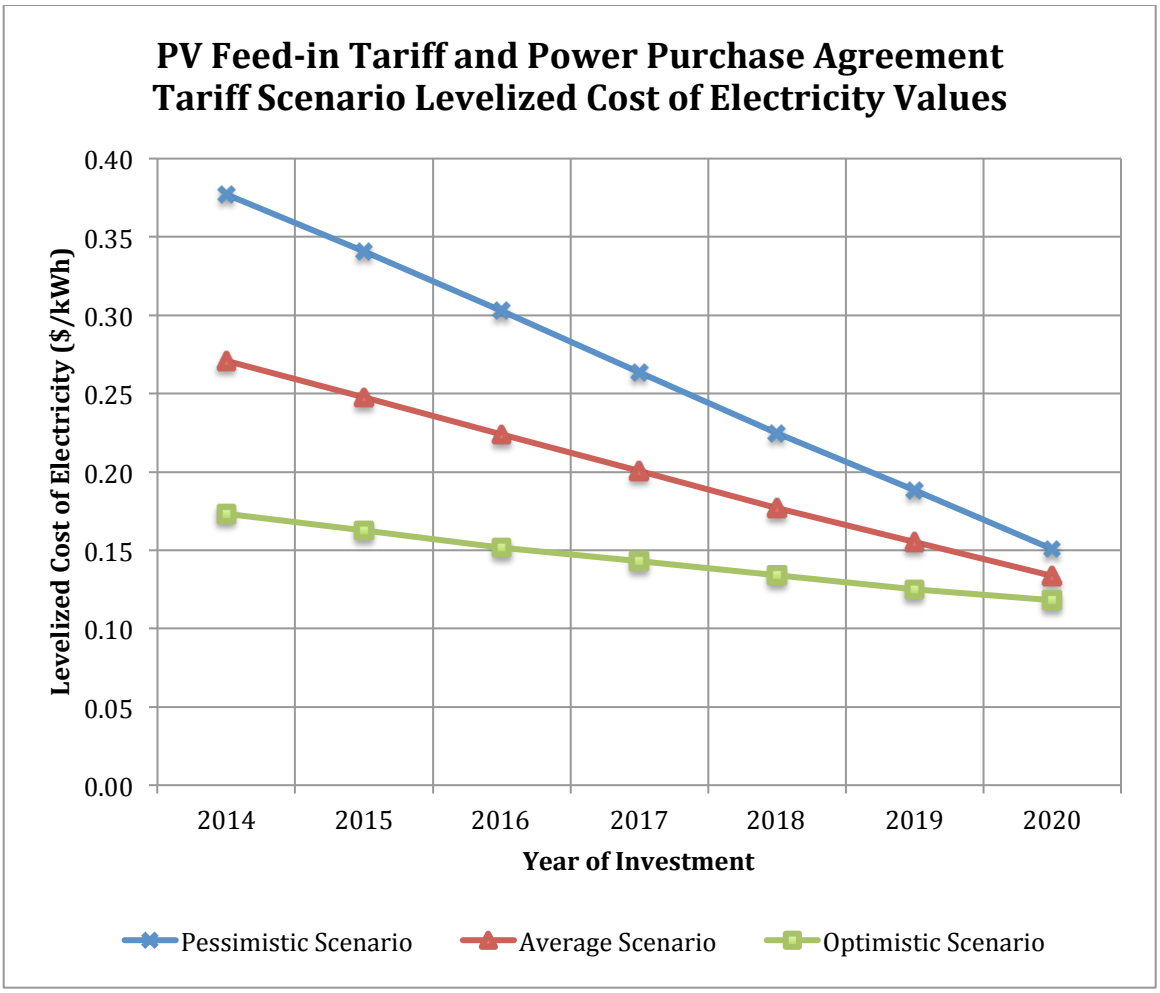


Figure 82. Levelized cost of electricity figures for the feed-in tariff and power purchase agreement tariff scenarios for PV technology.

Figure 82 illustrated decreasing levelized cost of electricity figures over time. This trend matched the declining LCOE figures for both PV and CPV technologies under the time-of-use and global adjustment tariff offsetting scenarios from Sections 8.1.1 and 8.1.3, respectively.

One of the two tariff scenarios under investigation in this section, the FIT scenario, presumed that a static price was paid all solar electricity produced and sold over the 20-year timeframe. Feed-in tariff prices for projects commencing between the years 2014 and 2020 were listed in Table 24 in Section 4.3.2. This payment arrangement was perfect for testing the accuracy of the LCOE, since the levelized cost of electricity calculation outputted a single break-even price value. As such, it was

expected that the positive discounted net present values associated with PV technology under the feed-in tariff scenario would correlate with levelized cost of electricity numbers from Figure 82. For example, under the "average" scenario for a PV project commencing operations in 2014, the FIT price was USD 0.30/kWh. Since this was above the calculated LCOE of USD 0.271/kWh under the same pricing scenario and year of investment, the expectation was that this project would be profitable. Looking at Table 76 in Section 6.2, the return on investment was listed as 11.6% and thus the project was profitable. Under the same scenario in 2015, the FIT price was USD 0.261/kWh while the LCOE was USD 0.247/kWh. Once again, the price paid per kilowatt-hour of electricity produced exceeded the levelized cost of electricity. Turning again to Table 76 in Section 6.2, the positive return on investment of 5.6% was listed in 2015 under the "average" scenario.

However, in 2016, the FIT price was listed as USD 0.220/kWh while the LCOE under the "average" pricing scenario was USD 0.224/kWh. According to Table 76 in Section 6.2, the PV system commencing operations in this year under the "average" pricing scenario had a return on investment of -1.9%. This negative ROI was expected, given that the FIT price was less than the calculated LCOE. Unlike the time-of-use and global adjustment tariff offsetting scenarios from Section 8.1 where the price of electricity varied, the static electricity prices under the feed-in tariff scenario meant that the LCOE conformed to expectations. Consequently, in situations where the FIT price was greater than the LCOE, the PV system was profitable (and vice versa).

8.2.2 Photovoltaic Technology Variability Analysis

Below, Table 133 provides the 95% confidence intervals associated with the levelized cost of electricity metric for PV technology under the 20-year feed-in tariff and power purchase agreement tariff scenarios:

Year	Pessimistic Scenario		Average Scenario		Optimistic Scenario	
	95% Lower CI Value	95% Upper CI Value	95% Lower CI Value	95% Upper CI Value	95% Lower CI Value	95% Upper CI Value
2014	0.3750	0.3791	0.2695	0.2725	0.1723	0.1740
2015	0.3390	0.3423	0.2462	0.2488	0.1616	0.1633
2016	0.3013	0.3047	0.2228	0.2252	0.1511	0.1525
2017	0.2620	0.2648	0.1995	0.2015	0.1421	0.1437
2018	0.2235	0.2260	0.1760	0.1779	0.1332	0.1346
2019	0.1872	0.1892	0.1544	0.1561	0.1243	0.1257
2020	0.1498	0.1515	0.1329	0.1343	0.1173	0.1185

Table 133. Levelized cost of electricity 95% confidence intervals for PV technology under the feed-in tariff and power purchase agreement tariff offsetting scenarios.

According to Table 133, the widest 95% confidence interval was found in the year 2014 under the "pessimistic" pricing scenario. The difference between the upper LCOE of USD 0.3791/kWh and the lower LCOE of USD 0.3750/kWh was USD 0.0041/kWh. Given that the broadest 95% confidence was less than one penny, LCOE variability due to fluctuating energy yield was hardly a major concern.

In terms of variability as a proportion of the mean, the following table indicates where 95% of the levelized cost of electricity data points generated by the Monte Carlo simulation were located with respect to the mean value in each of the years 2014 to 2020:

Levelized Cost of Electricity Variability due to Energy Yield				
Year	**% Above/Below Central Estimate**	**Pessimistic Scenario**	**Average Scenario**	**Optimistic Scenario**
2014	% above central estimate	0.546%	0.549%	0.491%
	% below central estimate	-0.546%	-0.549%	-0.491%
2015	% above central estimate	0.471%	0.526%	0.527%
	% below central estimate	-0.471%	-0.526%	-0.527%
2016	% above central estimate	0.560%	0.525%	0.481%
	% below central estimate	-0.560%	-0.525%	-0.481%
2017	% above central estimate	0.529%	0.505%	0.543%
	% below central estimate	-0.529%	-0.505%	-0.543%
2018	% above central estimate	0.555%	0.523%	0.525%
	% below central estimate	-0.555%	-0.523%	-0.525%
2019	% above central estimate	0.539%	0.529%	0.548%
	% below central estimate	-0.539%	-0.529%	-0.548%
2020	% above central estimate	0.556%	0.503%	0.508%
	% below central estimate	-0.556%	-0.503%	-0.508%

Table Notes:

- "Central estimate" is the mean LCOE value from the Monte Carlo simulation
- The above figures represent variability as a proportion of the mean with 95% confidence
- *Values that are exceptional due to the central estimate being close to zero

Table 134. Levelized cost of electricity variability due to energy yield for PV technology and a 20-year project lifespan.

Table 134 indicated that, at most, the levelized cost of electricity fluctuated due to variable system output by 0.560%. This was in the year 2016 under the "pessimistic" scenario. Analogous to the results from Sections 8.1.1 and 8.1.3, energy yield varied the LCOE by less than plus or minus 1% of the mean, meaning that it was not a significant source of risk to either increasing or decreasing the value of the levelized cost of electricity.

Turning to LCOE variability due to system cost as well as O&M and degradation, Table 135 below indicates that system costs were capable of varying the LCOE to a larger degree than O&M and degradation:

Levelized Cost of Electricity Variability due to System Cost and O&M and Degradation			
Year	**% Above/Below Central Estimate**	**System Cost⊙**	**O&M and Degradation❖**
2014	% above central estimate	39.13%	5.23%
	% below central estimate	-36.12%	-5.20%
2015	% above central estimate	37.57%	5.57%
	% below central estimate	-34.36%	-5.47%
2016	% above central estimate	35.25%	6.00%
	% below central estimate	-32.23%	-5.81%
2017	% above central estimate	31.39%	6.52%
	% below central estimate	-28.72%	-6.22%
2018	% above central estimate	27.07%	7.18%
	% below central estimate	-24.28%	-6.73%
2019	% above central estimate	21.22%	7.96%
	% below central estimate	-19.46%	-7.35%
2020	% above central estimate	12.74%	8.99%
	% below central estimate	-11.75%	-8.16%

Table Notes:

- ⊙Range from literature: Aanesen, Heck, and Pinner (2012), Ardani et al. (2013).
- ❖Range from literature: Branker et al. (2011), Di Francia (2013), Lowder et al. (2013), National Renewable Energy Laboratory (2013a), Zweibel (2010).
- "Central estimate" is the "average" LCOE value with zero variability
- *Values that are exceptional due to the central estimate being close to zero

Table 135. Percentage of levelized cost of electricity variability due to system cost, as well as O&M and degradation for PV technology and a 20-year project lifespan.

The levelized cost of electricity was affected by system costs more so in 2014 than in 2020, and the magnitude of variability was higher above the central estimate than below the central estimate. Even though O&M and degradation had a comparatively smaller impact on the LCOE than system costs, the size of the impact from the former grew by 3.77% above the mean and 2.96% below the mean between 2014 and 2020. In comparison, LCOE variability due to system cost dropped by 26.39% above the mean and 24.37% below the mean between 2014 and 2020. Accordingly, an investor looking to minimize LCOE variability risk stemming from system price was better off investing closer to 2020 than 2014, while an investor wishing to minimize LCOE variability risk due to O&M and degradation was wiser to invest closer to 2014.

LCOE variability due to system cost was consistently higher than variability due to O&M and degradation. As indicated by Table 136, LCOE variability due to system cost was at most 7.49 times higher than variability due to O&M and degradation:

Ratio of Variability due to System Cost to Variability due to O&M and Degradation		
Year	**Ratio Above/Below Central Estimate**	**Ratio**
2014	Ratio above central estimate	7.49
	Ratio below central estimate	6.95
2015	Ratio above central estimate	6.74
	Ratio below central estimate	6.28
2016	Ratio above central estimate	5.88
	Ratio below central estimate	5.55
2017	Ratio above central estimate	4.82
	Ratio below central estimate	4.62
2018	Ratio above central estimate	3.77
	Ratio below central estimate	3.61
2019	Ratio above central estimate	2.67
	Ratio below central estimate	2.65
2020	Ratio above central estimate	1.42
	Ratio below central estimate	1.44

Table Note:

- "Central estimate" is the "average" LCOE value with zero variability

Table 136. Ratio of variability due to system cost to variability due to O&M and degradation for PV technology and a 20-year project lifespan.

This peak value was observed above the mean in 2014. However, by 2020, this gap had closed to just 1.42 times greater. Comparatively, LCOE variability due to O&M and degradation was between 9.47 and 17.88 times greater than variability due to energy yield over the same timeframe as per Table 137:

Ratio of O&M and Degradation Variability to Energy Yield Variability				
Year	**Ratio Above/Below Central Estimate**	**Pessimistic Scenario**	**Average Scenario**	**Optimistic Scenario**
2014	Ratio above central estimate	9.57	9.51	10.65
	Ratio below central estimate	9.53	9.47	10.60
2015	Ratio above central estimate	11.84	10.60	10.58
	Ratio below central estimate	11.63	10.41	10.39
2016	Ratio above central estimate	10.71	11.42	12.46
	Ratio below central estimate	10.37	11.06	12.06
2017	Ratio above central estimate	12.32	12.91	12.00
	Ratio below central estimate	11.76	12.31	11.44
2018	Ratio above central estimate	12.93	13.72	13.67
	Ratio below central estimate	12.14	12.87	12.83
2019	Ratio above central estimate	14.76	15.03	14.52
	Ratio below central estimate	13.63	13.88	13.41
2020	Ratio above central estimate	16.17	17.88	17.69
	Ratio below central estimate	14.68	16.23	16.06

Table Note:

- "Central estimate" is the mean LCOE value from the Monte Carlo simulation
- *Values that are exceptional due to the central estimate being close to zero

Table 137. A comparison of how much more levelized cost of electricity variability is due to O&M and degradation compared with energy yield for PV technology and a 20-year project lifespan.

The ratio figures in Table 137 were larger in later years under each of the three pricing scenarios. The numeric values in the above table were relatively close to one another during each of the years 2014 to 2020, meaning the ratios were increasing at comparable rates.

8.2.3 Concentrated Photovoltaic Technology

For CPV technology, the following levelized cost of electricity values were calculated for each of the three pricing scenarios using Equation (5) from Section 3.3.1.4:

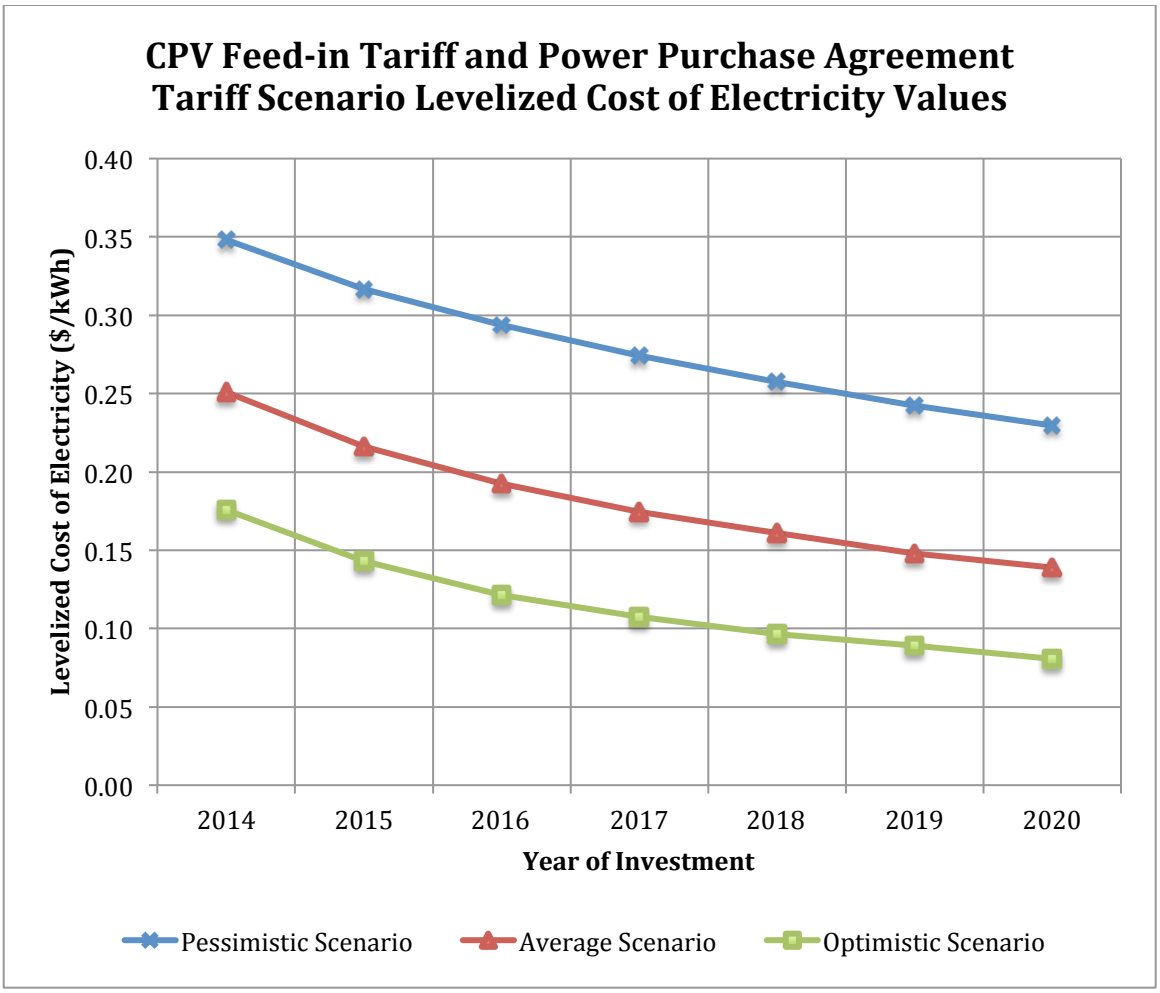


Figure 83. Levelized cost of electricity figures for the feed-in tariff and power purchase agreement tariff scenarios for CPV technology.

Figure 83 exhibited decreasing levelized cost of electricity values between 2014 and 2020. Given that CPV system costs decreased over this same timeframe according to Table 19 in Section 4.2, the decrease was anticipated. At this point, it can be stated that levelized cost of electricity values under each of the three pricing scenarios decreased over time regardless of whether a 20- or 25-year timeframe was assumed.

The static FIT prices from Table 24 in Section 4.3.2 were once again used to test the accuracy of the LCOE metric. For the "average" scenario, the levelized cost of electricity in 2016 was USD 0.192/kWh according to Figure 83. In that same year, the FIT price was USD 0.220/kWh. Given that the FIT price was greater than the

LCOE, the CPV installation was expected to be profitable. Table 77 in Section 6.2 revealed a return on investment of 16.9% in that year, and thus profitability was confirmed. In 2017, the LCOE was calculated as USD 0.174/kWh, while the FIT price was USD 0.186/kWh. Once again, Table 77 in Section 6.2 indicated that a CPV project commencing in 2017 under the "average" scenario had a positive return on investment of 8.0%.

However, in 2018, the LCOE was calculated to be USD 0.161/kWh. In that same year, the FIT price dropped to USD 0.158/kWh. Consequently, the FIT price was below the LCOE and a negative return on investment of -2.4% was observed according to Table 77 in Section 6.2. In this case, and in all other cases displayed in Figure 83, when the LCOE was less than the FIT price, the CPV installation investment was not profitable. With a static price paid for electricity, the LCOE was a valuable metric because it accurately reported what it was intended to measure. However, as shown via examples in Sections 8.1.1 and 8.1.3, when electricity prices were variable the LCOE was not a reliable metric to depend upon.

8.2.4 Concentrated Photovoltaic Technology Variability Analysis

The 95% levelized cost of electricity confidence intervals under CPV technology and an assumed 20-year operational lifetime are shown in Table 138 below:

Year	Pessimistic Scenario		Average Scenario		Optimistic Scenario	
	95% Lower CI Value	95% Upper CI Value	95% Lower CI Value	95% Upper CI Value	95% Lower CI Value	95% Upper CI Value
2014	0.3449	0.3517	0.2485	0.2531	0.1739	0.1772
2015	0.3133	0.3197	0.2140	0.2182	0.1419	0.1444
2016	0.2910	0.2968	0.1904	0.1946	0.1203	0.1227
2017	0.2713	0.2768	0.1726	0.1762	0.1063	0.1084
2018	0.2550	0.2597	0.1594	0.1623	0.0956	0.0974
2019	0.2401	0.2448	0.1466	0.1495	0.0882	0.0898
2020	0.2273	0.2318	0.1375	0.1402	0.0799	0.0813

Table 138. Levelized cost of electricity 95% confidence intervals for CPV technology under the feed-in tariff and power purchase agreement tariff scenarios.

According to the figures in the above table, the largest 95% confidence interval was USD 0.0068/kWh in the year 2014 under the "pessimistic" scenario. All of the widest 95% confidence intervals in Chapter 8 were located in the year 2014 and under the "pessimistic" pricing scenario. Thus, this is when the levelized cost of electricity was subject to the greatest risk of variability due to fluctuating energy yields.

For 20-year CPV projects, the following table provides figures for LCOE variability as a proportion of the levelized cost of electricity mean for the years 2014 to 2020:

Levelized Cost of Electricity Variability due to Energy Yield				
Year	**% Above/Below Central Estimate**	**Pessimistic Scenario**	**Average Scenario**	**Optimistic Scenario**
2014	% above central estimate	0.978%	0.906%	0.937%
	% below central estimate	-0.978%	-0.906%	-0.937%
2015	% above central estimate	1.020%	0.986%	0.863%
	% below central estimate	-1.020%	-0.986%	-0.863%
2016	% above central estimate	0.991%	1.080%	0.986%
	% below central estimate	-0.991%	-1.080%	-0.986%
2017	% above central estimate	1.007%	1.029%	0.981%
	% below central estimate	-1.007%	-1.029%	-0.981%
2018	% above central estimate	0.917%	0.898%	0.924%
	% below central estimate	-0.917%	-0.898%	-0.924%
2019	% above central estimate	0.962%	0.948%	0.889%
	% below central estimate	-0.962%	-0.948%	-0.889%
2020	% above central estimate	0.981%	0.970%	0.885%
	% below central estimate	-0.981%	-0.970%	-0.885%

Table Notes:

- "Central estimate" is the mean LCOE value from the Monte Carlo simulation
- The above figures represent variability as a proportion of the mean with 95% confidence
- *Values that are exceptional due to the central estimate being close to zero

Table 139. Levelized cost of electricity variability due to energy yield for CPV technology and a 20-year project lifespan.

According to Table 139, LCOE variability due to energy yield exceeded the 1% mark for the first time. This occurred in 2015 under the "pessimistic" scenario as well as in 2016 and 2017 under the "average" scenario. The largest value in Table 139 was plus or minus 1.080% on either side of the mean, and this was found in 2016. Provided that the widest calculated confidence interval meant that 95% of the LCOE

data points from the Monte Carlo simulation fell within 1.080% of the mean, energy yield variability was not a significant contributor to LCOE variability.

System costs as well as O&M and degradation had a much larger impact on LCOE variability compared with energy yields. System cost, for instance, could have varied the LCOE by as much as 38.87% above and 29.95% below the mean LCOE value in 2014; by 2020, this range was 65.27% above and 41.94% below:

Levelized Cost of Electricity Variability due to System Cost and O&M and Degradation			
Year	**% Above/Below Central Estimate**	**System Cost⊙**	**O&M and Degradation❖**
2014	% above central estimate	38.87%	5.90%
	% below central estimate	-29.95%	-5.75%
2015	% above central estimate	46.40%	6.59%
	% below central estimate	-33.77%	-6.43%
2016	% above central estimate	52.56%	7.21%
	% below central estimate	-36.89%	-7.03%
2017	% above central estimate	57.13%	7.80%
	% below central estimate	-38.43%	-7.60%
2018	% above central estimate	60.03%	8.34%
	% below central estimate	-39.96%	-8.11%
2019	% above central estimate	63.78%	8.92%
	% below central estimate	-39.87%	-8.68%
2020	% above central estimate	65.27%	9.40%
	% below central estimate	-41.94%	-9.15%

Notes:

- ⊙Range from literature: Haysom et al. (2014).
- ❖Range from literature: Drury et al. (2013), Gerstmaier et al. (2014).
- "Central estimate" is the "average" LCOE value with zero variability
- *Values that are exceptional due to the central estimate being close to zero

Table 140. Percentage of levelized cost of electricity variability due to system cost, as well as O&M and degradation for CPV technology and a 20-year project lifespan.

Comparatively, the LCOE could have fluctuated at most by 9.40% above and 9.15% below the mean LCOE value on account of O&M and degradation. These two highest values were observed in the year 2020 in Table 140. Thus, the quantity of LCOE variability due to system costs as well as O&M and degradation increased as time progressed towards 2020. Both sources of variability, however, increased at

different rates between 2014 and 2020 as indicated by the ratio values in Table 141 that sometimes increased between years and at other times decreased:

Ratio of Variability due to System Cost to Variability due to O&M and Degradation		
Year	**Ratio Above/Below Central Estimate**	**Ratio**
2014	Ratio above central estimate	6.59
	Ratio below central estimate	5.21
2015	Ratio above central estimate	7.04
	Ratio below central estimate	5.26
2016	Ratio above central estimate	7.29
	Ratio below central estimate	5.25
2017	Ratio above central estimate	7.32
	Ratio below central estimate	5.06
2018	Ratio above central estimate	7.20
	Ratio below central estimate	4.92
2019	Ratio above central estimate	7.15
	Ratio below central estimate	4.59
2020	Ratio above central estimate	6.94
	Ratio below central estimate	4.58

Table Note:

- "Central estimate" is the "average" LCOE value with zero variability

Table 141. Ratio of variability due to system cost to variability due to O&M and degradation for CPV technology and a 20-year project lifespan.

All of the ratio values in Table 141 were greater than 1, which meant that system costs had a larger impact on LCOE variability than O&M and degradation.

Turning to a comparison of the impact of O&M and degradation as well as energy yield on the LCOE, Table 142 indicated that the former was between 5.88 and 10.63 times greater than the latter:

Ratio of O&M and Degradation Variability to Energy Yield Variability				
Year	**Ratio Above/Below Central Estimate**	**Pessimistic Scenario**	**Average Scenario**	**Optimistic Scenario**
2014	Ratio above central estimate	6.03	6.52	6.30
	Ratio below central estimate	5.88	6.35	6.14
2015	Ratio above central estimate	6.47	6.69	7.65
	Ratio below central estimate	6.30	6.52	7.45
2016	Ratio above central estimate	7.28	6.68	7.31
	Ratio below central estimate	7.09	6.51	7.12
2017	Ratio above central estimate	7.75	7.59	7.95
	Ratio below central estimate	7.54	7.39	7.75
2018	Ratio above central estimate	9.10	9.28	9.02
	Ratio below central estimate	8.85	9.03	8.78
2019	Ratio above central estimate	9.27	9.41	10.03
	Ratio below central estimate	9.02	9.16	9.76
2020	Ratio above central estimate	9.59	9.70	10.63
	Ratio below central estimate	9.33	9.43	10.34

Table Note:

- "Central estimate" is the mean LCOE value from the Monte Carlo simulation
- *Values that are exceptional due to the central estimate being close to zero

Table 142. A comparison of how much more levelized cost of electricity variability is due to O&M and degradation compared with energy yield for CPV technology and a 20-year project lifespan.

As was the case throughout this section, the ratio values in Table 142 across each of the three pricing scenarios increased over all between 2014 and 2020. As well, the values were relatively similar in each of the seven years under investigation.

8.3 Summary

Chapter 8 provided details about the levelized cost of electricity, the fourth and final metric analyzed by this thesis. A criticism of using the LCOE with intermittent energy sources, such as solar, was brought forward and support for this criticism was provided by the analysis. Using the time-of-use pricing scenario as an example, Sections 8.1.1 and 8.1.3 demonstrated that both PV and CPV installations could be profitable even if they did not always offset grid-produced electricity that was valued higher than the breakeven point indicated by the LCOE. Instead, system profitability was likely more dependent upon *when* the installation produced power. Based upon the analysis in this thesis, solar installations produced the majority of

their output during midday over the summer months, which happened to coincide with when electricity prices were at their peak. Due to this fact, some installations were indeed profitable even if they were offsetting electricity that was below the LCOE during certain times of each day.

However, the usefulness of the LCOE was illustrated by examples in Section 8.2.1 and 8.2.3. Using the "average" pricing scenario and flat-rate feed-in tariff scenario as an example, the analysis successfully demonstrated that the solar installation investment was profitable when the FIT rate was above the LCOE. On the other hand, the solar installation investment was not profitable when the FIT price dropped below the LCOE. The levelized cost of electricity metric was in fact very accurate at determining the breakeven price for electricity in this case when the electricity price was static.

Between the years 2014 and 2020, the levelized cost of electricity decreased. This phenomenon was likely due to decreasing system costs. In terms of LCOE variability, energy yield fluctuations from both PV and CPV systems had only a very minor impact on the levelized cost of electricity. System costs as well as O&M and degradation were found to have a larger impact on LCOE variability than energy output. In the next section, Chapter 9, the results from Chapters 5 through 8 will be summarized. As well, a brief exploration of how energy payment allocation factors, which were used under the power purchase agreement tariff scenario, bolstered the financial metrics for PV and CPV projects.

Chapter 9: Results Summary

This chapter will provide summary charts and tables of the large number of results presented in Chapters 5 through 8. The summaries will be listed according to tariff scenario, and will include charts of the financial metric results as well as tables summarizing the extent of discounted net present value and internal rate of return

variability. Similar summary charts and tables pertaining to the levelized cost of electricity metric will be presented separately, since these figures were calculated independently from the tariffs. This chapter will also include a brief discussion about energy payment allocation factors, which were included as part of the power purchase agreement tariff scenario. This supplemental subsection will focus upon the role these factors play in improving the financial attractiveness of solar technology. As well, a subsection will be devoted to quantifying and comparing the variability of the inputs and one of the four outputs from the Monte Carlo simulation.

9.1 Time-of-Use Tariff Scenario Summary

Below, Table 143 and Table 144 display charts summarizing the financial metrics of discounted net present value, return on investment, and internal rate of return for PV and CPV technologies, respectively:

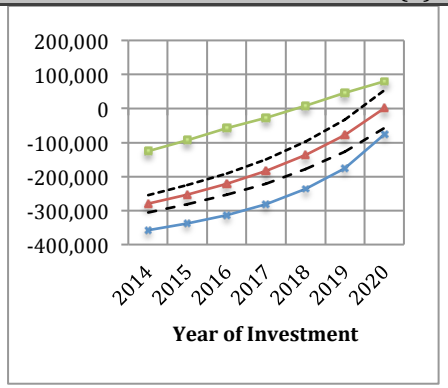
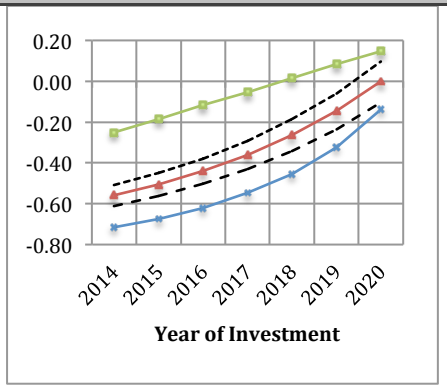
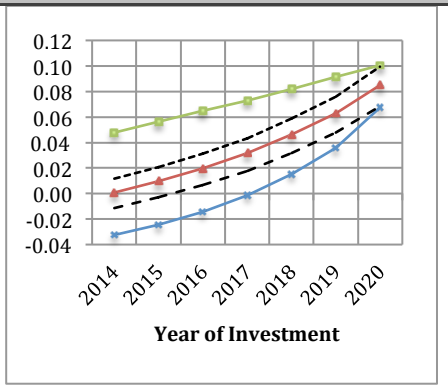
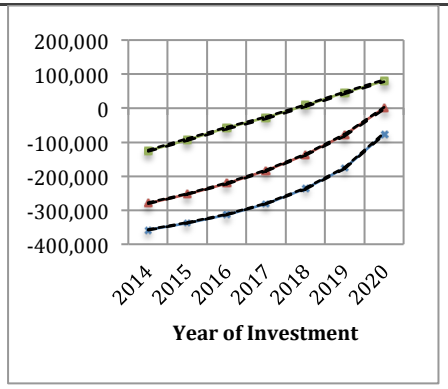
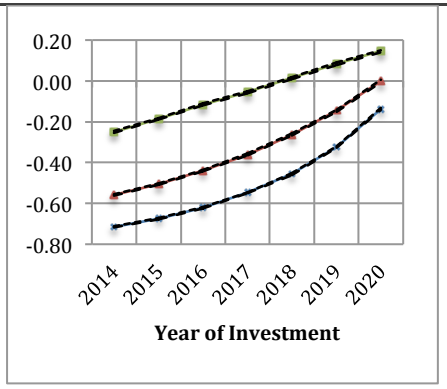
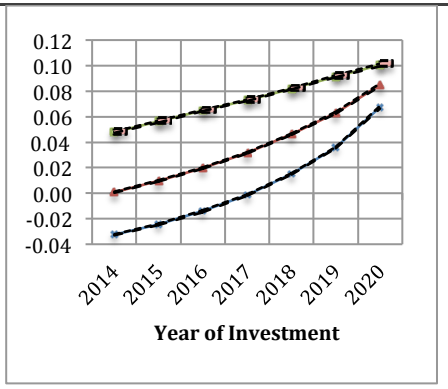
Time-of-Use Tariff Scenario PV Summary			
	Discounted Net Present Value ($)	Return on Investment	Internal Rate of Return
PV (Zero Variability)			
PV (Variability, average of 250 Monte Carlo simulations with 95% CI's)			
Legend	Zero variability: green squares = "optimistic" scenario; red triangles = "average" scenario; blue crosses = "pessimistic" scenario. Tight dashed line above "average" scenario = "average" costs with "optimistic" O&M and degradation; spaced dashed line below "average" scenario = "average" costs with "pessimistic" O&M and degradation. Variability: Tight dashed line = upper 95% confidence interval; spaced dashed line = lower 95% confidence interval.		

Table 143. Summary of the PV discounted net present value, return on investment, and internal rate of return figures under the time-of-use tariff scenario.

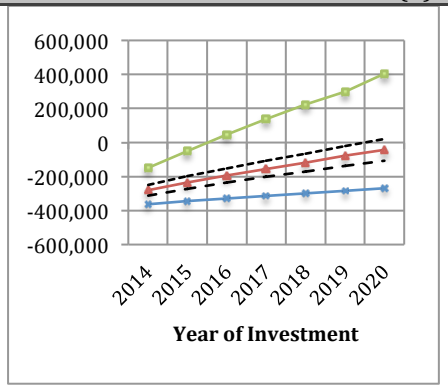
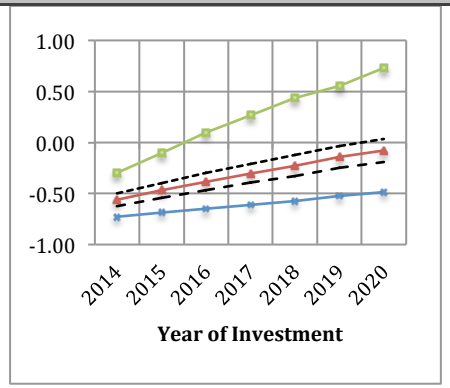
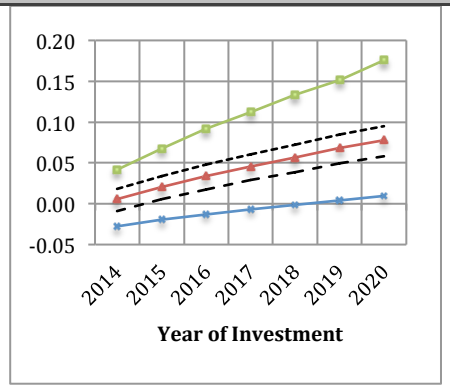
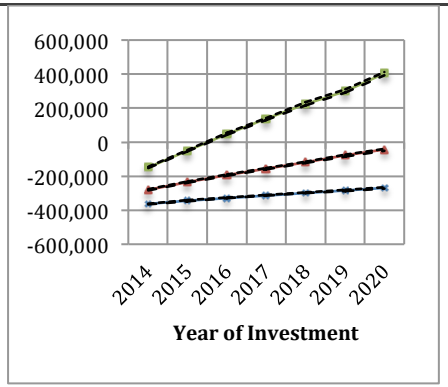
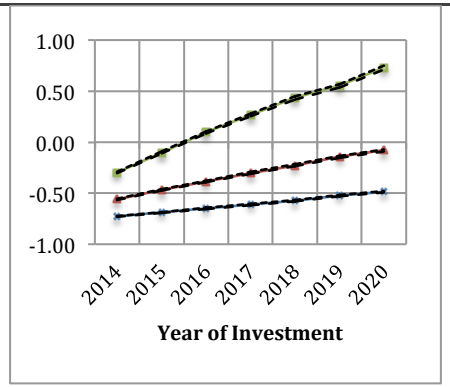
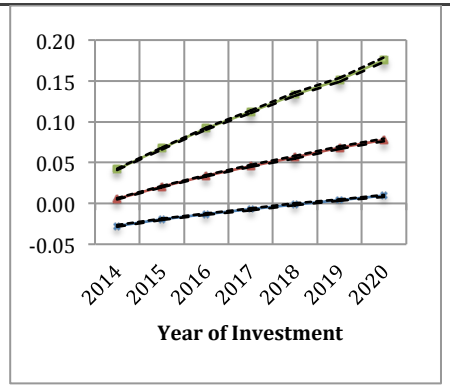
Time-of-Use Tariff Scenario CPV Summary			
	Discounted Net Present Value ($)	Return on Investment	Internal Rate of Return
CPV (Zero Variability)			
CPV (Variability, average of 250 Monte Carlo simulations with 95% CI's)			
Legend	Zero variability: green squares = "optimistic" scenario; red triangles = "average" scenario; blue crosses = "pessimistic" scenario. Tight dashed line above "average" scenario = "average" costs with "optimistic" O&M and degradation; spaced dashed line below "average" scenario = "average" costs with "pessimistic" O&M and degradation. Variability: Tight dashed line = upper 95% confidence interval; spaced dashed line = lower 95% confidence interval.		

Table 144. Summary of the CPV discounted net present value, return on investment, and internal rate of return figures under the time-of-use tariff scenario.

As evidenced by Table 143 and Table 144, both the PV and CPV financial metrics improved as time progressed between 2014 and 2020. The optimal year to invest was in 2020 under the "optimistic" pricing scenario for both PV and CPV technologies. The 95% confidence intervals in both tables were rather narrow and hard to distinguish for both PV and CPV technologies, meaning that energy yield variability did not have a significant impact on discounted net present value, return on investment, or internal rate of return.

Continuing with summarizing the results from the TOU tariff scenario, Table 145 below provides a summary of the range of discounted net present values above and below the mean under different sources of variability:

Discounted Net Present Value ($)					
Technology	**Variability Source**	**Above/Below Mean**	**Discounted NPV Range (2014-2020)**	**Average Discounted NPV (2014-2020)**	**Discounted NPV (2017)**
PV	Energy Yield (Pessimistic)*	Above Mean	930.24 to 2,717.25	1,649.72	1,468.75
		Below Mean	-2,717.25 to -930.24	-1,649.72	-1,468.75
	Energy Yield (Average)*	Above Mean	1,283.37 to 3,194.29	1,995.14	1,849.50
		Below Mean	-3,194.29 to -1,283.37	-1,995.14	-1,849.50
	Energy Yield (Optimistic)*	Above Mean	1,910.14 to 3,283.73	2,539.86	2,469.01
		Below Mean	-3,283.73 to -1,910.14	-2,539.86	-2,469.01
	System Price**	Above Mean	80,439.40 to 162,997.11	140,307.66	156,519.39
		Below Mean	-100,279.43 to -75,929.87	-89,253.29	-96,377.68
	O&M and Degradation**	Above Mean	24,875.40 to 54,203.56	36,663.01	34,434.29
		Below Mean	-57,289.17 to -26,166.17	-38,659.32	-36,282.73
CPV	Energy Yield (Pessimistic)*	Above Mean	1,847.43 to 3,378.73	2,670.07	2,764.58
		Below Mean	-3,378.73 to -1,847.43	-2,670.07	-2,764.58
	Energy Yield (Average)*	Above Mean	2,603.11 to 5,495.01	4,102.80	4,029.01
		Below Mean	-5,495.01 to -2,603.11	-4,102.80	-4,029.01
	Energy Yield (Optimistic)*	Above Mean	3,424.19 to 9,672.38	6,624.75	6,235.90
		Below Mean	-9,672.38 to -3,424.19	-6,624.75	-6,235.90
	System Price**	Above Mean	131,935.35 to 447,978.76	288,239.80	290,523.01
		Below Mean	-224,880.81 to -82,984.81	-156,423.08	-158,259.18
	O&M and Degradation**	Above Mean	31,518.44 to 63,140.29	47,693.57	47,951.61
		Below Mean	-63,140.29 to -31,518.44	-47,693.57	-47,951.61

* Mean refers to a value calculated from the 250 Monte Carlo simulations. Range above/below mean represents 95% confidence interval.
** Mean refers to a discounted net present value associated with the "average" pricing scenario.

Table 145. Ranges of discounted net present values due to different sources of variability under the time-of-use tariff scenario. All values are in USD.

For variability from energy yield in the above table, results for all three of the "pessimistic," "average," and "optimistic" pricing scenarios were presented. The input values that comprised these scenarios were defined in Sections 4.1 for PV technology and 4.2 for CPV technology. The mean value associated with variability due to energy yield referred to an average calculated from the 250 Monte Carlo simulation results, and the upper and lower values comprising the "range" referred to *actual* 95% confidence intervals. These CI's were computed using the calculated mean and standard deviations derived from the Monte Carlo simulation results.

Looking at the PV "Energy Yield (Pessimistic)" values, the results in Table 145 indicated that between 2014 and 2020 the upper bound of the 95% discounted NPV confidence interval ranged from USD 930.24 to USD 2,717.25 above the mean. These results were mirrored below the mean, where the lower bound of the 95% confidence interval ranged between USD -2,717.25 and USD -930.24 over the same timeframe. Thus, according to the "pessimistic" pricing scenario, discounted NPV could vary at most by plus or minus USD 2,717.25 above or below the mean between 2014 and 2020 on account of system energy yield variability. The average amount of discounted net present value variability above or below the mean over this same timeframe was plus or minus USD 1,649.72 according to Table 145. In this case, "average" referred to either the sum of the seven discounted net present values above the mean divided by seven, or the sum of the seven discounted net present values below the mean divided by seven. Lastly, the 95% confidence interval calculation in 2017 indicated that discounted NPV varied by plus or minus USD 1,468.75 on either side of the average value in that year. Note that these figures reflected the 95% confidence intervals surrounding only the "pessimistic" plot of discounted net present values found in the leftmost chart on the bottom row of Table 143. Similarly, the "average" and "optimistic" energy yield variability figures from Table 145 reflected the "average" and "optimistic" plots found in the same leftmost chart on the bottom row of Table 143. For CPV technology, the discounted NPV figures from Table 145 linked to energy yield variability referred to the 95% confidence intervals from the leftmost chart on the bottom row of Table 144.

For variability tied to system price as well as O&M and degradation, the mean in this case referred to the discounted net present value or internal rate of return figure associated with the "average" pricing scenario. This was not a true 95% confidence interval per se but was assumed as such according to the discussion in Section 5.1.2.2. Accordingly, the PV "System Price" discounted net present values in Table 145 ranged below the mean from USD -100,279.43 to USD -75,929.87 between 2014 and 2020. These figures corresponded with the difference between the plot of "pessimistic" discounted net present values and the plot of "average" discounted net present values from the leftmost table on the top row of Table 143. Above the mean, discounted net present values associated with the "optimistic" pricing scenario were between USD 80,439.40 and USD 162,997.11 above the discounted net present values tied to the "average" pricing scenario between 2014 and 2020. These plot lines were also observable in the leftmost table on the top row of Table 143. For CPV system prices, the leftmost chart on the top row of Table 144 illustrated the system price ranges found in the bottom part of Table 145.

In terms of variability due to "O&M and degradation," the PV discounted NPV range figures in Table 145 were shown by the dashed lines on either side of the plot of "average" discounted net present values in the leftmost chart on the top row of Table 143. On the other hand, the CPV discounted NPV range figures from Table 145 were demonstrated by the dashed lines surrounding the "average" plot of discounted net present values in the leftmost chart on the top row of Table 144.

The same principles described over the preceding paragraphs applied to the internal rate of return ranges provided in Table 146 below:

			Internal Rate of Return (%)		
Technology	**Variability Source**	**Above/Below Mean**	**IRR Range (2014-2020)**	**Average IRR (2014-2020)**	**IRR (2017)**
PV	Energy Yield (Pessimistic)*	Above Mean	0.045 to 0.079	0.058	0.054
		Below Mean	-0.079 to -0.045	-0.058	-0.054
	Energy Yield (Average)*	Above Mean	0.043 to 0.088	0.058	0.054
		Below Mean	-0.088 to -0.043	-0.058	-0.054
	Energy Yield (Optimistic)*	Above Mean	0.051 to 0.086	0.066	0.063
		Below Mean	-0.086 to -0.051	-0.066	-0.063
	System Price**	Above Mean	1.545 to 4.687	3.707	4.127
		Below Mean	-3.399 to -1.763	-3.004	-3.287
	O&M and Degradation**	Above Mean	1.068 to 1.425	1.211	1.184
		Below Mean	-1.656 to -1.230	-1.402	-1.370
CPV	Energy Yield (Pessimistic)*	Above Mean	0.088 to 0.117	0.104	0.111
		Below Mean	-0.117 to -0.088	-0.104	-0.111
	Energy Yield (Average)*	Above Mean	0.089 to 0.153	0.118	0.114
		Below Mean	-0.153 to -0.089	-0.118	-0.114
	Energy Yield (Optimistic)*	Above Mean	0.091 to 0.287	0.176	0.156
		Below Mean	-0.287 to -0.091	-0.176	-0.156
	System Price**	Above Mean	3.624 to 9.838	6.663	6.683
		Below Mean	-6.849 to -3.310	-5.193	-5.280
	O&M and Degradation**	Above Mean	1.257 to 1.753	1.503	1.500
		Below Mean	-1.948 to -1.439	-1.691	-1.689

* Mean refers to a value calculated from the 250 Monte Carlo simulations. Range above/below mean represents 95% confidence interval.
** Mean refers to an internal rate of return value associated with the "average" pricing scenario.

Table 146. Ranges of internal rates of return due to different sources of variability under the time-of-use tariff scenario.

The IRR ranges associated with PV technology were illustrated by the internal rate of return charts in the rightmost column of Table 143, while the IRR ranges associated with CPV technology were displayed by the internal rate of return charts in the rightmost column of Table 144. Above, Table 146 displayed the differences between the mean IRR and the actual or assumed 95% IRR confidence interval displayed by the charts referenced in the prior sentence.

Turning to a different measure, Table 147 below presents ratios that measure the extent to which one source of variability impacts discounted net present value compared to another source. The ratios included for analysis include energy yield variability from each of the three pricing scenarios to O&M and degradation variability, as well as system price to O&M and degradation. The values in the table below were calculated from the figures found within Table 145 and cover both PV and CPV technologies:

			Discounted Net Present Value		
Technology	**Ratio**	**Above/Below Mean**	**Range of Ratios (2014-2020)**	**Average Ratio (2014-2020)**	**2017 Ratio**
PV	Energy Yield (Pessimistic) to O&M and Degradation	Above Mean	0.037 to 0.050	0.045	0.043
		Below Mean	0.036 to 0.047	0.043	0.040
	Energy Yield (Average) to O&M and Degradation	Above Mean	0.051 to 0.059	0.054	0.054
		Below Mean	0.049 to 0.056	0.052	0.051
	Energy Yield (Optimistic) to O&M and Degradation	Above Mean	0.061 to 0.079	0.069	0.072
		Below Mean	0.057 to 0.075	0.066	0.068
	System Price to O&M and Degradation	Above Mean	1.484 to 6.205	3.827	4.545
		Below Mean	1.325 to 2.987	2.309	2.656
CPV	Energy Yield (Pessimistic) to O&M and Degradation	Above Mean	0.054 to 0.059	0.056	0.058
		Below Mean	0.054 to 0.059	0.056	0.058
	Energy Yield (Average) to O&M and Degradation	Above Mean	0.080 to 0.090	0.086	0.084
		Below Mean	0.080 to 0.090	0.086	0.084
	Energy Yield (Optimistic) to O&M and Degradation	Above Mean	0.109 to 0.155	0.139	0.130
		Below Mean	0.109 to 0.155	0.139	0.130
	System Price to O&M and Degradation	Above Mean	4.186 to 7.095	6.044	6.059
		Below Mean	2.633 to 3.562	3.280	3.300

Table 147. Summary of discounted net present value ratios above and below the mean between 2014 and 2020 under the time-of-use tariff scenario.

As per the ratios presented in the above table, discounted net present value variability due to O&M plus degradation was consistently greater than variability due to fluctuating system energy yield for both PV and CPV technologies. This was denoted by the ratio values less than "1" found under each of the "pessimistic," "average," and "optimistic" pricing scenarios. Table 147 also indicated that system price variability had a consistently larger impact on discounted NPV than variability due to O&M plus degradation. This was indicated by the system price ratio figures greater than "1," and was applicable to both PV and CPV technologies. For example, above the mean, discounted NPV variability due to system price was between 1.484 and 6.205 times greater than variability due to O&M and degradation for PV technology over the years 2014 to 2020. Above the mean for CPV, the range of the ratios was 4.186 to 7.095. Also included in Table 147 were the mean ratio between the years 2014 and 2020 and the precise ratio value in the year 2017.

Below, Table 148 includes the same ratios but for the metric internal rate of return. The figures in the table below are based upon the values contained within Table 146 from this section, and they can be interpreted in the same manner as described in the previous paragraph. For instance, below the mean, internal rate of return variability due to system price was between 1.065 and 2.721 times greater than variability stemming from O&M plus degradation over the years 2014 to 2020 for PV technology. For CPV, the range values below the mean of 2.633 to 3.562 for the same ratio were even greater. As was the case in Table 147, Table 148 includes an average ratio value over the years 2014 to 2020 as well as the precise ratio value for the year 2017:

Internal Rate of Return					
Technology	**Ratio**	**Above/Below Mean**	**Range of Ratios (2014-2020)**	**Average Ratio (2014-2020)**	**2017 Ratio**
PV	Energy Yield (Pessimistic) to O&M and Degradation	Above Mean	0.043 to 0.055	0.048	0.046
		Below Mean	0.037 to 0.048	0.041	0.039
	Energy Yield (Average) to O&M and Degradation	Above Mean	0.040 to 0.062	0.048	0.046
		Below Mean	0.035 to 0.053	0.041	0.039
	Energy Yield (Optimistic) to O&M and Degradation	Above Mean	0.048 to 0.060	0.054	0.053
		Below Mean	0.041 to 0.052	0.047	0.046
	System Price to O&M and Degradation	Above Mean	1.084 to 4.389	3.061	3.486
		Below Mean	1.065 to 2.721	2.143	2.398
CPV	Energy Yield (Pessimistic) to O&M and Degradation	Above Mean	0.067 to 0.074	0.069	0.074
		Below Mean	0.060 to 0.066	0.062	0.066
	Energy Yield (Average) to O&M and Degradation	Above Mean	0.068 to 0.088	0.079	0.076
		Below Mean	0.060 to 0.079	0.070	0.068
	Energy Yield (Optimistic) to O&M and Degradation	Above Mean	0.072 to 0.164	0.117	0.104
		Below Mean	0.063 to 0.147	0.104	0.092
	System Price to O&M and Degradation	Above Mean	2.884 to 5.611	4.433	4.454
		Below Mean	2.300 to 3.516	3.070	3.127

Table 148. Summary of internal rate of return ratios above and below the mean between 2014 and 2020 under the time-of-use tariff scenario.

The summaries of the remaining tariff scenarios and the levelized cost of electricity metric in Sections 9.2 to 9.5 will follow the same format as this section, Section 9.1. As such, interpretations of the results within these forthcoming sections can be based upon the discussions presented throughout Section 9.1.

9.2 Feed-in Tariff Scenario Summary

On the next two pages, Table 149 and Table 150 provide a summary of the charts associated with the financial metrics of discounted NPV, ROI, and IRR for photovoltaic and concentrated photovoltaic technologies, respectively:

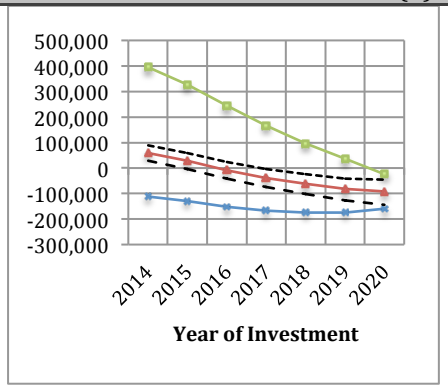
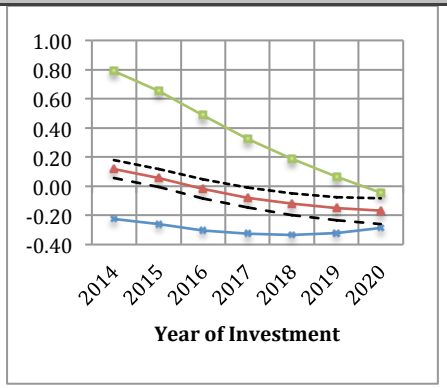
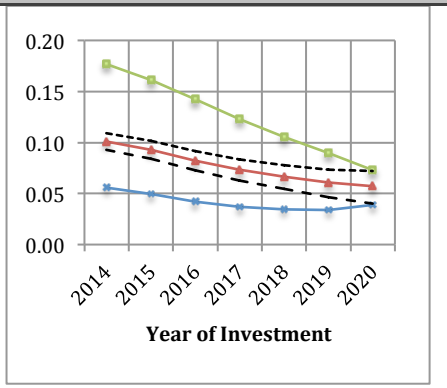
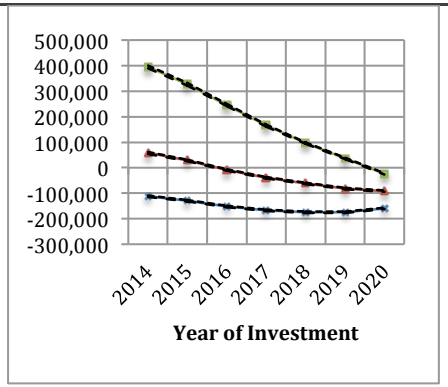
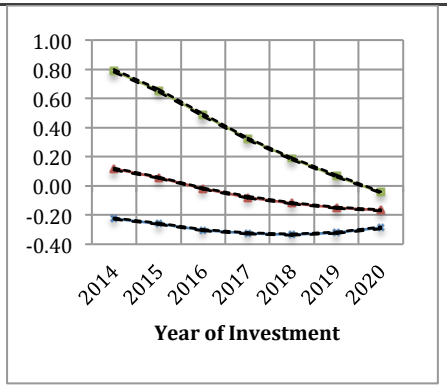
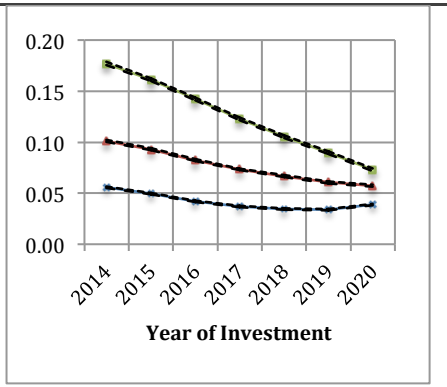
Feed-in Tariff Scenario PV Summary			
	Discounted Net Present Value ($)	Return on Investment	Internal Rate of Return
PV (Zero Variability)			
PV (Variability, average of 250 Monte Carlo simulations with 95% CI's)			
Legend	Zero variability: green squares = "optimistic" scenario; red triangles = "average" scenario; blue crosses = "pessimistic" scenario. Tight dashed line above "average" scenario = "average" costs with "optimistic" O&M and degradation; spaced dashed line below "average" scenario = "average" costs with "pessimistic" O&M and degradation. Variability: Tight dashed line = upper 95% confidence interval; spaced dashed line = lower 95% confidence interval.		

Table 149. Summary of the PV discounted net present value, return on investment, and internal rate of return figures under the feed-in tariff scenario.

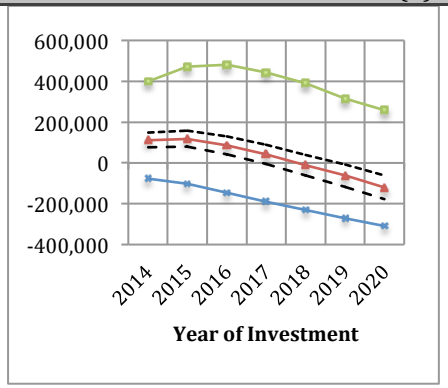
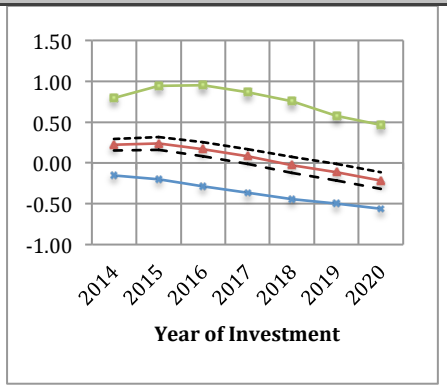
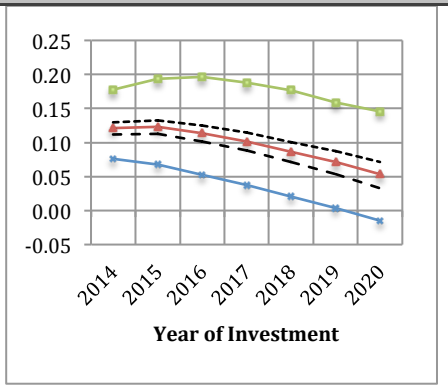
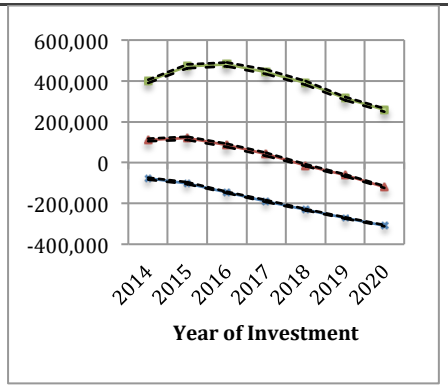
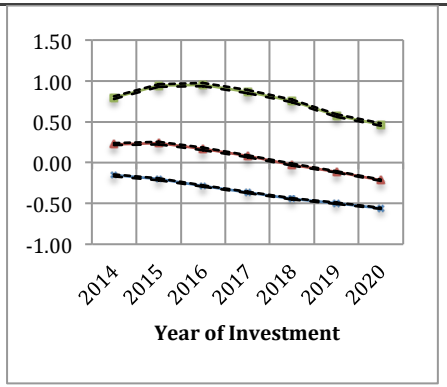
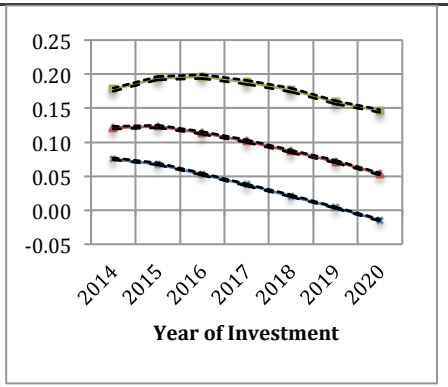
Feed-in Tariff Scenario CPV Summary			
	Discounted Net Present Value ($)	Return on Investment	Internal Rate of Return
CPV (Zero Variability)			
CPV (Variability, average of 250 Monte Carlo simulations with 95% CI's)			
Legend	Zero variability: green squares = "optimistic" scenario; red triangles = "average" scenario; blue crosses = "pessimistic" scenario. Tight dashed line above "average" scenario = "average" costs with "optimistic" O&M and degradation; spaced dashed line below "average" scenario = "average" costs with "pessimistic" O&M and degradation. Variability: Tight dashed line = upper 95% confidence interval; spaced dashed line = lower 95% confidence interval.		

Table 150. Summary of the CPV discounted net present value, return on investment, and internal rate of return figures under the feed-in tariff scenario.

The plots of the results in Table 149 were noticeably different from those in Table 150. Whereas the PV results clearly indicated that investment should be made in 2014 under the "optimistic" scenario to realize the highest discounted NPV, the CPV results indicated that investment should be deferred until the year 2016 under the "optimistic" scenario in order to experience the best discounted net present value. As was the case with the previous tariff scenario, the 95% confidence intervals shown in the charts on the bottom rows of both tables were very narrow. In contrast, the plots of "average" system prices with O&M and degradation from the "pessimistic" and "optimistic" scenarios were noticeably further away from the plot of the "average" values in the charts found on the upper row of Table 149 and Table 150.

The next four tables present additional summary figures. Firstly, Table 151 illustrates the range of discounted net present value variability above and below the mean between 2014 and 2020. The table includes ranges categorized according to variability source, as well as average discounted net present values above and below the mean over the same timeframe as well as a specific discounted NPV for 2017. These range values were included as part of the 95% confidence intervals shown by the discounted NPV charts on the bottom rows of Table 149 and Table 150 for PV and CPV technologies, respectively. Secondly, Table 152 includes the same categories as Table 151, but the figures within the table relate to the internal rate of return metric. The third table, Table 153, provides ratio figures between the years 2014 and 2020 for discounted net present value, while the fourth table, Table 154, presents ratio figures over the same timeframe for internal rate of return.

			Discounted Net Present Value ($)		
Technology	**Variability Source**	**Above/Below Mean**	**Discounted NPV Range (2014-2020)**	**Average Discounted NPV (2014-2020)**	**Discounted NPV (2017)**
PV	Energy Yield (Pessimistic)*	Above Mean	1,976.99 to 2,598.54	2,261.76	2,112.55
		Below Mean	-2,598.54 to -1,976.99	-2,261.76	-2,112.55
	Energy Yield (Average)*	Above Mean	2,494.40 to 3,294.38	2,784.31	2,606.69
		Below Mean	-3,294.38 to -2,494.40	-2,784.31	-2,606.69
	Energy Yield (Optimistic)*	Above Mean	2,698.25 to 4,585.44	3,733.96	3,868.69
		Below Mean	-4,585.44 to -2,698.25	-3,733.96	-3,868.69
	System Price**	Above Mean	67,927.03 to 337,584.29	205,921.90	205,732.18
		Below Mean	-169,553.40 to -65,822.72	-123,852.69	-126,431.89
	O&M and Degradation**	Above Mean	30,731.27 to 47,439.18	36,776.45	34,928.13
		Below Mean	-51,186.28 to -29,348.31	-37,664.07	-35,608.17
CPV	Energy Yield (Pessimistic)*	Above Mean	2,922.93 to 4,824.53	3,910.36	4,021.09
		Below Mean	-4,824.53 to -2,922.93	-3,910.36	-4,021.09
	Energy Yield (Average)*	Above Mean	4,990.72 to 7,295.59	6,090.52	6,608.88
		Below Mean	-7,295.59 to -4,990.72	-6,090.52	-6,608.88
	Energy Yield (Optimistic)*	Above Mean	8,010.05 to 10,567.40	9,231.98	10,288.94
		Below Mean	-10,567.40 to -8,010.05	-9,231.98	-10,288.94
	System Price**	Above Mean	286,016.87 to 404,047.76	370,973.78	404,047.76
		Below Mean	-230,566.03 to -189,576.47	-212,435.73	-229,293.02
	O&M and Degradation**	Above Mean	35,131.95 to 57,234.33	46,859.43	47,313.54
		Below Mean	-57,234.33 to -35,131.95	-46,859.43	-47,313.54

* Mean refers to a value calculated from the 250 Monte Carlo simulations. Range above/below mean represents 95% confidence interval.
** Mean refers to a discounted net present value associated with the "average" pricing scenario.

Table 151. Ranges of discounted net present values due to different sources of variability under the feed-in tariff scenario. All values are in USD.

			Internal Rate of Return (%)		
Technology	**Variability Source**	**Above/Below Mean**	**IRR Range (2014-2020)**	**Average IRR (2014-2020)**	**IRR (2017)**
PV	Energy Yield (Pessimistic)*	Above Mean	0.061 to 0.073	0.063	0.061
		Below Mean	-0.073 to -0.061	-0.063	-0.061
	Energy Yield (Average)*	Above Mean	0.085 to 0.092	0.086	0.085
		Below Mean	-0.092 to -0.085	-0.086	-0.085
	Energy Yield (Optimistic)*	Above Mean	0.126 to 0.130	0.127	0.126
		Below Mean	-0.130 to -0.126	-0.127	-0.126
	System Price**	Above Mean	1.580 to 7.609	4.829	4.960
		Below Mean	-4.526 to -1.815	-3.465	-3.634
	O&M and Degradation**	Above Mean	0.793 to 1.469	1.065	1.014
		Below Mean	-1.717 to -0.796	-1.163	-1.091
CPV	Energy Yield (Pessimistic)*	Above Mean	0.122 to 0.151	0.136	0.135
		Below Mean	-0.151 to -0.122	-0.136	-0.135
	Energy Yield (Average)*	Above Mean	0.153 to 0.206	0.176	0.190
		Below Mean	-0.206 to -0.153	-0.176	-0.190
	Energy Yield (Optimistic)*	Above Mean	0.221 to 0.301	0.257	0.280
		Below Mean	-0.301 to -0.221	-0.257	-0.280
	System Price**	Above Mean	5.625 to 9.258	8.101	8.686
		Below Mean	-6.796 to -4.539	-6.096	-6.427
	O&M and Degradation**	Above Mean	0.891 to 1.834	1.316	1.280
		Below Mean	-2.031 to -0.924	-1.405	-1.350

* Mean refers to a value calculated from the 250 Monte Carlo simulations. Range above/below mean represents 95% confidence interval.
** Mean refers to an internal rate of return value associated with the "average" pricing scenario.

Table 152. Ranges of internal rates of return due to different sources of variability under the feed-in tariff scenario.

			Discounted Net Present Value		
Technology	**Ratio**	**Above/Below Mean**	**Range of Ratios (2014-2020)**	**Average Ratio (2014-2020)**	**2017 Ratio**
PV	Energy Yield (Pessimistic) to O&M and Degradation	Above Mean	0.054 to 0.077	0.062	0.060
		Below Mean	0.051 to 0.081	0.060	0.059
	Energy Yield (Average) to O&M and Degradation	Above Mean	0.053 to 0.107	0.076	0.075
		Below Mean	0.049 to 0.112	0.074	0.073
	Energy Yield (Optimistic) to O&M and Degradation	Above Mean	0.057 to 0.149	0.102	0.111
		Below Mean	0.053 to 0.156	0.099	0.109
	System Price to O&M and Degradation	Above Mean	1.432 to 10.985	5.599	5.890
		Below Mean	1.286 to 5.777	3.288	3.551
CPV	Energy Yield (Pessimistic) to O&M and Degradation	Above Mean	0.051 to 0.136	0.083	0.085
		Below Mean	0.051 to 0.136	0.083	0.085
	Energy Yield (Average) to O&M and Degradation	Above Mean	0.087 to 0.175	0.130	0.140
		Below Mean	0.087 to 0.175	0.130	0.140
	Energy Yield (Optimistic) to O&M and Degradation	Above Mean	0.140 to 0.255	0.197	0.217
		Below Mean	0.140 to 0.255	0.197	0.217
	System Price to O&M and Degradation	Above Mean	6.595 to 9.050	7.917	8.540
		Below Mean	3.312 to 5.529	4.533	4.846

Table 153. Summary of discounted net present value ratios above and below the mean between 2014 and 2020 under the feed-in tariff scenario.

			Internal Rate of Return		
Technology	**Ratio**	**Above/Below Mean**	**Range of Ratios (2014-2020)**	**Average Ratio (2014-2020)**	**2017 Ratio**
PV	Energy Yield (Pessimistic) to O&M and Degradation	Above Mean	0.042 to 0.092	0.059	0.060
		Below Mean	0.036 to 0.092	0.054	0.056
	Energy Yield (Average) to O&M and Degradation	Above Mean	0.058 to 0.116	0.081	0.084
		Below Mean	0.049 to 0.116	0.074	0.078
	Energy Yield (Optimistic) to O&M and Degradation	Above Mean	0.086 to 0.165	0.119	0.125
		Below Mean	0.074 to 0.164	0.109	0.116
	System Price to O&M and Degradation	Above Mean	1.076 to 9.596	4.535	4.894
		Below Mean	1.057 to 5.682	2.980	3.331
CPV	Energy Yield (Pessimistic) to O&M and Degradation	Above Mean	0.068 to 0.165	0.103	0.106
		Below Mean	0.062 to 0.159	0.097	0.100
	Energy Yield (Average) to O&M and Degradation	Above Mean	0.084 to 0.197	0.134	0.148
		Below Mean	0.076 to 0.190	0.126	0.140
	Energy Yield (Optimistic) to O&M and Degradation	Above Mean	0.120 to 0.282	0.195	0.219
		Below Mean	0.109 to 0.272	0.183	0.207
	System Price to O&M and Degradation	Above Mean	5.047 to 7.240	6.156	6.785
		Below Mean	3.347 to 5.231	4.338	4.759

Table 154. Summary of internal rate of return ratios above and below the mean between 2014 and 2020 under the feed-in tariff scenario.

9.3 Power Purchase Agreement Tariff Scenario Summary

Below, Table 155 and Table 156 present a summary of discounted net present value, return on investment, and internal rate of return figures for PV and CPV technologies, respectively, under the power purchase agreement tariff scenario:

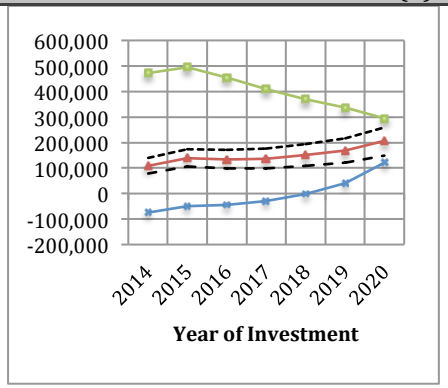
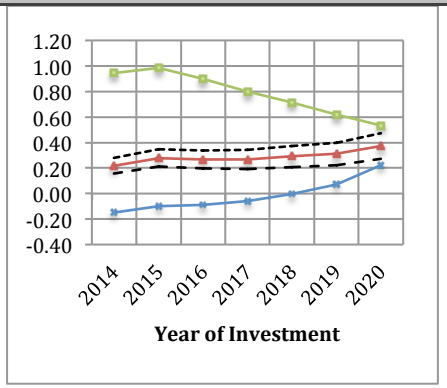
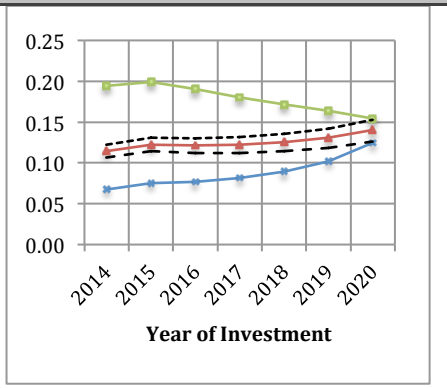
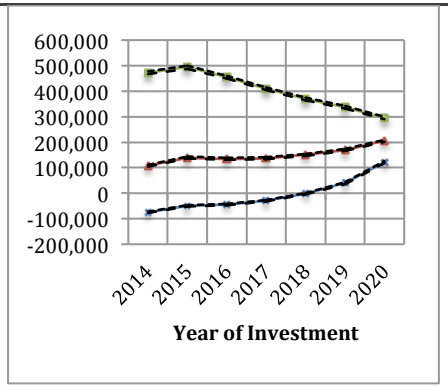
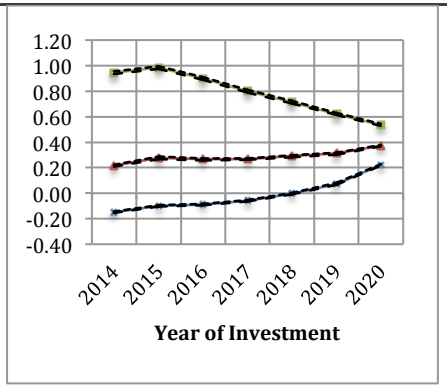
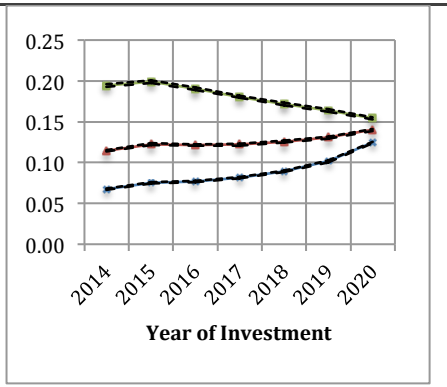
Power Purchase Agreement Tariff Scenario PV Summary			
	Discounted Net Present Value ($)	Return on Investment	Internal Rate of Return
PV (Zero Variability)			
PV (Variability, average of 250 Monte Carlo simulations with 95% CI's)			
Legend	Zero variability: green squares = "optimistic" scenario; red triangles = "average" scenario; blue crosses = "pessimistic" scenario. Tight dashed line above "average" scenario = "average" costs with "optimistic" O&M and degradation; spaced dashed line below "average" scenario = "average" costs with "pessimistic" O&M and degradation. Variability: Tight dashed line = upper 95% confidence interval; spaced dashed line = lower 95% confidence interval.		

Table 155. Summary of the PV discounted net present value, return on investment, and internal rate of return figures under the power purchase agreement tariff scenario.

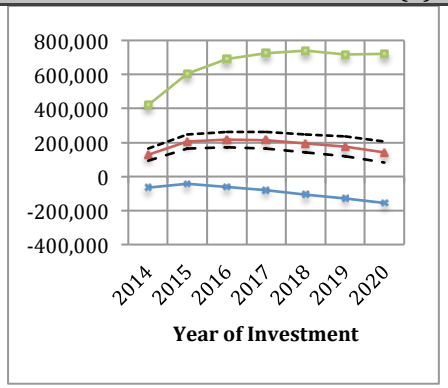
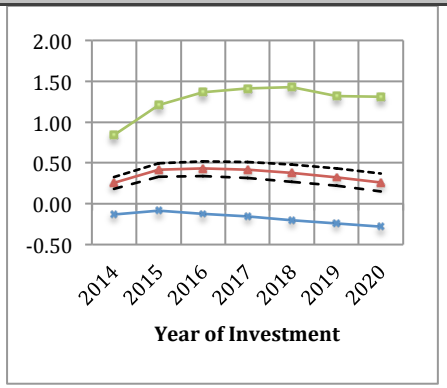
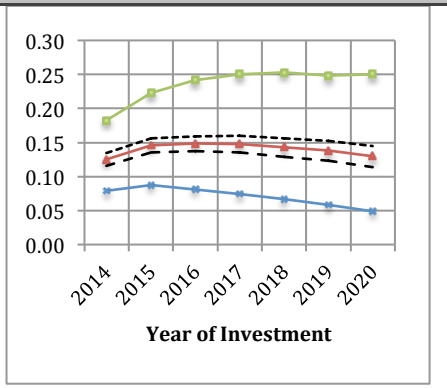
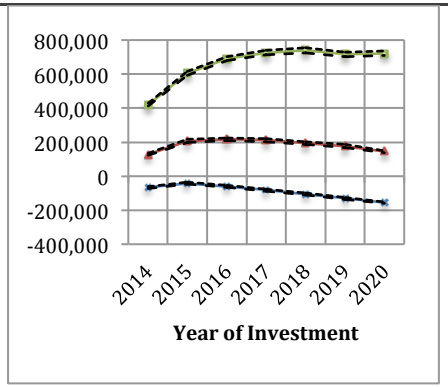
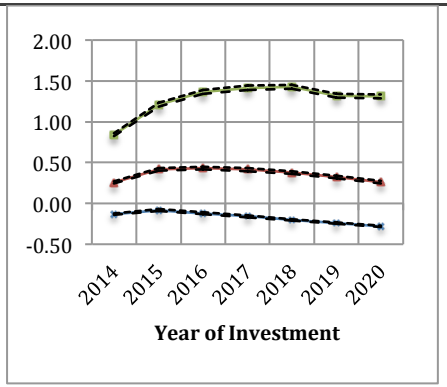
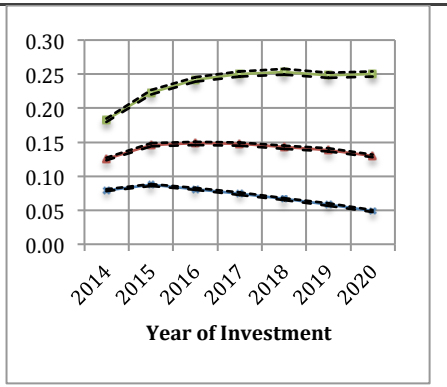
Power Purchase Agreement Tariff Scenario CPV Summary			
	Discounted Net Present Value ($)	Return on Investment	Internal Rate of Return
CPV (Zero Variability)			
CPV (Variability, average of 250 Monte Carlo simulations with 95% CI's)			
Legend	Zero variability: green squares = "optimistic" scenario; red triangles = "average" scenario; blue crosses = "pessimistic" scenario. Tight dashed line above "average" scenario = "average" costs with "optimistic" O&M and degradation; spaced dashed line below "average" scenario = "average" costs with "pessimistic" O&M and degradation. Variability: Tight dashed line = upper 95% confidence interval; spaced dashed line = lower 95% confidence interval.		

Table 156. Summary of the CPV discounted net present value, return on investment, and internal rate of return figures under the power purchase agreement tariff scenario.

As was the case under the feed-in tariff scenario from Section 9.2, the PV and CPV results shown in the two tables above were rather different from one another. The optimal time to invest with PV technology was in 2015 under the "optimistic" scenario, while the most favourable time to initiate a new CPV installation was in 2018 also under the "optimistic" scenario. The 95% confidence intervals were somewhat distinguishable according to the charts found on the bottom row of Table 155 and Table 156 for PV and CPV technologies, respectively. In contrast, these confidence intervals were much narrower than the assumed 95% confidence intervals associated with system price as well as O&M plus degradation variability found in the charts on the upper row of the same two tables.

A summary of the range of discounted net present values and internal rates of return is found within Table 157 and Table 158, respectively, on the next two pages. These tables summarize previously stated information from Chapters 5 and 7. Following these two tables, Table 159 and Table 160 provide ratios indicating that system energy yield has less of an impact than both O&M plus degradation and system price on discounted net present value and internal rate of return variability.

Discounted Net Present Value ($)					
Technology	**Variability Source**	**Above/Below Mean**	**Discounted NPV Range (2014-2020)**	**Average Discounted NPV (2014-2020)**	**Discounted NPV (2017)**
PV	Energy Yield (Pessimistic)*	Above Mean	2,501.03 to 3,532.93	2,911.42	2,917.70
		Below Mean	-3,532.93 to -2,501.03	-2,911.42	-2,917.70
	Energy Yield (Average)*	Above Mean	3,241.01 to 3,896.48	3,638.74	3,575.65
		Below Mean	-3,896.48 to -3,241.01	-3,638.74	-3,575.65
	Energy Yield (Optimistic)*	Above Mean	4,463.44 to 5,298.78	4,873.96	4,770.97
		Below Mean	-5,298.78 to -4,463.44	-4,873.96	-4,770.97
	System Price**	Above Mean	89,317.09 to 365,400.86	255,782.72	272,723.62
		Below Mean	-187,624.56 to -83,163.44	-154,624.57	-166,645.79
	O&M and Degradation**	Above Mean	31,958.90 to 54,805.42	41,160.53	39,292.76
		Below Mean	-56,097.11 to -30,166.73	-40,586.79	-38,517.93
CPV	Energy Yield (Pessimistic)*	Above Mean	4,279.07 to 5,702.73	5,128.11	5,380.20
		Below Mean	-5,702.73 to -4,279.07	-5,128.11	-5,380.20
	Energy Yield (Average)*	Above Mean	6,581.16 to 9,125.79	7,928.69	9,125.79
		Below Mean	-9,125.79 to -6,581.16	-7,928.69	-9,125.79
	Energy Yield (Optimistic)*	Above Mean	8,842.12 to 13,596.70	12,205.29	13,484.56
		Below Mean	-13,596.70 to -8,842.12	-12,205.29	-13,484.56
	System Price**	Above Mean	292,407.50 to 578,612.49	477,218.98	513,140.34
		Below Mean	-307,203.37 to -194,863.65	-274,857.29	-294,662.20
	O&M and Degradation**	Above Mean	35,379.73 to 61,431.62	49,401.34	50,052.89
		Below Mean	-61,431.62 to -35,379.73	-49,401.34	-50,052.89

* Mean refers to a value calculated from the 250 Monte Carlo simulations. Range above/below mean represents 95% confidence interval.
** Mean refers to a discounted net present value associated with the "average" pricing scenario.

Table 157. Ranges of discounted net present values due to different variability sources under the PPA tariff scenario. All values are in USD.

			Internal Rate of Return (%)		
Technology	**Variability Source**	**Above/Below Mean**	**IRR Range (2014-2020)**	**Average IRR (2014-2020)**	**IRR (2017)**
PV	Energy Yield (Pessimistic)*	Above Mean	0.075 to 0.104	0.086	0.086
		Below Mean	-0.104 to -0.075	-0.086	-0.086
	Energy Yield (Average)*	Above Mean	0.094 to 0.111	0.103	0.101
		Below Mean	-0.111 to -0.094	-0.103	-0.101
	Energy Yield (Optimistic)*	Above Mean	0.123 to 0.149	0.136	0.133
		Below Mean	-0.149 to -0.123	-0.136	-0.133
	System Price**	Above Mean	1.421 to 8.027	5.403	5.841
		Below Mean	-4.713 to -1.529	-3.723	-4.091
	O&M and Degradation**	Above Mean	0.782 to 1.266	0.978	0.944
		Below Mean	-1.388 to -0.779	-1.025	-0.982
CPV	Energy Yield (Pessimistic)*	Above Mean	0.142 to 0.173	0.160	0.165
		Below Mean	-0.173 to -0.142	-0.160	-0.165
	Energy Yield (Average)*	Above Mean	0.186 to 0.258	0.226	0.258
		Below Mean	-0.258 to -0.186	-0.226	-0.258
	Energy Yield (Optimistic)*	Above Mean	0.245 to 0.405	0.353	0.390
		Below Mean	-0.405 to -0.245	-0.353	-0.390
	System Price**	Above Mean	5.706 to 12.035	9.594	10.253
		Below Mean	-8.092 to -4.594	-6.891	-7.308
	O&M and Degradation**	Above Mean	0.886 to 1.543	1.203	1.196
		Below Mean	-1.623 to -0.918	-1.254	-1.242

* Mean refers to a value calculated from the 250 Monte Carlo simulations. Range above/below mean represents 95% confidence interval.
** Mean refers to an internal rate of return value associated with the "average" pricing scenario.

Table 158. Ranges of internal rates of return due to different sources of variability under the power purchase agreement tariff scenario.

			Discounted Net Present Value		
Technology	**Ratio**	**Above/Below Mean**	**Range of Ratios (2014-2020)**	**Average Ratio (2014-2020)**	**2017 Ratio**
PV	Energy Yield (Pessimistic) to O&M and Degradation	Above Mean	0.064 to 0.079	0.071	0.074
		Below Mean	0.063 to 0.084	0.072	0.076
	Energy Yield (Average) to O&M and Degradation	Above Mean	0.071 to 0.112	0.088	0.091
		Below Mean	0.069 to 0.118	0.090	0.093
	Energy Yield (Optimistic) to O&M and Degradation	Above Mean	0.082 to 0.166	0.118	0.121
		Below Mean	0.080 to 0.176	0.120	0.124
	System Price to O&M and Degradation	Above Mean	1.630 to 11.433	6.214	6.941
		Below Mean	1.482 to 6.078	3.810	4.326
CPV	Energy Yield (Pessimistic) to O&M and Degradation	Above Mean	0.070 to 0.138	0.104	0.107
		Below Mean	0.070 to 0.138	0.104	0.107
	Energy Yield (Average) to O&M and Degradation	Above Mean	0.119 to 0.196	0.160	0.182
		Below Mean	0.119 to 0.196	0.160	0.182
	Energy Yield (Optimistic) to O&M and Degradation	Above Mean	0.219 to 0.279	0.247	0.269
		Below Mean	0.219 to 0.279	0.247	0.269
	System Price to O&M and Degradation	Above Mean	8.265 to 10.322	9.660	10.252
		Below Mean	4.894 to 6.059	5.564	5.887

Table 159. Summary of discounted net present value ratios above and below the mean between 2014 and 2020 under the power purchase agreement tariff scenario.

Internal Rate of Return					
Technology	**Ratio**	**Above/Below Mean**	**Range of Ratios (2014-2020)**	**Average Ratio (2014-2020)**	**2017 Ratio**
PV	Energy Yield (Pessimistic) to O&M and Degradation	Above Mean	0.082 to 0.098	0.088	0.091
		Below Mean	0.075 to 0.098	0.084	0.088
	Energy Yield (Average) to O&M and Degradation	Above Mean	0.088 to 0.131	0.105	0.107
		Below Mean	0.080 to 0.130	0.100	0.103
	Energy Yield (Optimistic) to O&M and Degradation	Above Mean	0.097 to 0.191	0.139	0.141
		Below Mean	0.089 to 0.191	0.132	0.136
	System Price to O&M and Degradation	Above Mean	1.123 to 10.262	5.524	6.190
		Below Mean	1.102 to 6.048	3.631	4.166
CPV	Energy Yield (Pessimistic) to O&M and Degradation	Above Mean	0.092 to 0.176	0.133	0.138
		Below Mean	0.088 to 0.170	0.127	0.133
	Energy Yield (Average) to O&M and Degradation	Above Mean	0.136 to 0.235	0.188	0.216
		Below Mean	0.129 to 0.227	0.180	0.208
	Energy Yield (Optimistic) to O&M and Degradation	Above Mean	0.254 to 0.328	0.293	0.326
		Below Mean	0.243 to 0.317	0.281	0.314
	System Price to O&M and Degradation	Above Mean	6.439 to 8.594	7.972	8.571
		Below Mean	4.987 to 5.965	5.497	5.883

Table 160. Summary of internal rate of return ratios above and below the mean between 2014 and 2020 under the power purchase agreement tariff scenario.

9.4 Global Adjustment Tariff Offsetting Scenario Summary

Table 161 and Table 162 on the next two pages summarize the discounted net present value, return on investment, and internal rate of return results in chart form under the global adjustment tariff offsetting scenario for both PV and CPV technologies:

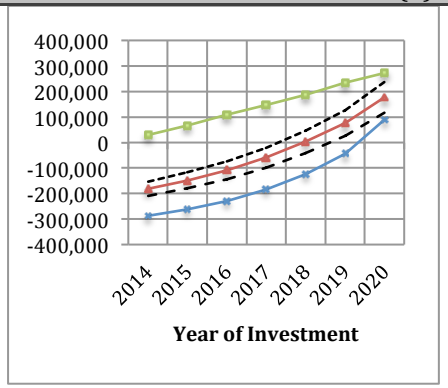
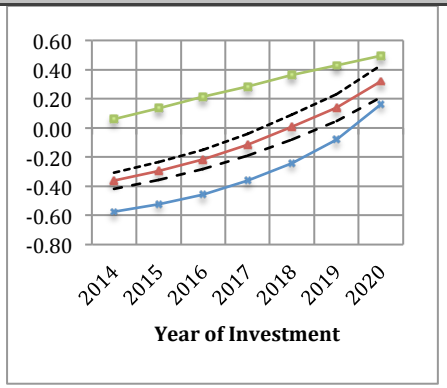
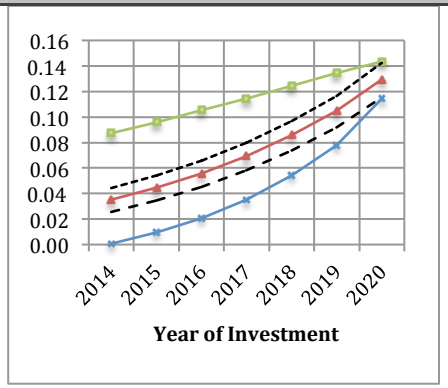
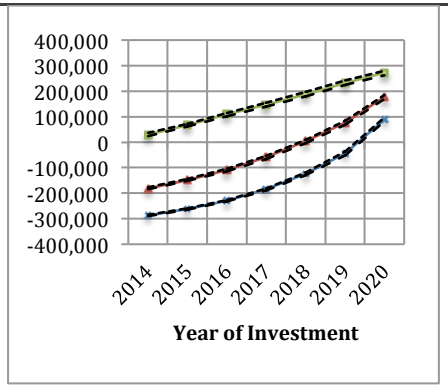
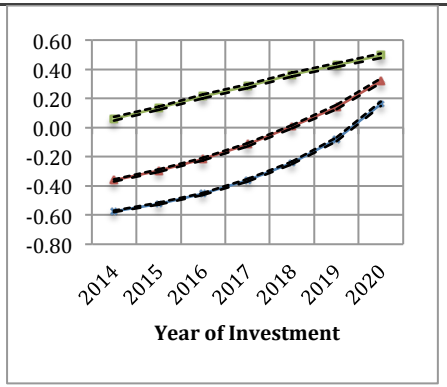
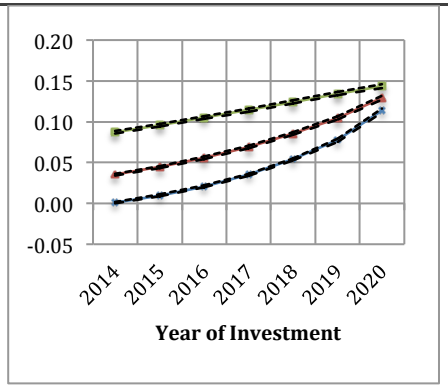
Global Adjustment Tariff Offsetting Scenario PV Summary			
	Discounted Net Present Value ($)	Return on Investment	Internal Rate of Return
PV (Zero Variability)			
PV (Variability, average of 250 Monte Carlo simulations with 95% CI's)			
Legend	Zero variability: green squares = "optimistic" scenario; red triangles = "average" scenario; blue crosses = "pessimistic" scenario. Tight dashed line above "average" scenario = "average" costs with "optimistic" O&M and degradation; spaced dashed line below "average" scenario = "average" costs with "pessimistic" O&M and degradation. Variability: Tight dashed line = upper 95% confidence interval; spaced dashed line = lower 95% confidence interval.		

Table 161. Summary of the PV discounted net present value, return on investment, and internal rate of return figures under the global adjustment tariff offsetting scenario.

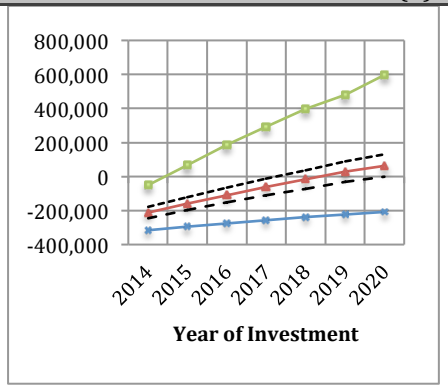
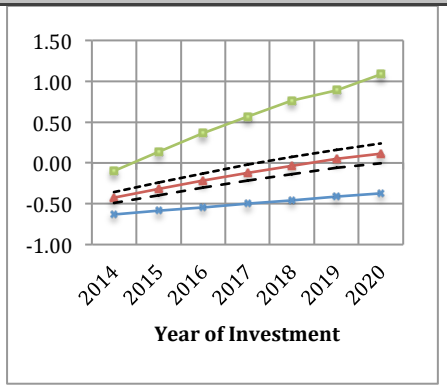
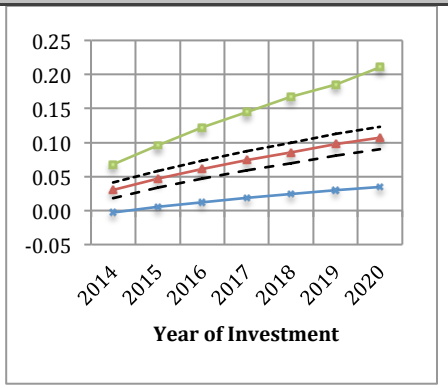
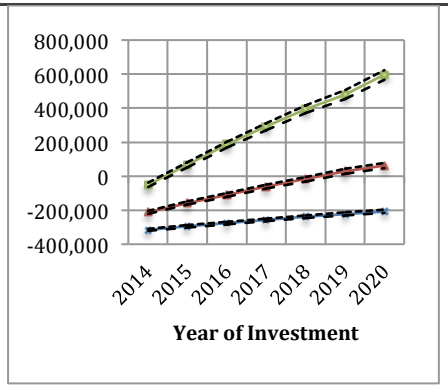
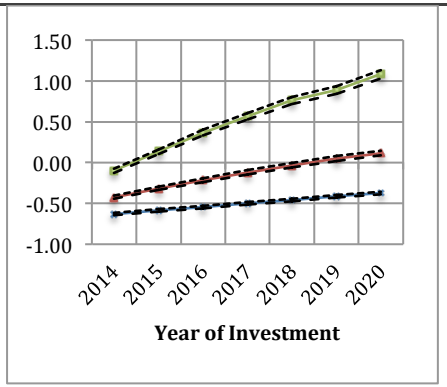
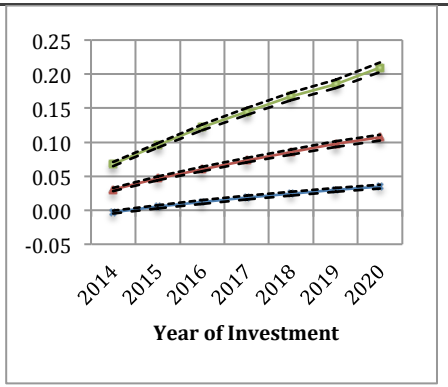
Global Adjustment Tariff Offsetting Scenario CPV Summary			
	Discounted Net Present Value ($)	Return on Investment	Internal Rate of Return
CPV (Zero Variability)			
CPV (Variability, average of 250 Monte Carlo simulations with 95% CI's)			
Legend	Zero variability: green squares = "optimistic" scenario; red triangles = "average" scenario; blue crosses = "pessimistic" scenario. Tight dashed line above "average" scenario = "average" costs with "optimistic" O&M and degradation; spaced dashed line below "average" scenario = "average" costs with "pessimistic" O&M and degradation. Variability: Tight dashed line = upper 95% confidence interval; spaced dashed line = lower 95% confidence interval.		

Table 162. Summary of the CPV discounted net present value, return on investment, and internal rate of return figures under the global adjustment tariff offsetting scenario.

The results in Table 161 and Table 162 were comparable to the time-of-use summary tables in Section 9.1 in that the financial metrics improved as time progressed towards 2020. In the above tables, the optimal time to invest was in the year 2020 under the "optimistic" pricing scenario according to the results for both PV and CPV technologies. However, CPV technology produced comparatively healthier financial figures in the optimal year for investment. The results in Table 161 and Table 162 accounted for both energy yield and tariff variability, and as such the 95% confidence intervals were the widest and most distinguishable compared with the 95% confidence intervals found under other tariff scenarios in Sections 9.1 to 9.3 which took only energy yield variability into account.

Turning to variability summaries, the following four tables summarize key financial metric information. Firstly, the ranges of the figures that define the discounted net present value 95% confidence intervals displayed in Table 161 and Table 162 are shown in Table 163. The table also includes an average value for the discounted NPV 95% CI above and below the mean over the years 2014 to 2020, as well as the precise 95% confidence interval value for the year 2017. Similarly, Table 164 displays ranges of figures pertaining to the internal rate of return, as well as an average IRR value above and below the mean between 2014 and 2020 and a precise IRR value for 2017. Table 165 and Table 166 present ratios that define the extent to which different sources of variability impact discounted net present value and internal rate of return, respectively.

Discounted Net Present Value ($)					
Technology	**Variability Source**	**Above/Below Mean**	**Discounted NPV Range (2014-2020)**	**Average Discounted NPV (2014-2020)**	**Discounted NPV (2017)**
PV	Energy Yield (Pessimistic)*	Above Mean	2,480.37 to 8,369.77	4,759.87	4,015.49
		Below Mean	-8,369.77 to -2,480.37	-4,759.87	-4,015.49
	Energy Yield (Average)*	Above Mean	3,615.54 to 8,130.15	5,601.70	5,546.75
		Below Mean	-8,130.15 to -3,615.54	-5,601.70	-5,546.75
	Energy Yield (Optimistic)*	Above Mean	5,949.00 to 8,868.61	7,209.36	7,214.35
		Below Mean	-8,868.61 to -5,949.00	-7,209.36	-7,214.35
	System Price**	Above Mean	95,013.45 to 216,717.17	183,633.92	205,669.68
		Below Mean	-128,378.91 to -87,648.98	-114,809.72	-125,672.98
	O&M and Degradation**	Above Mean	2,7760.73 to 59,307.09	40,445.66	38,054.47
		Below Mean	-60,691.53 to -28,089.73	-41,181.08	-38,696.17
CPV	Energy Yield (Pessimistic)*	Above Mean	6,359.82 to 9,185.69	8,018.65	7,944.50
		Below Mean	-9,185.69 to -6,359.82	-8,018.65	-7,944.50
	Energy Yield (Average)*	Above Mean	8,786.64 to 15,198.60	12,561.62	12,928.21
		Below Mean	-15,198.60 to -8,786.64	-12,561.62	-12,928.21
	Energy Yield (Optimistic)*	Above Mean	12,826.59 to 28,546.69	20,405.42	20,733.30
		Below Mean	-28,546.69 to -12,826.59	-20,405.42	-20,733.30
	System Price**	Above Mean	161,919.45 to 534,303.13	348,070.66	352,849.37
		Below Mean	-271,660.56 to -103,179.79	-191,557.01	-194,928.01
	O&M and Degradation**	Above Mean	32,864.73 to 65,273.78	49,486.29	49,787.12
		Below Mean	-65,273.78 to -32,864.73	-49,486.29	-49,787.12

* Mean refers to a value calculated from the 250 Monte Carlo simulations. Range above/below mean represents 95% confidence interval.

** Mean refers to a discounted net present value associated with the "average" pricing scenario.

Table 163. Ranges of discounted net present values due to different sources of variability under the GA tariff offsetting scenario. All values are in USD.

			Internal Rate of Return (%)		
Technology	**Variability Source**	**Above/Below Mean**	**IRR Range (2014-2020)**	**Average IRR (2014-2020)**	**IRR (2017)**
PV	Energy Yield (Pessimistic)*	Above Mean	0.087 to 0.230	0.141	0.120
		Below Mean	-0.230 to -0.087	-0.141	-0.120
	Energy Yield (Average)*	Above Mean	0.102 to 0.217	0.150	0.146
		Below Mean	-0.217 to -0.102	-0.150	-0.146
	Energy Yield (Optimistic)*	Above Mean	0.142 to 0.223	0.176	0.172
		Below Mean	-0.223 to -0.142	-0.176	-0.172
	System Price**	Above Mean	1.413 to 5.188	4.003	4.514
		Below Mean	-3.509 to -1.540	-3.041	-3.389
	O&M and Degradation**	Above Mean	0.910 to 1.272	1.056	1.029
		Below Mean	-1.412 to -0.981	-1.156	-1.124
CPV	Energy Yield (Pessimistic)*	Above Mean	0.227 to 0.275	0.253	0.246
		Below Mean	-0.275 to -0.227	-0.253	-0.246
	Energy Yield (Average)*	Above Mean	0.242 to 0.404	0.334	0.338
		Below Mean	-0.404 to -0.242	-0.334	-0.338
	Energy Yield (Optimistic)*	Above Mean	0.306 to 0.730	0.505	0.497
		Below Mean	-0.730 to -0.306	-0.505	-0.497
	System Price**	Above Mean	3.752 to 10.374	7.046	7.122
		Below Mean	-7.204 to -3.318	-5.400	-5.513
	O&M and Degradation**	Above Mean	1.097 to 1.582	1.338	1.337
		Below Mean	-1.707 to -1.212	-1.458	-1.456

* Mean refers to a value calculated from the 250 Monte Carlo simulations. Range above/below mean represents 95% confidence interval.
** Mean refers to an internal rate of return value associated with the "average" pricing scenario.

Table 164. Ranges of internal rates of return due to different sources of variability under the global adjustment tariff offsetting scenario.

			Discounted Net Present Value		
Technology	**Ratio**	**Above/Below Mean**	**Range of Ratios (2014-2020)**	**Average Ratio (2014-2020)**	**2017 Ratio**
PV	Energy Yield (Pessimistic) to O&M and Degradation	Above Mean	0.089 to 0.141	0.118	0.106
		Below Mean	0.088 to 0.138	0.116	0.104
	Energy Yield (Average) to O&M and Degradation	Above Mean	0.130 to 0.146	0.138	0.146
		Below Mean	0.129 to 0.143	0.136	0.143
	Energy Yield (Optimistic) to O&M and Degradation	Above Mean	0.150 to 0.218	0.178	0.190
		Below Mean	0.146 to 0.215	0.175	0.186
	System Price to O&M and Degradation	Above Mean	1.602 to 7.603	4.540	5.405
		Below Mean	1.444 to 3.778	2.788	3.248
CPV	Energy Yield (Pessimistic) to O&M and Degradation	Above Mean	0.141 to 0.194	0.162	0.160
		Below Mean	0.141 to 0.194	0.162	0.160
	Energy Yield (Average) to O&M and Degradation	Above Mean	0.232 to 0.267	0.254	0.260
		Below Mean	0.232 to 0.267	0.254	0.260
	Energy Yield (Optimistic) to O&M and Degradation	Above Mean	0.388 to 0.437	0.412	0.416
		Below Mean	0.388 to 0.437	0.412	0.416
	System Price to O&M and Degradation	Above Mean	4.927 to 8.186	7.034	7.087
		Below Mean	3.140 to 4.162	3.871	3.915

Table 165. Summary of discounted net present value ratios above and below the mean between 2014 and 2020 under the global adjustment tariff offsetting scenario.

			Internal Rate of Return		
Technology	**Ratio**	**Above/Below Mean**	**Range of Ratios (2014-2020)**	**Average Ratio (2014-2020)**	**2017 Ratio**
PV	Energy Yield (Pessimistic) to O&M and Degradation	Above Mean	0.096 to 0.181	0.134	0.117
		Below Mean	0.089 to 0.163	0.122	0.107
	Energy Yield (Average) to O&M and Degradation	Above Mean	0.112 to 0.171	0.142	0.142
		Below Mean	0.104 to 0.154	0.130	0.130
	Energy Yield (Optimistic) to O&M and Degradation	Above Mean	0.151 to 0.176	0.167	0.168
		Below Mean	0.140 to 0.158	0.152	0.153
	System Price to O&M and Degradation	Above Mean	1.110 to 5.703	3.791	4.385
		Below Mean	1.091 to 3.520	2.631	3.014
CPV	Energy Yield (Pessimistic) to O&M and Degradation	Above Mean	0.174 to 0.207	0.189	0.184
		Below Mean	0.161 to 0.187	0.174	0.169
	Energy Yield (Average) to O&M and Degradation	Above Mean	0.221 to 0.267	0.250	0.253
		Below Mean	0.200 to 0.247	0.229	0.232
	Energy Yield (Optimistic) to O&M and Degradation	Above Mean	0.279 to 0.462	0.377	0.372
		Below Mean	0.252 to 0.428	0.346	0.341
	System Price to O&M and Degradation	Above Mean	3.421 to 6.556	5.265	5.329
		Below Mean	2.738 to 4.219	3.704	3.787

Table 166. Summary of internal rate of return ratios above and below the mean between 2014 and 2020 under the global adjustment tariff offsetting scenario.

9.5 Levelized Cost of Electricity Summary

9.5.1 25-Year PV and CPV Projects

For the LCOE metric, Table 167 and Table 168 below summarize the results for both photovoltaic and concentrated photovoltaic projects, respectively, with 25-year operational lifespans:

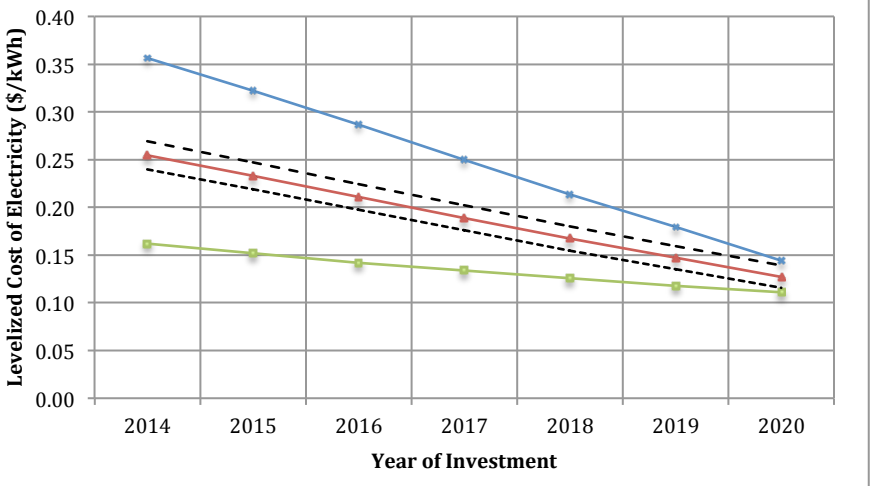
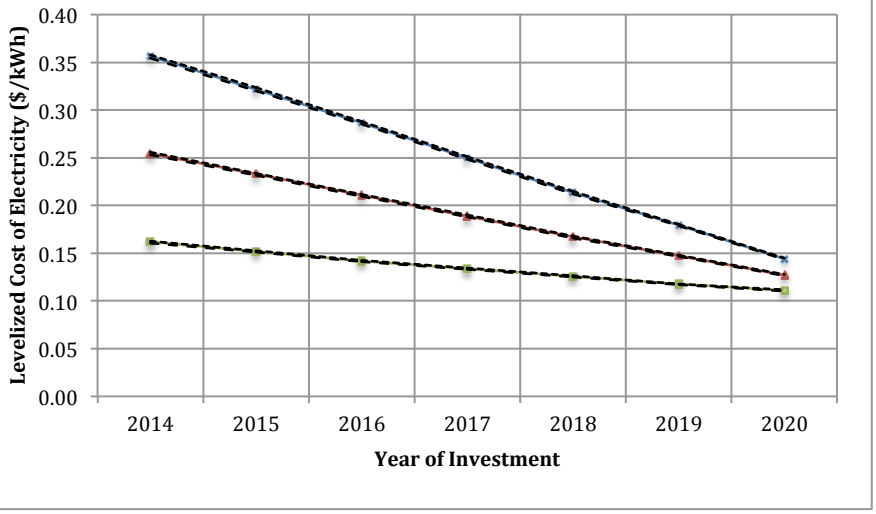
Technology	LCOE Chart (25-Years)
Photovoltaic (Zero Variability)	
Photovoltaic (Variability)	
Legend	Zero variability: green squares = "optimistic" scenario; red triangles = "average" scenario; blue crosses = "pessimistic" scenario. Tight dashed line above "average" scenario = "average" costs with "optimistic" O&M and degradation; spaced dashed line below "average" scenario = "average" costs with "pessimistic" O&M and degradation. Variability: Tight dashed line = upper 95% confidence interval; spaced dashed line = lower 95% confidence interval.

Table 167. LCOE charts summarizing PV results from the time-of-use and global adjustment tariff offsetting scenarios.

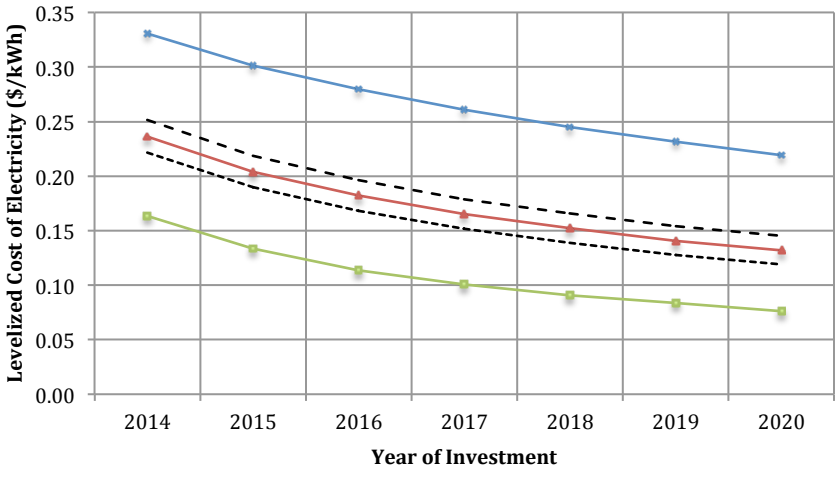
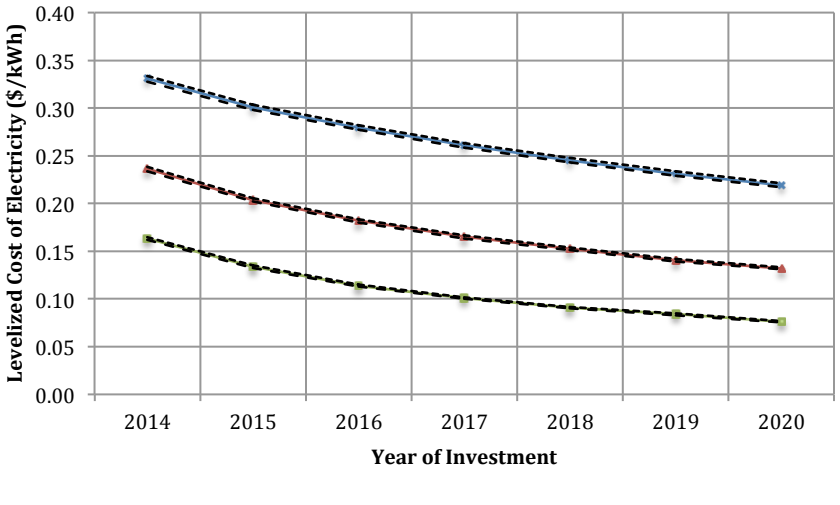
Technology	LCOE Chart (25-Years)
Concentrated Photovoltaic (Zero Variability)	
Concentrated Photovoltaic (Variability)	
Legend	Zero variability: green squares = "optimistic" scenario; red triangles = "average" scenario; blue crosses = "pessimistic" scenario. Tight dashed line above "average" scenario = "average" costs with "optimistic" O&M and degradation; spaced dashed line below "average" scenario = "average" costs with "pessimistic" O&M and degradation. Variability: Tight dashed line = upper 95% confidence interval; spaced dashed line = lower 95% confidence interval.

Table 168. LCOE charts summarizing CPV results from the time-of-use and global adjustment tariff offsetting scenarios.

For both PV and CPV technologies, the LCOE diminished as time moved forward from 2014 to 2020. This was attributable to lower system costs and greater system output in future years. The plots of photovoltaic LCOE values declined in a more linear manner than the plots of concentrated photovoltaic LCOE figures, which were noticeably curved. The dissimilar plot shapes in Table 167 and Table 168 were likely attributable to the different methodologies used to forecast future system

prices, a discussion of which was covered in Section 3.3.1.2. In both tables above, the 95% confidence intervals were quite narrow, and this indicated that variable system energy yield did not have a significant impact on the levelized cost of electricity.

Below, Table 169 summarizes the range of values comprising the 95% LCOE confidence intervals in Table 167 and Table 168. This table also defines the range of values that comprise the assumed 95% confidence intervals in the case of system price and O&M plus degradation variability. Additionally, a mean confidence interval value is provided, as is the precise 95% CI value for the year 2017. After Table 169, Table 170 provides ratios comparing the number of times that either system energy yield or system price can vary the levelized cost of electricity metric compared with O&M plus degradation.

			Levelized Cost of Electricity ($/kWh)		
Technology	**Variability Source**	**Above/Below Mean**	**LCOE Range (2014-2020)**	**Average LCOE (2014-2020)**	**LCOE (2017)**
PV	Energy Yield (Pessimistic)*	Above Mean	0.0007 to 0.0018	0.0013	0.0013
		Below Mean	-0.0018 to -0.0007	-0.0013	-0.0013
	Energy Yield (Average)*	Above Mean	0.0007 to 0.0013	0.0009	0.0009
		Below Mean	-0.0013 to -0.0007	-0.0009	-0.0009
	Energy Yield (Optimistic)*	Above Mean	0.0005 to 0.0007	0.0006	0.0006
		Below Mean	-0.0007 to -0.0005	-0.0006	-0.0006
	System Price**	Above Mean	0.0173 to 0.1015	0.0605	0.0607
		Below Mean	-0.0929 to -0.016	-0.0550	-0.0552
	O&M and Degradation**	Above Mean	0.0123 to 0.0145	0.0134	0.0134
		Below Mean	-0.0145 to -0.0112	-0.0128	-0.0128
CPV	Energy Yield (Pessimistic)*	Above Mean	0.0021 to 0.003	0.0025	0.0025
		Below Mean	-0.003 to -0.0021	-0.0025	-0.0025
	Energy Yield (Average)*	Above Mean	0.0012 to 0.0021	0.0015	0.0015
		Below Mean	-0.0021 to -0.0012	-0.0015	-0.0015
	Energy Yield (Optimistic)*	Above Mean	0.0007 to 0.0014	0.0009	0.0008
		Below Mean	-0.0014 to -0.0007	-0.0009	-0.0008
	System Price**	Above Mean	0.0872 to 0.0977	0.0938	0.0960
		Below Mean	-0.0725 to -0.0558	-0.0642	-0.0643
	O&M and Degradation**	Above Mean	0.0133 to 0.0151	0.0140	0.0139
		Below Mean	-0.0147 to -0.0129	-0.0136	-0.0135

* Mean refers to a value calculated from the 250 Monte Carlo simulations. Range above/below mean represents 95% confidence interval.
** Mean refers to a levelized cost of electricity value associated with the "average" pricing scenario.

Table 169. Ranges of levelized cost of electricity fluctuations due to different variability sources for 25-year projects. All values are in USD.

			Levelized Cost of Electricity		
Technology	**Ratio**	**Above/Below Mean**	**Range of Ratios (2014-2020)**	**Average Ratio (2014-2020)**	**2017 Ratio**
PV	Energy Yield (Pessimistic) to O&M and Degradation	Above Mean	0.056 to 0.123	0.096	0.094
		Below Mean	0.061 to 0.124	0.100	0.098
	Energy Yield (Average) to O&M and Degradation	Above Mean	0.054 to 0.088	0.070	0.069
		Below Mean	0.059 to 0.088	0.073	0.072
	Energy Yield (Optimistic) to O&M and Degradation	Above Mean	0.045 to 0.052	0.048	0.047
		Below Mean	0.048 to 0.052	0.050	0.049
	System Price to O&M and Degradation	Above Mean	1.414 to 6.988	4.523	4.544
		Below Mean	1.435 to 6.389	4.286	4.306
CPV	Energy Yield (Pessimistic) to O&M and Degradation	Above Mean	0.157 to 0.200	0.177	0.177
		Below Mean	0.161 to 0.206	0.182	0.183
	Energy Yield (Average) to O&M and Degradation	Above Mean	0.087 to 0.141	0.110	0.105
		Below Mean	0.090 to 0.145	0.113	0.108
	Energy Yield (Optimistic) to O&M and Degradation	Above Mean	0.049 to 0.090	0.066	0.059
		Below Mean	0.051 to 0.093	0.068	0.060
	System Price to O&M and Degradation	Above Mean	6.267 to 6.927	6.696	6.927
		Below Mean	4.329 to 4.970	4.718	4.775

Table 170. Summary of levelized cost of electricity ratios above and below the mean between 2014 and 2020 for PV and CPV projects with 25-year lifespans.

9.5.2 20-Year PV and CPV Projects

The plots shown below in Table 171 and Table 172 summarize the results tied to LCOE figures for projects with 20-year operational lifespans:

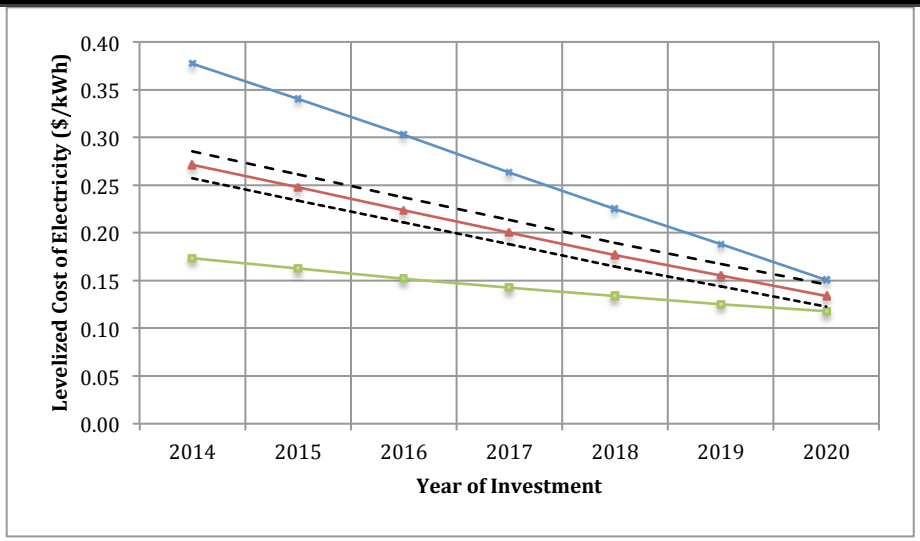
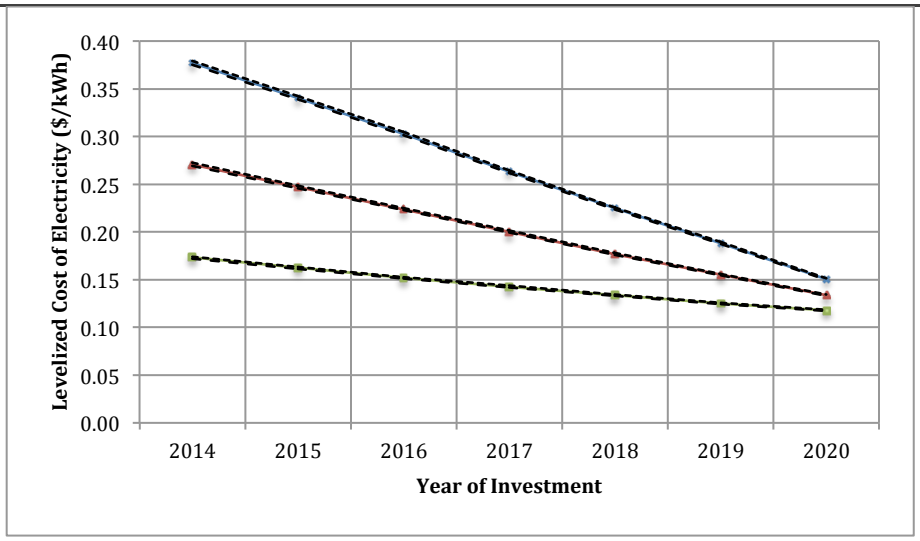
Technology	LCOE Chart (20-Years)
Photovoltaic (Zero Variability)	
Photovoltaic (Variability)	
Legend	Zero variability: green squares = "optimistic" scenario; red triangles = "average" scenario; blue crosses = "pessimistic" scenario. Tight dashed line above "average" scenario = "average" costs with "optimistic" O&M and degradation; spaced dashed line below "average" scenario = "average" costs with "pessimistic" O&M and degradation. Variability: Tight dashed line = upper 95% confidence interval; spaced dashed line = lower 95% confidence interval.

Table 171. LCOE charts summarizing PV results from the feed-in tariff and power purchase agreement tariff scenarios.

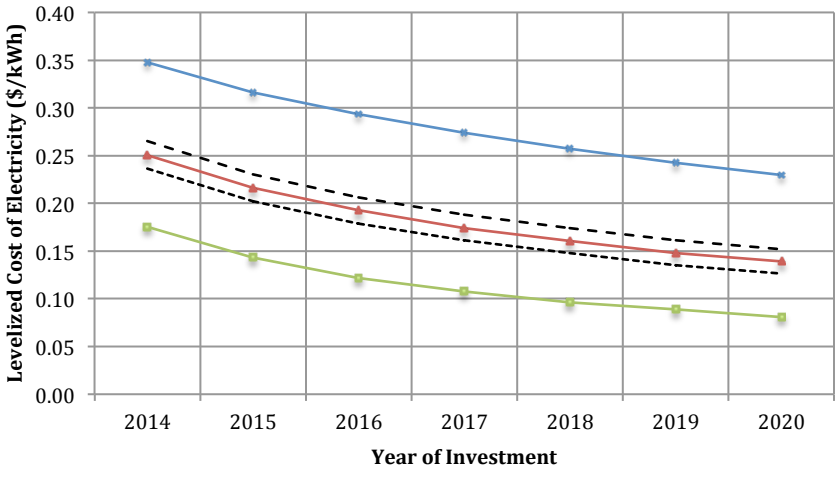
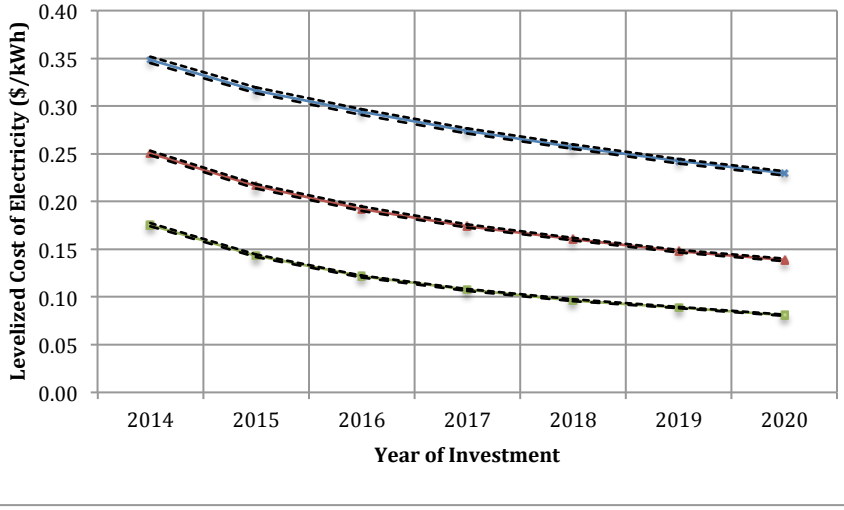
Technology	LCOE Chart (20-Years)
Concentrated Photovoltaic (Zero Variability)	
Concentrated Photovoltaic (Variability)	
Legend	Zero variability: green squares = "optimistic" scenario; red triangles = "average" scenario; blue crosses = "pessimistic" scenario. Tight dashed line above "average" scenario = "average" costs with "optimistic" O&M and degradation; spaced dashed line below "average" scenario = "average" costs with "pessimistic" O&M and degradation. Variability: Tight dashed line = upper 95% confidence interval; spaced dashed line = lower 95% confidence interval.

Table 172. LCOE charts summarizing CPV results from the feed-in tariff and power purchase agreement tariff scenarios.

The plots in the tables above followed a similar pattern to those from the 25-year LCOE charts in Section 9.5.1. PV levelized cost of electricity values declined in a somewhat linear manner, while CPV levelized cost of electricity values declined in a more curved fashion. Once again, this was attributable to the manner in which future system prices were forecasted from Section 3.3.1.2. The 95% upper and lower confidence intervals were also rather narrow in the above tables, which meant that LCOE values were not especially influenced by energy variability.

In Table 173 below, the range values comprising the 95% confidence intervals illustrated in Table 171 and Table 172 are precisely specified. Other figures are provided as well that assist with defining the characteristics of the 95% confidence intervals associated with the levelized cost of electricity over the years 2014 to 2020. Afterwards, Table 174 displays ratios that illustrate the extent to which one source of variability is capable of varying the levelized cost of electricity compared with another source of variability.

			Levelized Cost of Electricity ($/kWh)		
Technology	**Variability Source**	**Above/Below Mean**	**LCOE Range (2014-2020)**	**Average LCOE (2014-2020)**	**LCOE (2017)**
PV	Energy Yield (Pessimistic)*	Above Mean	0.0008 to 0.0021	0.0014	0.0014
		Below Mean	-0.0021 to -0.0008	-0.0014	-0.0014
	Energy Yield (Average)*	Above Mean	0.0007 to 0.0015	0.0011	0.0010
		Below Mean	-0.0015 to -0.0007	-0.0011	-0.0010
	Energy Yield (Optimistic)*	Above Mean	0.0006 to 0.0009	0.0007	0.0008
		Below Mean	-0.0009 to -0.0006	-0.0007	-0.0008
	System Price**	Above Mean	0.0170 to 0.1061	0.0627	0.0629
		Below Mean	-0.0979 to -0.0157	-0.0574	-0.0576
	O&M and Degradation**	Above Mean	0.0120 to 0.0142	0.0131	0.0131
		Below Mean	-0.0141 to -0.0109	-0.0125	-0.0125
CPV	Energy Yield (Pessimistic)*	Above Mean	0.0023 to 0.0034	0.0028	0.0028
		Below Mean	-0.0034 to -0.0023	-0.0028	-0.0028
	Energy Yield (Average)*	Above Mean	0.0013 to 0.0023	0.0018	0.0018
		Below Mean	-0.0023 to -0.0013	-0.0018	-0.0018
	Energy Yield (Optimistic)*	Above Mean	0.0007 to 0.0016	0.0011	0.0011
		Below Mean	-0.0016 to -0.0007	-0.0011	-0.0011
	System Price**	Above Mean	0.0906 to 0.1012	0.0972	0.0996
		Below Mean	-0.0751 to -0.0583	-0.0668	-0.0670
	O&M and Degradation**	Above Mean	0.0131 to 0.0148	0.0137	0.0136
		Below Mean	-0.0144 to -0.0127	-0.0134	-0.0133

* Mean refers to a value calculated from the 250 Monte Carlo simulations. Range above/below mean represents 95% confidence interval.

** Mean refers to a levelized cost of electricity value associated with the "average" pricing scenario.

Table 173. Ranges of levelized cost of electricity fluctuations due to different variability sources for 20-year projects. All values are in USD.

			Levelized Cost of Electricity		
Technology	**Ratio**	**Above/Below Mean**	**Range of Ratios (2014-2020)**	**Average Ratio (2014-2020)**	**2017 Ratio**
PV	Energy Yield (Pessimistic) to O&M and Degradation	Above Mean	0.070 to 0.145	0.108	0.107
		Below Mean	0.077 to 0.146	0.113	0.112
	Energy Yield (Average) to O&M and Degradation	Above Mean	0.056 to 0.105	0.081	0.077
		Below Mean	0.062 to 0.106	0.085	0.081
	Energy Yield (Optimistic) to O&M and Degradation	Above Mean	0.050 to 0.062	0.057	0.059
		Below Mean	0.055 to 0.063	0.060	0.062
	System Price to O&M and Degradation	Above Mean	1.416 to 7.486	4.794	4.817
		Below Mean	1.439 to 6.945	4.598	4.621
CPV	Energy Yield (Pessimistic) to O&M and Degradation	Above Mean	0.172 to 0.230	0.200	0.203
		Below Mean	0.177 to 0.236	0.205	0.208
	Energy Yield (Average) to O&M and Degradation	Above Mean	0.103 to 0.154	0.130	0.132
		Below Mean	0.106 to 0.157	0.133	0.135
	Energy Yield (Optimistic) to O&M and Degradation	Above Mean	0.055 to 0.111	0.078	0.077
		Below Mean	0.056 to 0.114	0.080	0.080
	System Price to O&M and Degradation	Above Mean	6.586 to 7.320	7.069	7.320
		Below Mean	4.584 to 5.255	4.991	5.057

Table 174. Summary of levelized cost of electricity ratios above and below the mean between 2014 and 2020 for PV and CPV projects with 20-year lifespans.

9.6 The Benefit of Energy Payment Allocation Factors

The discounted net present value results from the feed-in tariff and power purchase agreement scenarios were worth further exploration, since these two scenarios used similar base prices yet had dissimilar outcomes. The feed-in tariff scenario used historic *rooftop* solar prices and a logarithmic regression to forecast future FIT rates. On the other hand, the power purchase agreement scenario used historic *ground mount* solar prices and a logarithmic regression to forecast future baseline PPA rates. As discussed in Section 4.3.3, the ground mount FIT rates were used as part of the power purchase agreement tariff scenario because of a previous example from Ontario where the baseline PPA price corresponded with a ground mount solar FIT rate.

During the years 2016 through 2020, the ground mount solar FIT rates indicated by Table 26 in Section 4.3.3 exceeded the rooftop solar FIT rates provided by Table 24 in Section 4.3.2. Thus, the PPA scenario had higher electricity tariffs than the FIT scenario for the most part. Although the higher prices paid for solar-produced electricity were expected to yield greater revenues, the significantly better financial metrics observed under the PPA scenario were likely due to the additional element of energy payment allocation factors (references to the location of the financial results presented earlier in this thesis will be made throughout this section). Energy payment allocation factors were incorporated into the power purchase agreement scenario but not the feed-in tariff scenario, and according to the discussion in Section 4.3.3 they scaled the price paid for solar produced electricity either up or down according to a fixed schedule. In the next two subsections, a discussion about the positive financial metric impact made by energy payment allocations factors will be discussed for both PV and CPV technology.

9.6.1 Photovoltaic Technology

In Section 5.2.1.1, Figure 29 displayed the discounted net present values for PV technology under the feed-in tariff scenario. According to this chart, the plot lines of the discounted net present values from the "optimistic" and "average" costing scenarios were both positive in 2014, but had crossed into negative territory by 2016 under the "average" pricing scenario and by 2020 under the "optimistic" costing scenario. In fact, in 2020 all three of the pricing scenarios showed negative discounted net present values. In comparison, Figure 39 from Section 5.3.1.1 showed plots of discounted net present values under the power purchase agreement tariff scenario for PV technology. Although the underlying prices paid for electricity under this tariff scenario were comparable to the prices used by the feed-in tariff scenario, the "optimistic" and "average" costing scenarios under the PPA tariff had positive discounted net present values in each of the years between 2014 and 2020, inclusive. Moreover, the most expensive "pessimistic" pricing scenario, which started off negative in 2014, eventually turned positive in the year 2019. In contrast with the FIT scenario discounted net present values, which were negative in 2020 under all three pricing scenarios, the discounted net present values under the PPA tariff scenario from all three pricing scenarios were positive in that same year.

While the price paid for electricity under the feed-in tariff scenario remained the same each hour of each day over 20 years, the price paid for electricity under the power purchase agreement tariff scenario varied according to energy payment allocation factors, which were discussed in Section 4.3.3. In brief, energy payment allocation factors either increased or decreased the price paid for electricity, which under the PPA scenario meant that the contractual price paid for solar-produced electricity either grew or diminished depending on the time of day.

According to Table 27 in Section 4.3.3, the time between 12:00 and 18:00 from the start of June through the end of September was considered "on-peak," and this

corresponded with an energy payment allocation factor of 2.07 from Table 28 in Section 4.3.3. Thus, during midday over the summer months, the baseline price paid for solar produced electricity under the power purchase agreement tariff scenario was increased by a factor of 2.07. Between the hours of 08:00 until 12:00 during the same summer months, energy payment allocation factors increased the tariff price by 1.19. For the remainder of the calendar year, October 1st to May 31st, and the hours of 08:00 to 21:00, the baseline price paid for solar-produced electricity was raised by a factor of 1.03. As a result, during daylight hours throughout the year when the solar modules were producing electricity, the power produced was sold for a price that was greater than the baseline contracted price.

At the same time, according to the information provided by Table 28, there were times of the day where the price paid for solar-produced electricity was less than the contracted price. However, these times, which were also provided by Table 27, were when solar modules either produced zero electricity or a smaller amount of electricity, which, even if sold at a high price, may not have been enough to generate significant revenues. Consequently, the results from the PPA tariff scenario found that a solar installation's profitability was higher when peak prices paid for solar-produced electricity matched with peak solar energy production. This was in contrast to the FIT scenario where a static price was paid for solar-produced electricity no matter when it was generated. This finding remained true even though the price paid for solar-produced electricity fell below the contracted price during certain times of the day under the power purchase agreement tariff scenario.

9.6.2 Concentrated Photovoltaic Technology

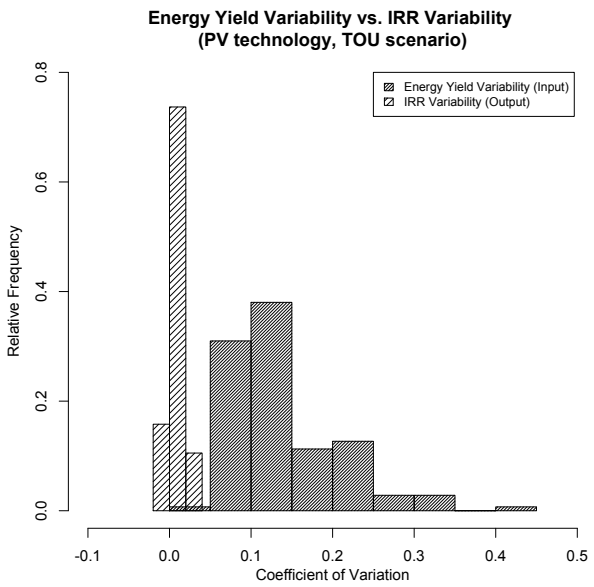
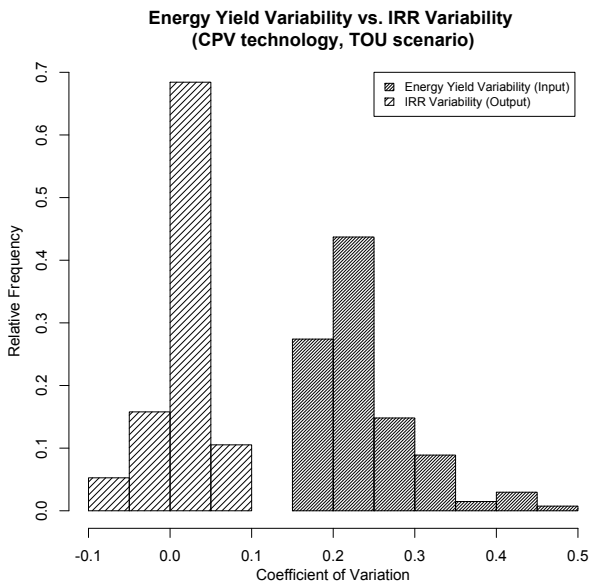
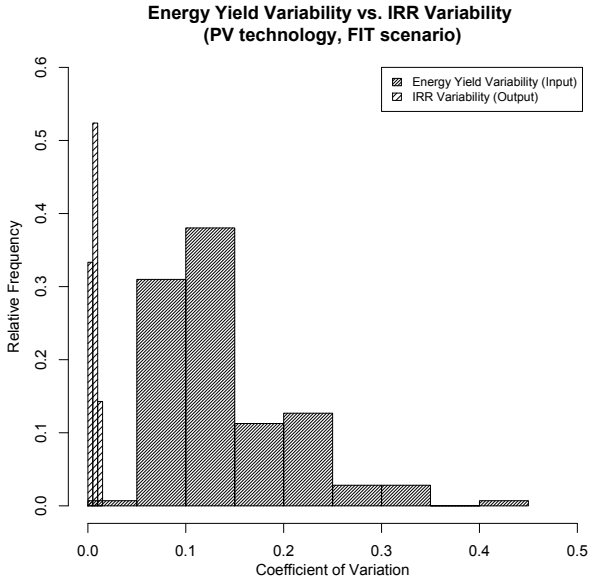
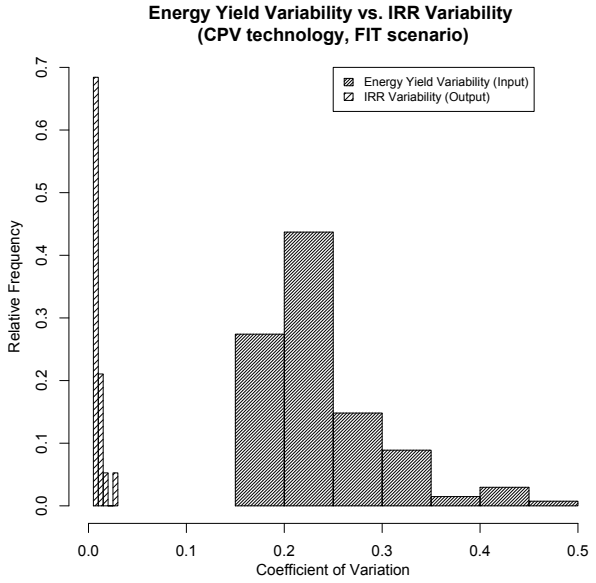
Similar financial results were found for CPV in that the discounted net present values under the power purchase agreement tariff scenario were significantly better than those found under the feed-in tariff scenario. This was expected since the same energy payment allocation factors were used for CPV technology, and they were all greater than "1" at times during the day when solar modules produced their greatest

amount of electricity. Figure 44 in Section 5.3.1.2, which showed the discounted net present value results under the power purchase agreement scenario, illustrated that both the "optimistic" and "average" pricing scenarios had positive discounted net present values in each of the years 2014 through 2020. In contrast, under the FIT scenario, Figure 30 in Section 5.2.1.2 indicated that only the "optimistic" costing scenario had positive discounted net present values in each of the years 2014 through 2020. This same figure specified that the "average" pricing scenario began with positive discounted net present values, but that these figures turned negative in 2018. The "pessimistic," most expensive costing scenarios under both tariff scenarios, however, did not realize any positive discounted net present values.

Focusing upon the "optimistic" costing scenario as an example, the positive discounted net present values observed were notably higher under the PPA tariff scenario compared with the FIT scenario. While the maximum discounted net present value observed under the feed-in tariff scenario over the years 2014 to 2020 was USD 480,682.59, the maximum discounted NPV under the PPA tariff scenario over the same timeframe was USD 740, 241.27. In fact, the minimum discounted NPV under the PPA scenario was USD 420,535.93, only USD 60,146.66 lower than the maximum observed value under the FIT scenario. Thus, analogous to the PV results, the energy payment allocation factors had a distinct impact on the discounted net present values observed under CPV technology. When the CPV installation produced its greatest amount of electricity at times corresponding with the highest price paid for solar-produced electricity, the system's profitability was higher than if the same system sold the power it produced at a flat rate. This even offset the instances where the power produced was sold below the contractual price during off-peak times, when the energy payment allocation factors were less than "1."

9.7 Monte Carlo Simulation Input/Output Variability Analysis

To further quantify the bankability of PV and CPV investments, an analysis of the variability of Monte Carlo simulation inputs and outputs was performed. The charts in Table 175 below illustrate the differences in variability between system energy yield, a Monte Carlo simulation input, and the internal rate of return, a simulation output and one of the four key financial metrics. The charts assess variability under the time-of-use, feed-in tariff, and power purchase agreement tariff scenarios for both PV and CPV technologies:

Scenario	PV Technology	CPV Technology
Time-of-Use		
Feed-in Tariff		

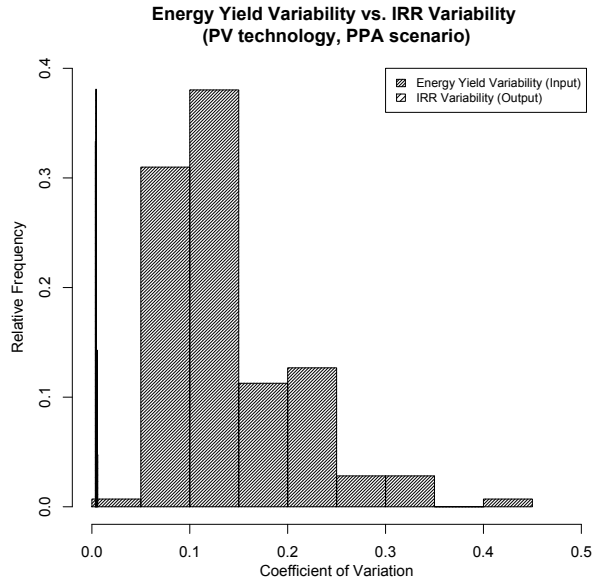
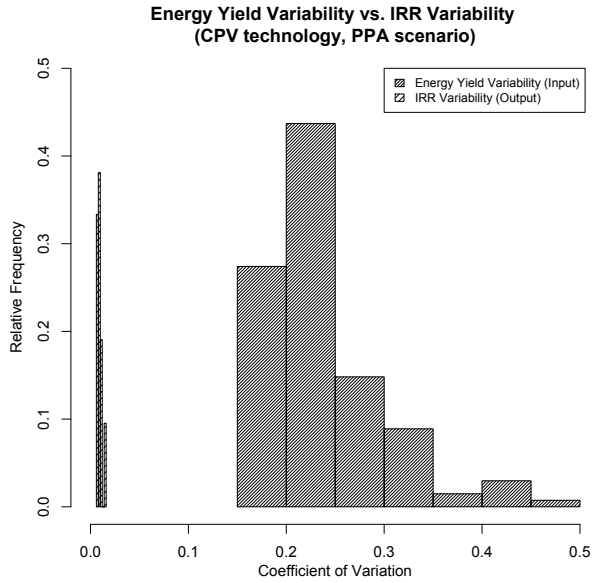
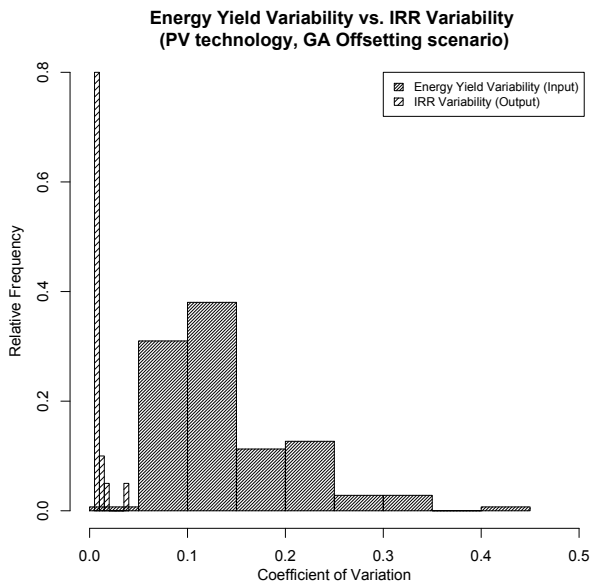
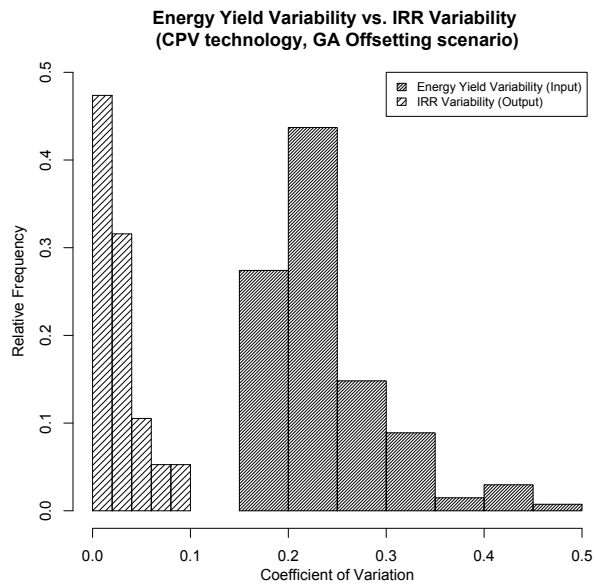
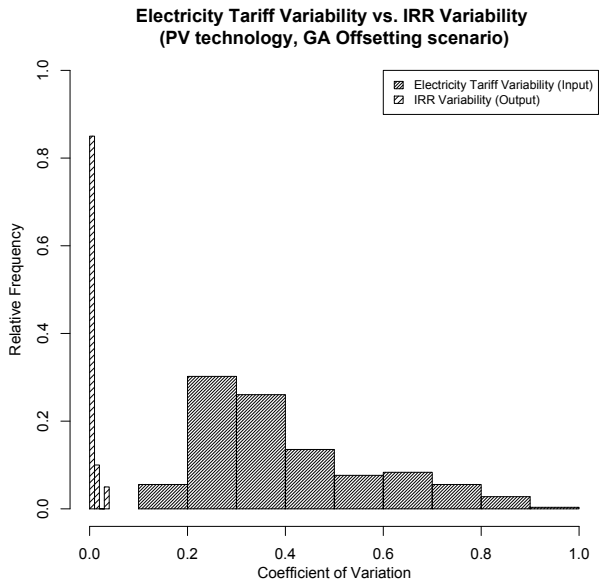
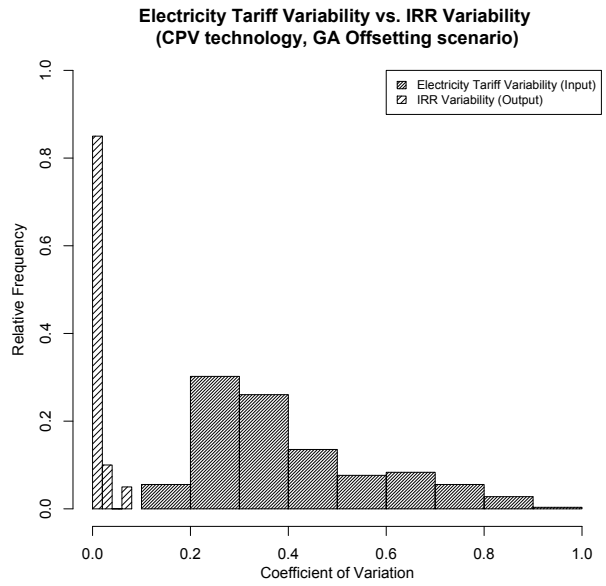
Scenario	PV Technology	CPV Technology
Power Purchase Agreement		

Table 175. Relative frequency histograms comparing coefficients of variation from the Monte Carlo simulation input of "energy yield variability" with the simulation output of "internal rate of return" for the time-of-use, feed-in tariff, and power purchase agreement tariff scenarios. The energy yield variability coefficients of variation are, in nearly every case, larger than the internal rate of return coefficients of variation. Thus, variable system output did not translate into significant PV or CPV project investment risk as measured by variability of the internal rate of return.

The coefficient of variation, which was defined and discussed in Section 5.1.2.2, was used to compare energy yield and internal rate of return variability in the charts presented in Table 175. Relative frequency histograms were created to illustrate the percentage of coefficient of variation values lying within a specific range. For example, the largest percentage – 73.68% – of internal rate of return coefficient of variation values fell between 0.00 and 0.02, while the largest percentage – 38.03% – of energy yield coefficient of variation values fell between 0.10 and 0.15.

Under the same tariff scenario, IRR coefficient of variation values ranged between -0.02 and 0.04, while energy yield coefficient of variation values spanned 0.00 to 0.45. The latter was a much larger range, and thus internal rate of return variability was smaller than system energy yield variability. This further supported the finding that system energy yield variability did not pose a significant risk to the bankability of PV or CPV investments as measured by IRR variability.

Separate from the time-of-use, feed-in tariff, and power purchase agreement tariff scenarios, the global adjustment tariff offsetting scenario included electricity tariff variability in addition to variability in PV and CPV system energy yield. Below, Table 176 presents relative frequency histograms for the coefficients of variation associated with energy yield variability, electricity tariff variability, as well as both energy yield and electricity tariff variability under the global adjustment tariff offsetting scenario:

Scenario	PV Technology	CPV Technology
Energy Yield Variability		
Tariff Variability		

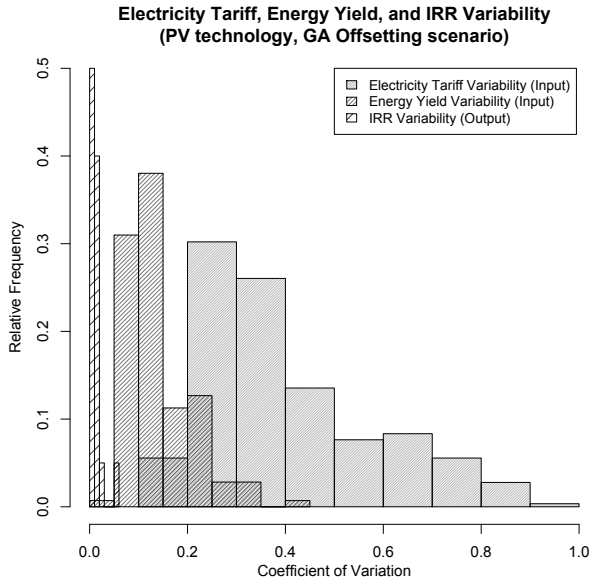
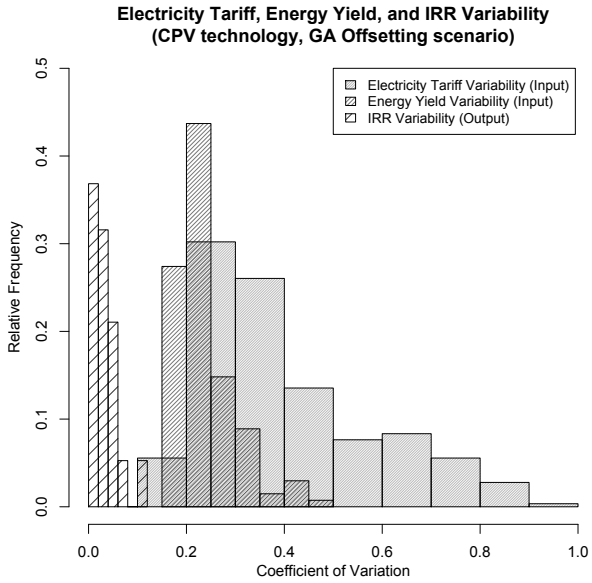
Scenario	PV Technology	CPV Technology
Energy Yield and Tariff Variability		

Table 176. Relative frequency histograms comparing the coefficients of variation from the Monte Carlo simulation inputs of "energy yield" and "electricity tariff" variability with the simulation output "internal rate of return" under the global adjustment tariff offsetting scenario. The variable energy yield and variable electricity tariff coefficients of variation were larger than the internal rate of return coefficients of variation in almost every case, meaning neither source of variability, even when combined, posed significant PV or CPV project investment risk according to the variability of the internal rate of return.

According to the six relative frequency histograms in Table 176, the IRR coefficients of variation did not extend across nearly as many values as the coefficients of variation for system energy yield or electricity tariff variability. Even under the scenario that included both sources of input variability, the IRR coefficient of variation values spanned a smaller range of figures compared with the energy yield and electricity tariff coefficients of variation. Thus, under the global adjustment tariff offsetting scenario, fluctuating PV and CPV system output as well as electricity prices did not result in a notable amount of internal rate of return variability. In other terms, variable system energy yield and electricity rates under this tariff scenario did not pose a significant investment risk as measured by internal rate of return variability.

As a final component of the Monte Carlo simulation input and output analysis, Table 177 below presents average coefficient of variation values associated with the relative frequency histograms displayed in Table 175 and Table 176:

	PV Technology			CPV Technology		
Tariff Scenario	**Energy Yield Average Value**	**Electricity Tariff Average Value**	**Internal Rate of Return Average Value**	**Energy Yield Average Value**	**Electricity Tariff Average Value**	**Internal Rate of Return Average Value**
Time-of-Use	0.1384	N/A	0.00494	0.2375	N/A	0.00683
Feed-in Tariff	0.1384	N/A	0.00633	0.2375	N/A	0.01077
Power Purchase Agreement	0.13834	N/A	0.00438	0.2375	N/A	0.00922
Global Adjustment Tariff Offsetting	0.1384	0.4016	0.01348	0.2375	0.4016	0.03296

Table 177. Average coefficient of variation values from the relative frequency histograms displayed in this section.

In each of the four tariff scenarios in Table 176, the average internal rate of return value was smaller than the average energy yield and, where applicable, electricity tariff figure.

9.8 Summary

In Chapter 9, the results from Chapters 5 through 8 were summarized via charts and tables. These charts included illustrations of results for discounted net present value, return on investment, internal rate of return, and levelized cost of electricity over the years 2014 to 2020. Both scenarios with and without energy yield and tariff variability were included as part of the results. For the scenarios with variability, tables with ranges of discounted net present value, internal rate of return, and levelized cost of energy 95% confidence interval variability figures were included. These ranges illustrated the impact of energy yield, system price, as well as operations and maintenance plus degradation variability on the metrics of discounted NPV, ROI, IRR, and LCOE.

For PV technology, the highest discounted NPV was reported under the power purchase agreement tariff scenario. The next highest was under the feed-in tariff scenario, followed by the global adjustment and time-of-use tariff scenarios. For CPV, the highest discounted NPV was also recorded under the PPA scenario, but the next highest discounted NPV was found under the global adjustment tariff offsetting scenario, followed by FIT and TOU.

Consistently, system prices had a greater impact on variability than O&M and degradation. In turn, the impact on variability from O&M and degradation exceeded that of energy yield in nearly all instances. From a risk management perspective, the two largest sources of risk, system prices as well as O&M and degradation, could be controlled via fixed system costs as well as contractually agreed upon operations and maintenance fees. However, these risk reduction initiatives might not be possible in practice given that future system prices, for instance, are uncertain and it would be unreasonable to expect that an installer would have a $/W cost available for a project set to commence more than a year or two into the future. While module degradation could not be controlled in this manner, it had only a small impact on the financial attractiveness of an installation that it needed to be combined with

operations and maintenance. To illustrate, consider that in this analysis a PV project commencing operations in 2014 under the FIT scenario had an assumed degradation rate of 0.5% and a net present value of USD 58,060.82. By increasing (decreasing) the degradation rate by 0.1%, the NPV for this project decreased (increased) by approximately USD 4,930. The third contributing source of risk, fluctuating system energy yields, was uncontrollable but had a comparatively smaller impact than system price and operations and maintenance plus degradation on discounted net present value, internal rate of return, and levelized cost of electricity. This finding was particularly important since many concerns about solar technology surround its variable output.

The amount of variability tied to CPV technology was approximately double that of PV technology. One possible explanation for this phenomenon had to do with how these two technologies interacted with solar irradiance. PV technology absorbs both direct and diffuse irradiance, meaning that even on a cloudy day a PV module can absorb a small quantity of irradiance and convert this into a limited amount of electricity. CPV technology, on the other hand, absorbs only direct irradiance, which means that no electricity will be produced on a cloudy day. Thus, CPV output was more akin to "all or nothing," whereas PV output varied within the "all or nothing" range due to its ability to absorb diffuse irradiance.

The benefit of energy payment allocation factors was also discussed. These factors scaled the price paid for electricity either up or down according to a fixed schedule under the power purchase agreement tariff scenario. Energy payment allocation factors had a noticeable positive impact on the financial results presented by the analysis. Even though the PPA tariff scenario and the FIT scenario saw similar baseline prices paid per kilowatt-hour of solar-produced electricity, the highest PV discounted net present value from the PPA tariff scenario was approximately 25% greater than the highest discounted net present value from the FIT scenario. For CPV, the highest discounted NPV from the PPA tariff scenario was about 54% greater than the highest discounted NPV from the FIT scenario.

Finally, relative frequency histograms were used to compare the coefficients of variation of Monte Carlo simulation inputs "energy yield variability" and "electricity tariff variability" with the simulation output "internal rate of return." The charts illustrated that the simulation inputs were much more variable than the simulation output, which meant that energy yield and electricity tariff variability did not translate into a significantly fluctuating internal rate of return on a PV or CPV investment. In the next section, details pertaining to the validation of the financial model used by this thesis will be presented.

Chapter 10: Validation of Model

The accuracy of the financial model created for and used by this thesis was tested via inputting PV system costs from a separate solar study into this thesis' financial model and observing whether similar results were generated. The separate solar study was a white paper[8] prepared for Hydro Ottawa by Sunlab, a laboratory at the University of Ottawa focused upon the study of photovoltaics. Although the author of this thesis is listed as an author of the white paper, the financial model used in this thesis was not used to calculate the financial results in the white paper.

Inputs from the white paper included a system installation cost of $2.25/W, operation and maintenance fees of $18.00/kW/year, and a one-time inverter replacement cost of $0.16/W in the 13th year of PV system operations. The solar module degradation rate was set at -0.5% per year. However, no discount rate was provided, and there was no cost to recycle the PV modules at the end of their useful life. A few slight modifications made to the financial model used by this thesis were necessary in order to better match the results from the white paper, and they are as follows: the United States dollar/Canadian dollar exchange rate was removed; the

[8] The white paper is available online at: http://sunlab.eecs.uottawa.ca/build/wp-content/uploads/2014/pdf/PVPEAC-REPORT2.pdf

global adjustment charge was added back into year one of systems operation as part of the discounted NPV calculation; and the Hourly Ontario Energy Price was set to escalate at a fixed rate of 2% per year according to the LTEP. None of these changes significantly altered the underlying mechanics of financial model used by this thesis in any manner.

The PV system in the white paper offset the demand for grid-produced electricity in the same manner as the global adjustment tariff offsetting scenario, which was discussed in Section 4.3.4 of this thesis. Assuming a 25-year operational timeframe, the white paper indicated that the value of offsetting in year one before degradation, operation and maintenance costs, and discounting was $109,000. This amount varied over the 25-year of system operation, but in year 25 the final value was $155,448. Putting the same inputs into the financial model used by this thesis, the value from offsetting in year one before degradation, operation and maintenance costs, and discounting was $106,504, while value in year 25 was $157,626. Turning to one of the financial metrics, internal rate of return, the IRR calculated by the white paper was 8.70%. Comparatively, the internal rate of return calculated by the financial model used in this thesis was 8.07%. Although these two sets of figures were not identical, they were certainly comparable. This was acceptable, given that the objective of the validation process was to see if the discounted net present values and internal rates of return were similar, not necessarily identical.

In the white paper, alternative inputs that varied the financial results were also included. For example, an alternative scenario where the system price increased from $2.25/W to $3.00/W was provided, and under this change the new IRR was listed at 5.7%. When the system cost in the financial model used by this thesis was increased from $2.25/W to $3.00/W, the resulting internal rate of return was a comparable 5.1%. Similarly, the white paper indicated that at a system cost of $2.00/W, the internal rate of return was 10.1%. The financial model used by this thesis calculated an internal rate of return of 9.44% when the system cost was set at $2.00/W.

Further alternative input scenarios were presented in the white paper for operation and maintenance costs. For instance, in one case the operation and maintenance cost increased from $18.00/kW/year to $24.00/kW/year and as a result the internal rate of return became 8.40%. When the operation and maintenance cost was increased to $24.00/kW/year in this thesis' financial model, the IRR was calculated as 7.76%. Once more, these internal rates of return were not identical, but they were both in similar territory. Table 178 below provides a side-by-side comparison of the figures calculated by the financial model used in the white paper against the financial model used by this thesis:

Component	White Paper	Thesis
Year One Revenue ($)	109,000	106,504
Year 25 Revenue ($)	155,448	157,626
Internal Rate of Return at $2.25/W system cost (%)	8.70	8.07
Internal Rate of Return at $3.00/W system cost (%)	5.70	5.10
Internal Rate of Return at $2.00/W system cost (%)	10.10	9.44
Internal Rate of Return at $24.00/kW/year operation and maintenance cost (%)	8.40	7.76

Table 178. Comparison of the results when the inputs from the Hydro Ottawa white paper were inputted into the financial model used by this thesis.

As per Table 178, the values in the center and the right-hand column were in the vicinity of one another. The close proximity of these figures validated the financial model used by this thesis against another financial model that was already proven as valid.

Chapter 11: Conclusion

This thesis examined the viability of using PV and CPV technologies to reduce energy costs at data center facilities operating within the province of Ontario. The topic is both important and timely given that "digital storage market demand doubles every 18 months" (Mondal & Keisling, 2012, p.1), between 1.1% and 1.5% of worldwide electricity consumption is attributable to data center operations (Brady et al., 2013), and electricity expenses typically account for more than 50% of

the expenditures associated with operating a data center facility (Nazir, 2012). Consequently, countless new data centers will be required to satisfy the growing demand for cloud computing and cloud storage services, which, without some form of intervention, will result in more electricity consumed and increased energy costs for data center operators. The intervention mechanism proposed by this thesis was solar-generated energy produced by PV and CPV installations.

The business case for using PV and CPV systems to reduce energy costs at Ontario data center facilities was determined by assessing the expenses related to, and cost savings generated by, these solar technologies. Expenses tied to PV and CPV installations were determined via the literature review, while the quantity of cost savings generated was dependent upon solar installation energy yield and the price paid for the electricity produced. Four different tariff scenarios in place in the province of Ontario at the time of writing were compared: time-of-use pricing, feed-in tariff pricing, power purchase agreement pricing, and global adjustment tariff offsetting.

Using a financial model that synthesized solar technology costs, electricity tariffs, and solar installation electricity output to quantify cost savings, the financial metrics of discounted net present value, return on investment, and internal rate of return were calculated to gauge the profitability solar installation investment. Additionally, the energy industry metric levelized cost of electricity was also computed to measure the costliness of the energy produced by the solar installations. As indicated by the results of the analysis between Chapters 5 and 8, the four distinct tariff scenarios produced a variety of financial results. These results were calculated for solar installations that commenced operations at the beginning of the calendar year between 2014 and 2020, inclusive.

Since the solar installations under analysis in this thesis operated for a period of either 20- or 25-years into the future, a Monte Carlo simulation was employed to project the upper and lower limits of expected solar energy production over the

system's operational lifetime. The simulation used both empirical PV system output and solar irradiance data as inputs, and was applied as part of the analysis related to each of the four tariff scenarios. A Monte Carlo simulation was also used to determine future Hourly Ontario Energy Prices under the global adjustment tariff offsetting scenario. This was the only tariff scenario with truly variable electricity prices.

In addition to the results generated by a Monte Carlo simulation, deterministic results were also included for comparison under each of the four unique tariff scenarios. The deterministic results were also slightly different compared with the results that took energy yield and/or energy price variability into account. Using the four financial metrics, which covered the deterministic results as well as the results generated from a Monte Carlo simulation, this thesis answered the research question: is there a business case for using solar technology to offset electricity expenditures at data centers in Ontario?

11.1 Empirical Findings

Justification for the use of solar technology at data centers in Ontario to reduce electricity costs was established via positive discounted net present value and return on investment figures, as well as internal rates of return that exceed the cost of capital. These financial metrics were impacted by several factors including: whether photovoltaic or concentrated photovoltaic technology was used; the costs associated with system setup and operation; and the characteristics of the tariff scenario, such as the price paid per kilowatt-hour of solar-produced electricity, and when, if ever, prices paid for solar-produced electricity increased or decreased over the course of a day. Notably, according to the financial metric results presented in Chapters 5 to 7, the total value of solar-produced electricity generated over 20- or 25-years from identical solar installations varied as a result of the uniqueness of each tariff scenario. This concept was a key finding for prospective solar investors since presently there are multiple tariff options available for solar energy producers

in Ontario, and the business case for solar is stronger under some tariff structures than others according to the results of this thesis.

Variability had an impact on the financial results. Interestingly, however, variable system energy output had only a very minor effect on the financial metrics and thus the business case. This was indicated by the summary tables in Chapter 9, which compared the extent of discounted NPV and IRR fluctuations caused by variable solar installation output and system prices with discounted NPV and IRR fluctuations due to O&M cost plus degradation variability. In particular, the finding that variable system output did not have a significant impact on discounted NPV, ROI, or IRR dismissed the concern that the intermittent nature of solar-electricity production posed a significant risk to the attractiveness of solar installation investment.

As noted previously in this chapter, the financial metrics varied depending upon a number of factors. Therefore, the business case for investing in solar was non-existent in certain years where negative returns on investment or internal rates of return less than the cost of capital were observed. In other years, favourable financial metrics supported the business case for using solar technology to offset electricity costs at data centers in Ontario. However, positive discounted net present values and returns on investment did not necessarily indicate that initiating investment in a solar installation was a wise business decision.

Consider, for instance, a CPV installation commencing operations in the year 2016 under the time-of-use tariff scenario. According to Table 144 in Section 9.1, the discounted net present value associated with this investment was USD 48,072.74 and the return on investment was 9.5%. On the other hand, a CPV installation commencing operations in 2020 under the same tariff scenario had a discounted net present value of USD 404,408.37, which represented a 73.3% return on investment. These two solar investments each yielded positive discounted cash flows and returned additional sums of money after recovering all of the initial funds invested.

However, the 9.5% return on investment over 25-years from the first investment example may not have represented a strong business case for using solar technology to many investors, especially when compared to the second investment example. Thus, the presence of positive financial metrics did not necessarily translate into a guaranteed business case for investing in solar technology.

Furthermore, the business case for investing in solar could also depend upon the characteristics of the company seeking to leverage the technology. Consider, for example, Company "A," a well-known high-tech multinational with surplus cash reserves. The motivation of this organization to invest in solar may have more to do with optics rather than the bottom line. To this firm, the business case for investing in a solar installation on one of its data center roofs may be justified so long as the project instils the idea that the company is environmentally conscious. The company may not be particularly concerned that its solar installation only breaks even after 25-years of electricity output so long as public opinion about the organization increases after publicity about the solar installation investment. Alternatively, Company "B," a smaller high-tech firm with comparatively tighter budgetary constraints, may consider only the bottom line when deciding whether or not to implement a solar installation on the rooftop of one of its data centers. For this company, the business case rests solely upon the solar installation having an internal rate of return greater than the firm's cost of capital for it to be considered of value. Any positive public perception in this case is an added bonus.

For organizations like Company "B," the internal rate of return was a measure that could assist the company with selecting a single solar investment from multiple options. This financial metric was particularly useful because its calculation did not depend upon a pre-defined discount rate. As well, when valuing a solar installation investment, the IRR accounted for the fact that the price paid for solar-produced electricity varied at different times throughout the day over the installation's operational lifetime. Furthermore, the internal rate of return results indicated the maximum acceptable discount rate that would net a profitable solar installation

investment and provided a gauge of the attractiveness of a solar investment to *any* prospective investor. As an example of this metric's utility, consider that the IRR figures presented in Chapter 7 could be used by any potential investor to make an investment decision, even if the investor's cost of capital was not between the 8-10% range assumed by this thesis' calculations.

However, unlike the internal rate of return, the levelized cost of electricity metric was not particularly useful for accurately assessing the business case for using solar-produced energy. The LCOE, which defined the price per kilowatt-hour at which electricity must be sold over the solar installation's operational lifetime to breakeven, was accurate only under the feed-in tariff scenario. This was the sole tariff arrangement in the analysis where the price paid per kilowatt-hour of electrical output was static over the entire lifespan of the solar installation. Under all other tariff scenarios, the price paid per kilowatt-hour of solar-produced electricity varied to some degree. In some instances solar power was sold at prices below the LCOE during certain hours of the day, while at other times the price paid for this renewable energy exceeded the LCOE. Typically, the prices in excess of the LCOE were in place during the afternoon hours when solar modules produced their greatest quantity of energy output, and this was precisely when the solar installations produced a large proportion of their value. The results of this study indicated that a solar installation could sell electricity at prices *both above and below* the LCOE over the course of its operational lifetime yet still be profitable. Thus, unless the price paid per kilowatt-hour of electricity produced was static, the levelized cost of electricity was inappropriate to measure the business case for using solar-produced electricity.

This conclusion that the LCOE is a poor metric for assessing the financial attractiveness of solar energy supported the viewpoints stated in Section 2.4.2.2 of this thesis by Borenstein (2012), Branker et al. (2011), and Joskow (2011). It is therefore recommended that financial metrics such as discounted net present value, return on investment, and internal rate of return be used in place of the LCOE to

evaluate the financial merit of solar investment since these metrics capture the true value of solar-produced electricity while accounting for variable prices paid per kilowatt hour of solar energy produced. Furthermore, this thesis proposes that a new measure of solar installation financial attractiveness, levelized *profitability* of electricity, should be used as an alternative to the LCOE.

Unlike the complex calculation required to compute the LCOE, the proposed LPOE metric is simply equal to the solar installation's internal rate of return. This provides a superior assessment of a solar installation's investment worthiness by removing the assumption of a static price paid per kilowatt-hour of system output. Furthermore, assuming a potential investor is aware of their cost of capital, the LPOE provides a quick and easy assessment of the attractiveness of a possible solar installation investment.

11.2 Policy Implications

Currently, subsidies and other incentives are frequently included as part of the equation to strengthen the business case for setting up and operating solar installations. The Feed-in Tariff program, introduced as part of the Government of Ontario's Green Energy Act (2009), is an example of one such initiative, and feed-in tariffs were included as one of the four tariff scenarios incorporated into the analysis of this thesis. However, as evidenced by Figure 18 and Figure 19 in Section 4.3.2, feed-in tariff rates are projected to decline between 2014 and 2020. In turn, the attractiveness of solar installation investment under this particular tariff scenario generally decreases as time progresses towards 2020 according to Table 148 and Table 149 in Section 9.2.

While the incentive to invest under the feed-in tariff scenario tended to decrease over time, the merit of investing in a solar installation under the other tariff scenarios increased during the same timeframe. This point was supported by the summary charts and figures presented throughout Chapter 9. For both the time-of-

use and global adjustment tariff offsetting scenarios, investment in solar was considerably more financially rewarding in the years closer to 2020 than 2014 for both PV and CPV technologies. For the power purchase agreement scenario, investment was much more rewarding closer to 2020 than 2014 for only CPV technology. The increase in investment attractiveness in future years was also attributable to other factors, including the forecasted decline in both PV and CPV system prices. Thus, in the very near future under the right conditions, solar installation investments in Ontario will be able to generate appealing economic returns *without the Feed-in Tariff program or other economic incentives*.

The "right conditions" referred to in the previous sentence could be capitalized upon by Class "A" electricity customers in Ontario. These customers, who were defined as having peak energy demands exceeding three megawatts, were, according to the analysis, able to generate significant value by using solar technology to offset Hourly Ontario Energy Price charges, global adjustment costs, and electricity delivery fees. Thus, for these energy consumers specifically, the results of this thesis demonstrated that securing a FIT contract or a power purchase agreement was not necessarily required to justify investment in a PV or CPV installation. This was a positive finding, since the application process for a FIT contract or the bidding process to secure a power purchase agreement represented an additional barrier to implementing solar technology. Alternatively, the time-of-use and global adjustment tariff offsetting scenarios provided the path of least resistance to solar investment since PV or CPV technology could be leveraged to offset existing electricity charges without the need for a formal agreement.

11.3 Limitations of Study

The results in this study were subject to certain limitations. Firstly, instead of empirical data, the CPV results were based upon simulated energy yield data calculated using direct normal irradiance along with assumed system and solar cell

efficiencies as per Table 20 in Section 4.2. Actual CPV system output may in fact differ from the simulated data.

Secondly, this study employed forecasts of several items including PV and CPV system costs as well as electricity tariffs. This was necessary, however, since solar installations could commence operations at the beginning of any of the years 2014 to 2020 and were assumed to be operational for 20- or 25-years. Although every effort was made to forecast costs and other items with the utmost accuracy using reliable methods, actual future costs may deviate from what was predicted and used by the analysis in this thesis.

Thirdly, particularly for concentrated photovoltaics, some financial model inputs had to be estimated or based upon photovoltaic equivalents because of a lack of information available about this newer, evolving solar technology. For instance, CPV operations and maintenance costs, degradation rates, and recycling fees had to be assumed based upon PV data. Similar to the projected costs mentioned previously in this section, a discrepancy could exist between the estimated CPV O&M costs, degradation rates, and recycling fees used in this thesis' financial model and actual values.

Finally, the results from the power purchase agreement tariff scenario included energy payment allocation factors that were based upon values observed in California. Although not necessarily unrealistic for the reasons discussed in Section 4.3.3, actual energy payment allocation factors used as part of an Ontario PPA arrangement may differ from the values used in this study's analysis. It could also be possible that an Ontario PPA would not incorporate any energy payment allocation factors. If either was true, the financial results pertaining to this tariff scenario would be different than those reported in this study.

11.4 Next Steps and Future Research Directions

One possible next step for this thesis would be to update the CPV system energy yield data according to one of the following two methods. First, a more intricate CPV energy yield calculation could eventually be attempted whereby additional factors such as ambient temperature and solar cell efficiency under different combinations of junctions and elements within the CPV cells are incorporated into the calculation. As indicated by the limitations in Section 11.3, CPV system energy output in this thesis was calculated using only direct normal irradiance data with assumed system and solar cell efficiencies. At the present time, however, a more intricate CPV system energy yield calculation has minimal value given that concentrated photovoltaic technology is still in development and there is ongoing debate within the solar industry about the ideal composition of CPV cells. Only when this fundamental concentrated photovoltaic matter is resolved should these additional, more complex factors be taken into account when calculating CPV system energy yield. Second, data from an actual operational CPV installation in Ottawa, Ontario, once available, could be used in place of simulated CPV system output. These figures could be applied to the financial model in the same manner as the empirical PV data in the present study.

Since the analysis employed forecasts or estimates of such items wholesale electricity prices, as well as PV and CPV system prices, operations and maintenance costs, and inverter replacement charges, a second next step could include updating the financial calculations with non-forecasted inputs once those values become available. Future Hourly Ontario Energy Prices were approximations provided by the Government of Ontario; system price inputs for projects commencing in the future had to be forecasted; operations and maintenance fees for CPV installations specifically were unavailable for this study and had to be estimated due to the newness of this solar technology; and inverter replacement charges also had to be estimated. Any of the forecasted or estimated values could deviate from actual values observed at a later point in time, but using forecasts was absolutely

necessary for this study. The process of inputting actual values into the financial model in the future and comparing the resulting financial metrics with those reported by this thesis could provide an interesting study in the accuracy of this thesis' forecasting methods. In turn, this may provide guidance to subsequent similar studies to either replicate or modify the approach used by this thesis.

Finally, as noted in the literature review, energy inefficiencies arise when the direct current naturally produced by solar modules is converted into alternating current. This conversion is necessary, however, since standards govern that our buildings be equipped with AC power. While most electronic devices are configured to accept alternating current, some electronics such as computers require direct current for operation, and these devices must convert the electric charge they receive when plugged into a wall socket from alternating current into direct current. Given that the findings of this thesis support the business case for leveraging solar technology at data centers, future research could explore whether a solar installation at one of these facilities could successfully power the computers and servers housed within using an uninterrupted transmission of direct current.

11.5 Conclusion of Thesis

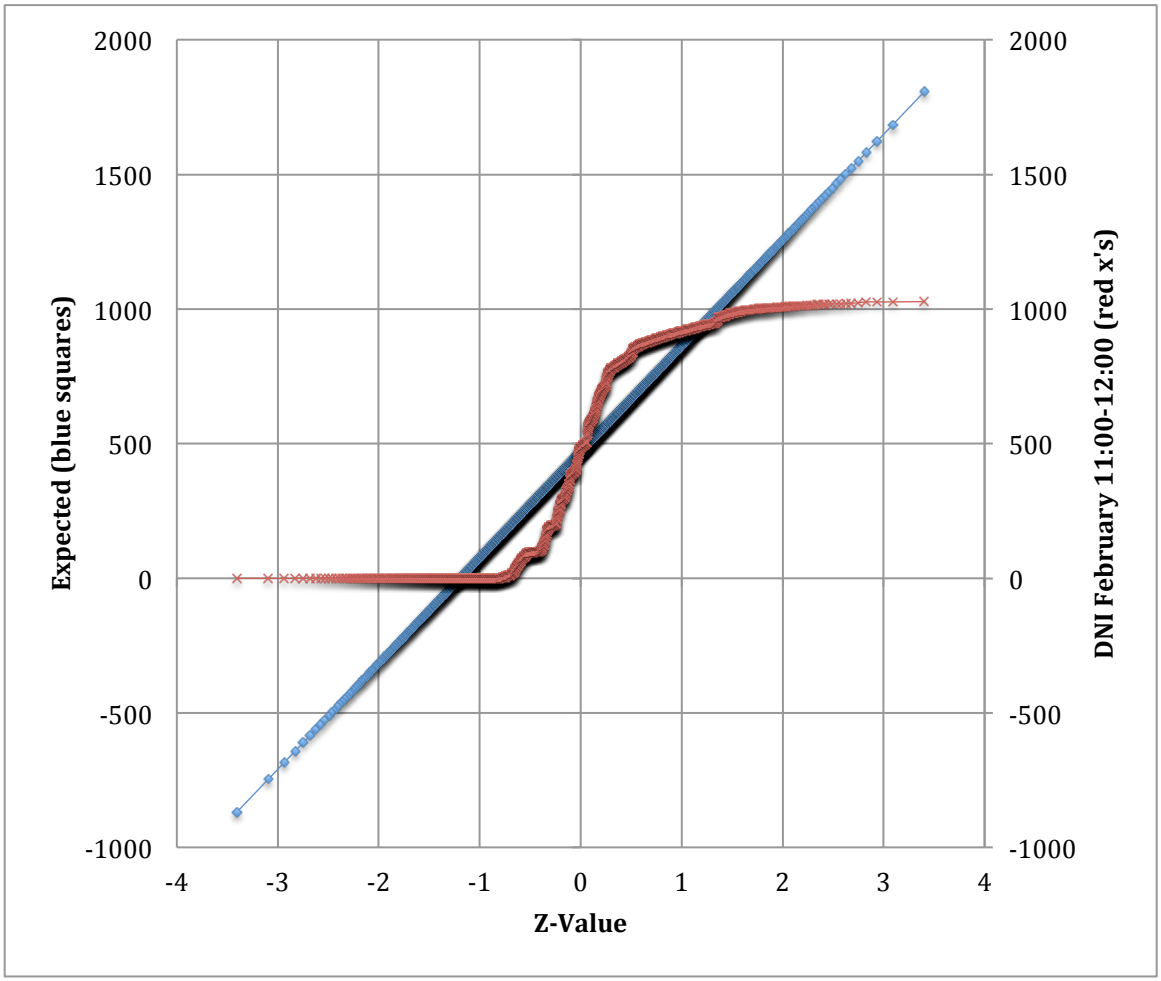
The results presented by this thesis indicated that there is in fact a business case for employing solar technology at data centers in Ontario to offset electricity costs. This thesis also established that subsidies and other financial support mechanisms are *not* a requirement for profitable investment in solar installations in Ontario, which runs contrary to a popular opinion held by a large segment of the province's population.

Currently, countless individuals oppose the use of solar technology because they believe that installations cannot operate without financial subsidies funded by electricity ratepayers. Ontario's Feed-in Tariff program in particular has become a target of politicized debate amongst many in the province, and feed-in tariffs are

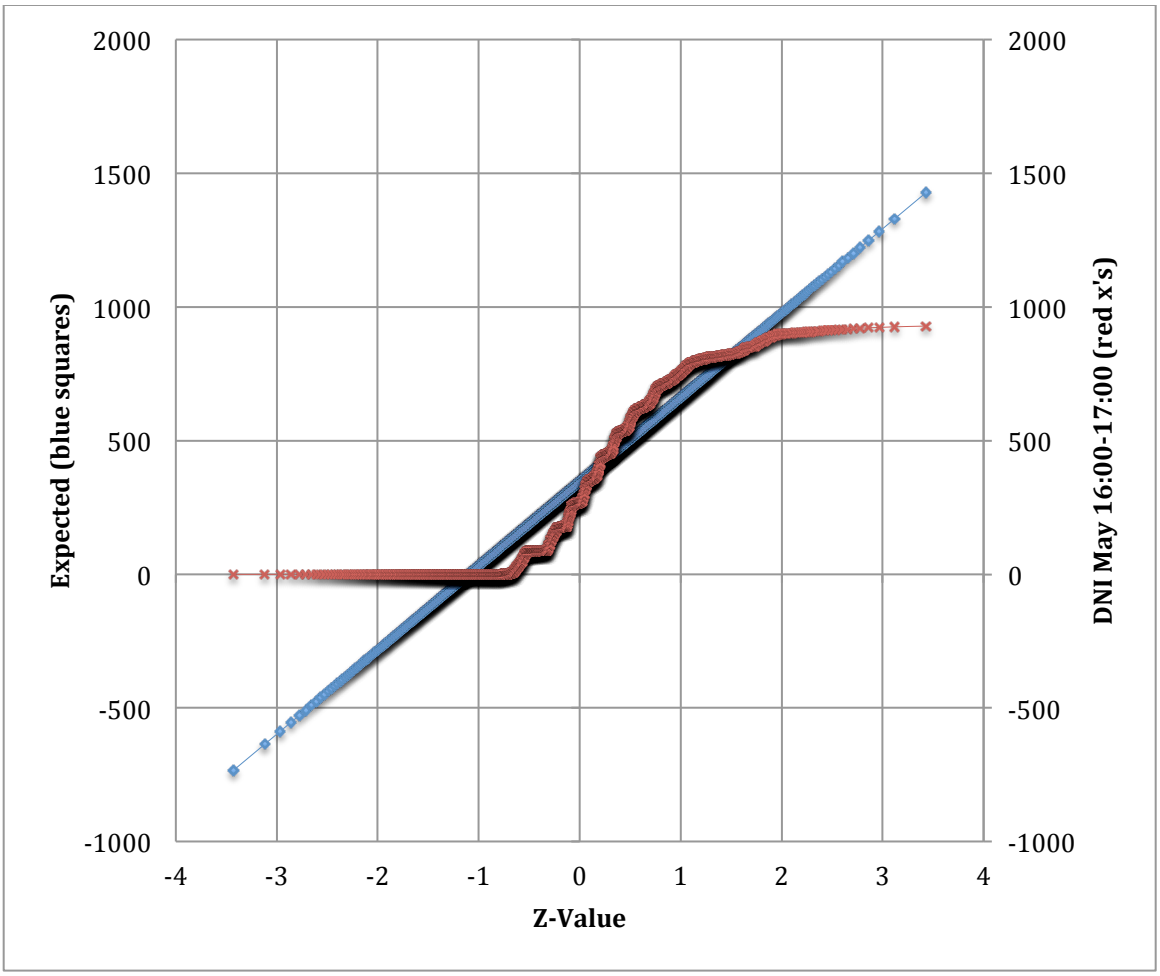
consistently singled out as a major contributing factor to the province's increasing electricity prices and, consequently, greater energy expenses paid by the province's electricity customers. Business leaders and political pundits in Ontario routinely blame the province's climbing electricity rates for the withdrawal of large manufacturers from the province. While it is true that electricity ratepayers do pay for the monetary incentives that comprise the feed-in tariff program, the Environmental Commissioner of Ontario calculated that the cost of renewable energy and energy conservation programs amounted to only 0.413 cents per kilowatt-hour (CAD 0.00413/kWh) of the approximate CAD 0.13/kWh all-in cost of electricity in 2010 (Environmental Commissioner of Ontario, 2011). Since 2010, the FIT price has declined and is likely a smaller proportion of today's all-in cost of electricity.

As per the results of this thesis, an opportunity currently exists for data centers operators in Ontario to lead by example and leverage solar technology at their facilities to offset electricity expenditures. Interestingly, the IESO includes both data centers *and manufacturers* as potential Class "A" customers (IESO, Changes to Class A Eligibility, 2015), meaning that manufacturers, a group routinely claimed to be in withdrawal from Ontario because of high electricity costs, could also take advantage of solar technology to offset their electricity charges. Rooftop and ground mount solar installations could become an effective solution to reducing the high electricity fees faced by Class "A" energy customers in Ontario. However, this will happen only if organizations pursue investments in solar energy while effectively promoting the economic benefits of leveraging the technology. Data centers represent progress in, and the future of, computing. As such, they are well situated to demonstrate that solar energy can be an integral part of a modern, efficient, and successful business operation.

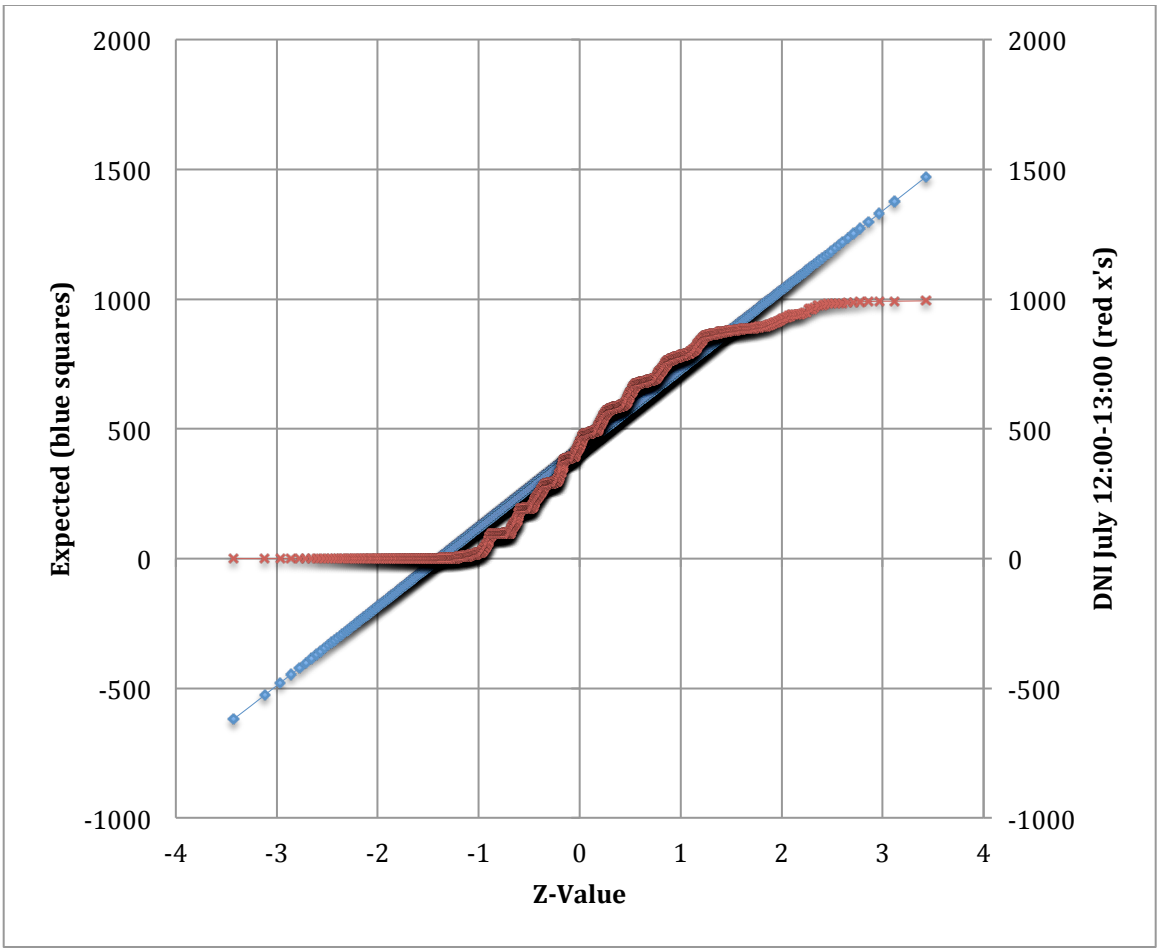
Appendix A: Raw Data Normality Tests



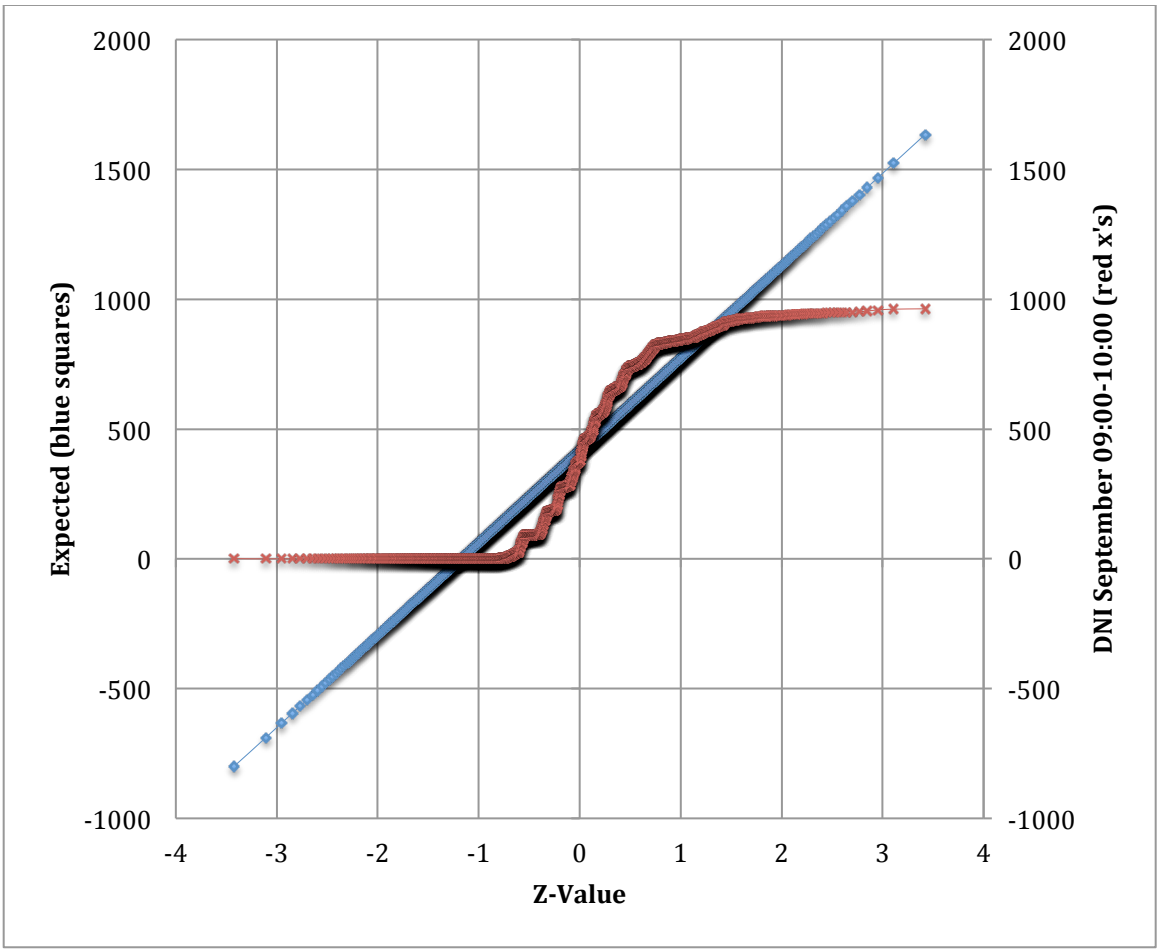
Normality test of the raw DNI measurements observed each day in February from 11:00 to 12:00 during the years 1953 to 2005.



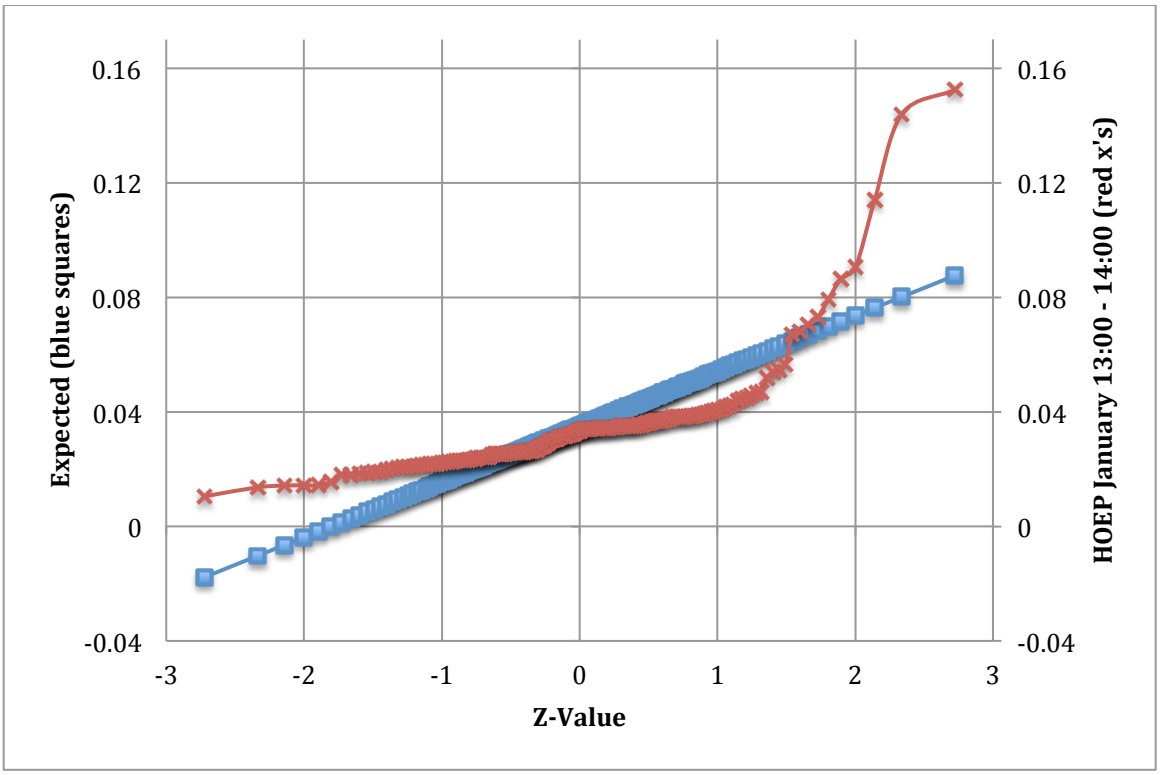
Normality test of the raw DNI measurements observed each day in May from 16:00 to 17:00 during the years 1953 to 2005.



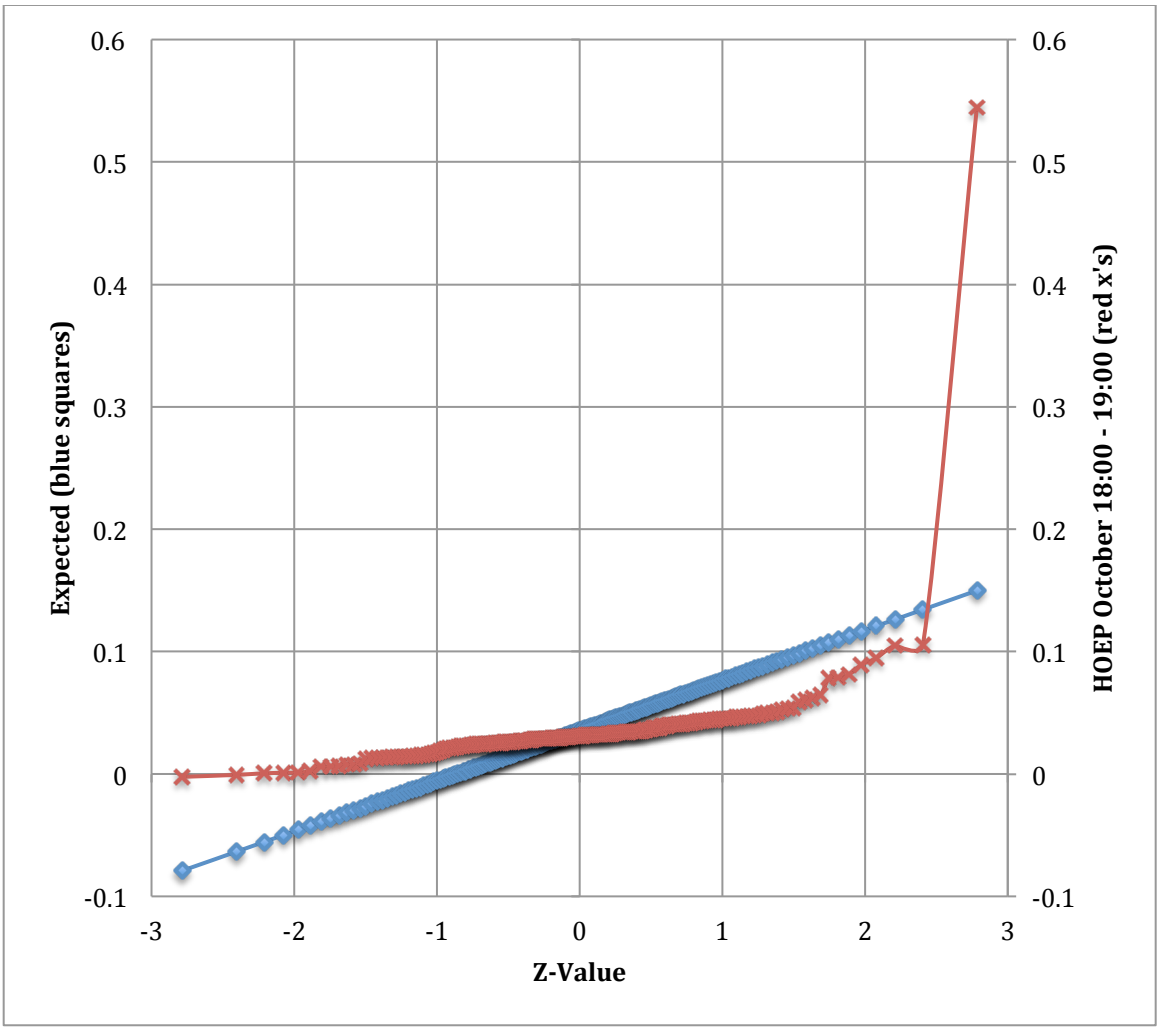
Normality test of the raw DNI measurements observed each day in July from 12:00 to 13:00 during the years 1953 to 2005.



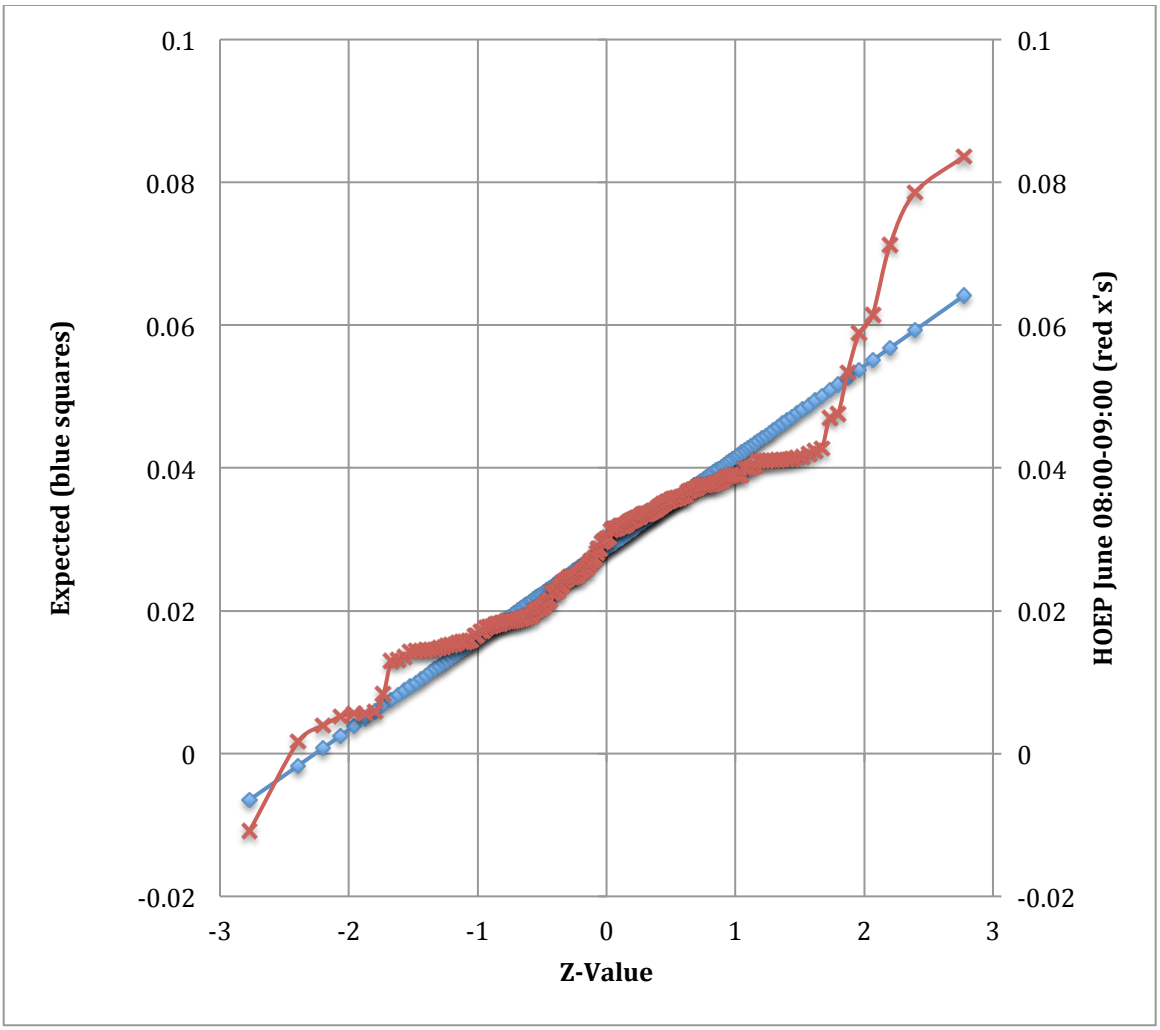
Normality test of the raw DNI measurements observed each day in September from 09:00 to 10:00 during the years 1953 to 2005.



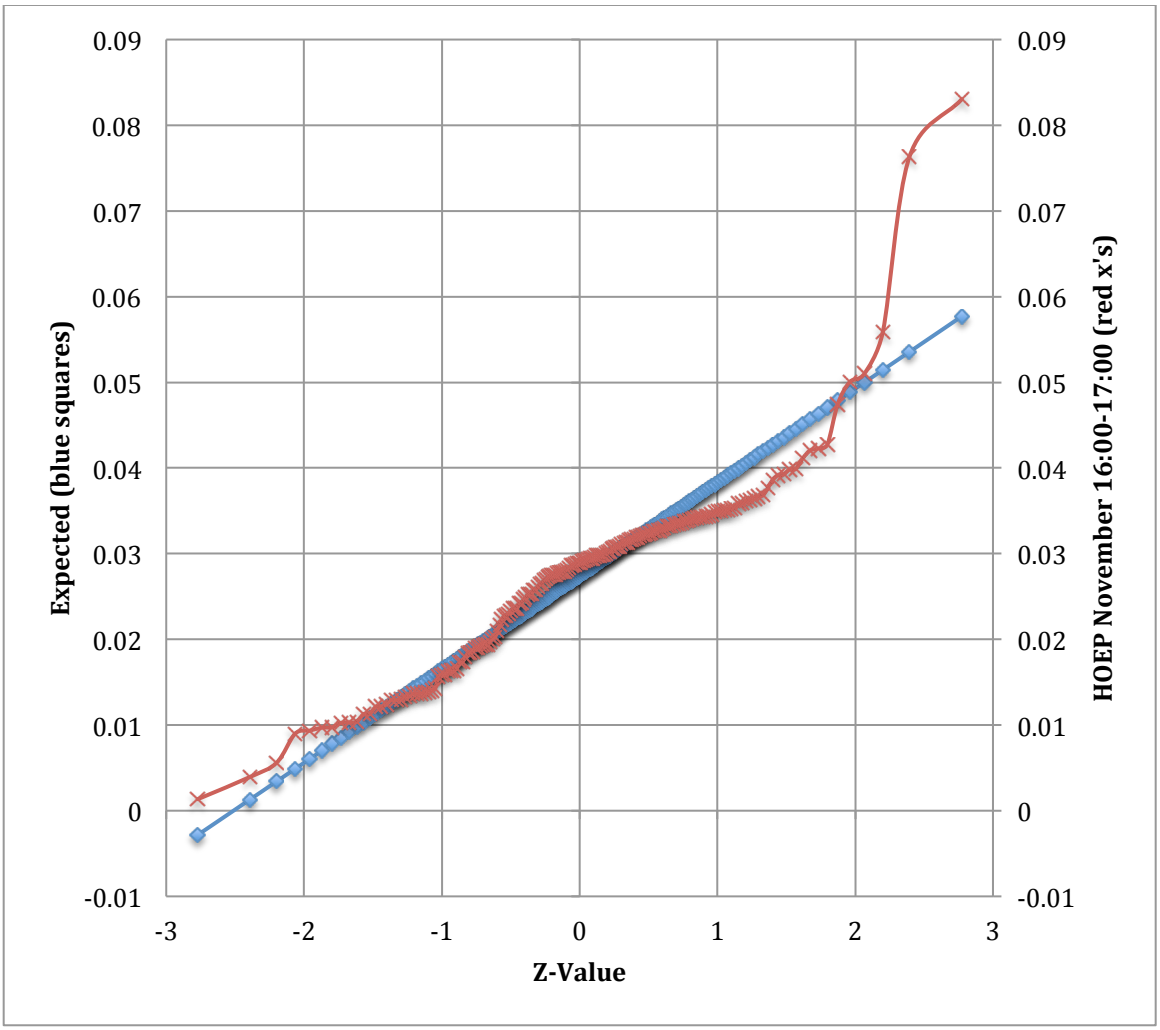
Normality test of the raw HOEP measurements observed each day in January from 13:00 to 14:00 during the years 2010 to 2014.



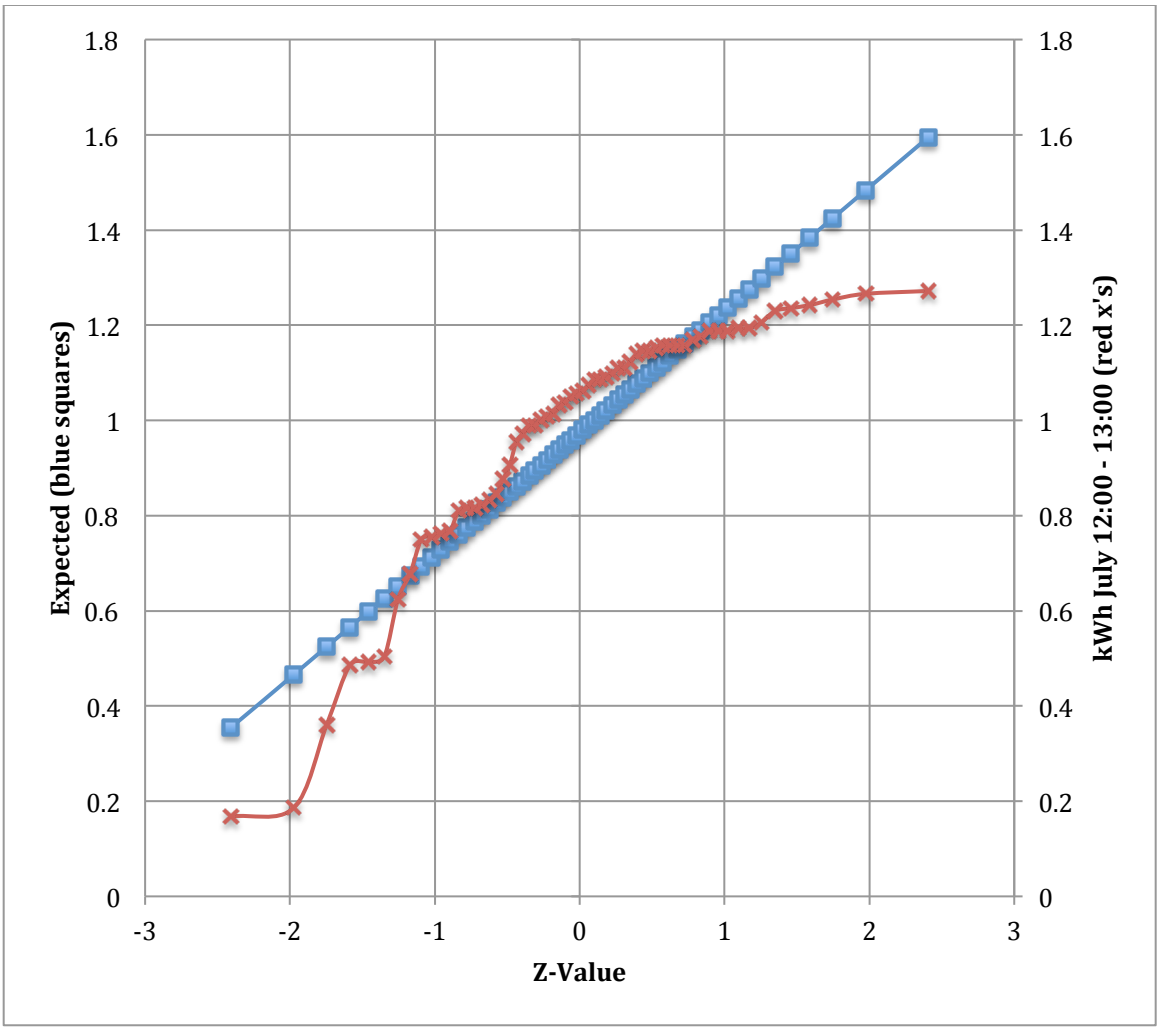
Normality test of the raw HOEP measurements observed each day in October from 18:00 to 19:00 during the years 2009 to 2014.



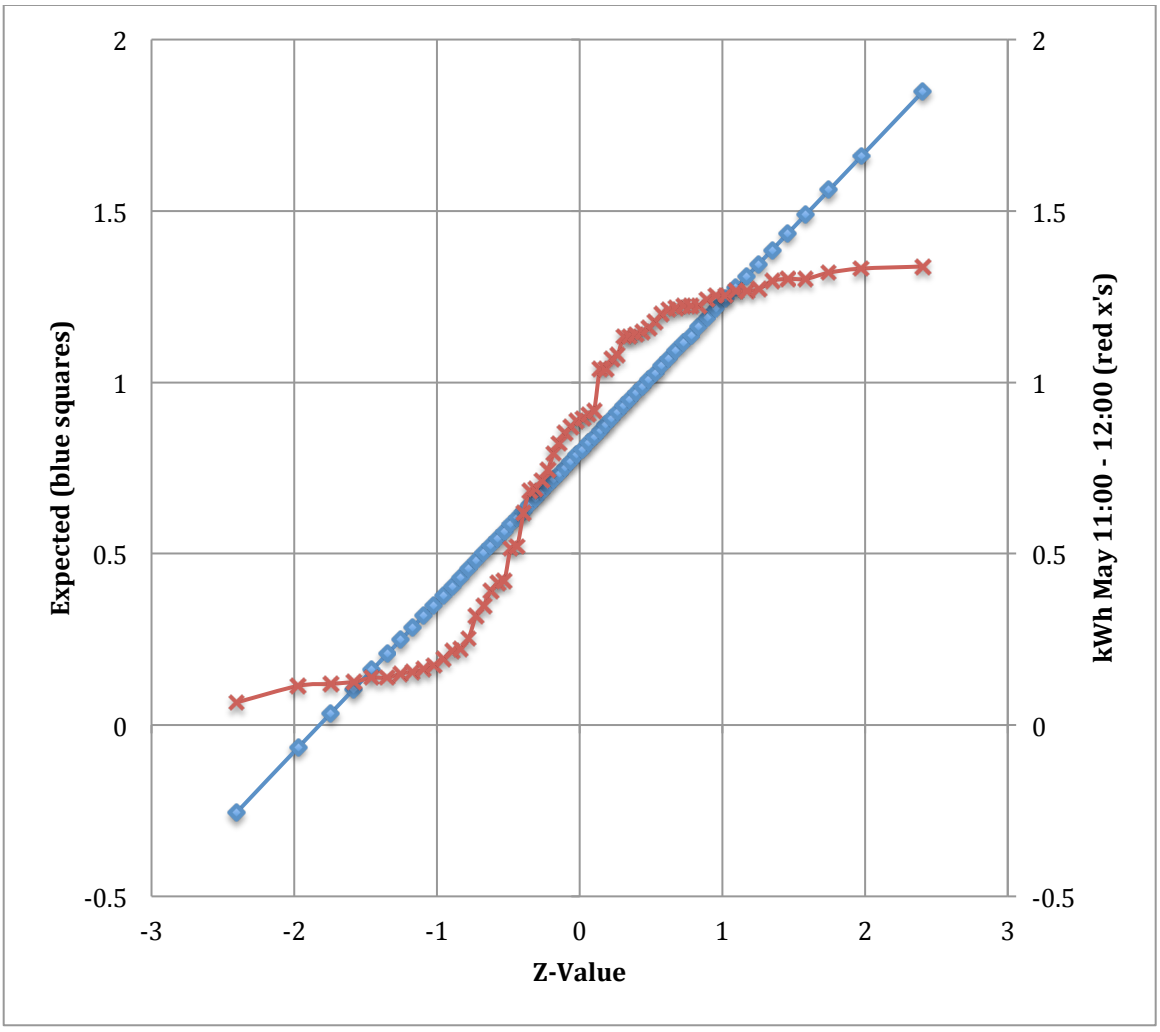
Normality test of the raw HOEP measurements observed each day in June from 08:00 to 09:00 during the years 2009 to 2014.



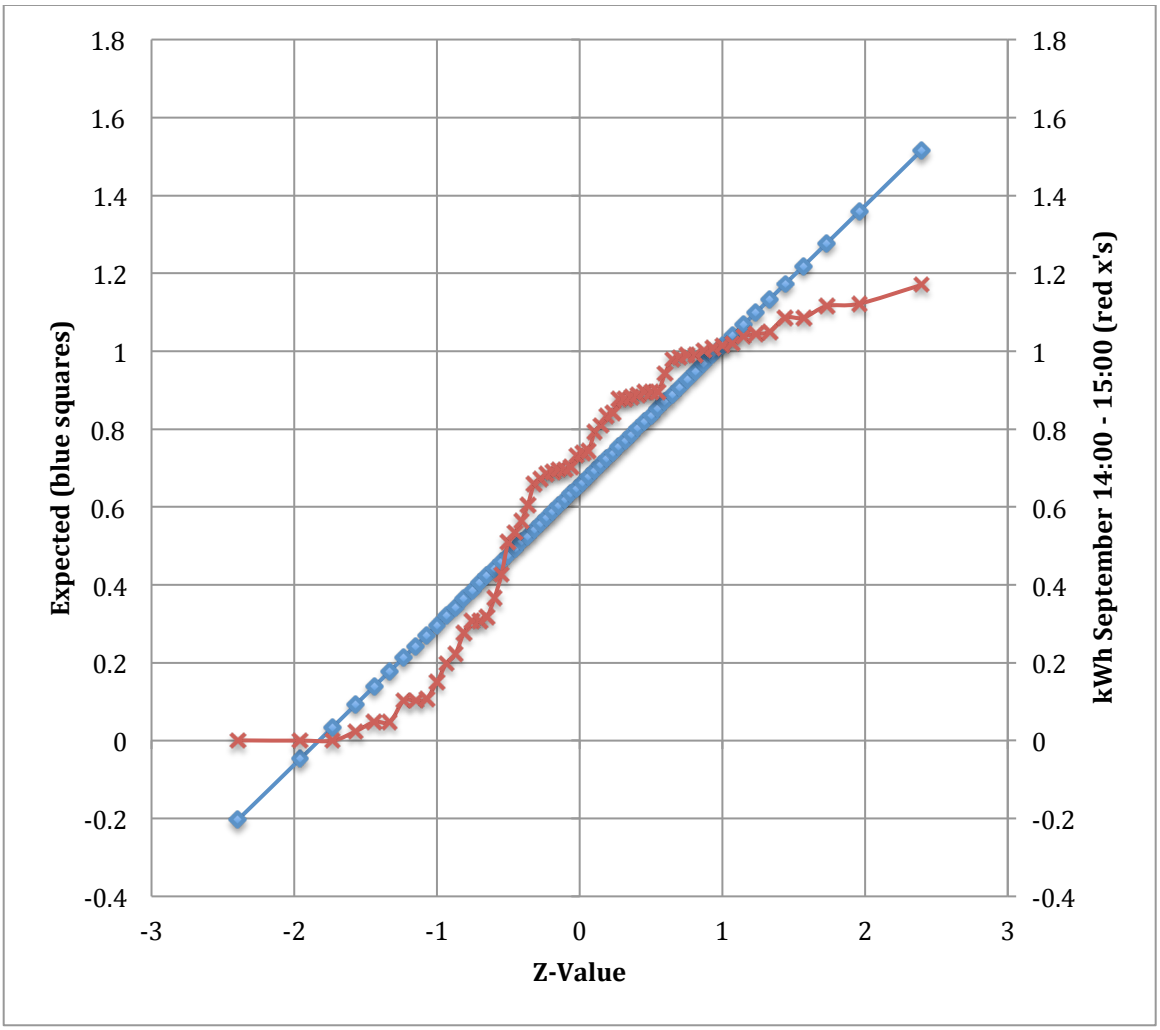
Normality test of the raw HOEP measurements observed each day in November from 16:00 to 17:00 during the years 2009 to 2014.



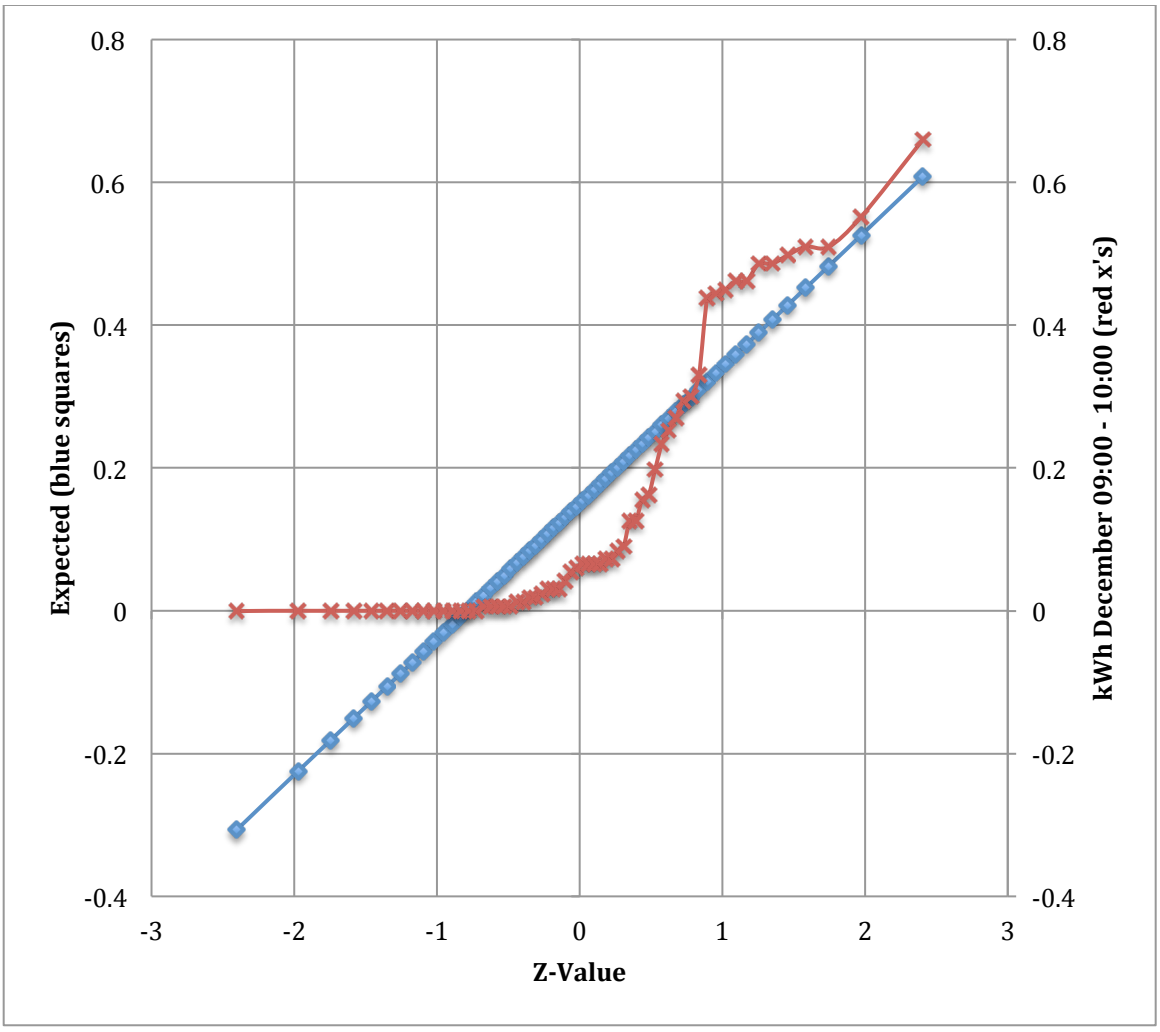
Normality test of the raw Hydro Ottawa PV energy yield measurements observed each day in July from 12:00 to 13:00 during the years 2011 and 2012.



Normality test of the raw Hydro Ottawa PV energy yield measurements observed each day in May from 11:00 to 12:00 during the years 2011 and 2012.

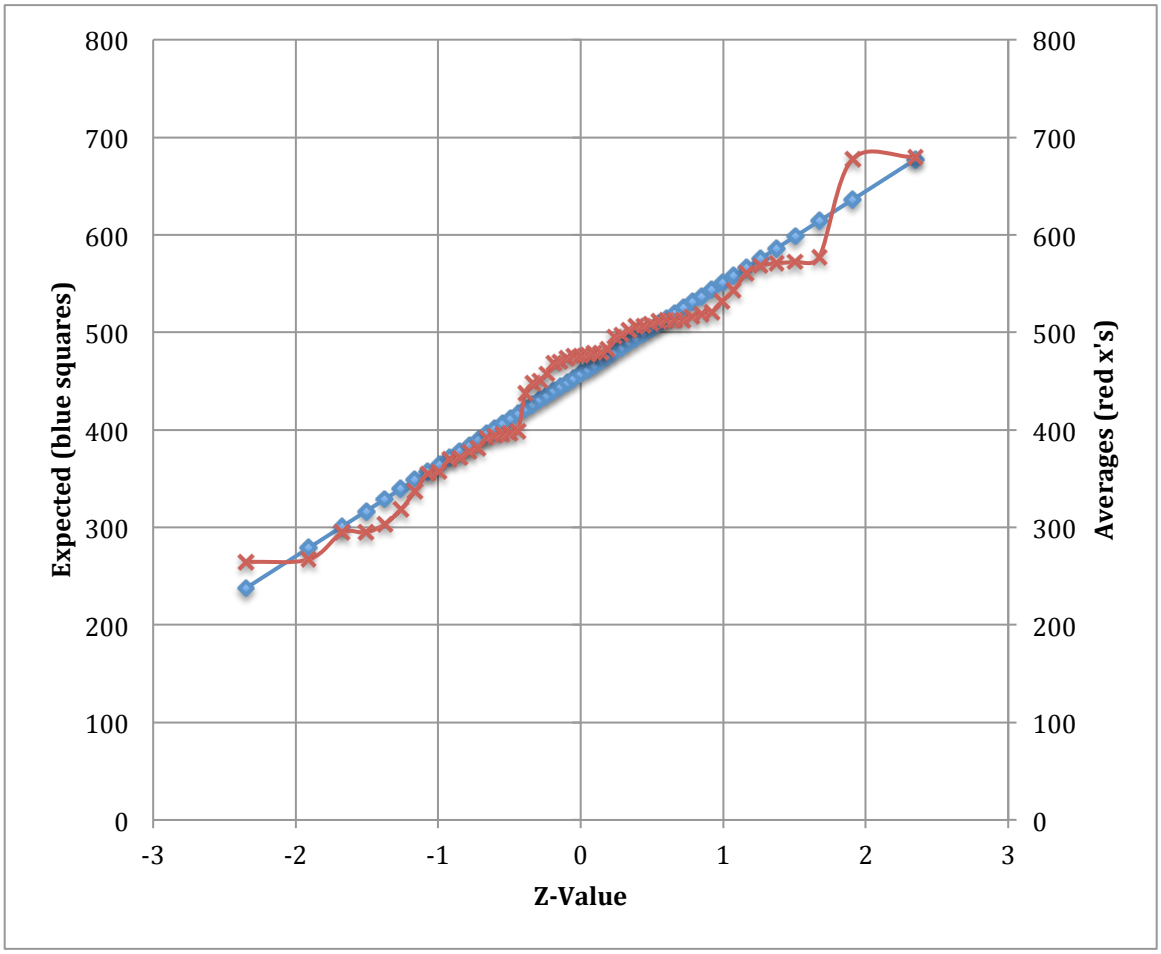


Normality test of the raw Hydro Ottawa PV energy yield measurements observed each day in September from 14:00 to 15:00 during the years 2011 and 2012.

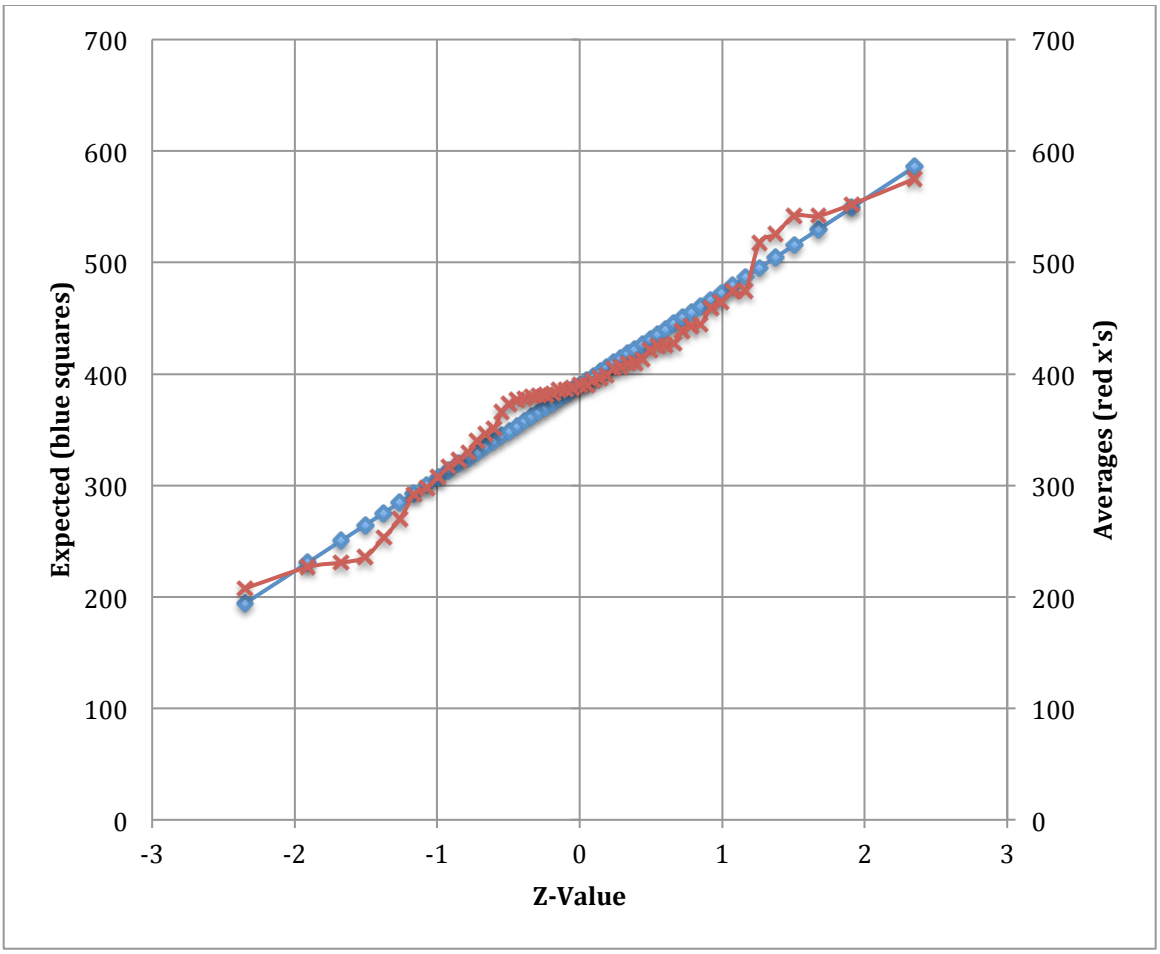


Normality test of the raw Hydro Ottawa PV energy yield measurements observed each day in December from 09:00 to 10:00 during the years 2011 and 2012.

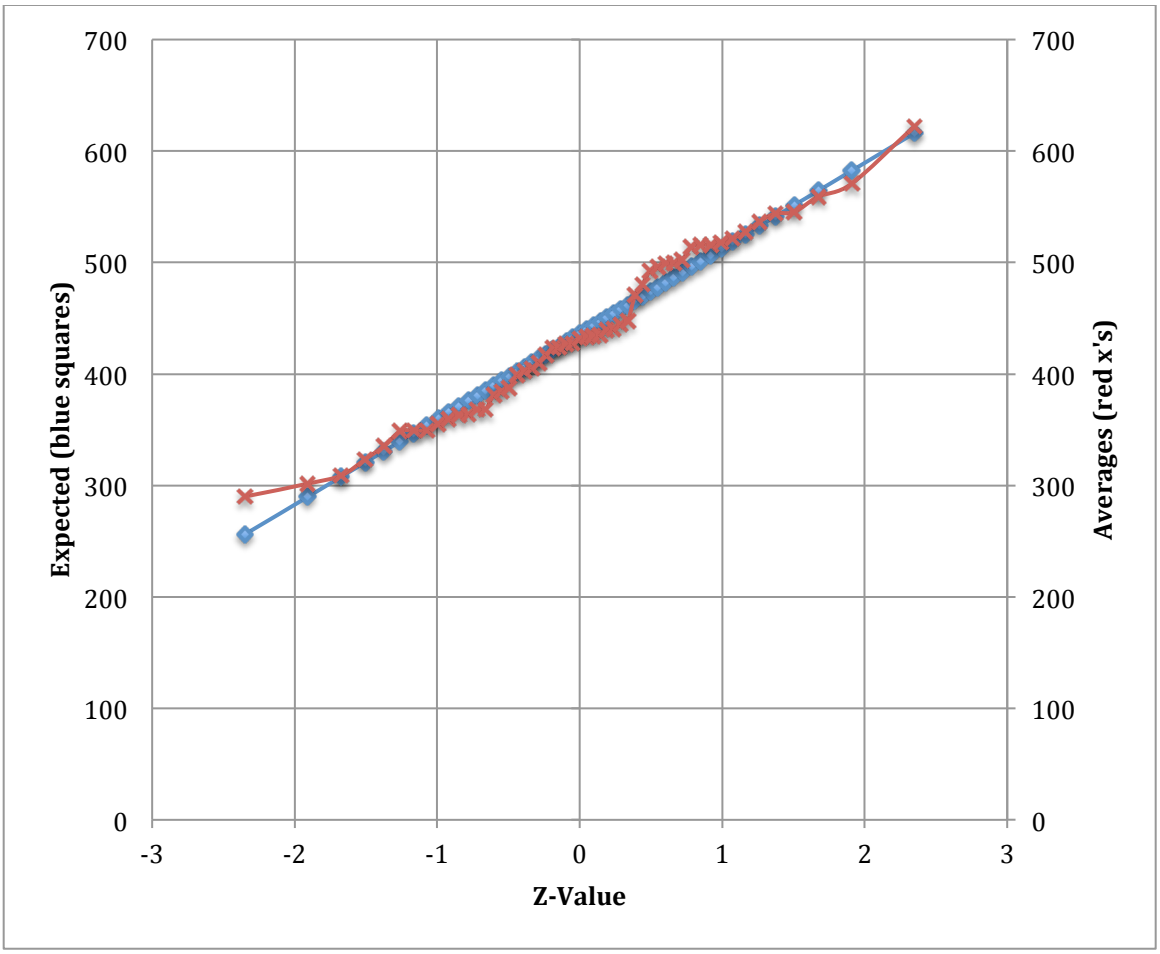
Appendix B: Calculated Means Normality Tests



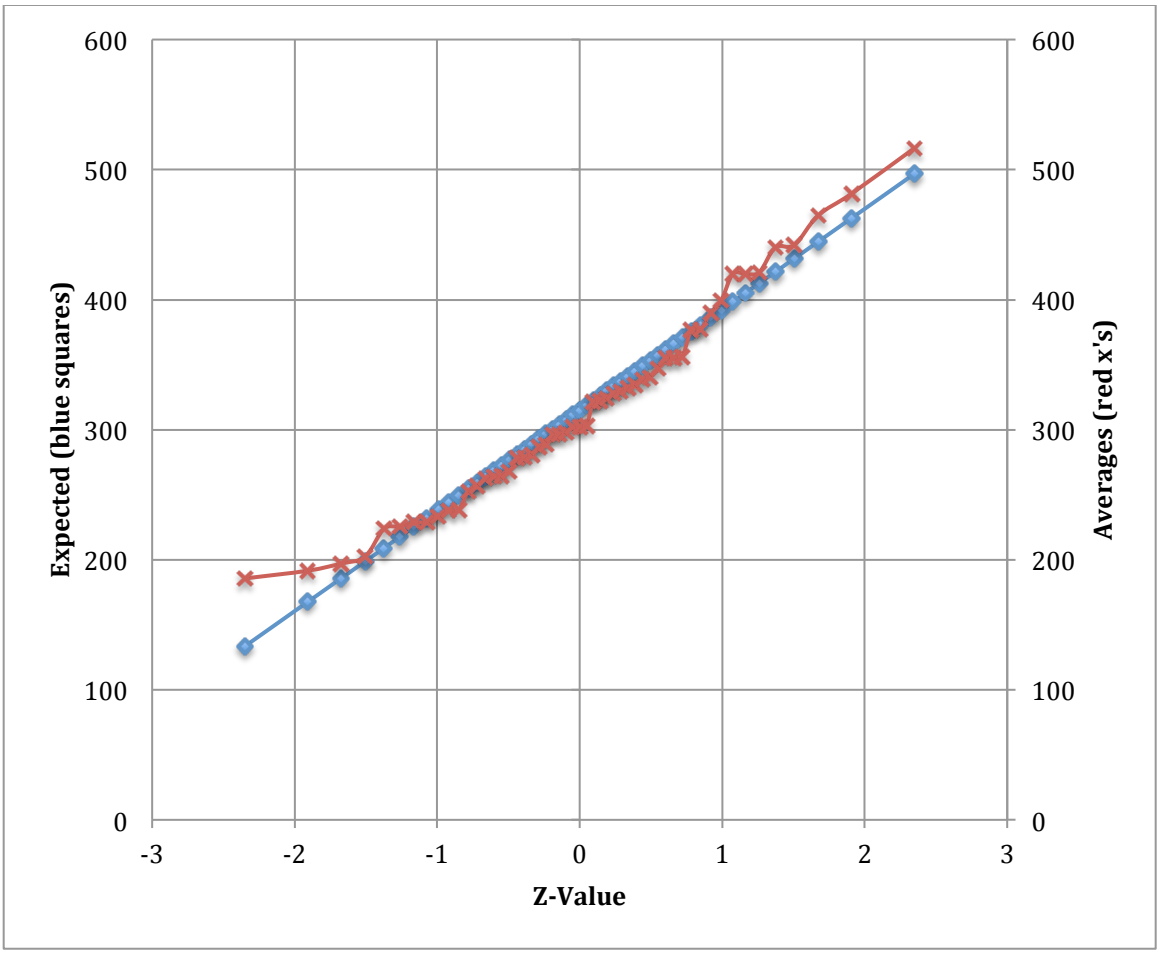
Normality test of the means calculated from the raw DNI measurements observed each day in February from 13:00 to 14:00 during the years 1953 and 2005.



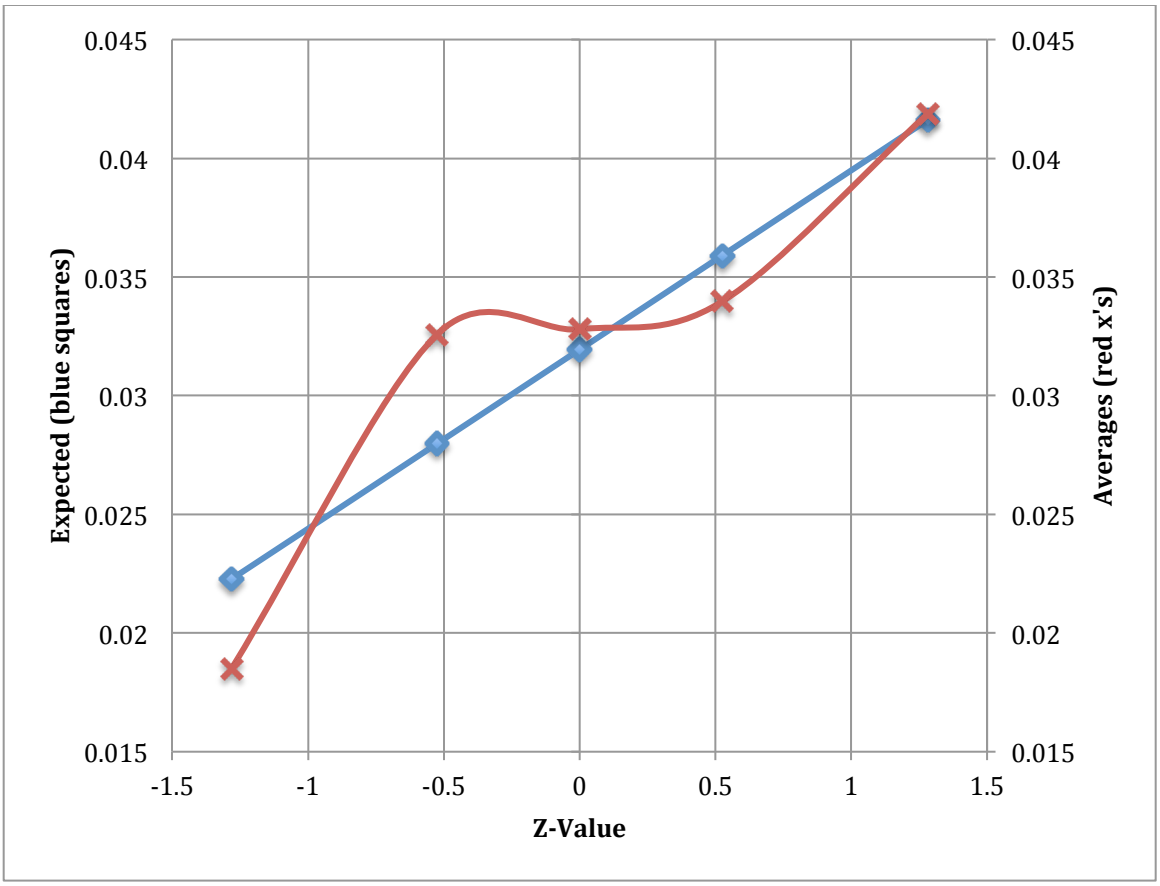
Normality test of the means calculated from the raw DNI measurements observed each day in May from 14:00 to 15:00 during the years 1953 and 2005.



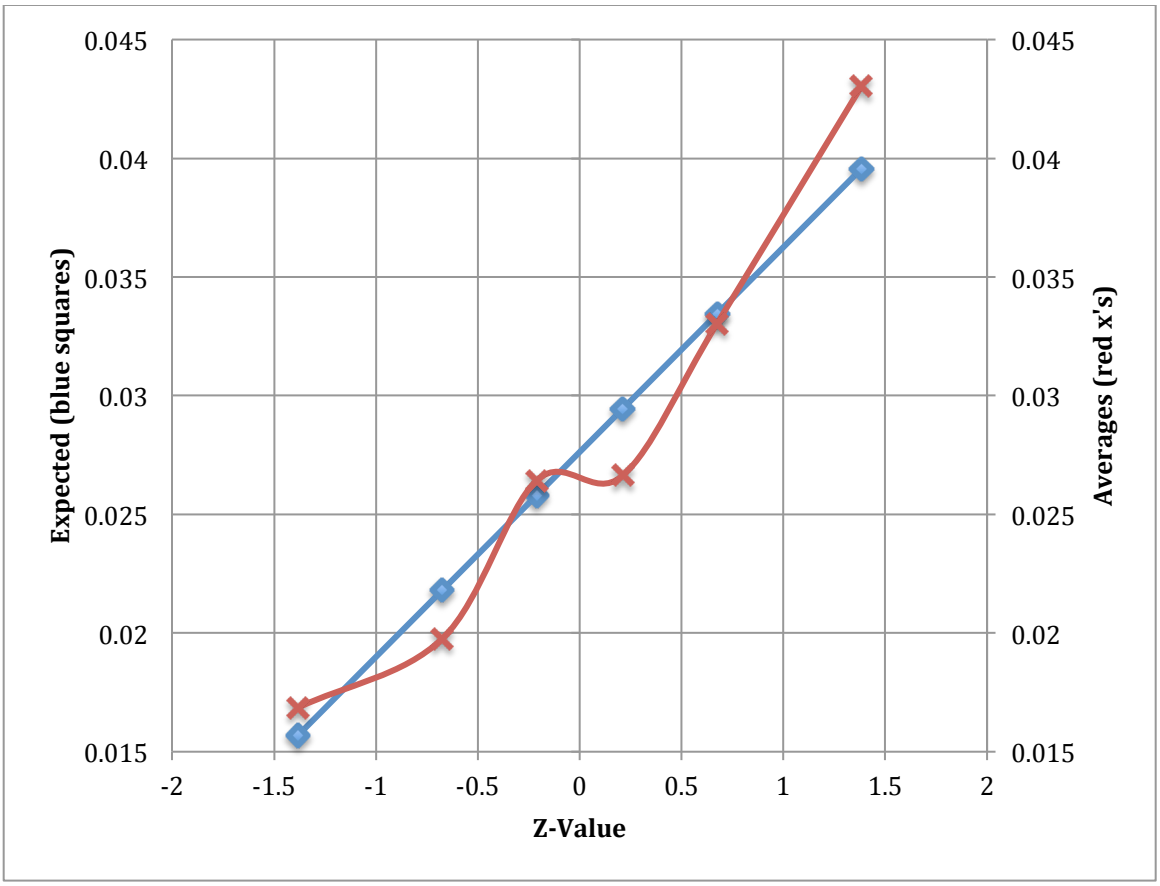
Normality test of the means calculated from the raw DNI measurements observed each day in August from 08:00 to 09:00 during the years 1953 and 2005.



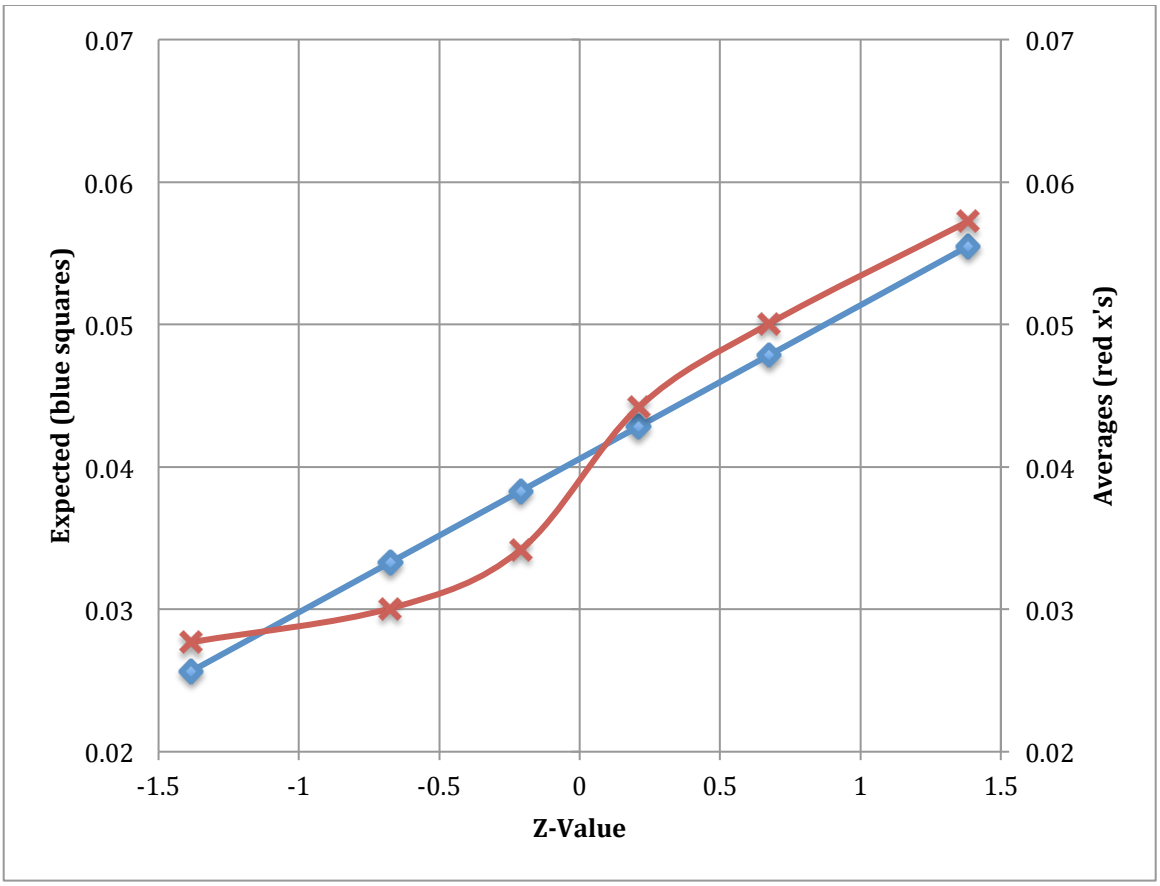
Normality test of the means calculated from the raw DNI measurements observed each day in December from 12:00 to 12:00 during the years 1953 and 2005.



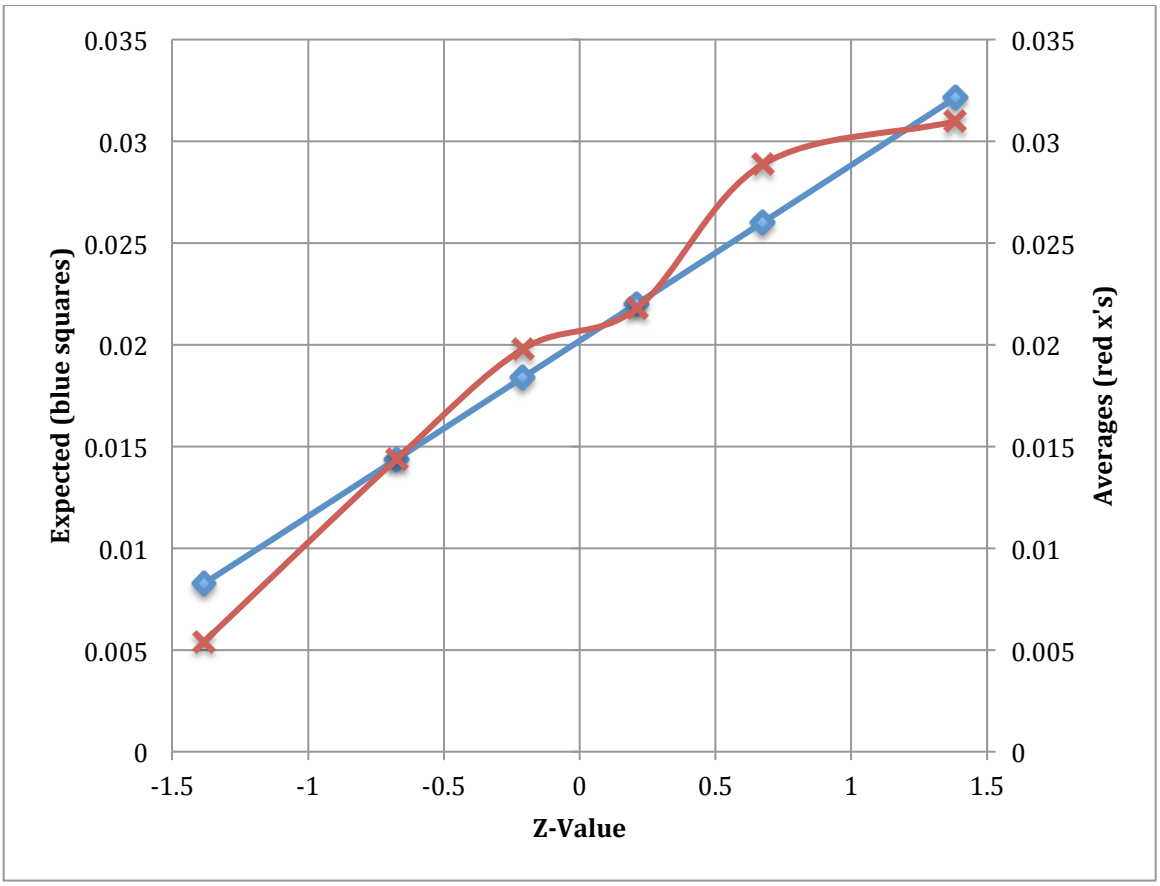
Normality test of the means calculated from the raw HOEP measurements observed each day in April from 11:00 to 12:00 during the years 2010 and 2014.



Normality test of the means calculated from the raw HOEP measurements observed each day in July from 08:00 to 09:00 during the years 2009 and 2014.

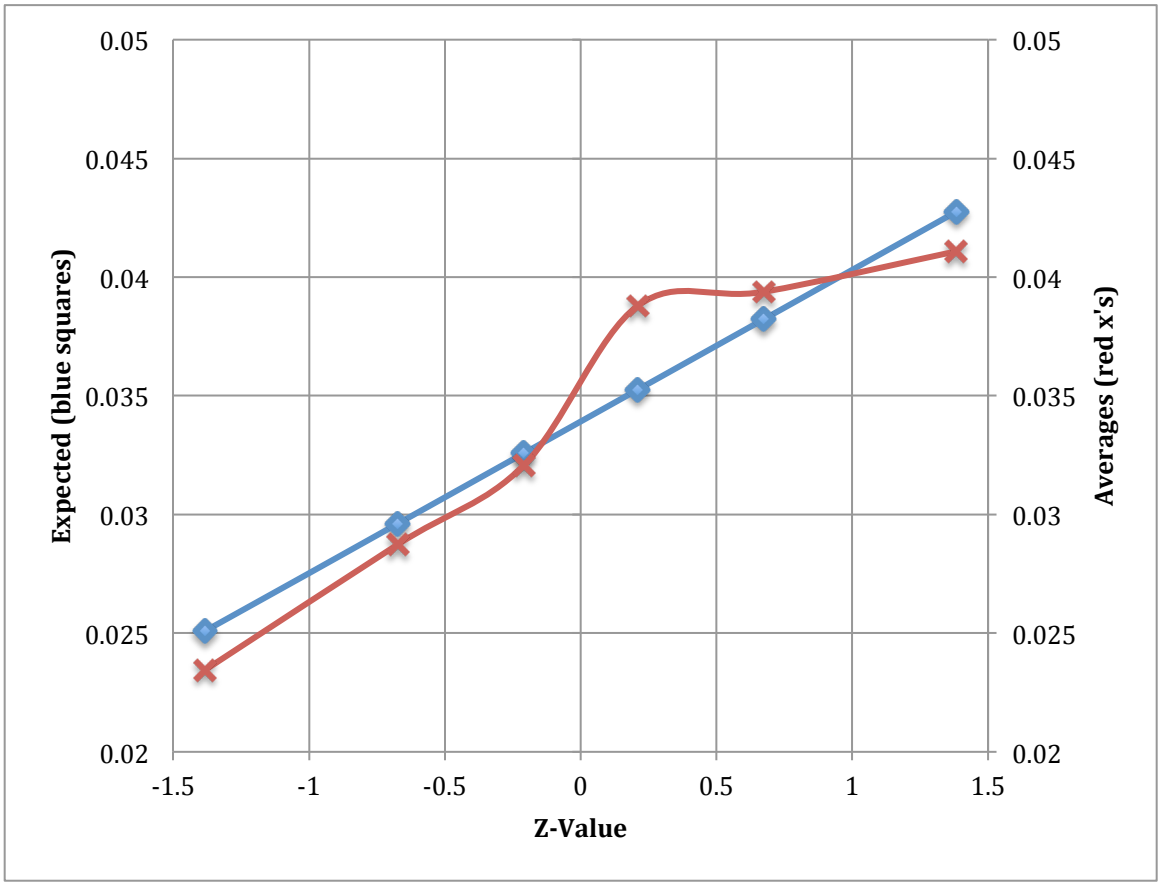


Normality test of the means calculated from the raw HOEP measurements observed each day in August from 15:00 to 16:00 during the years 2009 and 2014.

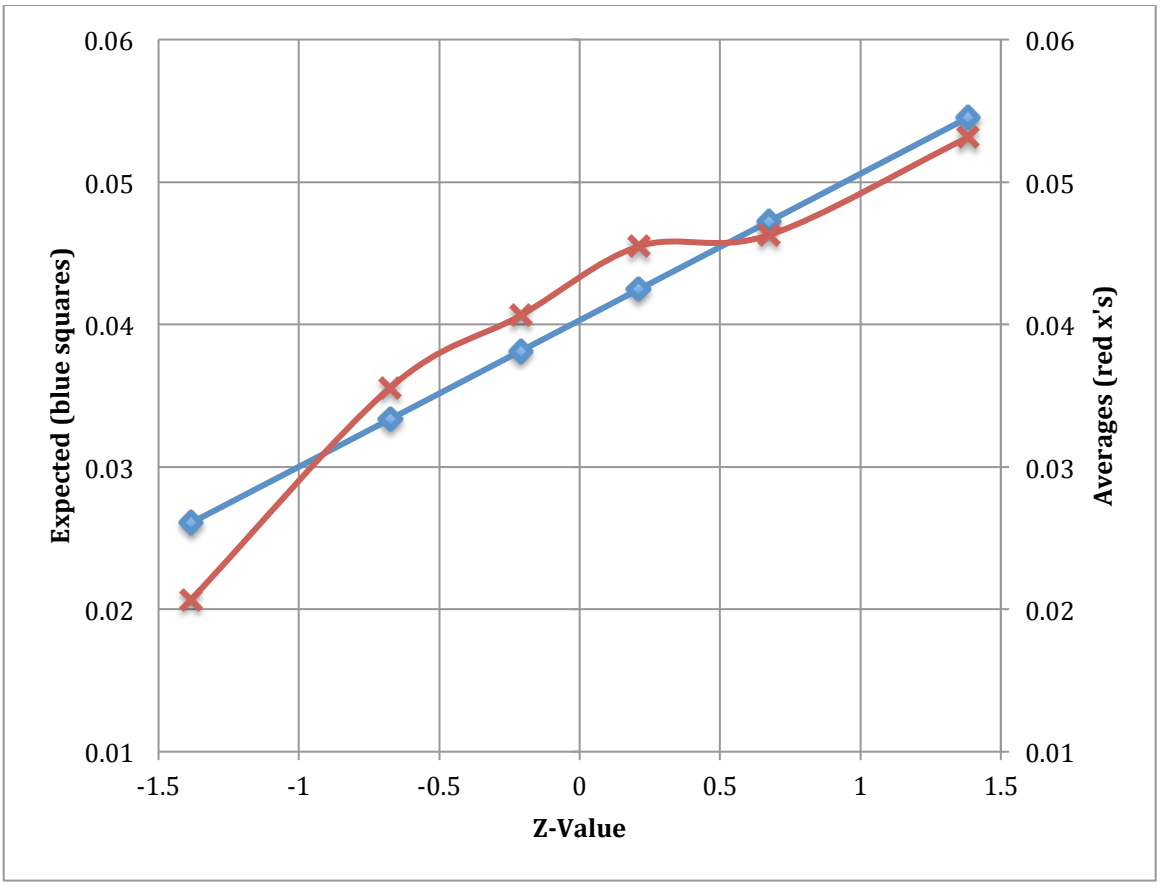


Normality test of the means calculated from the raw HOEP measurements observed each day in December from 01:00 to 02:00 during the years 2009 and 2014.

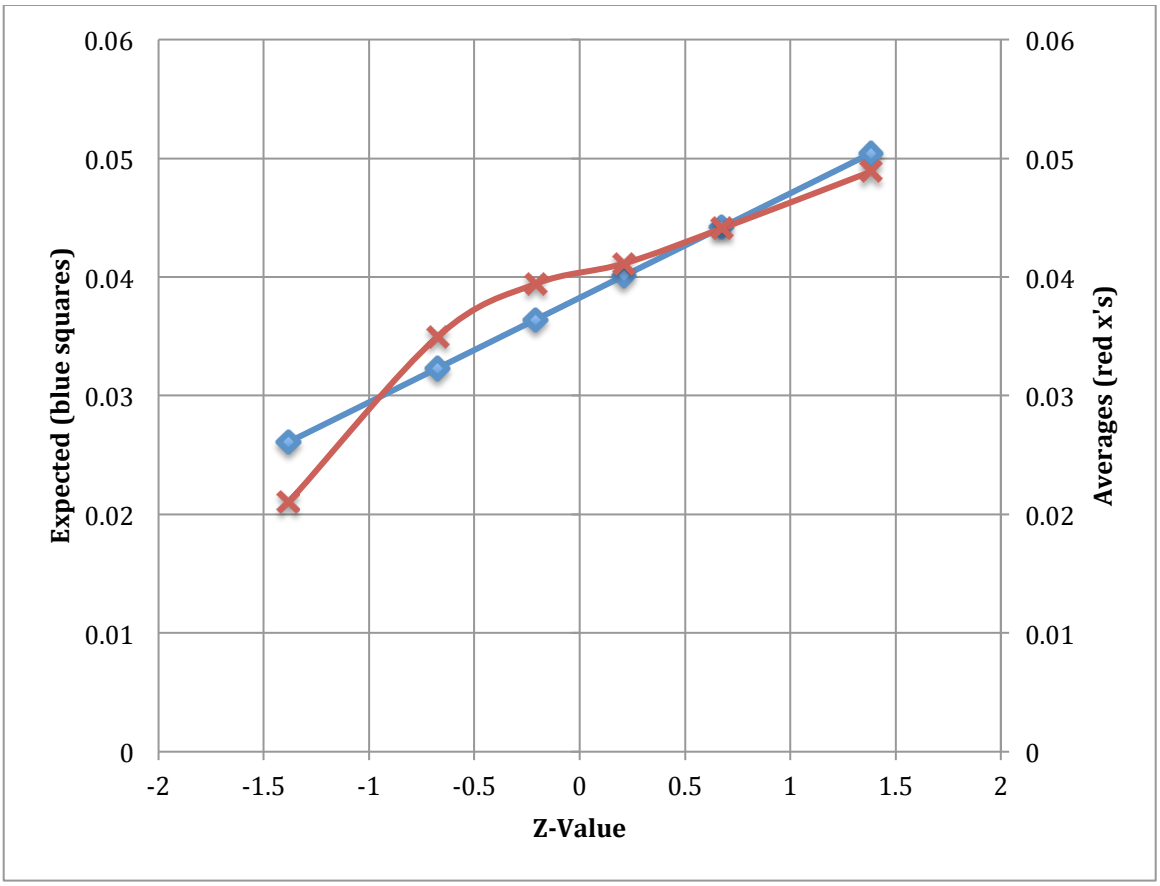
Appendix C: Generated Means Normality Tests



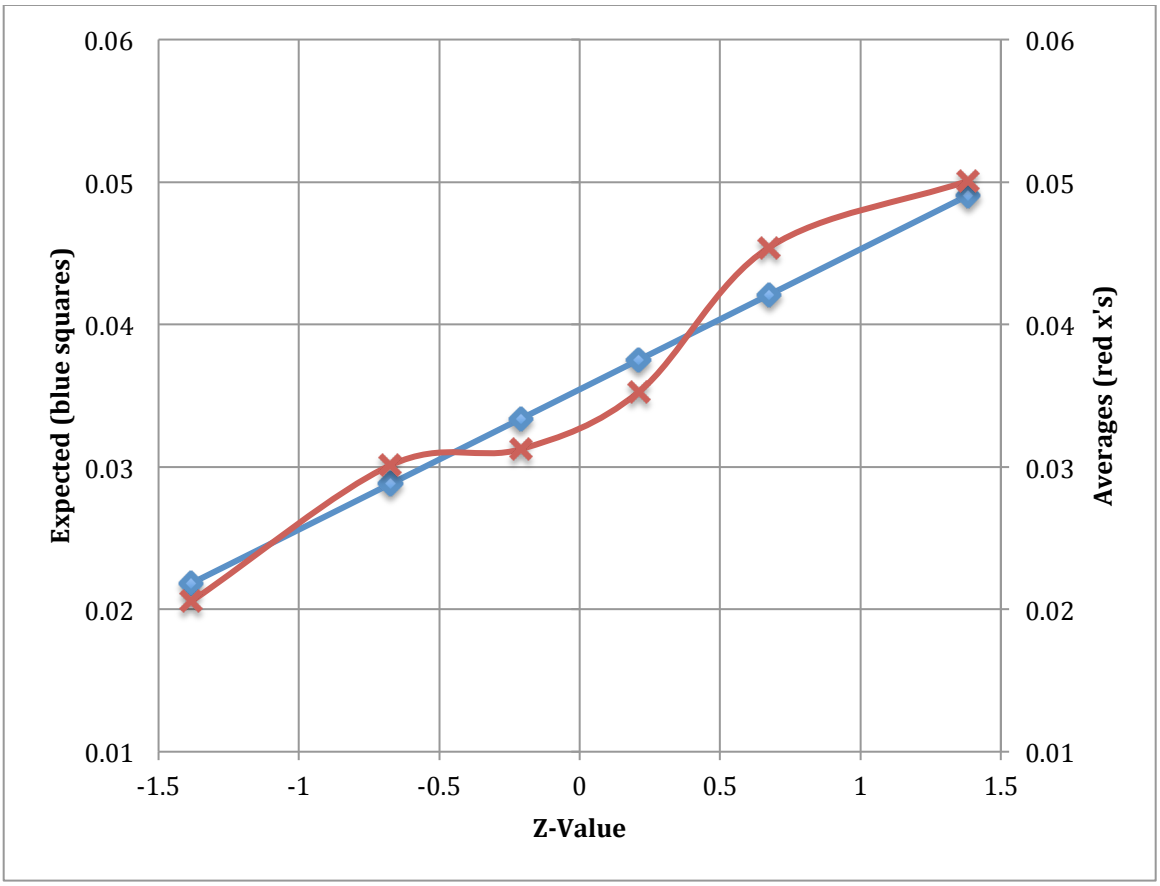
A normality test of a set of six numbers generated using the standard deviation and mean of the five HOEP calculated means for the hourly interval of 12:00-13:00 in the month of January between 2009 and 2014.



A normality test of a set of six numbers generated using the standard deviation and mean of the five HOEP calculated means for the hourly interval of 12:00-13:00 in the month of January between 2009 and 2014.



A normality test of a set of six numbers generated using the standard deviation and mean of the five HOEP calculated means for the hourly interval of 12:00-13:00 in the month of January between 2009 and 2014.



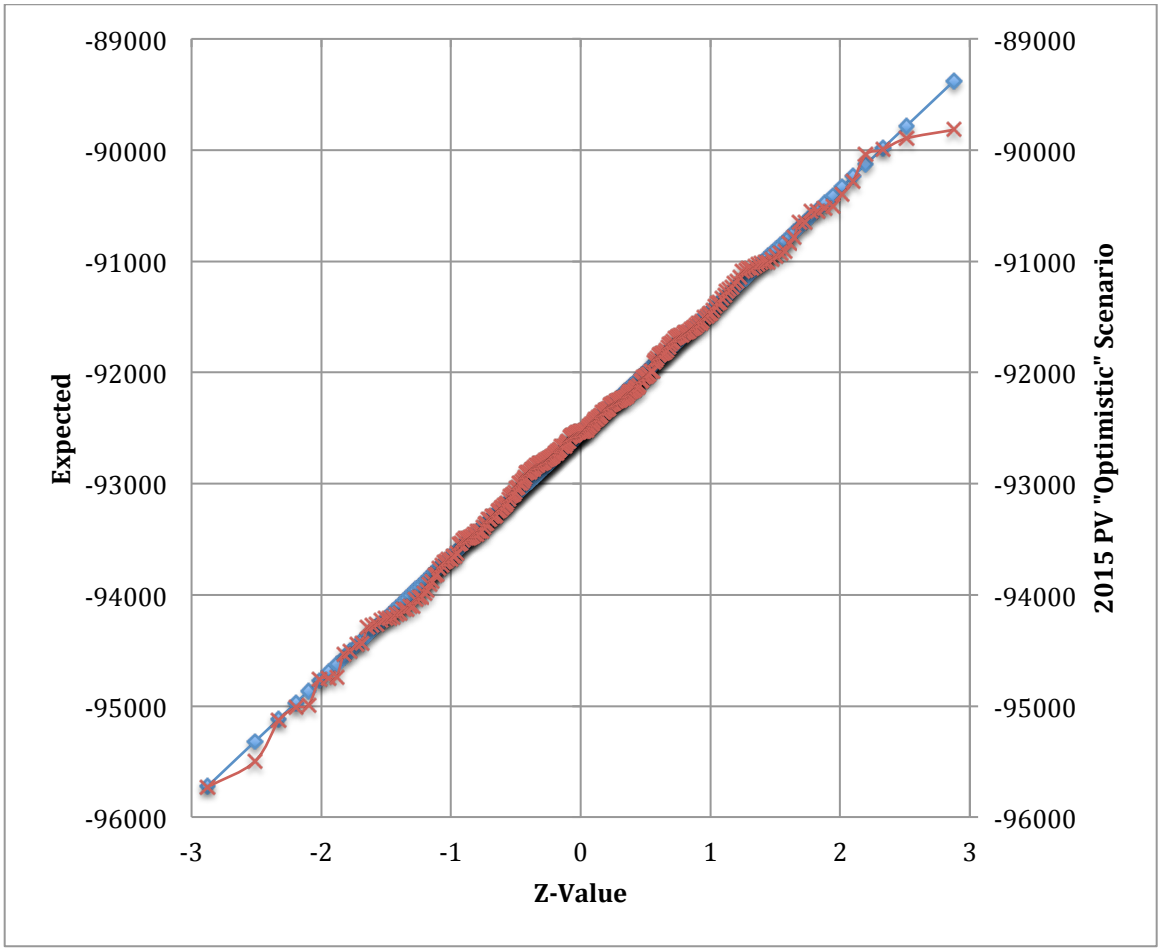
A normality test of a set of six numbers generated using the standard deviation and mean of the five HOEP calculated means for the hourly interval of 12:00-13:00 in the month of January between 2009 and 2014.

Appendix D: Additional PV and CPV Normality Tests of Monte Carlo Simulated Discounted NPV Data under the Time-of-Use Tariff Scenario

D.1 Time-of-Use Tariff Scenario

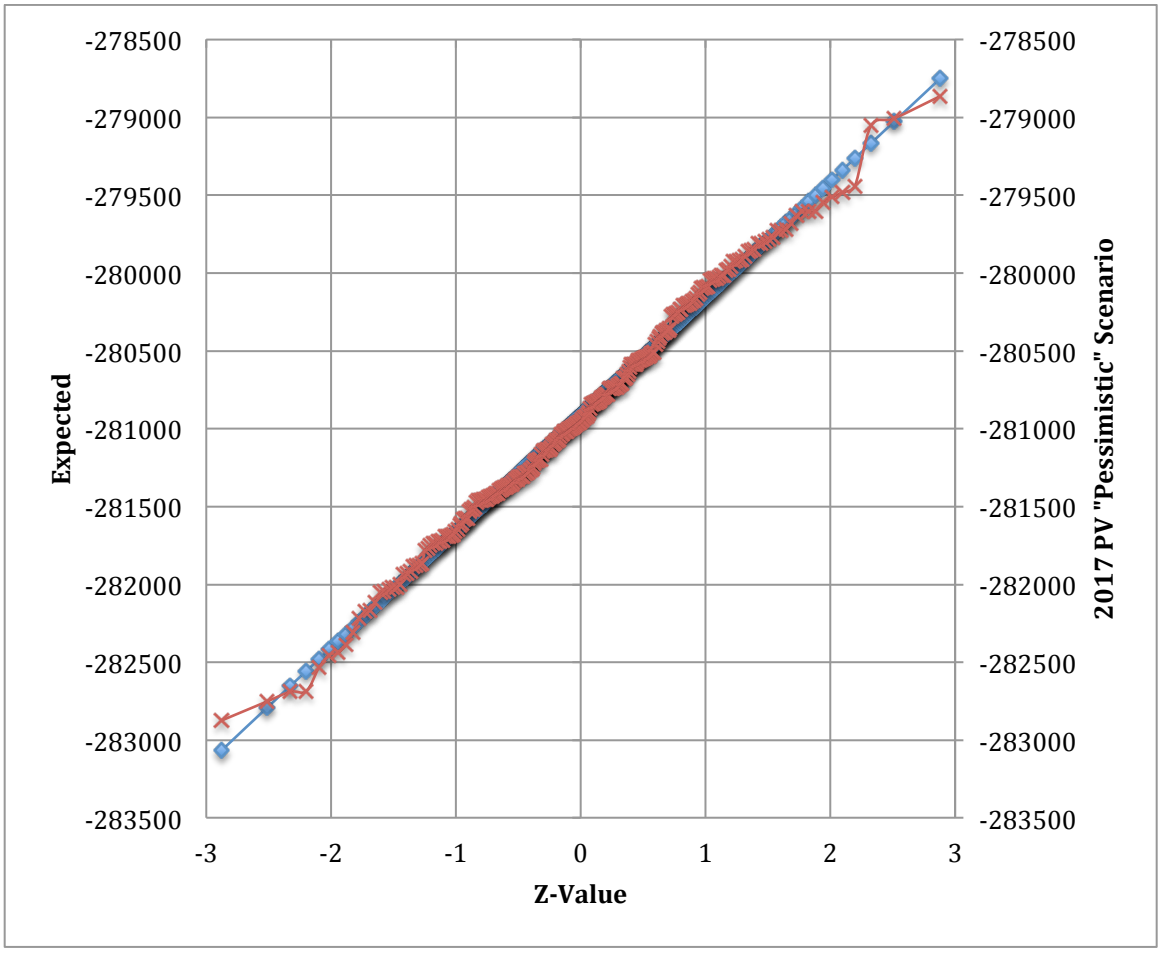
D.1.1 PV Technology

D.1.1.1 2015 "Optimistic" Scenario



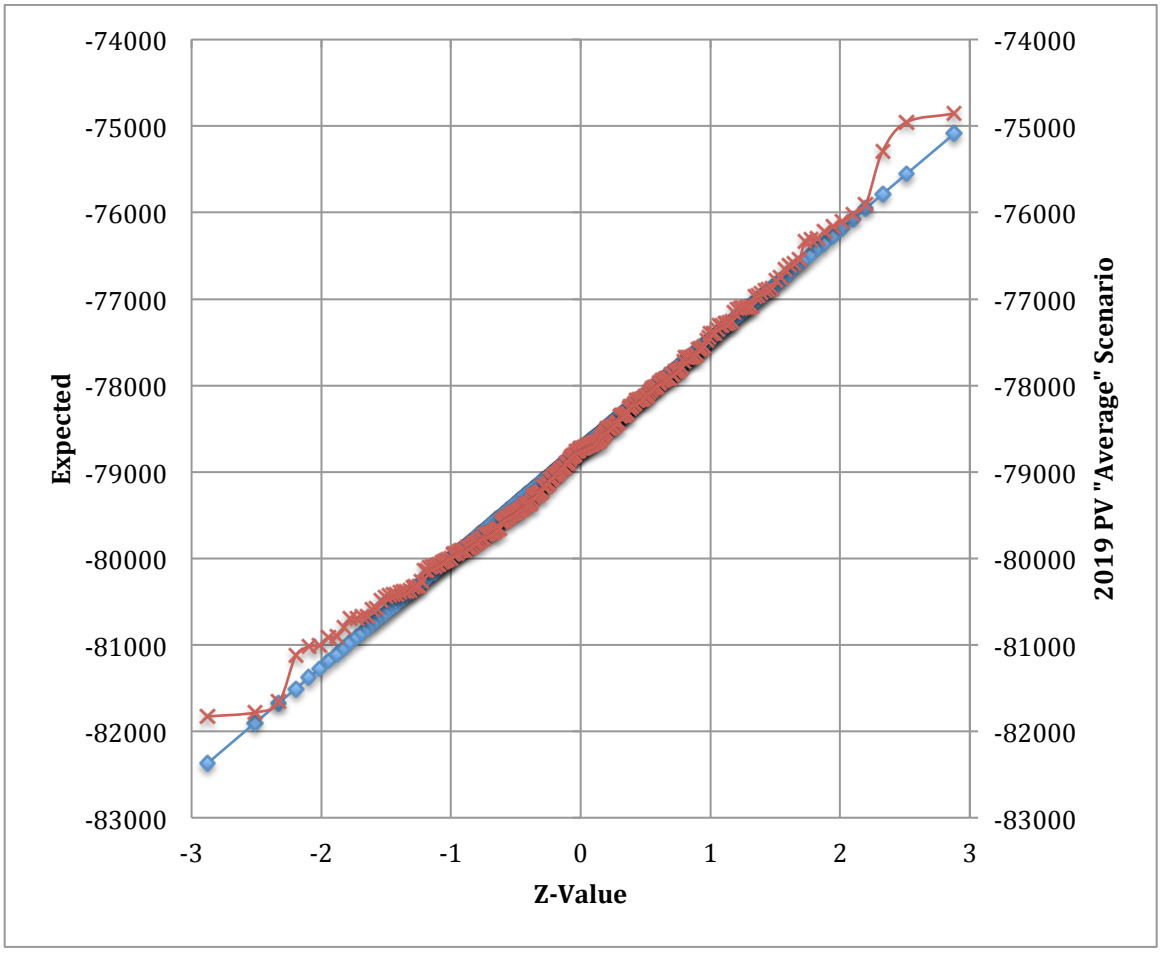
Normality test of 250 discounted net present values generated by a Monte Carlo simulation for the time-of-use tariff scenario and PV technology. This normality test is for discount net present values that comprise the 2015 PV "optimistic" scenario.

D.1.1.2 2017 "Pessimistic" Scenario



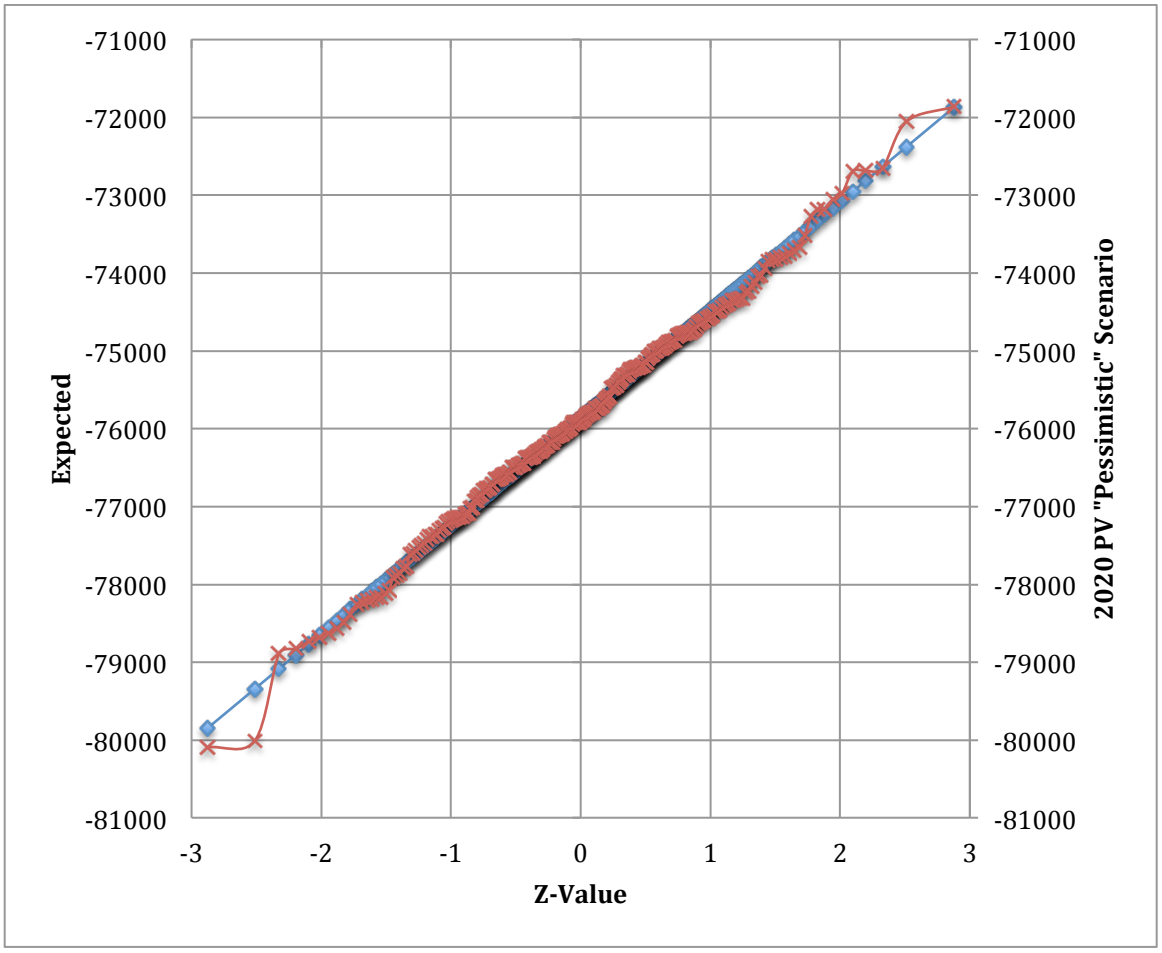
Normality test of 250 discounted net present values generated by a Monte Carlo simulation for the time-of-use tariff scenario and PV technology. This normality test is for discount net present values that comprise the 2017 PV "pessimistic" scenario.

D.1.1.3 2019 "Average" Scenario



Normality test of 250 discounted net present values generated by a Monte Carlo simulation for the time-of-use tariff scenario and PV technology. This normality test is for discount net present values that comprise the 2019 PV "average" scenario.

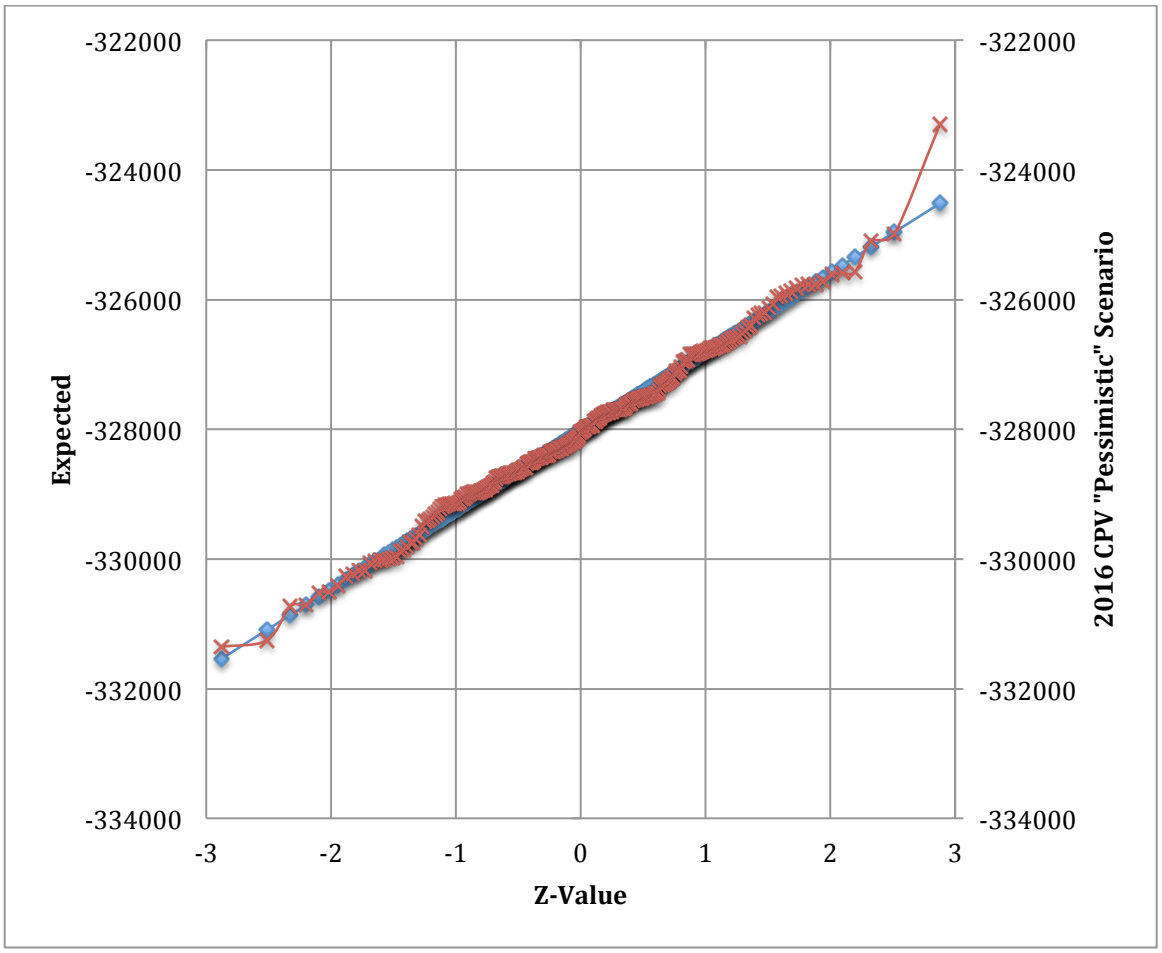
D.1.1.4 2020 "Pessimistic" Scenario



Normality test of 250 discounted net present values generated by a Monte Carlo simulation for the time-of-use tariff scenario and PV technology. This normality test is for discount net present values that comprise the 2020 PV "pessimistic" scenario.

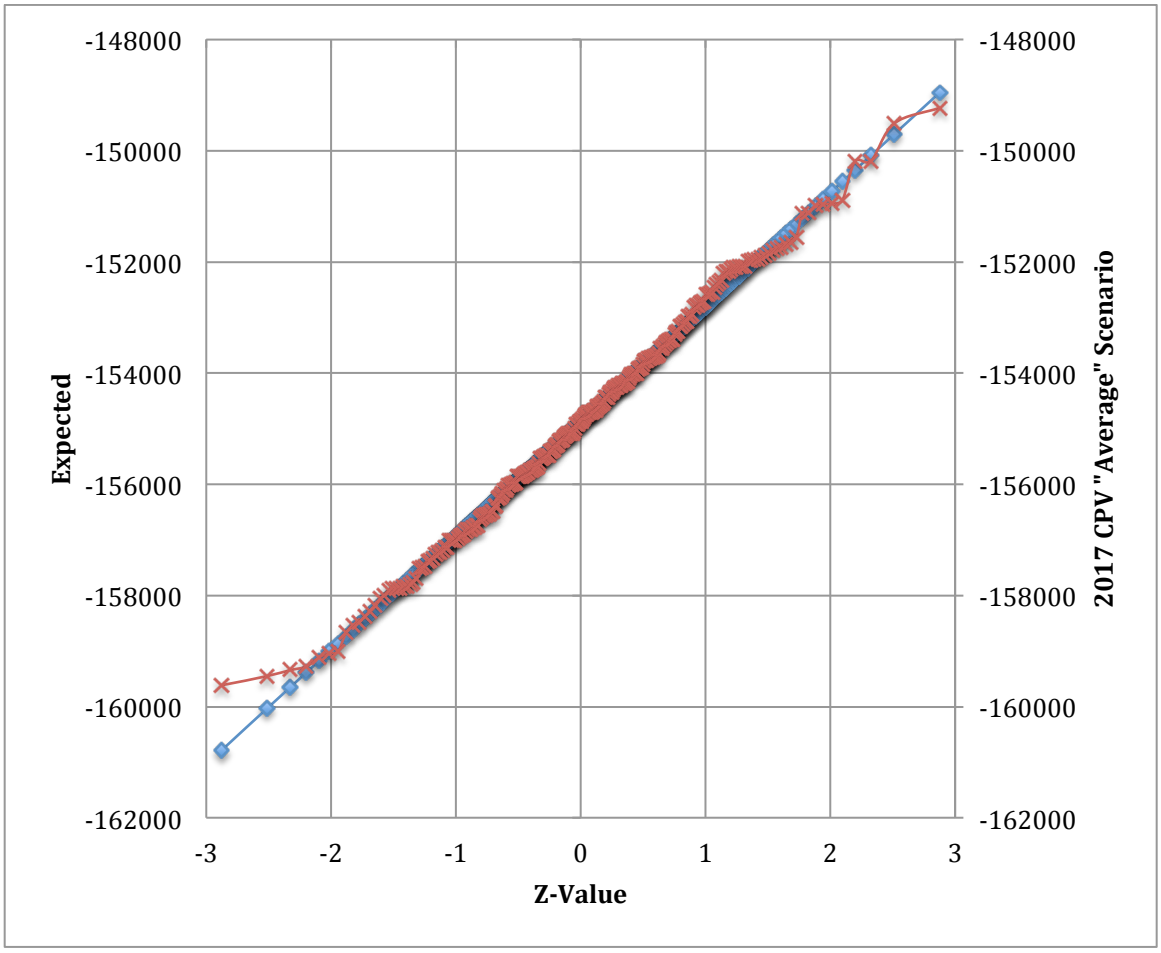
D.1.2 CPV Technology

D.1.2.1 2016 "Pessimistic" Scenario



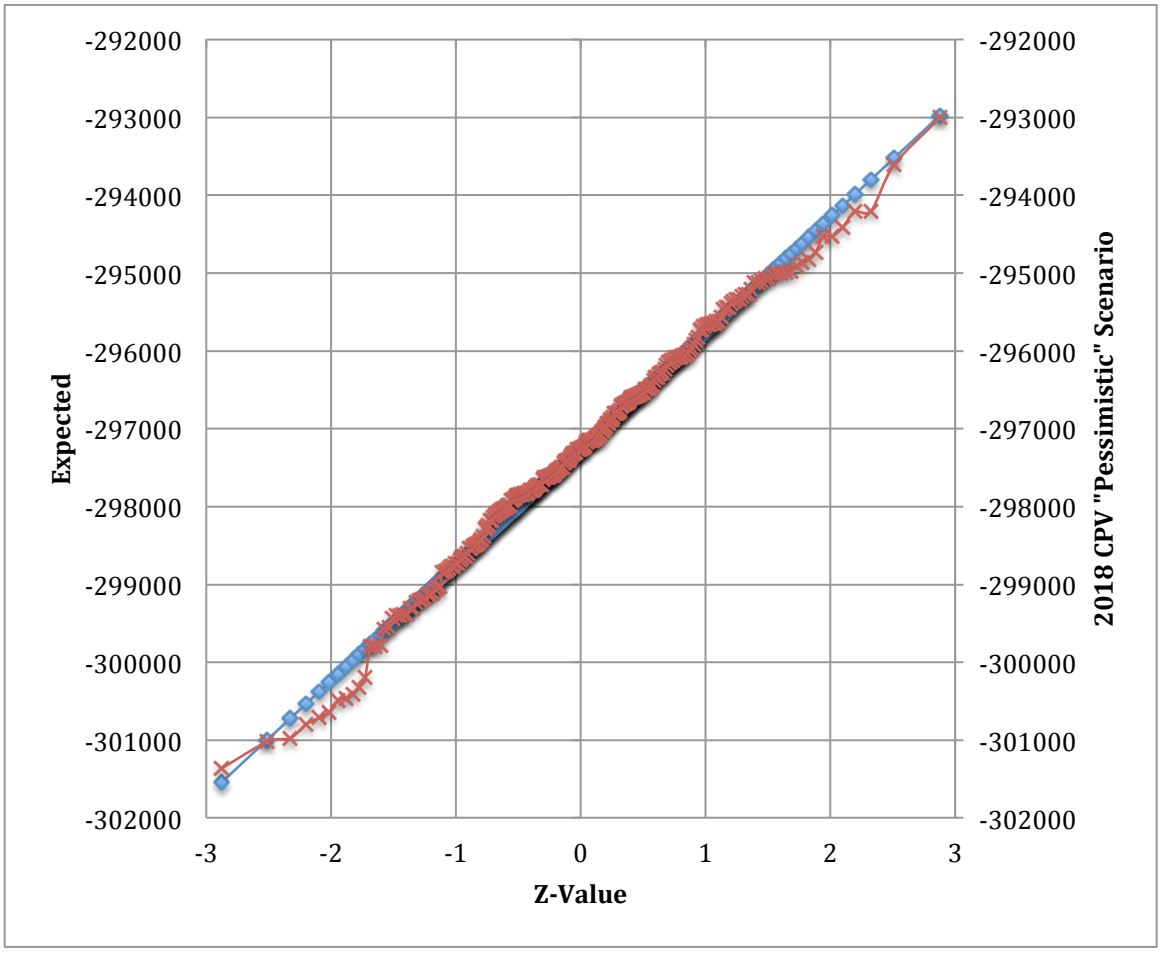
Normality test of 250 discounted net present values generated by a Monte Carlo simulation for the time-of-use tariff scenario and CPV technology. This normality test is for discount net present values that comprise the 2016 CPV "pessimistic" scenario.

D.1.2.2 2017 "Average" Scenario



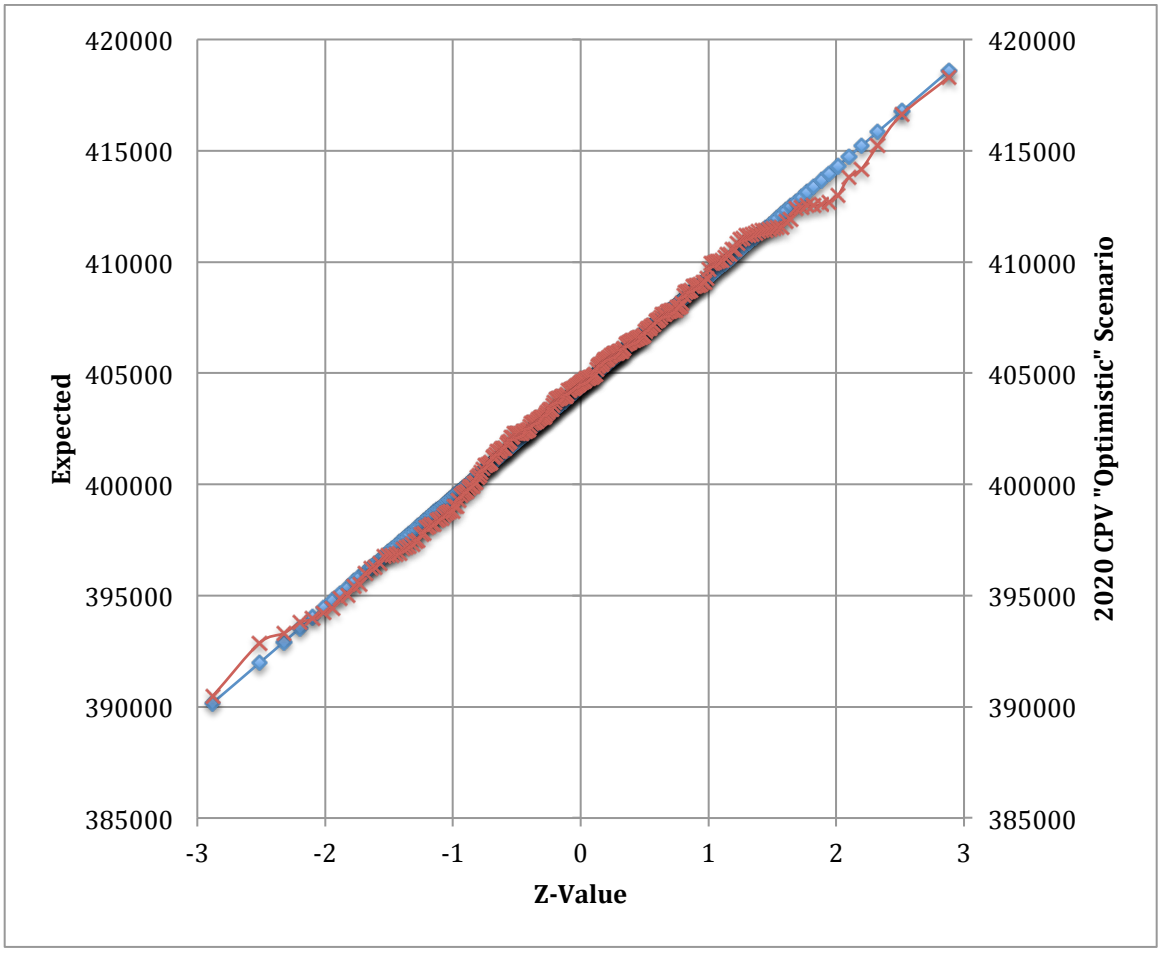
Normality test of 250 discounted net present values generated by a Monte Carlo simulation for the time-of-use tariff scenario and CPV technology. This normality test is for discount net present values that comprise the 2017 CPV "average" scenario.

D.1.2.3 2018 "Pessimistic" Scenario



Normality test of 250 discounted net present values generated by a Monte Carlo simulation for the time-of-use tariff scenario and CPV technology. This normality test is for discount net present values that comprise the 2018 CPV "pessimistic" scenario.

D.1.2.4 2020 "Optimistic" Scenario

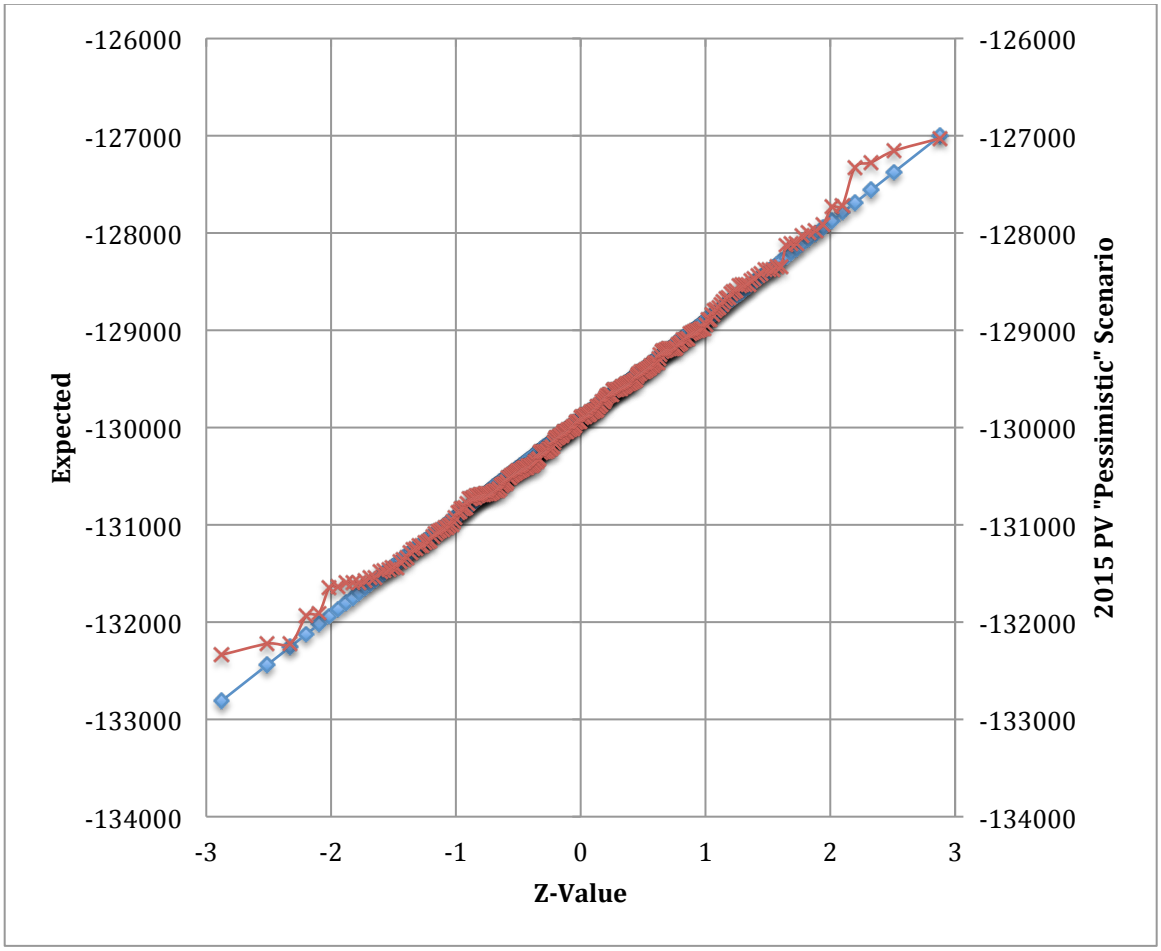


Normality test of 250 discounted net present values generated by a Monte Carlo simulation for the time-of-use tariff scenario and CPV technology. This normality test is for discount net present values that comprise the 2020 CPV "optimistic" scenario.

D.2 Feed-in Tariff Scenario

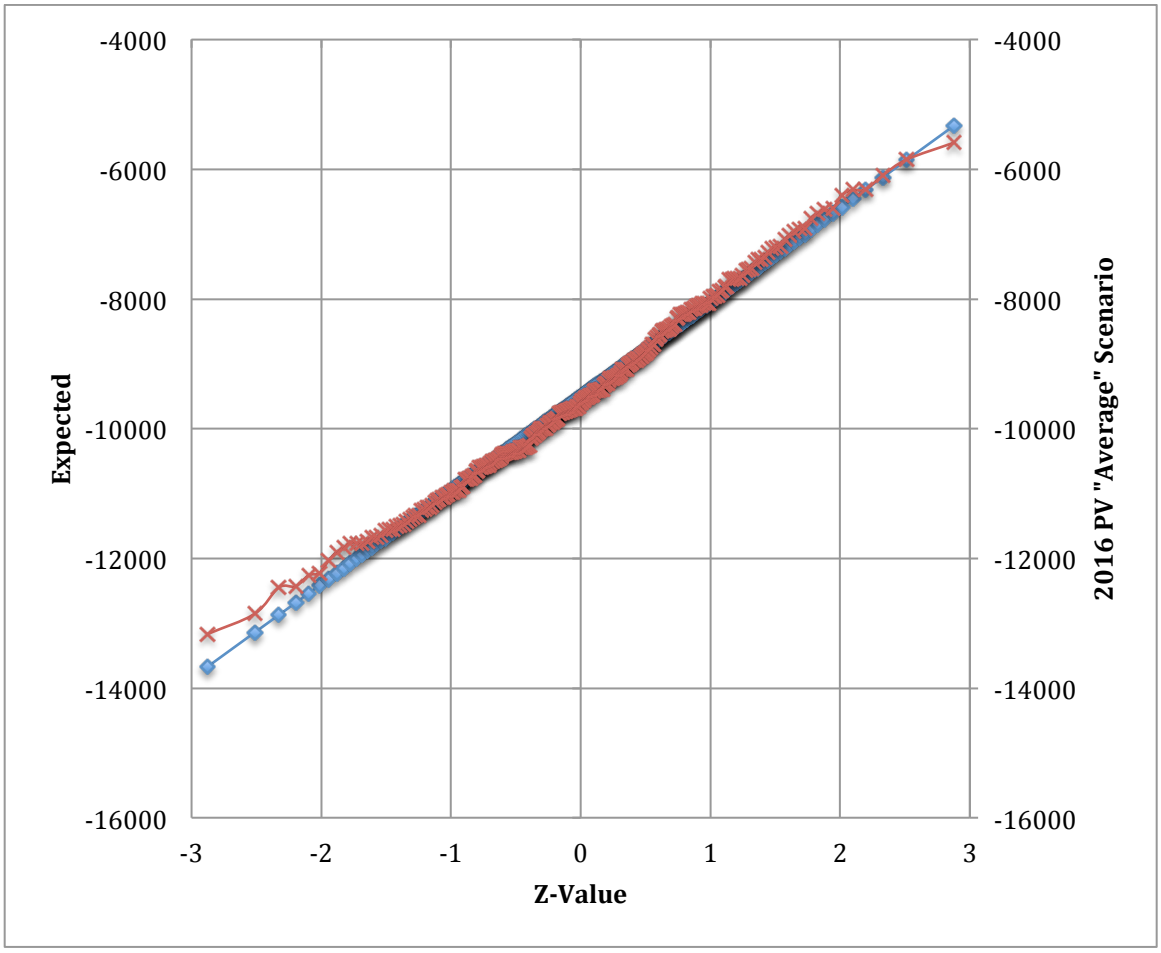
D.2.1 PV Technology

D.2.1.1 2015 "Pessimistic" Scenario



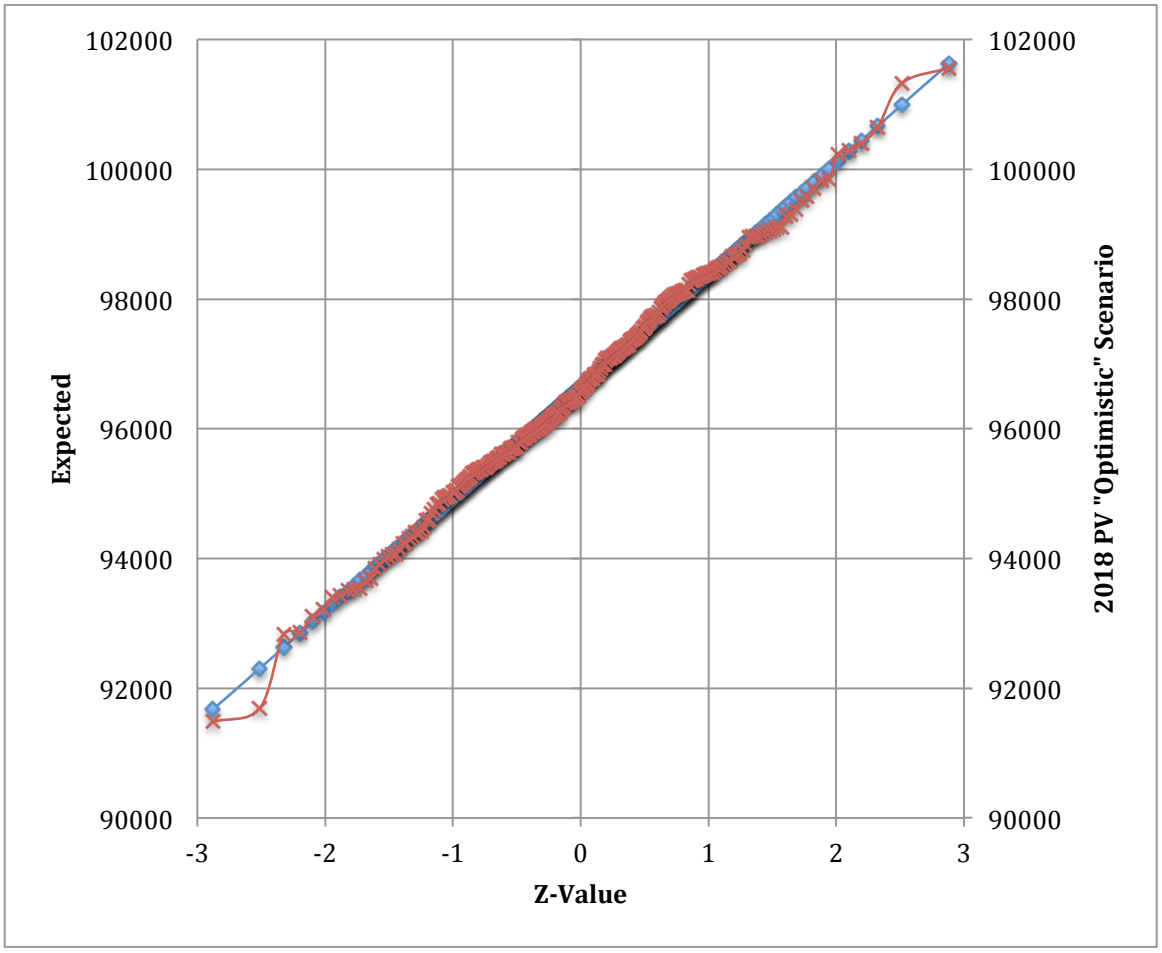
Normality test of 250 discounted net present values generated by a Monte Carlo simulation for the feed-in tariff scenario and PV technology. This normality test is for discount net present values that comprise the 2015 PV "pessimistic" scenario.

D.2.1.2 2016 "Average" Scenario



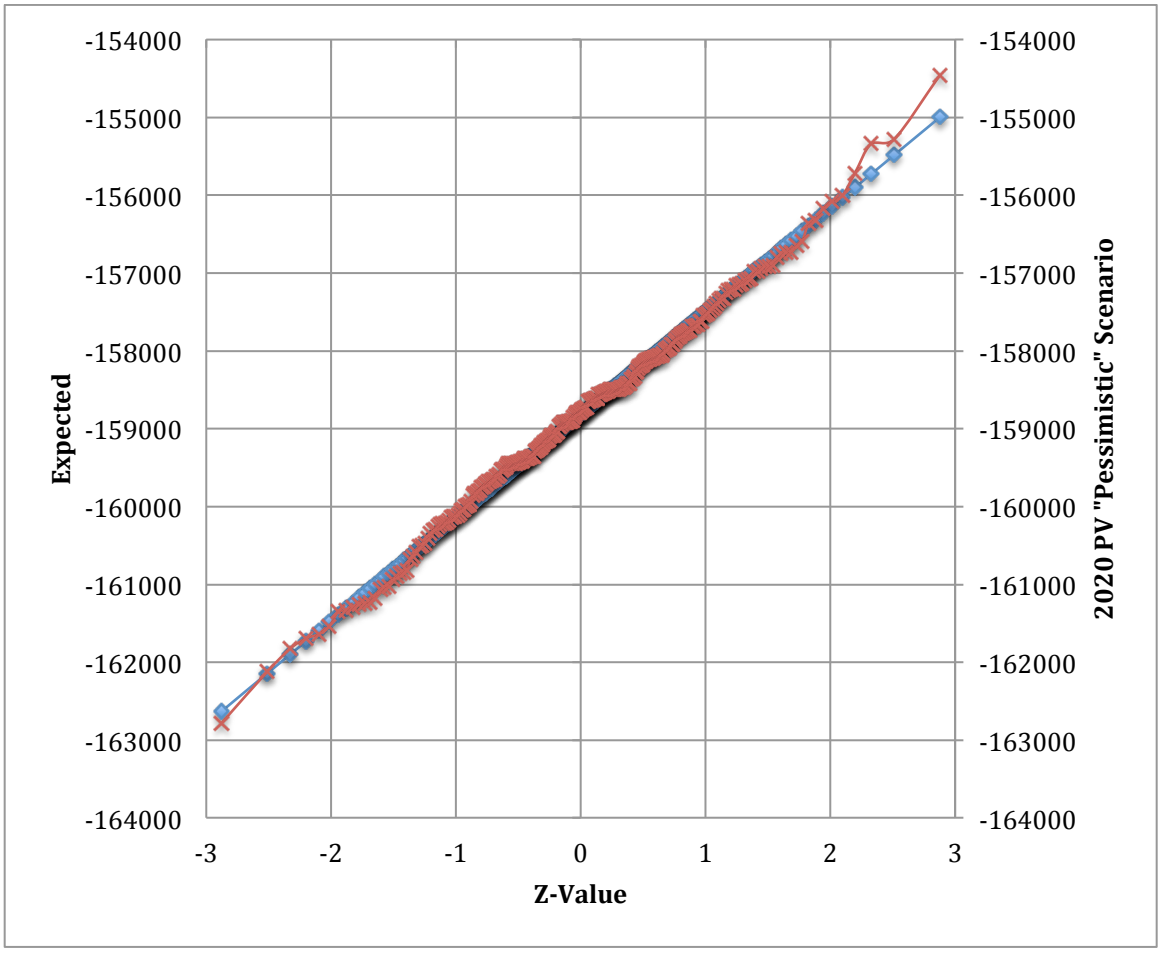
Normality test of 250 discounted net present values generated by a Monte Carlo simulation for the feed-in tariff scenario and PV technology. This normality test is for discount net present values that comprise the 2016 PV "average" scenario.

D.2.1.3 2018 "Optimistic" Scenario



Normality test of 250 discounted net present values generated by a Monte Carlo simulation for the feed-in tariff scenario and PV technology. This normality test is for discount net present values that comprise the 2018 PV "optimistic" scenario.

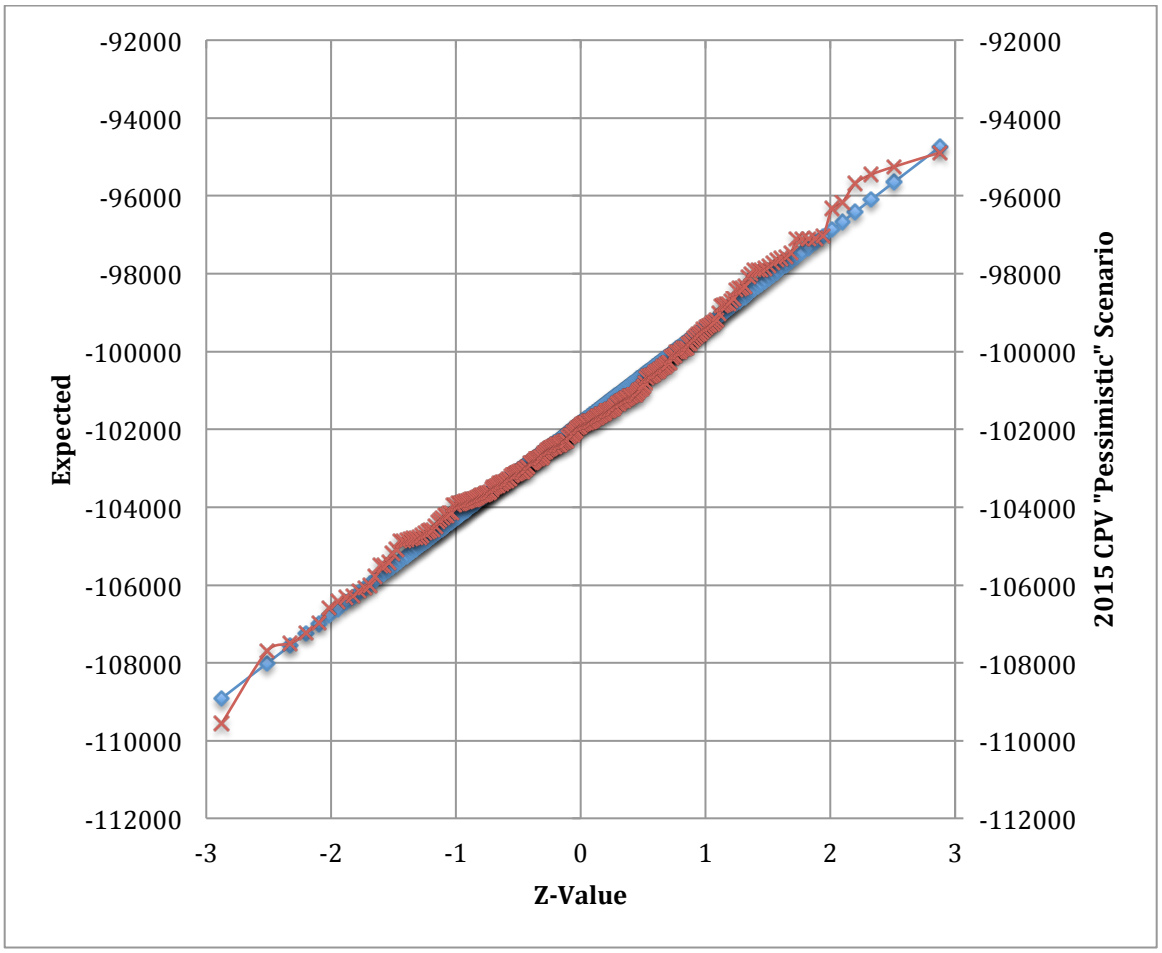
D.2.1.4 2020 "Pessimistic" Scenario



Normality test of 250 discounted net present values generated by a Monte Carlo simulation for the feed-in tariff scenario and PV technology. This normality test is for discount net present values that comprise the 2020 PV "pessimistic" scenario.

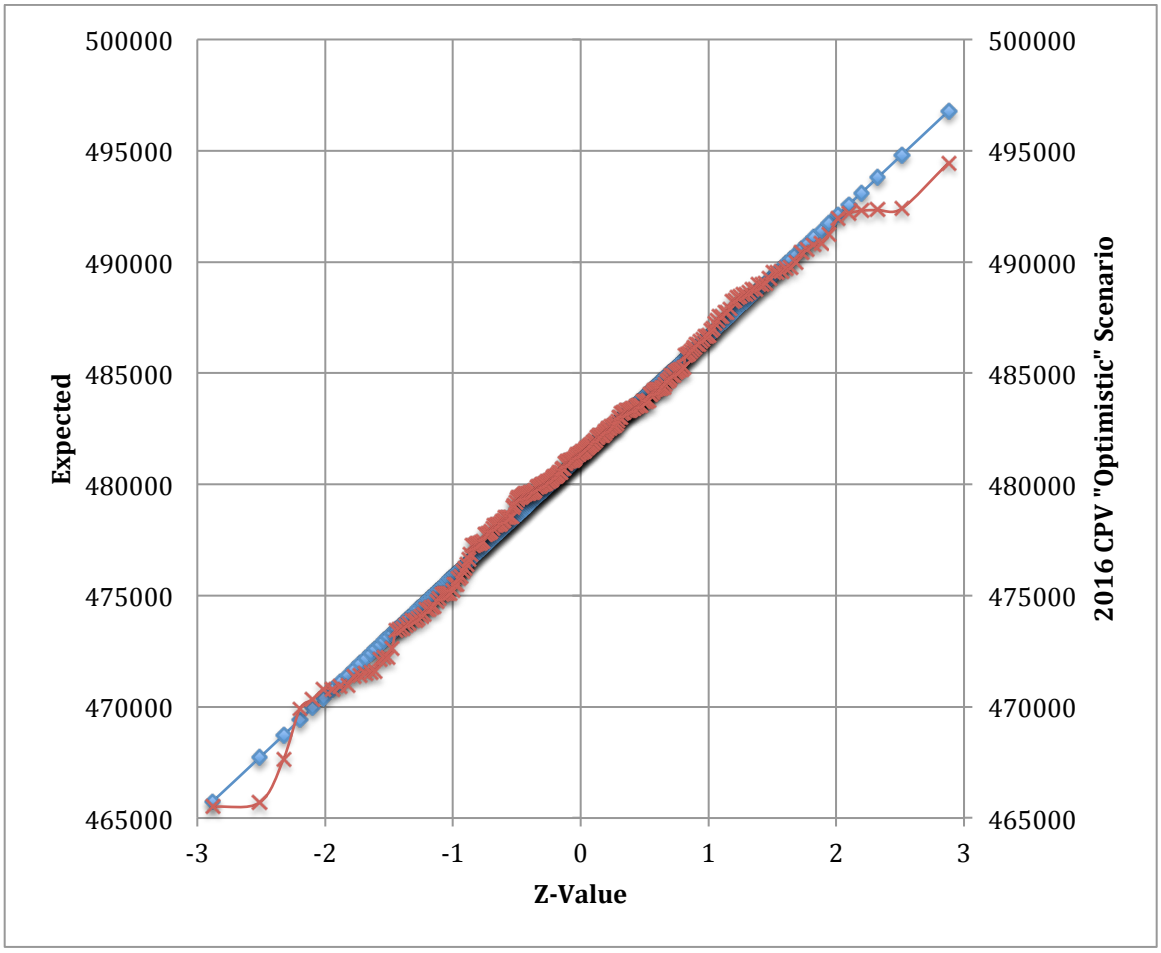
D.2.2 CPV Technology

D.2.2.1 2015 "Pessimistic" Scenario



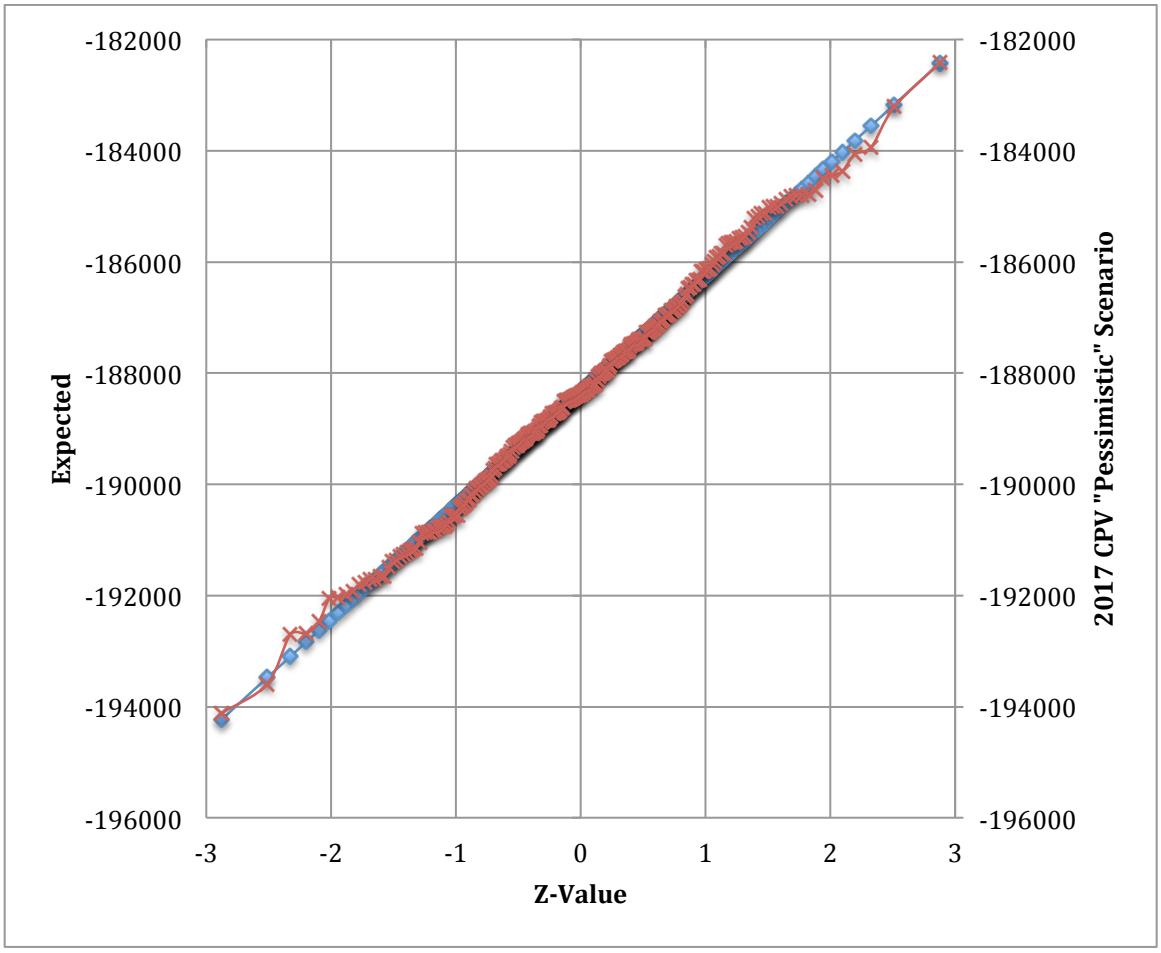
Normality test of 250 discounted net present values generated by a Monte Carlo simulation for the feed-in tariff scenario and CPV technology. This normality test is for discount net present values that comprise the 2015 CPV "pessimistic" scenario.

D.2.2.2 2016 "Optimistic" Scenario



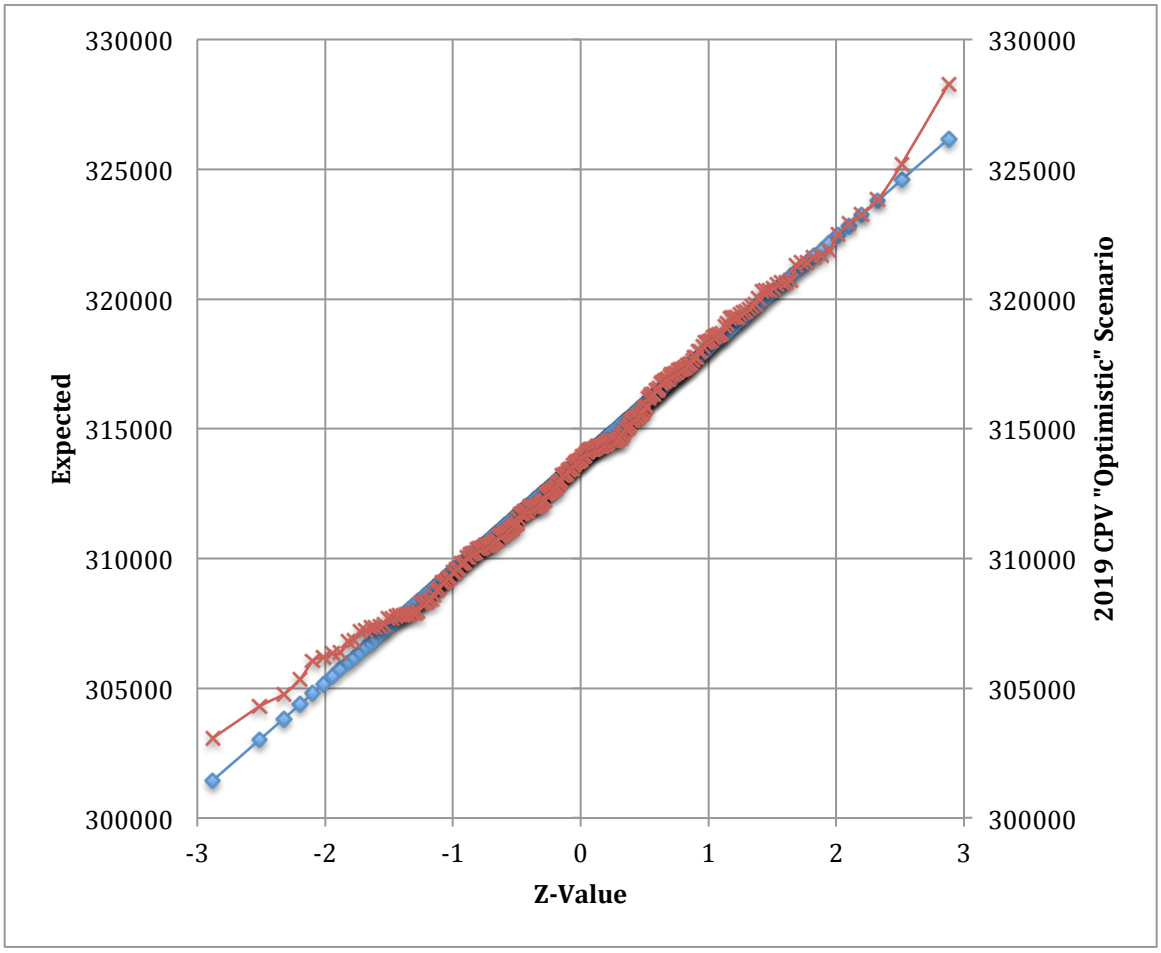
Normality test of 250 discounted net present values generated by a Monte Carlo simulation for the feed-in tariff scenario and CPV technology. This normality test is for discount net present values that comprise the 2016 CPV "optimistic" scenario.

D.2.2.3 2017 "Pessimistic" Scenario



Normality test of 250 discounted net present values generated by a Monte Carlo simulation for the feed-in tariff scenario and CPV technology. This normality test is for discount net present values that comprise the 2017 CPV "pessimistic" scenario.

D.2.2.4 2019 "Optimistic" Scenario

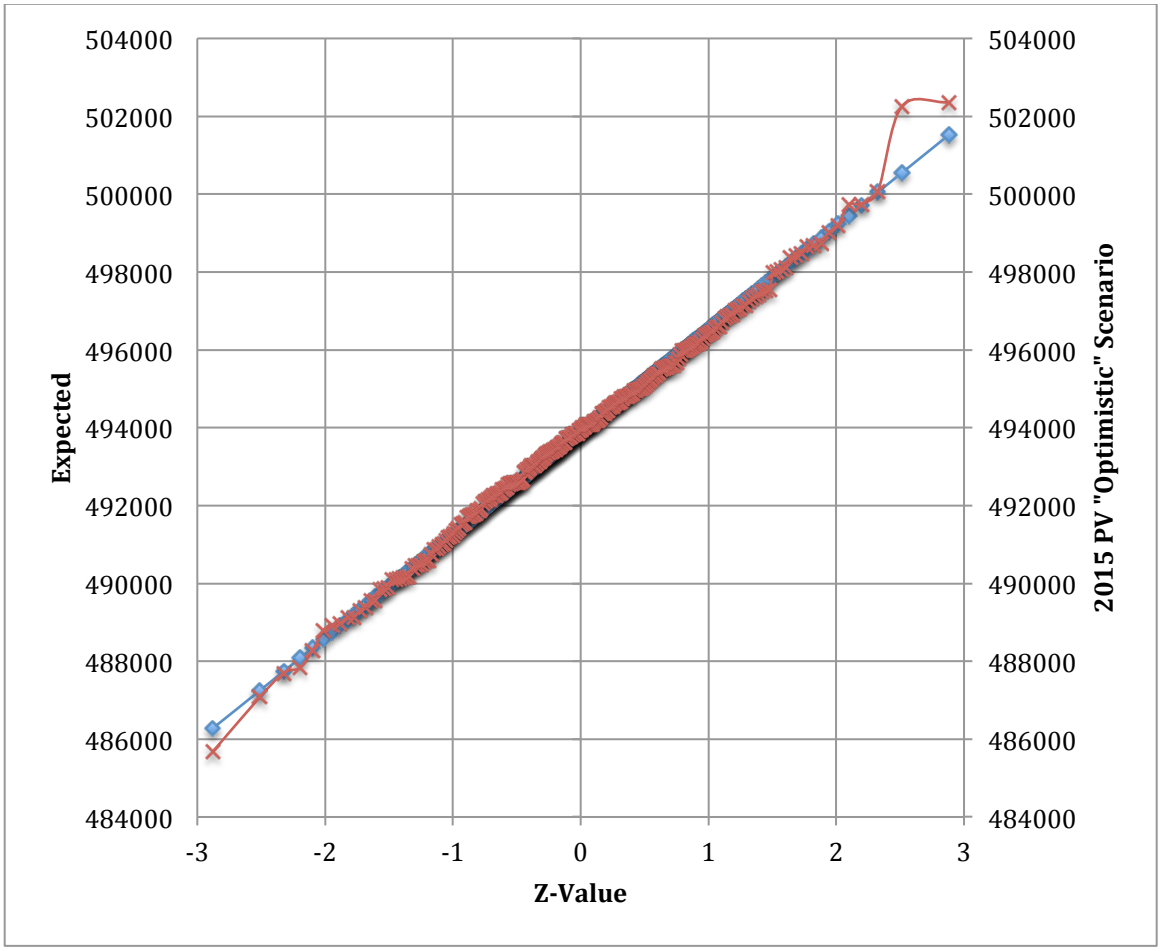


Normality test of 250 discounted net present values generated by a Monte Carlo simulation for the feed-in tariff scenario and CPV technology. This normality test is for discount net present values that comprise the 2019 CPV "optimistic" scenario.

D.3 Power Purchase Agreement Tariff Scenario

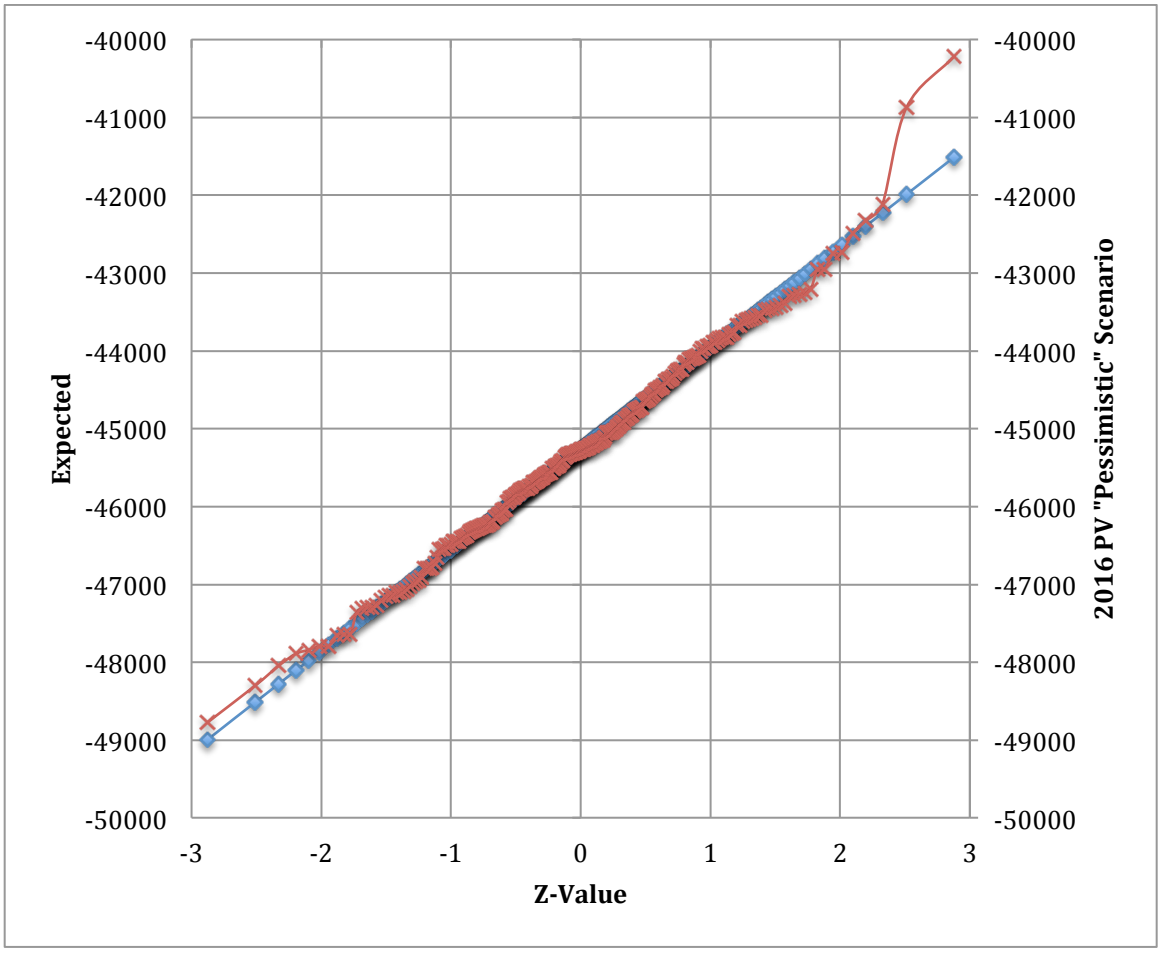
D.3.1 PV Technology

D.3.1.1 2015 "Optimistic" Scenario



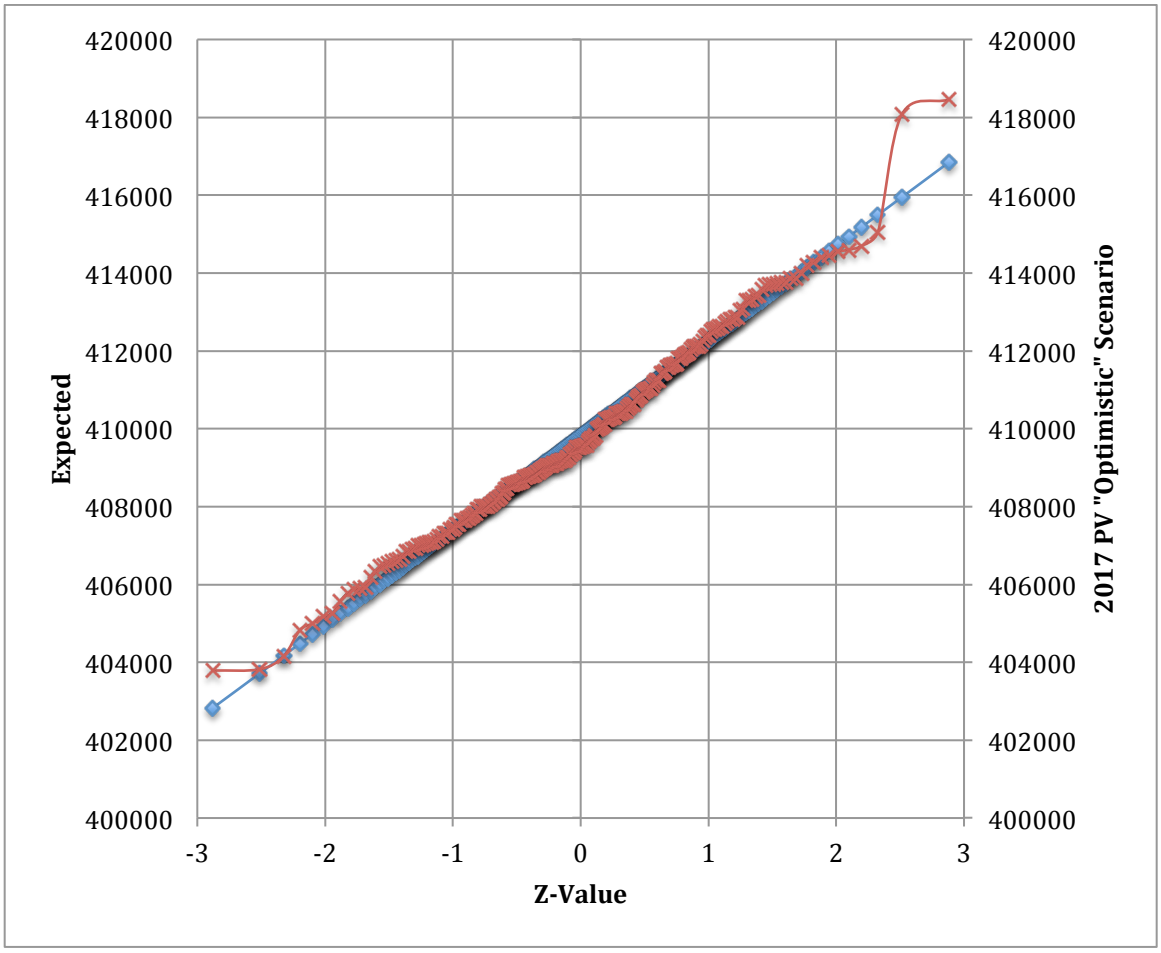
Normality test of 250 discounted net present values generated by a Monte Carlo simulation for the power purchase agreement tariff scenario and PV technology. This normality test is for discount net present values that comprise the 2015 PV "optimistic" scenario.

D.3.1.2 2016 "Pessimistic" Scenario



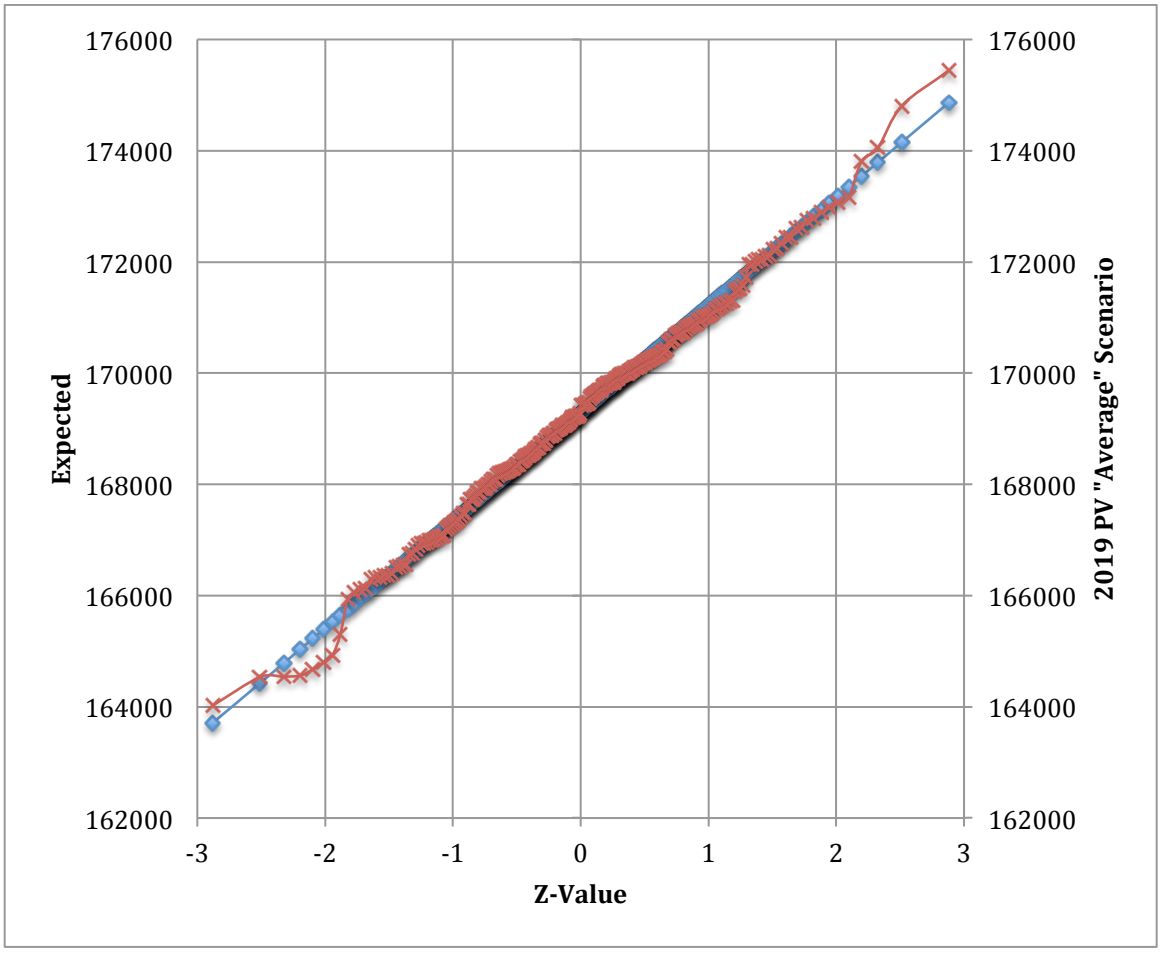
Normality test of 250 discounted net present values generated by a Monte Carlo simulation for the power purchase agreement tariff scenario and PV technology. This normality test is for discount net present values that comprise the 2016 PV "pessimistic" scenario.

D.3.1.3 2017 "Optimistic" Scenario



Normality test of 250 discounted net present values generated by a Monte Carlo simulation for the power purchase agreement tariff scenario and PV technology. This normality test is for discount net present values that comprise the 2017 PV "optimistic" scenario.

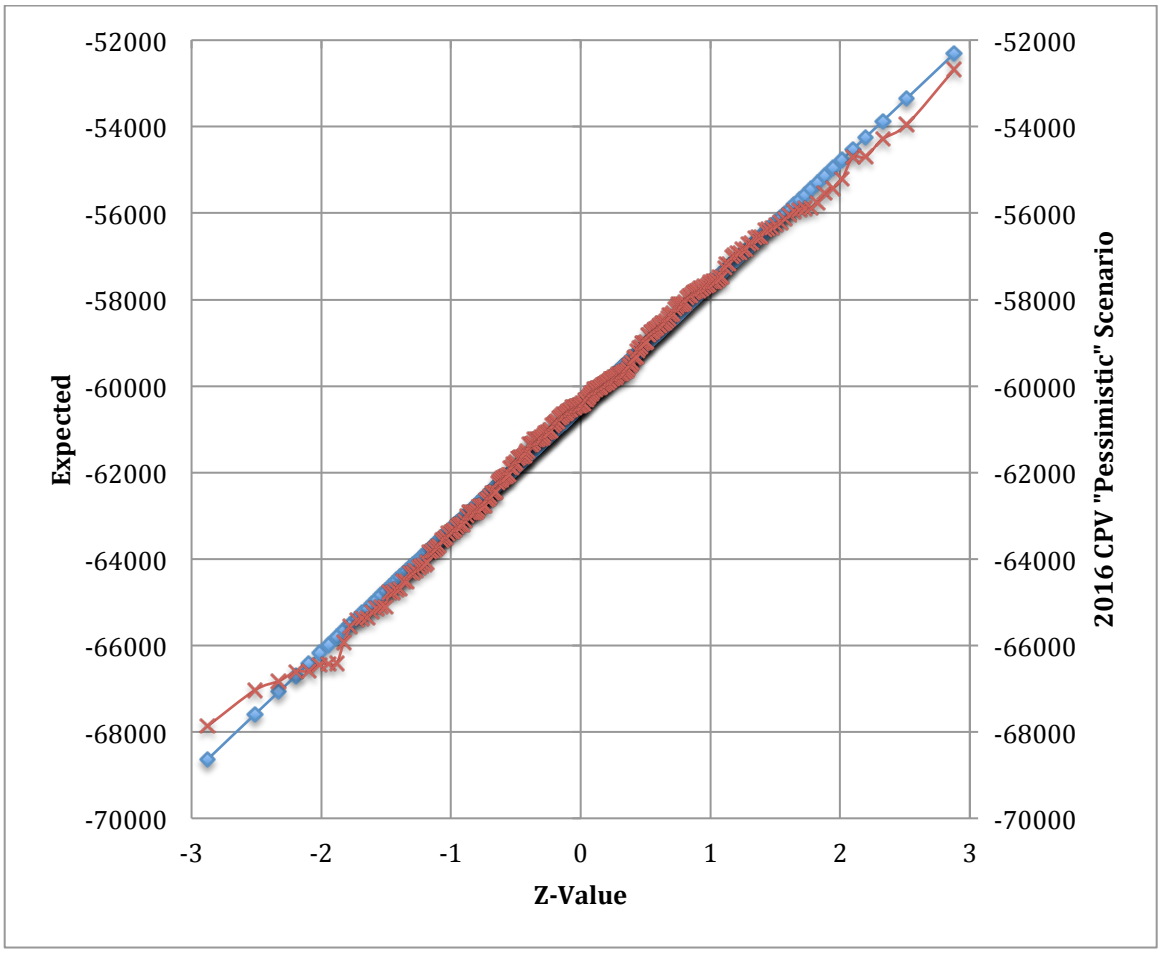
D.3.1.4 2019 "Average" Scenario



Normality test of 250 discounted net present values generated by a Monte Carlo simulation for the power purchase agreement tariff scenario and PV technology. This normality test is for discount net present values that comprise the 2019 PV "average" scenario.

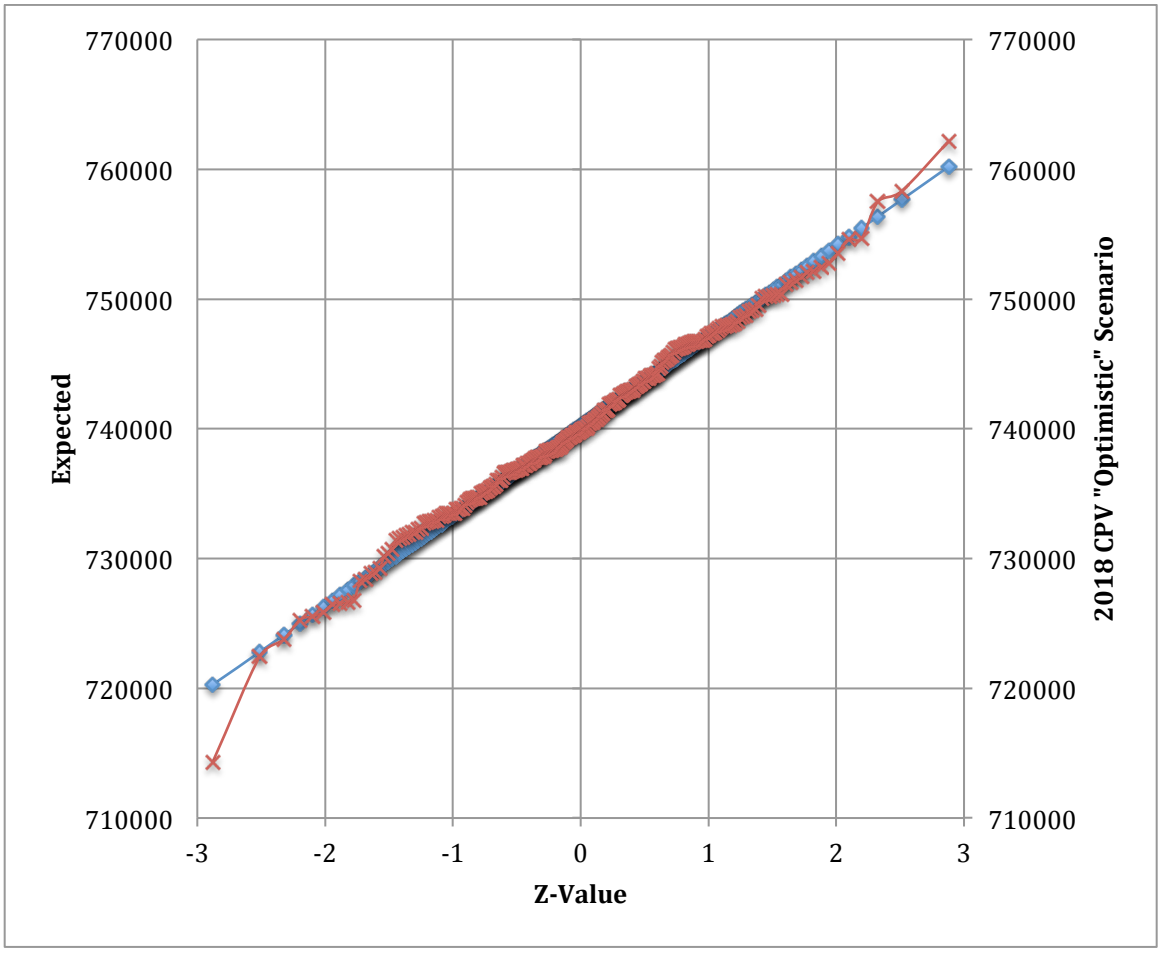
D.3.2 CPV Technology

D.3.2.1 2016 "Pessimistic" Scenario



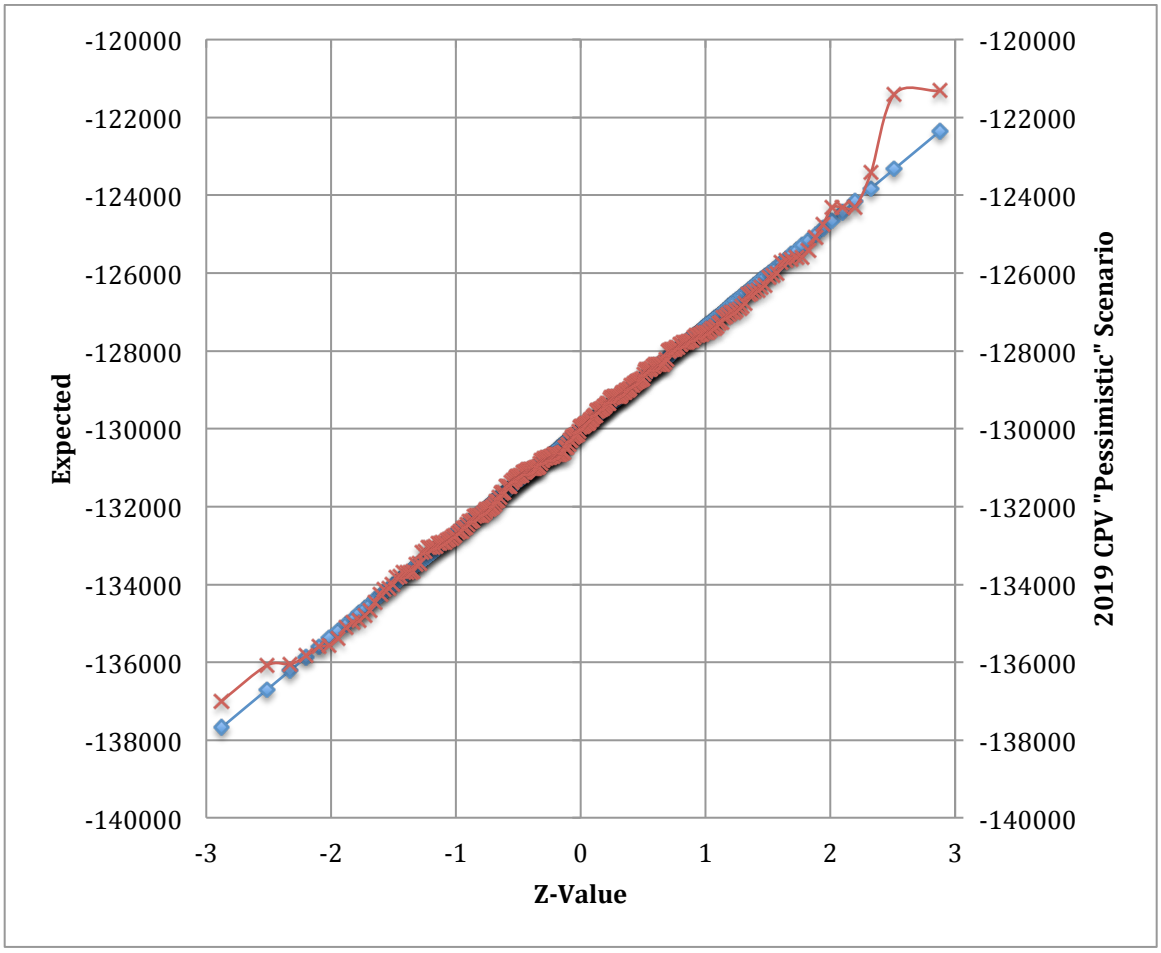
Normality test of 250 discounted net present values generated by a Monte Carlo simulation for the power purchase agreement tariff scenario and CPV technology. This normality test is for discount net present values that comprise the 2016 CPV "pessimistic" scenario.

D.3.2.2 2018 "Optimistic" Scenario



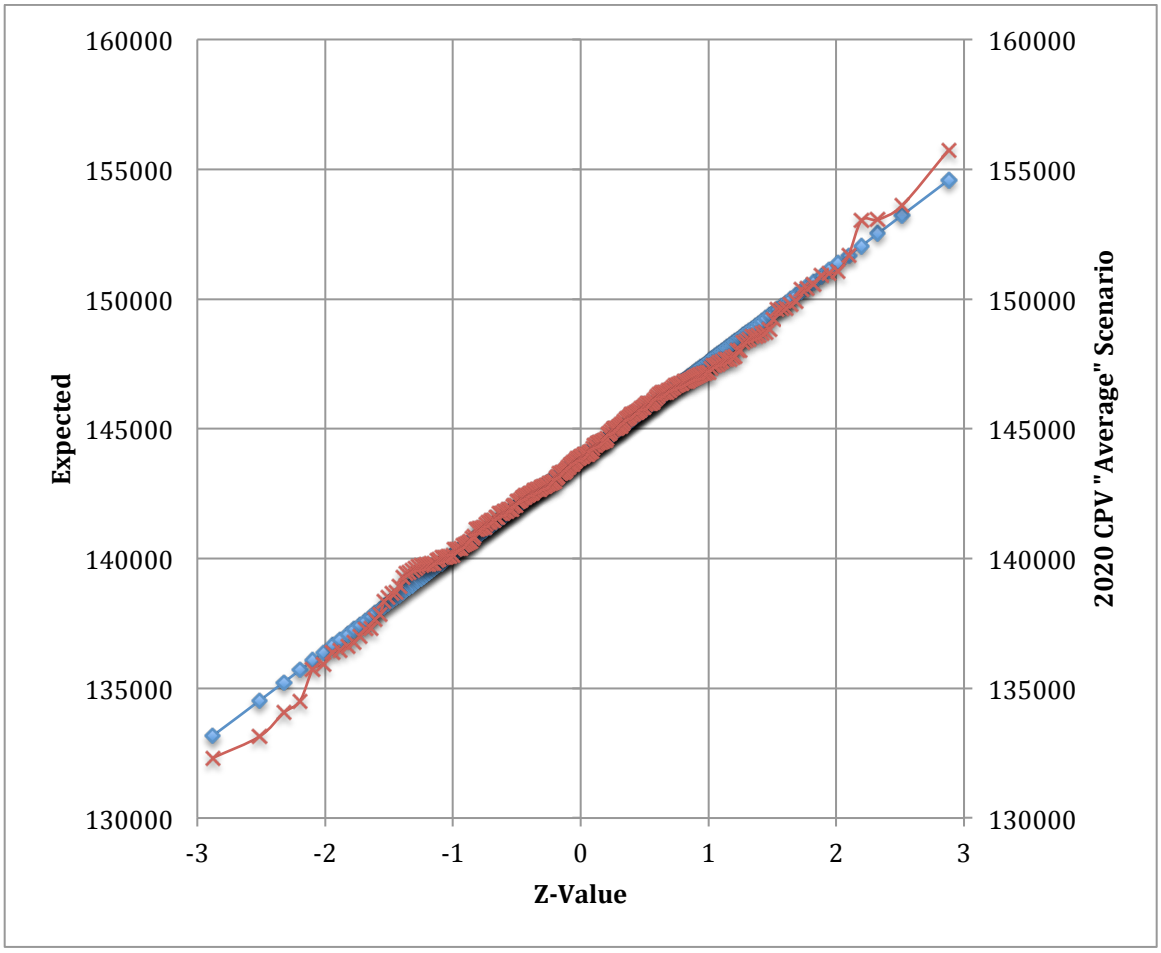
Normality test of 250 discounted net present values generated by a Monte Carlo simulation for the power purchase agreement tariff scenario and CPV technology. This normality test is for discount net present values that comprise the 2018 CPV "optimistic" scenario.

D.3.2.3 2019 "Pessimistic" Scenario



Normality test of 250 discounted net present values generated by a Monte Carlo simulation for the power purchase agreement tariff scenario and CPV technology. This normality test is for discount net present values that comprise the 2019 CPV "pessimistic" scenario.

D.3.2.4 2020 "Average" Scenario

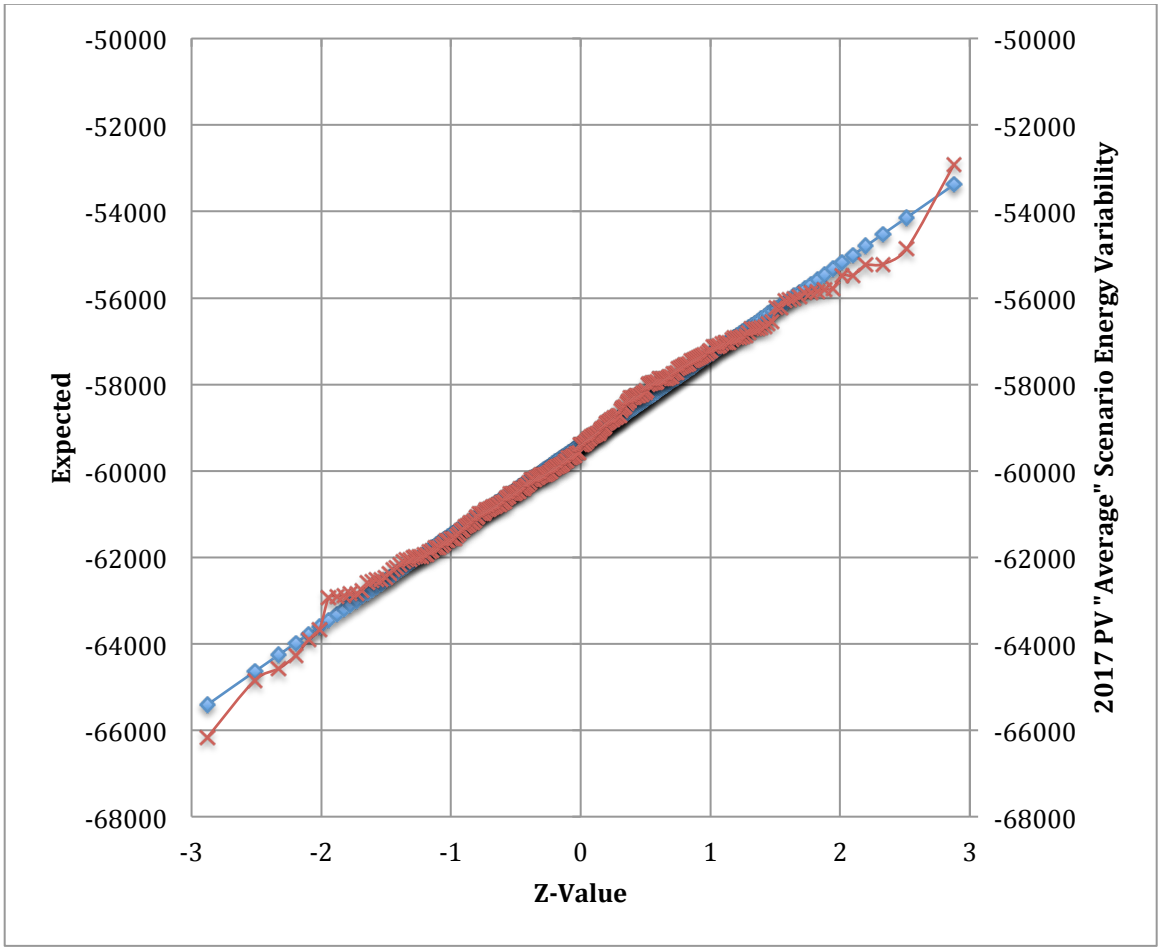


Normality test of 250 discounted net present values generated by a Monte Carlo simulation for the power purchase agreement tariff scenario and CPV technology. This normality test is for discount net present values that comprise the 2020 CPV "average" scenario.

D.4 Global Adjustment Tariff Offsetting Scenario

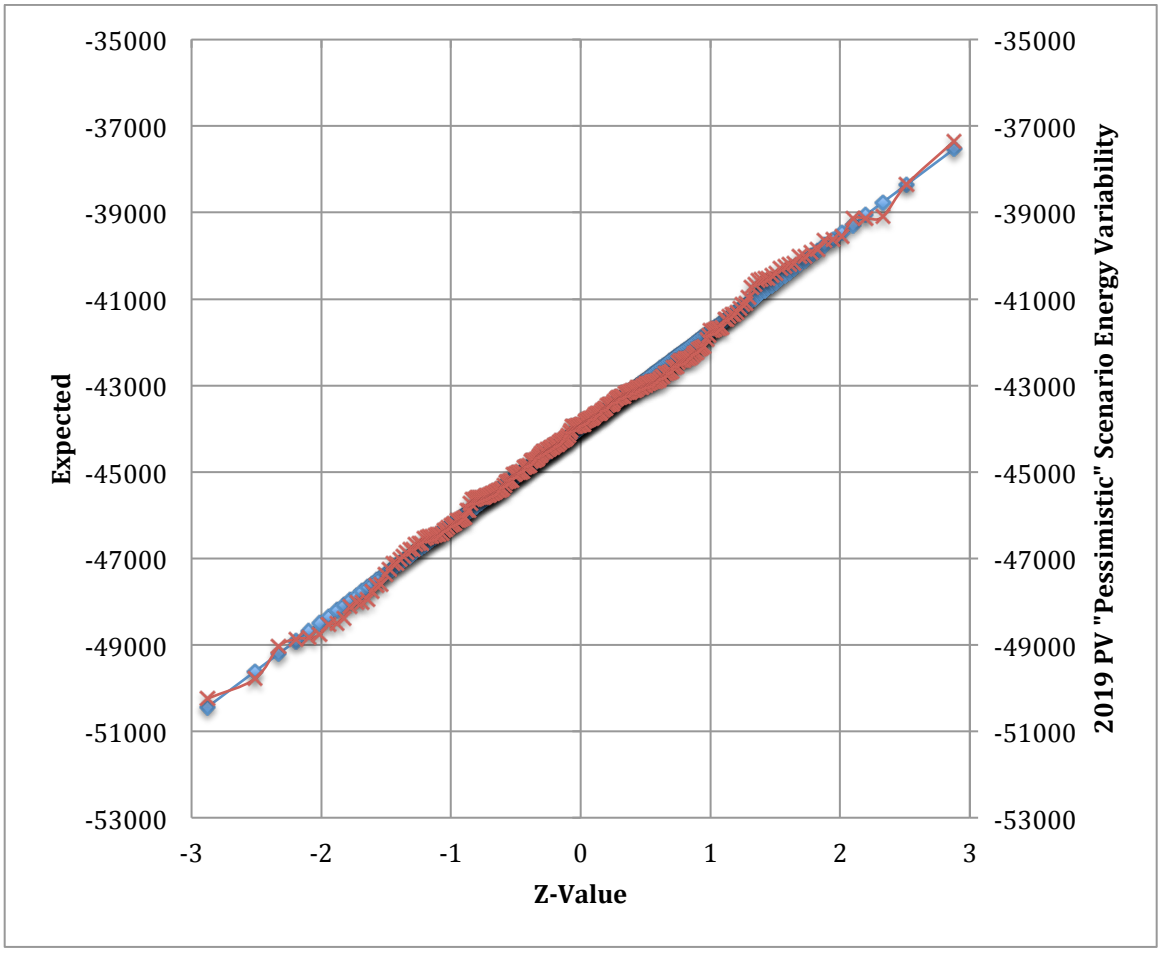
D.4.1 Energy Variance Only – PV Technology

D.4.1.1 2017 "Average" Scenario



Normality test of 250 discounted net present values generated by a Monte Carlo simulation for the global adjustment tariff offsetting scenario and PV technology. This normality test is for discount net present values that comprise the 2017 PV "average" scenario.

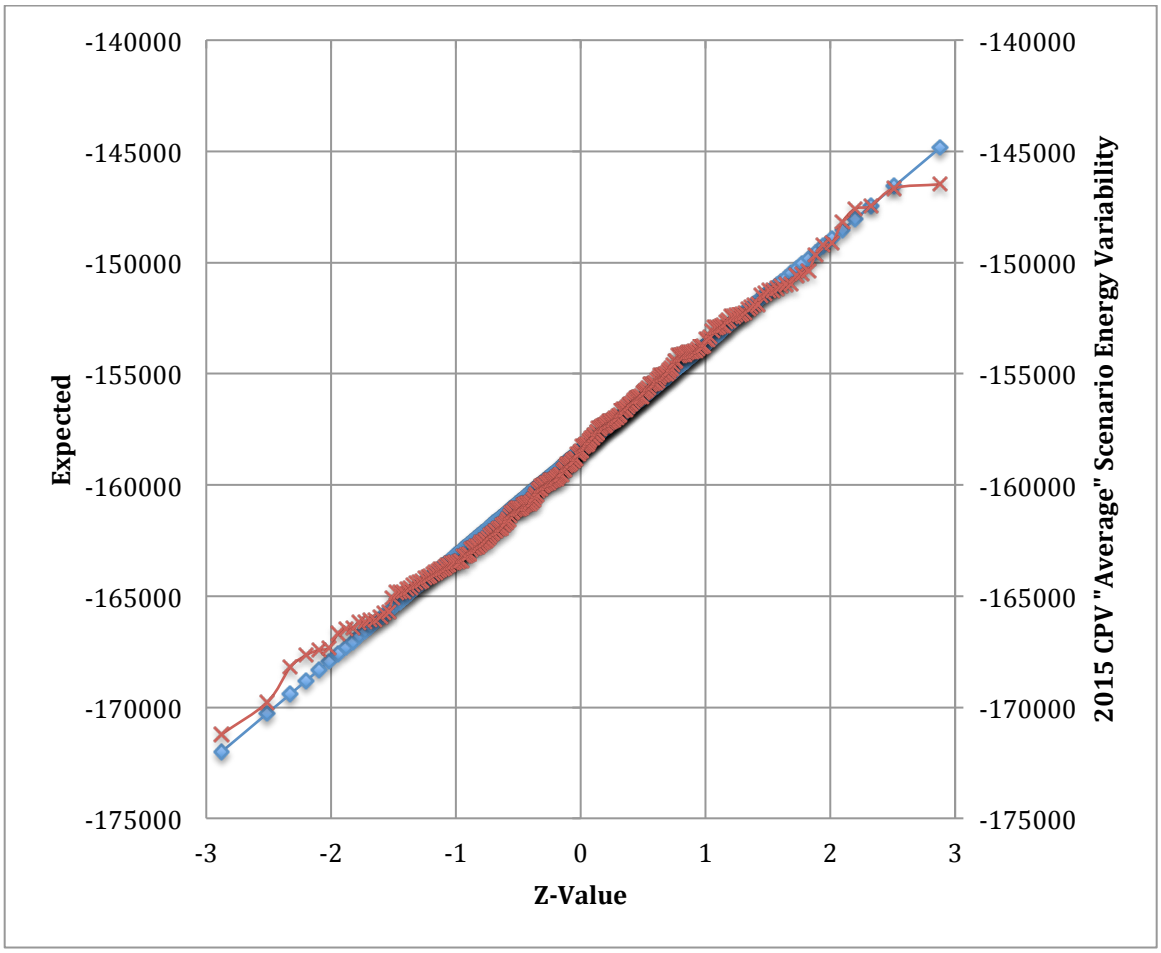
D.4.1.2 2019 "Pessimistic" Scenario



Normality test of 250 discounted net present values generated by a Monte Carlo simulation for the global adjustment tariff offsetting scenario and PV technology. This normality test is for discount net present values that comprise the 2019 PV "pessimistic" scenario.

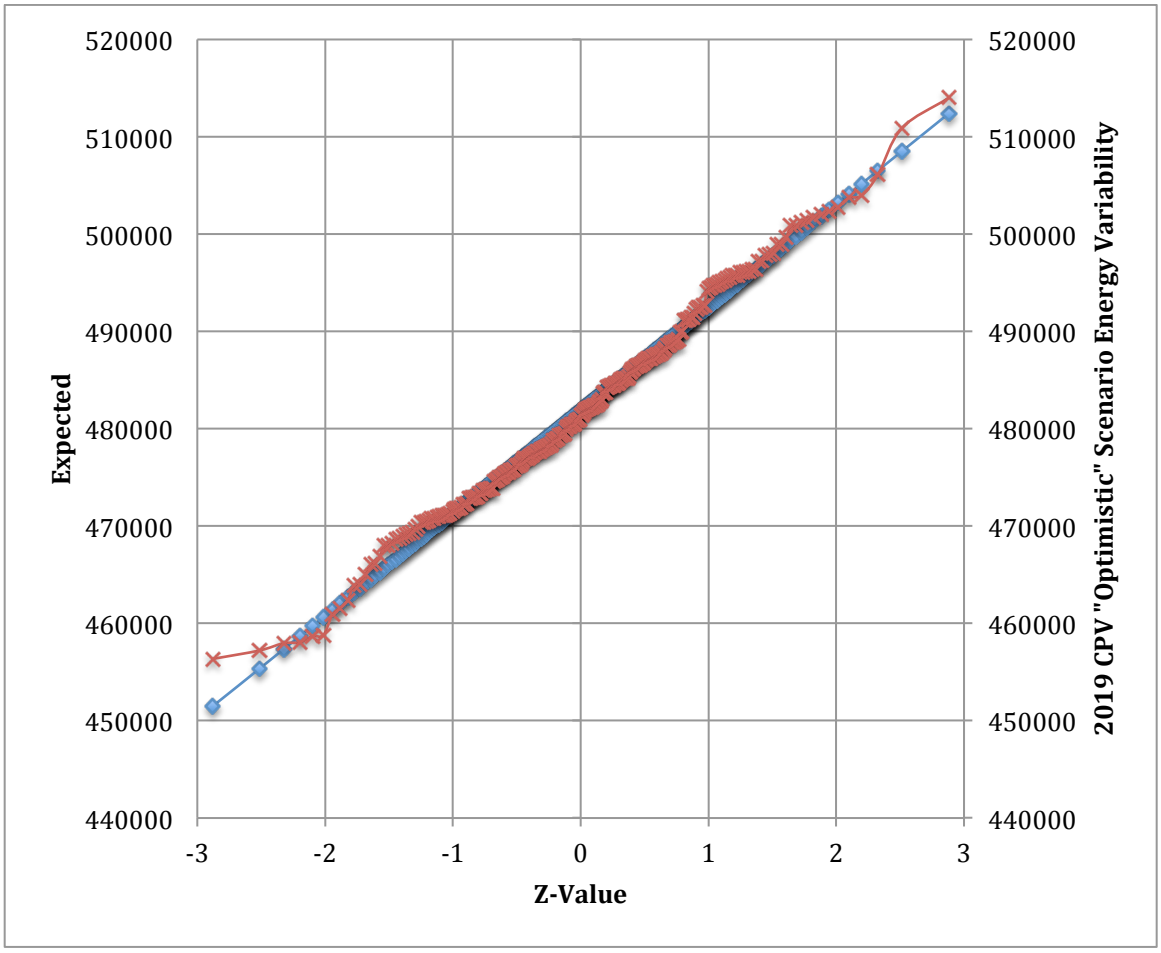
D.4.2 Energy Variance Only – CPV Technology

D.4.2.1 2015 "Average" Scenario



Normality test of 250 discounted net present values generated by a Monte Carlo simulation for the global adjustment tariff offsetting scenario and CPV technology. This normality test is for discount net present values that comprise the 2015 CPV "average" scenario.

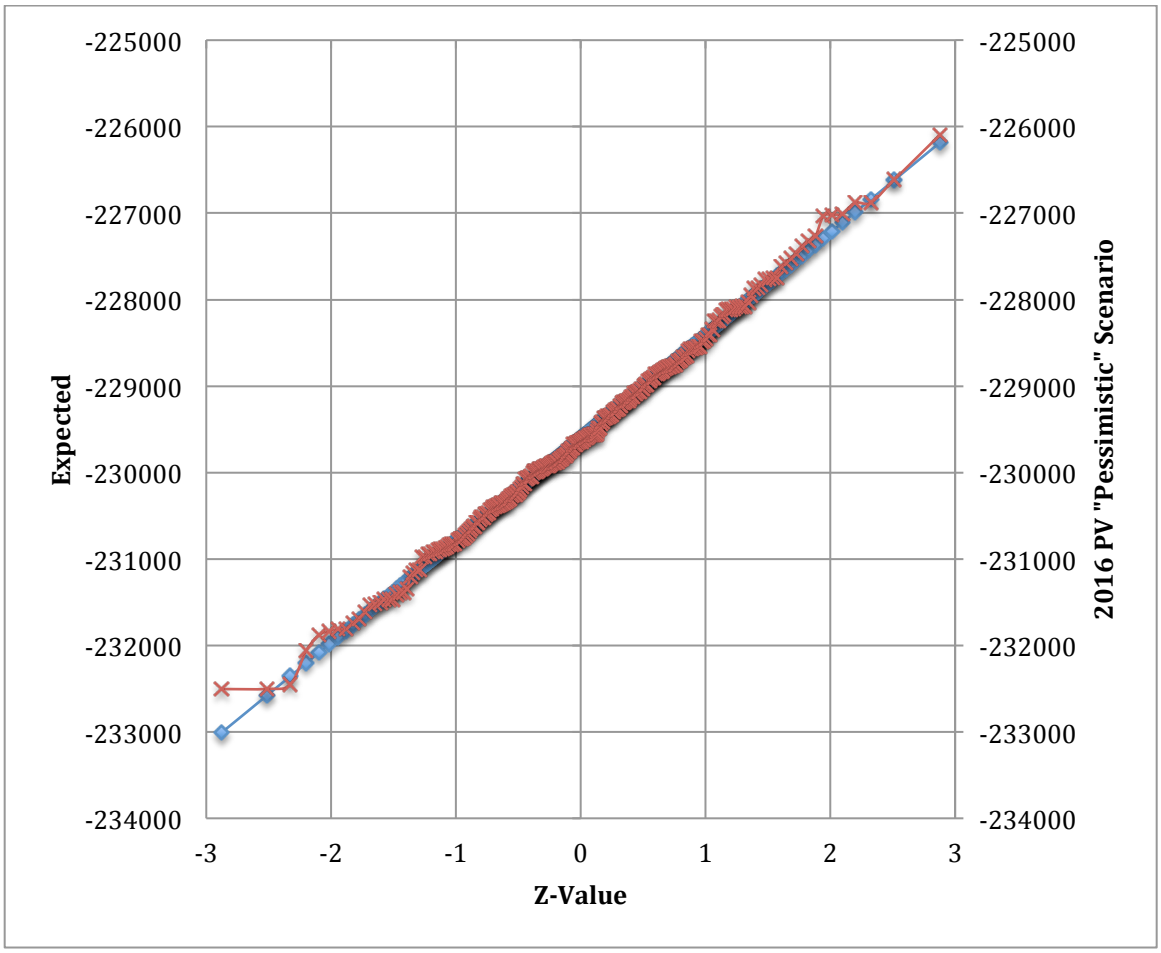
D.4.2.2 2019 "Optimistic" Scenario



Normality test of 250 discounted net present values generated by a Monte Carlo simulation for the global adjustment tariff offsetting scenario and CPV technology. This normality test is for discount net present values that comprise the 2019 CPV "optimistic" scenario.

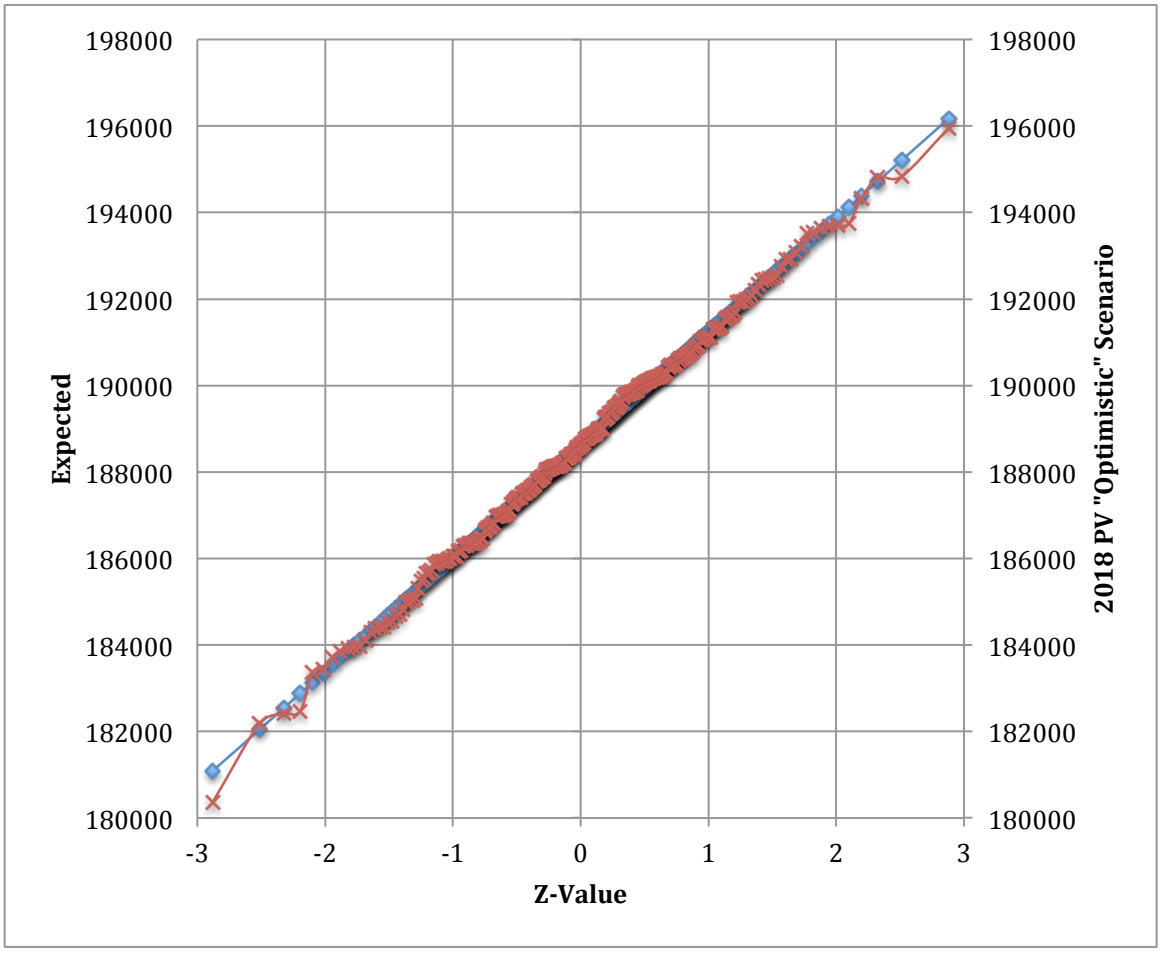
D.4.3 Tariff Variability Only – PV Technology

D.4.3.1 2016 "Pessimistic" Scenario



Normality test of 250 discounted net present values generated by a Monte Carlo simulation for the global adjustment tariff offsetting scenario and PV technology. This normality test is for discount net present values that comprise the 2016 PV "pessimistic" scenario.

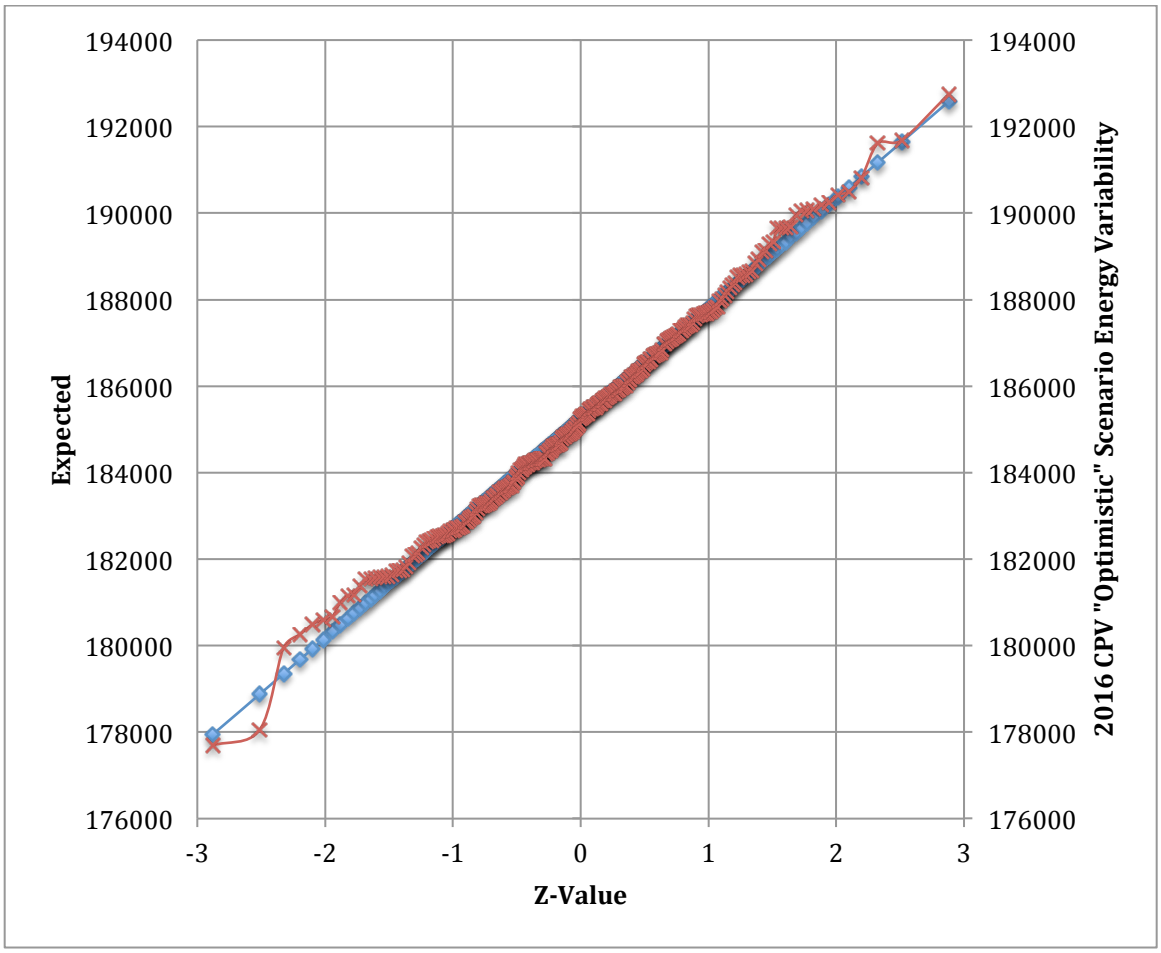
D.4.3.2 2018 "Optimistic" Scenario



Normality test of 250 discounted net present values generated by a Monte Carlo simulation for the global adjustment tariff offsetting scenario and PV technology. This normality test is for discount net present values that comprise the 2018 PV "optimistic" scenario.

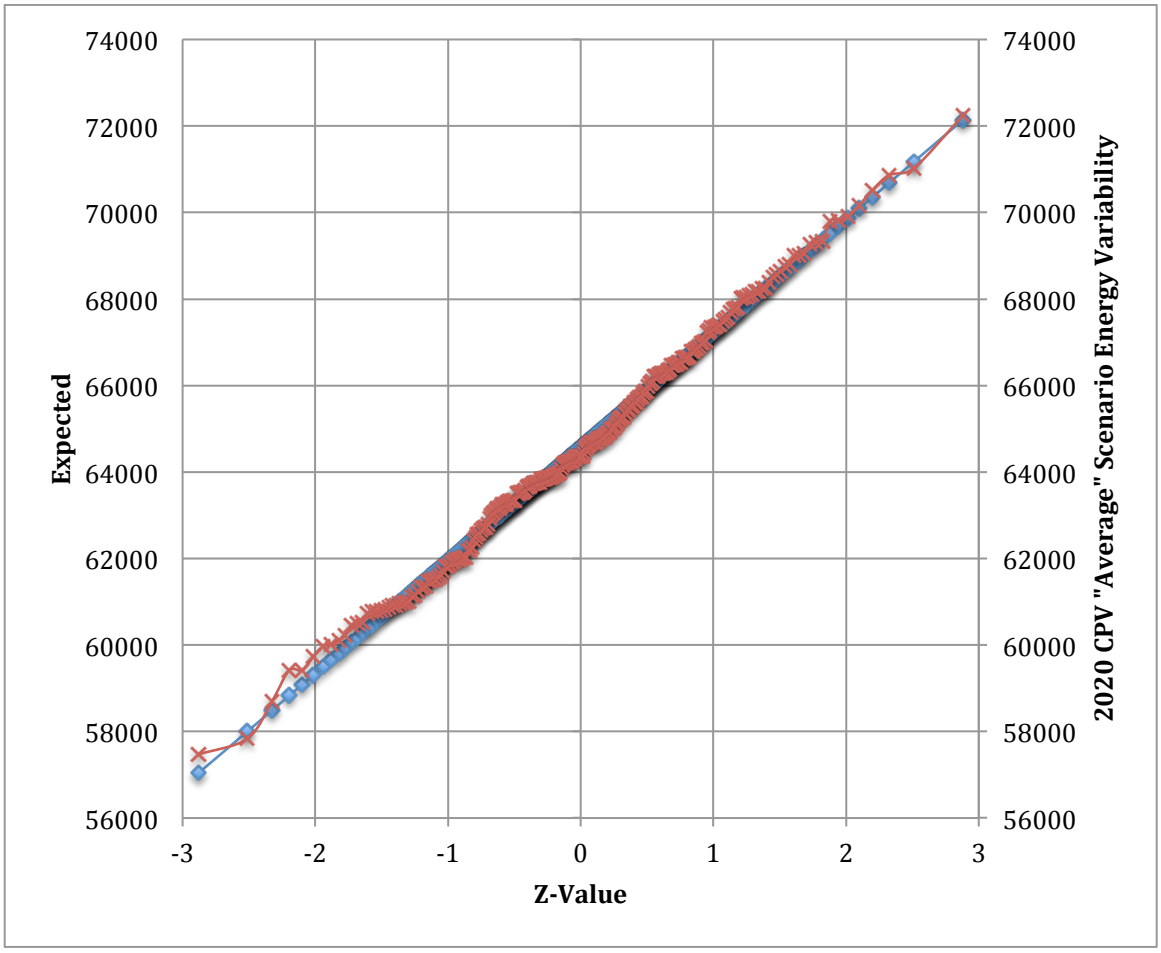
D.4.4 Tariff Variability Only – CPV Technology

D.4.4.1 2016 "Optimistic" Scenario



Normality test of 250 discounted net present values generated by a Monte Carlo simulation for the global adjustment tariff offsetting scenario and CPV technology. This normality test is for discount net present values that comprise the 2016 CPV "optimistic" scenario.

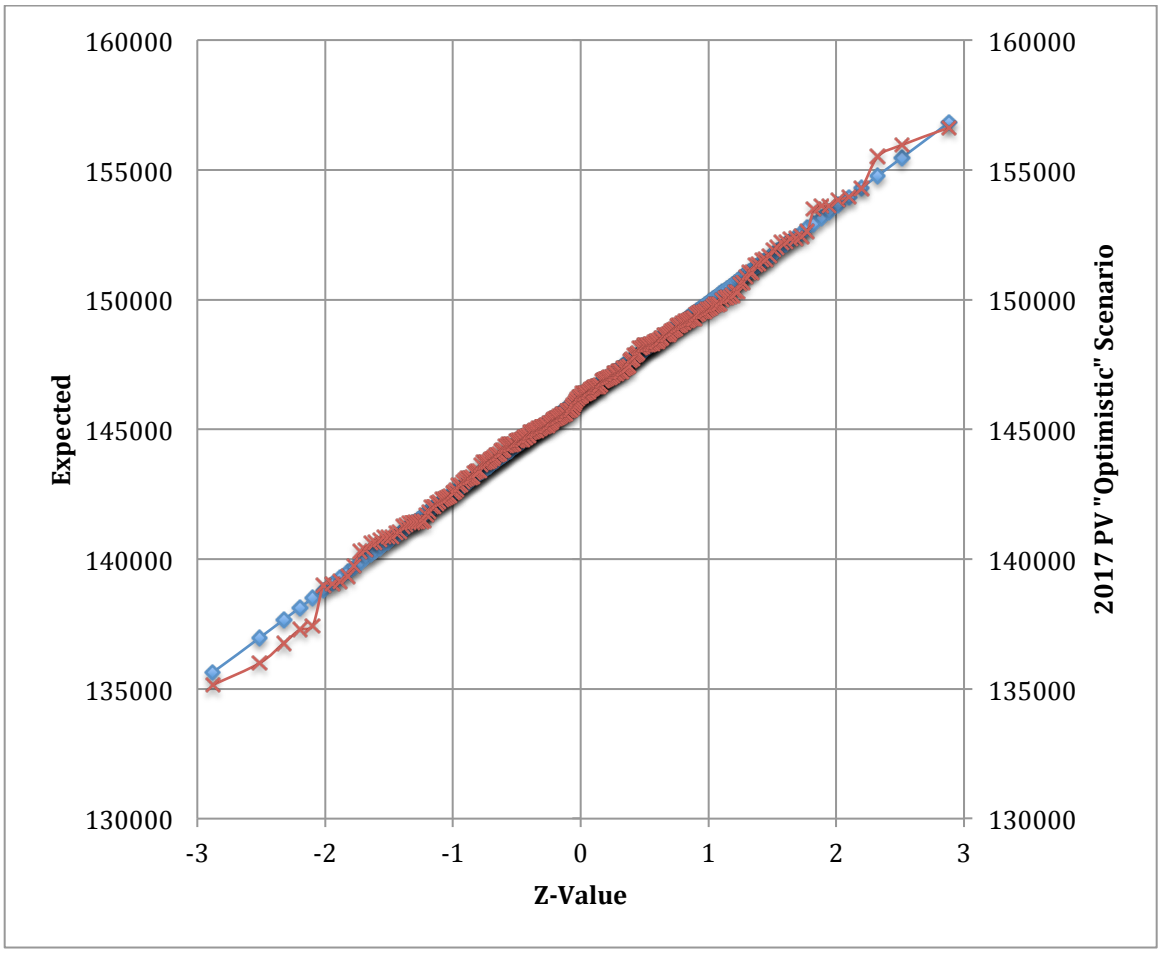
D.4.4.2 2020 "Average" Scenario



Normality test of 250 discounted net present values generated by a Monte Carlo simulation for the global adjustment tariff offsetting scenario and CPV technology. This normality test is for discount net present values that comprise the 2020 CPV "average" scenario.

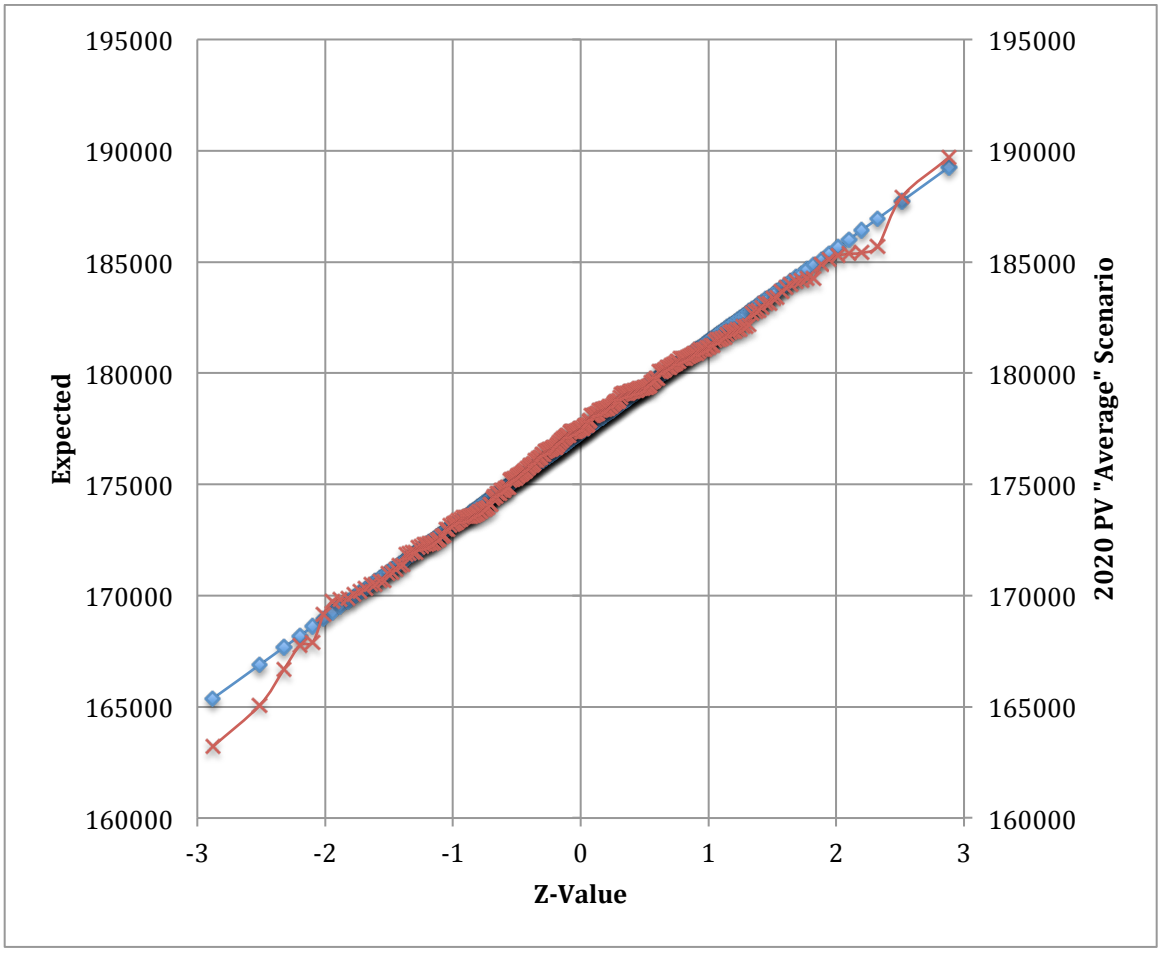
D.4.5 Energy and Tariff Variability – Photovoltaic Technology

D.4.5.1 2017 "Optimistic" Scenario



Normality test of 250 discounted net present values generated by a Monte Carlo simulation for the global adjustment tariff offsetting scenario and PV technology. This normality test is for discount net present values that comprise the 2017 PV "optimistic" scenario.

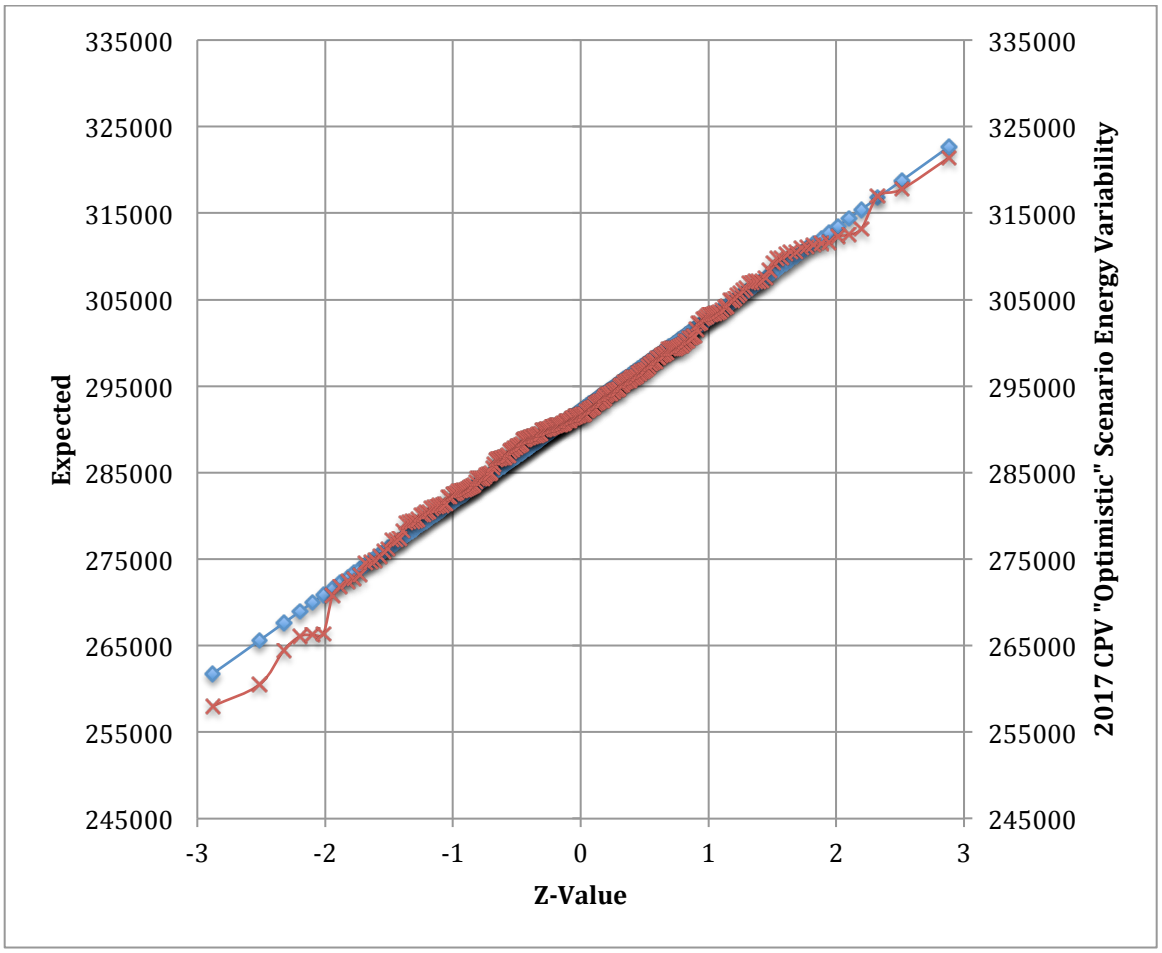
D.4.5.2 2020 "Average" Scenario



Normality test of 250 discounted net present values generated by a Monte Carlo simulation for the global adjustment tariff offsetting scenario and PV technology. This normality test is for discount net present values that comprise the 2020 PV "average" scenario.

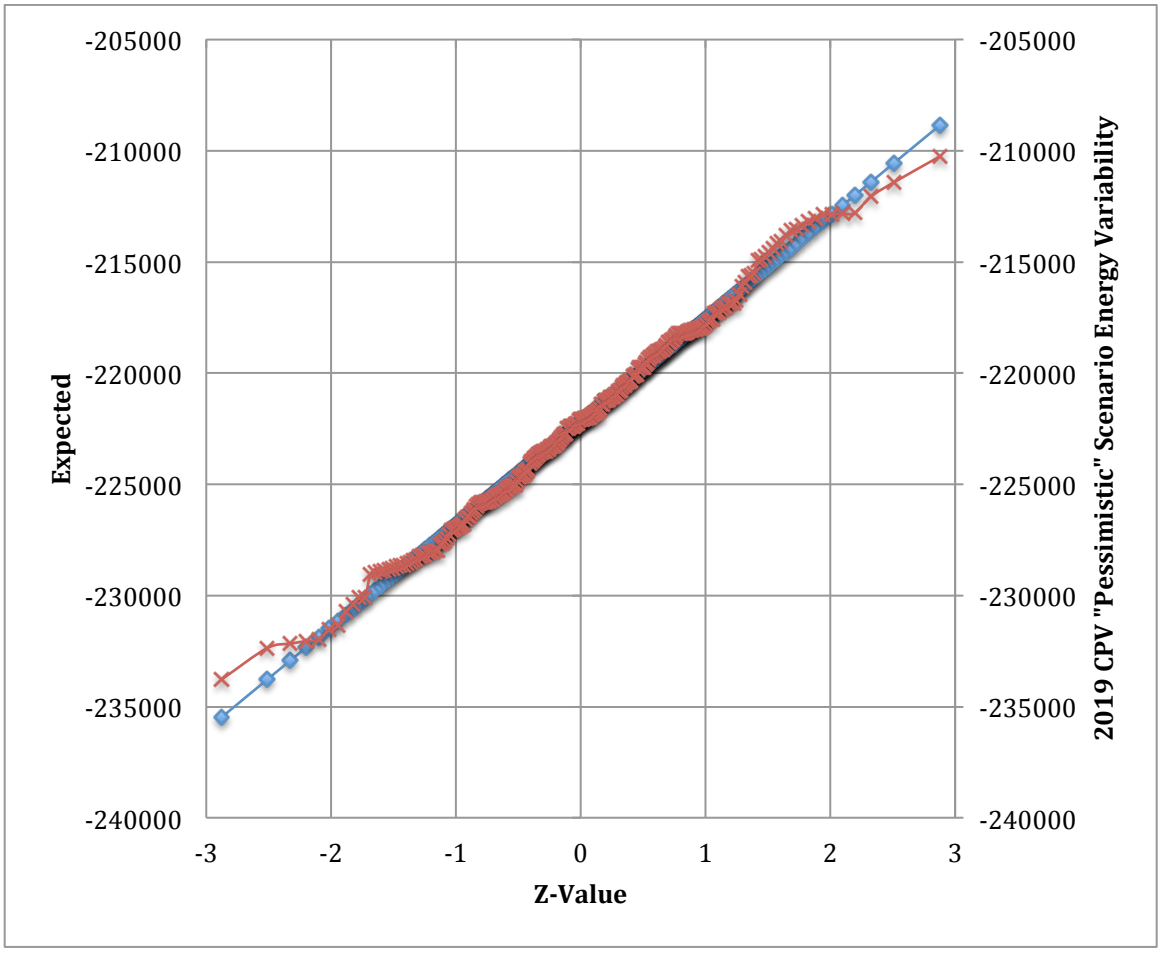
D.4.6 Energy and Tariff Variability – Concentrated Photovoltaic Technology

D.4.6.1 2017 "Optimistic" Scenario



Normality test of 250 discounted net present values generated by a Monte Carlo simulation for the global adjustment tariff offsetting scenario and CPV technology. This normality test is for discount net present values that comprise the 2017 CPV "optimistic" scenario.

D.4.6.2 2019 "Pessimistic" Scenario



Normality test of 250 discounted net present values generated by a Monte Carlo simulation for the global adjustment tariff offsetting scenario and CPV technology. This normality test is for discount net present values that comprise the 2019 CPV "pessimistic" scenario.

Appendix E: Chart Summarizing the Tariff and Pricing Scenarios Analyzed

Tariff Scenario	Pricing Scenario	No Variability (Deter-ministic)	Energy Yield Variability	Electricity Tariff Variability	Energy Yield and Electricity Tariff Variability
Time-of-Use	Optimistic	✔	✔		
	Average	✔	✔		
	Pessimistic	✔	✔		
Feed-in Tariff	Optimistic	✔	✔		
	Average	✔	✔		
	Pessimistic	✔	✔		
Power Purchase Agreement	Optimistic	✔	✔		
	Average	✔	✔		
	Pessimistic	✔	✔		
Global Adjustment Tariff Offsetting	Optimistic	✔	✔	✔	✔
	Average	✔	✔	✔	✔
	Pessimistic	✔	✔	✔	✔

The check marks in the above table indicate the conditions under which financial metric calculations were performed. Discounted net present value, return on investment, internal rate of return, and levelized cost of electricity were calculated under both deterministic and energy yield variability conditions for each of the four tariff scenarios and all three pricing scenarios. In addition to deterministic and energy yield variability conditions, the global adjustment tariff offsetting scenario included financial metric calculations under electricity tariff as well as energy yield and electricity tariff variability.

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