Charging and Discharging Algorithms for Electric Vehicles in Smart Grid Environment

By

Osama Aloqaily

Thesis submitted to the Faculty of Graduate and Postdoctoral Studies in partial fulfillment of the requirements for the degree of Master of Applied Science (MASc) in Electrical and Computer Engineering

Ottawa-Carleton Institute for Electrical and Computer Engineering

School of Electrical Engineering and Computer Science

Faculty of Engineering

University of Ottawa

Abstract

Power demands will increase day-by-day because of widely adopting of Plug-in Electric Vehicles (PEVs) in the world and growing population. Finding and managing additional power resources for upcoming demands is a challenge. Renewable power is one of the alternatives. However, to manage and control renewable resources, we need suitable Energy Storage System (ESS). PEVs have a large battery pack that is used mainly to supply electric motor. Moreover, PEV battery could be used as an ESS to store power at a certain time and use it at another time. Nevertheless, it can play the same role with electric power grids, so it can store power at a time and return it at another time. This role might help the grid to meet the growing demands. In this thesis, we propose a charging and discharging coordination algorithm that effectively addresses the problem of power demand on peak time using the PEV's batteries as a backup power storage, namely, Flexible Charging and Discharging (FCD) algorithm. The FCD algorithm aims to manage high power demands at peak times using Vehicle to Home (V2H) technologies in Smart Grid and PEV's batteries. Intensive computer simulation is used to test FCD algorithm. The FCD algorithm shows a significant reduction in power demands and total cost, in proportion to two other algorithms, without affecting the performance of the PEV or the flexibility of PEV owner's trip schedule.

Acknowledgements

My first and most gratitude to my supervisor Professor Hussein Mouftah for his contributions of time, ideas, and funding to make my life dream come true. It has been an honor to be one of his students during the master's program.

My sincerest gratitude to my parents for unlimited support. To my father who burned his life candles to light our path. To my mother, I have no enough expressions that describe my thankfulness for your love and care. This success and all successes are yours.

Special warmest thanks goes to my brothers, family in-law, i am so blessed to have you in my life. I would like to extend my warmest thanks to my wife Ala Shakhatreh for her support, sacrifice encourage and patience.

To my darling babies, Auwn, Mohammad and Ayoub. You are my sweet heart, and to whom I dedicate my whole life to endless care and love.

Table of Contents

List of Figures

List of Tables

List of Acronyms

BEV	Battery Electric Vehicle
BSS	Battery Swap Station
CEN	European Standardization Commission
DR	Demand Response
DRM	Demand Response Management
DSM	Demand Side Management
EDTA	Electric Drive Transport Association
ESS	Power Storage System
EV	Electric Vehicle
EVSE	Electric Vehicle Supply Equipment
FCD	Flexible Charging and Discharging
G2V	Grid to Vehicle
ICE	Internal Composition Engine
IEC	International Electrotechnical Commission

IEEE	Institute of Electrical and Electronic Engineering
ISO	International Standard Organization
JEVS	Japan EV Association Standards
JIS	Japanese Industry Standards
Li-ion	Lithium ion
NiMH	Nickel Metal Hydride
P	Penetration ratio
PEV	Plug-in Electric Vehicle
PHEV	Plug-in Hybrid Electric Vehicle
RTP	Real Time Price
SAE	Society of Automotive Engineers
ToU	Time of Use
TUD	Time Use Data
V2G	Vehicle to Grid
V2H	Vehicle to Home
V2V	Vehicle to Vehicle

List of Symbols

$A_{t,n}$	n^th Appliance at time solt t
Ch_{eff}	Charge efficiency
Ch_{rate}	Charging rate
Ch_{step}	Charge step
$Cost_{Con}$	Cost of consumed power
$Cost_{Exp}$	Cost of returned power
$Cost_{Totsl}$	Total cost of consumed and returned power
D_t^v	Trip distance for vehicle v at time slot t
D_{Max}	Maximum range
$DisCh_{eff}$	Discharge efficiency
$DisCh_{rate}$	Discharging rate
$DisCh_{step}$	Discharging Rate
$Ev\_ratio(t)$	Ratio of participating PEVs at time slot t.
H	Number of houses
N	Number of appliances
$O_{T,n}$	Operational set of timeslots.

$\mathrm{P}_{App,n}$	Total power consumed for all appliances
$P_{C,n}$	Total appliances power consumption
P_G	Total consumed power from the grid
P_{houses}	Total power consumed for all houses in neighborhood
P_H	Total house power consumption
Price	Power Price
S	Time step
SoC_{Con}	Consumed SoC
SoC_{EV}	Current SoC at EV
SoC_{Exp}	Exported SoC
SoC_{full}	Full SoC
P_{h_Total}	Total power consumed by house
SoC_{Tot_Ch}	Total charged SoC
SoC_{Tot_Dis}	Total discharged SoC
SoC_{Trip}	SoC required for a trip
T	Time
th	Battery depletion threshold
V	Number of EVs
ε	Driving efficiency factor

Chapter 1: Introduction

1.1 Background

Electric Vehicles (EV), which are developed and built to be part of the future transportation, have gained additional interest for other reasons, such as environment friendly, power efficiency, safety, and potential energy management. Plug-in EV (PEV) are all vehicles that are powered either completely or partially by electricity. We will refer to PEV as EV in this thesis. EVs are classified into two types: Battery EV (BEV) and Plug-in Hybrid EV (PHEV). BEV has no Internal Combustion Engine (ICE), so it depends completely on battery packs that powered its electric motor [1]. The battery pack can be charged or replaced. In case of charging, battery should be connected to electric power supply to charge the battery. On the other hand, battery replacement is based on switching the battery pack at special places [2]. PHEVs are vehicles that have ICE's and electric motors. Current PHEVs have battery packs to supply the electric motor and a fuel tank to supply the ICE. In a PHEV, engine and motor work alternatively based on driving circumstances. ICE in PHEV works as a backup for the electric motor. Therefore, there is no worry about battery capacity or battery charge level. For the same reason, PHEV can be a light vehicle, a van, a truck, a bus or a train while BEV can only be used in a light vehicle [3]. EV battery pack can be considered as an Energy Storage System (ESS). ESS is used to store excessed or cheap power at a point of time and retrieve that power in the future [4].

Power prices and power demands are tightly correlated to each other. Energy companies change the power prices based on demands to force the users to change their habits to reduce consumption at certain times. Managing demands based on tight scheduling which will impose challenges in our life style (for example to change the times of using our washer, dryer, air condition, and heater) is considered intuitive solution. In addition, too many EVs will overload power grid by raising the demands. Therefore, additional power resources (non-renewable and renewable) should be integrated to meet demands.

Power resources might be non-renewable or renewable. Non-renewable resources, such as oil, coal, nuclear produce emissions that participate in pollution and harm environment. The margin of non-renewable resources degraded day–by-day, and it will not be common after fifty years [5]. On the other hand, renewable resources (or green power), such as wind power, hydropower, biomass power, solar power, and geothermal power, do not produce harmful emissions. Therefore, renewable resources are highly expected to replace non-renewable resources [5]. Most renewable resources are not available at all times and all places, as a result, generated power from these resources has to be stored in ESS or immediately consumed.

A EV battery, treated as an ESS, might be used to store power from the power grid regardless of the source of power i.e. renewable or non-renewable. A EV as an ESS has the challenge of battery aging, charging and discharging power loss, power prices, charging equipment, and EV performance as a vehicle. To formalize the relation between EV battery as an ESS and the power grid, a group of standards should be set and used to manage power transportation processes in a safe, secure, and reliable system. Moreover, Vehicle to Grid (V2G) and Vehicle to Home (V2H) technologies (these technologies includes standards, algorithms, and techniques) should be used to coordinate these processes and guarantee EV performance as a vehicle as well as an ESS [6].

Intensive research has been conducted to develop these standards and algorithms [7]. Researchers have also studied the impact of using EV on the power grid, EV battery aging, and the performance of the EV battery under various circumstances [8]. Research in this area can be classified into EV supporters approach and EV objectors approach. The first approach emphasized the benefits of using EVs and proved how much the EVs will support the future transportation system and power grid [1], [4], [5], [9–22]. On the contrary, the second approach has highlighted the negative consequences of using EV on the power grid [23–31]. Both approaches are very important for EV evolution, by taking the benefits presented in the first approach and minimize the impacts mentioned in the second approach; the results will serve people and help them in the future.

1.2 EV and Vehicle to Home Technology (V2H)

EV numbers are expected to grow year by year, 25% of light vehicles in the USA will be EV by 2020, and more than 60% by 2040 [11]. Therefore, EVs represent a promising future transportation as well as power management. For fulfilling these roles, EV will use other technologies, such as a V2H and V2G technologies. These technologies will be discussed further in Chapter 2. The basic idea of V2H is to coordinate the charging and discharging processes of a home- plugged EV. If we plug-in EV power connection in the power socket at home or other charging places, then the EV becomes part of the grid, and the grid can use the EV to store or retrieve power through charging or discharging processes [32].

Charging and discharging can happen at home, at work, at commercial places, or at supply stations. These places differes in used charging techologies, such as charging equipment, charger type, and charging speed [33]. In this thesis, charging at home is used for the purpose of stabilizing micro grid (i.e. neighborhood grid).

Charging and discharging at home have many advantages. In addition to stabilizing power consumption and reduce power bill, it is more convenient for users to charge their EVs at home. Also, it is cheaper for the user to charge at home during off peak times. Moreover, the user might benefit from EV governmental incentives [34].

Research in V2H focused on EV components and systems such as the batteries, onboard or off board chargers, and the role of renewable resources [18], [35], [36]. In most of these cases, researchers use what has been done in V2G; because V2H is a special case of V2G. However, V2G and V2H differs in many ways, such as V2G deals with the whole power grid while the V2H deals with home or group of homes. Therefore, many critical points in V2H need additional research.

Few works have studied V2H in the context of Smart Grid, the communication between both EV and Smart Grid sides, Impact of Electric Vehicles on Power Distribution networks, and management of house appliances [25], [26]. However, few works were done to develop and enhance the algorithms that regulate charging and discharging processes [6], [37]. Most of works have considered a partial solutions or solutions for special cases.

This thesis focuses on merging the V2H and the Smart Grid, and finding a solution that reduces power demands at peak time, reduce energy bill and solving the charging and discharging problems.

1.3 Motivation and Objective

Adopting EVs added new demands to the current power grid. However, uncoordinated EV charging will seriously affect power grid, and economy [25]. To meet new demands using current power grid and renewable resources, an ESS is needed. EVs can help the power grid using its battery. For example, Tesla S70 has 90 kWh battery capacity, and its daily consumption for trips is about 12.5% of this capacity (average daily distance for light vehicles is 53 Km [38]). Using simple math, 60 kWh can be used as an ESS after reduction of 20% depletion ratio.

Finding a solution of power demands problem at peak time is the main objective of this thesis. This solution intends to provide coordination algorithm for EVs charging and discharging operations, in the micro grid, to reduce consumed power at peak time and to reduce energy bill of the EV owner without affecting the performance of the EV as a vehicle. This solution will use V2H technologies in the Smart Grid environment.

1.4 Thesis Contribution

This thesis intends to provide an algorithm to coordinate EV charging and discharging operations. This algorithm will use V2H technologies in a Smart Grid environment to help power grid meets the expected power demands. The contribution of this thesis can be summerized as follows:

Flexible Charging and Discharging (FCD) algorithm that uses the EV battery as an ESS has been defined. This algorithm aims to use the EV battery to store power during off-peak times and retrieve power in peak times. In addition, the algorithm studied the consumed and returned power at peak time based on 30-minutes time-slot and 10-minutes time-slot. Finally, a Time of Use (ToU) pricing scheme has been used to evaluate the performance of the proposed coordination algorithm.

1.5 Thesis Outline

The thesis is organized as follows: Chapter 2 has four sections, section 1 reviews the literature of the EV and Smart Grid, Section 2 presents EV and House power consumption, section 3 shows EV charging levels, chargers, and EV batteries, section 4 reviews V2H standards and algorithms. In Chapter 3, we discuss the house and EV power consumption sub-models and EV charging-discharging coordination model. Chapter 4 verifies the advantages of considering the charging-discharging coordination algorithms. Also, we proved through analytical and implemented simulations that the FCD algorithm reduces the power demands, and reducing EV owner’s power bill without affecting the vehicle performance. Chapter 5 concludes our current research study and explores the future work we intend to target.

Chapter 2: State of the Art of EV

Designing new affordable, economical, efficient, comfortable, and compatible EVs with Smart Grids are the goals of EV industry. Enabling these features drive research in this area where researchers are interested in designing and developing new standards, techniques, algorithms, protocols and technologies to fulfill these requirements.

This chapter is divided into four main sections. In the first section, we will briefly discuss the development of EV's since the 19th century until now, EV and Smart Grid relationship, and the role of the EV in the future of the Smart Grid. The second section will discuss EV and house power consumption. In the third section, a review of EV chargers, charging levels, charging places, and EV battery. Finally, we will present previous works in V2H and V2G standards and algorithms.

2.1 EV and Smart Grid

2.1.1 EV History

The development of EV began in the 19^{th} century. Man did not stop his trials to design and develop a vehicle that is powered by electricity. This evolution grew slowly in the 20^{th} century because of using gas and ICE. EV continued development in the 21^{st} century. Nowadays, more than 30 different EVs are available in the market [39]. These EVs might be operated entirely or partially by electricity. It is anticipated that by 2025 all light vehicles sold in Europe will be electric or hybrid [40].

Figure 2-1 shows the Detroit EV in 1915 and to the right Tesla Model S in 2015. These two vehicles show how much EV industry has evolved.

Figure 2-1: Detroit EV 1915 and Tesla Model S 2015 [38], [41]

The race between EV makers is not limited to the electric motor or the battery pack only, but rather exceeds to compete conventional vehicles body design, comfortability, security, safety, range, and power efficiency. Soon, EV roofs will have solar panels that feed EV battery [42]. Therefore, EV will not consume too much power from the grid, which means less cost. Until the moment when these expectations become true, EV has another advantage; it has a battery pack that can work as an ESS. This ESS will store excess power from renewable resources.

2.1.2 Smart Grid

Smart Grid is defined as an electricity power grid that uses digital communications technology to detect and respond to local changes in power usage [41]. Smart Grid includes various power operational and measures, such as smart meters, smart appliances, renewable power resources, and power efficiency resources [34], in addition, power generation, power transmission, and power control are important aspects of Smart Grid [43]. The design of a Smart Grid is based on six issues: to have two ways power and communication flow, to be self-healing, to be secure, to have and use power storage, to use renewable power resources and efficient management of power and demand [12]. These issues will be discussed in light of Smart Grid in the following subsections.

Figure 2-2: Visionary Graph of Smart Grid [44]

2.1.2.1 Smart Grid Issues

Power and communication flow is one of the major issues in the Smart Grid [45]. To control power resources, and manage these resources, many researchers, e.g. [16], [46], [47], studied the algorithms and protocols that connect Smart Grid components together. To fulfill its required duties, these power and communication connections should be reliable, scalable and secure [48], [49].

Security of Smart Grid is another crucial issue. Cyber system in a Smart Grid environment is not 100% reliable [49], [50], especially in the case of power and communications connections [49]. For this reason, the whole Smart Grid should be secured against attacks of vulnerable system components. These attacks should be studied at various grid layers and domains [51], [52].

Reliability is another issue in the Smart Grid. It means that the system will be available all the time and present the same level of services that makes our life easy, economy and comfortable [53]. In other words, we need to protect the power grid against fluctuations, and provision power resources, which ensures that the grid will be available all the times [54]. However, this goal is not easy, a comprehensive effort that includes managing our demands, our habits, our preferences in addition to a group of algorithms, schemes, and good design, all of these together might achieve reliability for the Smart Grid.

Smart Grid required the support of renewable resources such as the wind and solar cells [46]. Other non-renewable resources can be used in the Smart Grid. However, in the future only renewable resources might be used [55], thus, to control and benefit from these resources, Smart Grid needs to use power storage.

2.1.2.2 Smart Grid Applications

Applications in Smart Grid are categorized into two groups. Real applications group, such as smart meter, smart appliances, smart vehicles, and developing applications group, such as smart cities, smart roads. In this subsection, we will present one of the real applications of Smart Grid.

Figure 2-3: Different Types of Smart Meters [41]

A smart meter is an advanced power meter that can read the consumed power per time unit [56]. Smart meter system consists of smart meter, bi-directional communication connection, and control devices. These components give the smart meter the ability to execute commands remotely [57]. After reading power consumption, smart meter communicates with the grid to submit the collected information [58], [59]. Finally, smart meters can calculate consumption using different pricing schemes [57].

Smart appliances are the devices that realize services in cooperation with another device like the phones and computers [60]. These appliances represent another application of the Smart Grid. The smart appliance can be operated in two ways: directly, where the user entered operational preferences, or remotely, where Smart Grid manage and control these devices by sending directions through communication channels [22]. In the case of remote access, Smart Grid uses a number of algorithms that schedules appliances uses based on expected required power, operational time, prices, user preferences and priorities. These algorithms also give instructions to stop, pause, and delay or resume appliance operation [61], [62].

2.1.2.3 Aggregators in Smart Grid

Aggregators work as mediators between electricity companies and customers. Each aggregator has the needed technologies to supply demanded power to the customers. In addition, they can communicate and install control devices (i.e. smart meters) at the customer side. The aggregator represents a number of customers who respond to them. Therefore, aggregators work as a broker in electricity market. They negotiate with electricity companies on behalf of their customers about prices and demands. Moreover, aggregators reduce electricity prices for the customers if they allow aggregators to manage appliances operations especially at peak times [63].

2.1.3 Use of EV as Part of Smart Grid

As we mentioned previously, EV can be managed and controlled by Smart Grid algorithms [1]. In this manner, vehicles will follow Smart Grid directions, especially in power management concerns. Day-by-day power demands of houses and factories are increased. These demands need more planning and designing to protect and recover the power grid [4]. Conventional power grid consists of generators, transformers, distribution grids and controllers. These components have a peak capacity and if the demands are increased, the performance, the efficiency and the age of these components will degrade [64].

2.2 EV and House Power Consumption

To understand power demands in proportion to generated power, Figure 2-4 represents Ontario power production and consumption for the period from March 2012 until August 2013. The solid line represents the weekly average power demand, the dashed line is the average generated power, and the range represents the minimum and maximum power demand for the same period. From the figure, we infer that maximum power demand could exceed generated power.

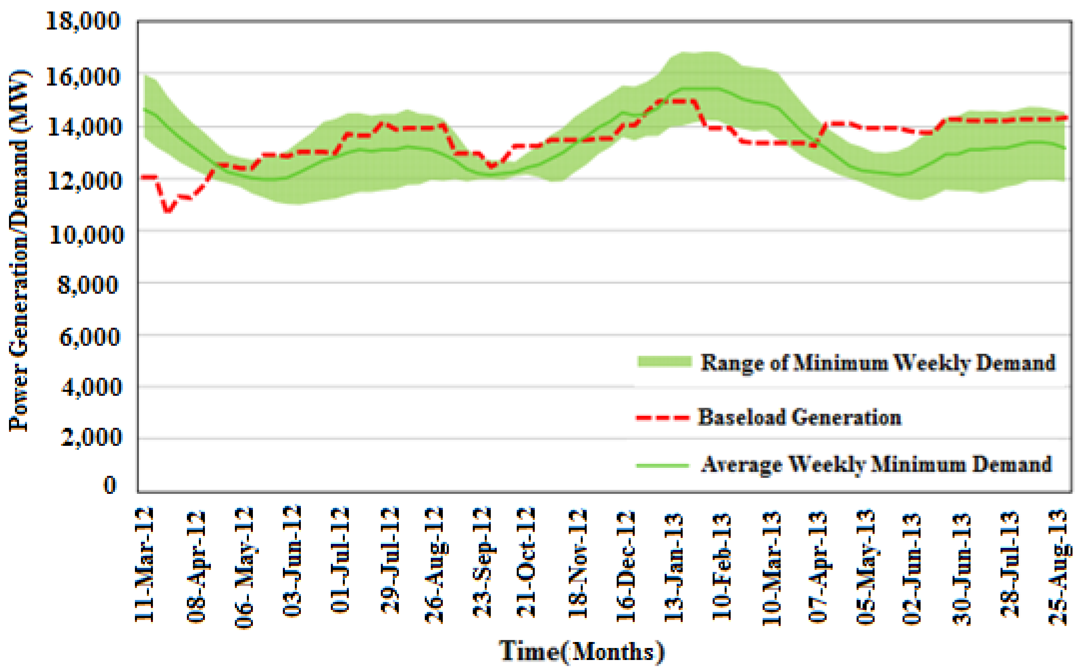

Figure 2-4: House Baseload and Minimum Demand [68]

House has a number of appliances and light system that represent the baseload of the house. Appliances such as water boilers, washers, dryers, air conditions, fridges, stoves, microwaves, and dishwashers represent the main load in the home. Appliances can be classified based on the ability to pause and resume into three types as proposed in [10]. These are interruptible and deferrable appliances, non-interruptible and deferrable appliances, and non-interruptible and non-deferrable appliances. Authors of [65] divided the appliances based on different control strategies into three classes: non-shiftable, time-shiftable, power-shiftable. In addition, in [22] appliances are divided into three types based on different working styles of primary power consumption units, induction coil, heating resistance, and an electronic circuit. All these classifications used by researchers to manage house power demands at peak times.

2.2.1 Demand Response Management (DRM)

DRM is defined as the group of methods and techniques that can be used for altering the user power consumption to match predefined goals, most of the times we use Demand Response (DR) instead of the DRM [66]. Power demand is growing at each moment for three reasons: power fluctuations at different times in the year, power consumption habits, and growing population.

Load management strategies are classified into direct and indirect strategies. Direct strategies uses the equipment such as smart meters to manage the load, while indirect strategies use the regulations, incentives and penalties (using different tariffs) to control the load. The goal of all strategies and classes is to lower demand during peak times [67]. To achieve this goal, power demands should be managed during the daytime by one of the following operations:

a) Peak shaving which aims to reduce the consumption of electricity during certain times, these times historically represent peaks of power consumption, and any increase in demand at these times could not be met and might affect the transformers [68].

b) Valley filling, which is a technique to transfer executing jobs from peak times to off-peak times, so we can change the time of executing jobs to minimize demands in high demands period [69].

c) Load shifting, this technique is a combination of the peak shaving and valley filling techniques. It aims to reduce consumption by rescheduling jobs or operations; this technique is used widely in the literature [70].

In addition, we have two complementary strategies: conservation strategy, and load growth strategy. These strategies care about performance and efficiency of the transformers and distribution network. Conservation strategy aims to reduce the consumption by increasing the efficiency of power use. While load growth strategy is designed to improve power transformers and generators by replacing inefficient fossil-fuel generators by high efficiency generators [64].

2.2.2 Householders Behavior and Electricity Use

To achieve the highest level of efficiency of electric system, researchers studied system components: the generators, the transformers, the distribution network and the appliances. They refabricated these components to meet efficiency requirements. For example, to leverage the efficiency of generators, authors of [55] suggested using new gas generators. In addition, they studied user behavior, because they found that user habits affect power consumption. They use various price schemes, and incentives to encourage users to follow power reduction recommendations.

2.2.2.1 Domestic Baseload

Domestic baseload or house base load represent the average consumed power of the houses in a city or a country for a period of time. The domestic baseload represents consumed power of house appliances and lights. To this end, EV power consumption is not included in the calculation of domestic baseload.

Household consumption varies significantly between different customers, day and night, weekdays and weekends, and summer and winter. Therefore, intensive study of customer's behavior will help solving power demand problem. Smart meters is used to collect information about house baseload. These pieces of information will be used to help customers to reduce their power bill; this reduction is based on changing negative habits related to power consumption, rescheduling appliances uses, using new efficient appliances, and using stored power in EV battery [19]. As shown in Table 2-1 residential sector consumed about 18% of the total produced power over the world. This percentage varies at different times and different places [71]. For example, people in North America and northern European countries use about 30% of total produced power for heating in winter.

Table 2-1: World Energy Consumption Sectors [72]

	Energy end use[2]	Electricity losses[3]	Total energy use[4]	Share of total energy use
End-use sectors				
Commercial	29	34	62	12%
Industrial	200	66	266	51%
Residential	52	40	92	18%
Transportation	101	2	103	20%
Total end-use sectors	382		524	
Electric power sector[4]	204			39%

Canada, for example, produced 539 and 503 TW for years 2005 and 2009 respectively [71]. Residential sector consumption was 28% in 2005 and ramped to 32% in 2009. These numbers justified government concern in finding solutions and other alternatives to meet the future power demands. Figure 2-5 from Natural Resources of Canada confirms these numbers.

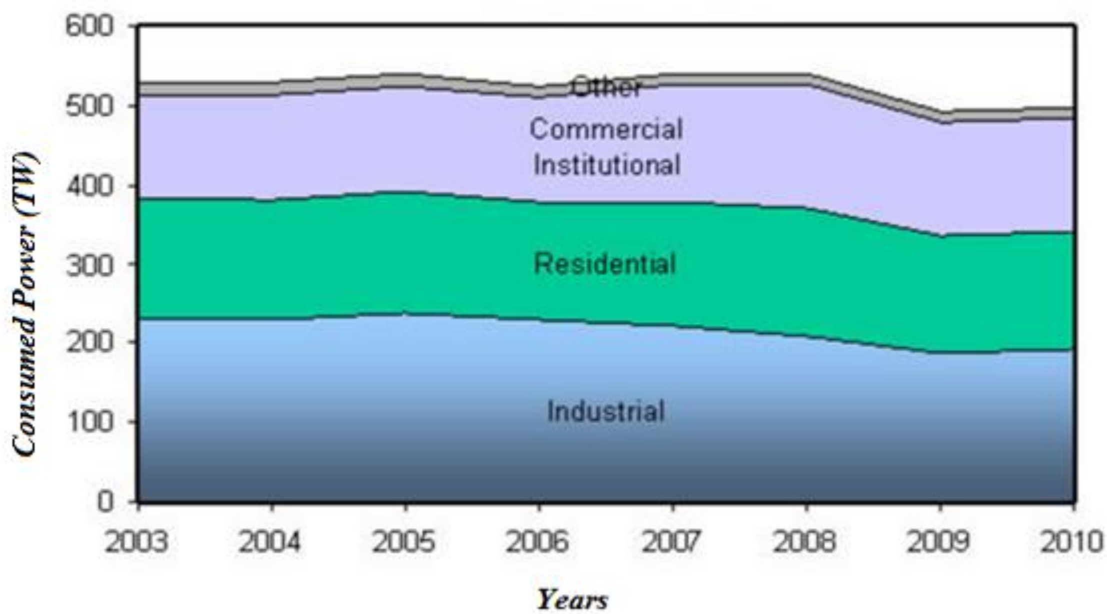

Figure 2-5: Canada Energy Consumption Sectors [71]

2.2.2.2 Time Use Data

To understand user behavior, the Time Use Data (TUD) technique is introduced. This technique ensures collecting data related to customer behavior at each time unit. Electricity use of household follow some patterns. These patterns can be inferred from the household activities. To estimate electricity use for houses, we collect user's information through surveys or smart meters. These pieces of information represent the activities, habits, and preferences of the users. To collect these pieces of information, authors of [73] suggest to give each person in the house a State of Activity (SoA) related to time. The transition from state to another means a change of activity. To use this assumption in the proper way, the authors determine many factors that should be considered, these are activity start time, activity type, activity place, and shared activities with another person.

Time use surveys gather data over time intervals through official statistics. In addition, gathered data is collected in one report. Then, TUD can be used to estimate the power consumption of the householder, this approach is used in [31]. Moreover, gathered data could be employed in the stochastic model to generate power consumption patterns synthetically [74].

2.2.3 EV Power Consumption

Power consumption of EV can be measured according to the range. A group of major factors dramatically affects consumed power, such as the vehicle weight, motor capacity, driving patterns, driving place, and engine efficiency. In addition, factors such as motor startup, using air condition, using other utilities inside EV, outside temperature, and route type also impacted consumed power [75]. For example, Tesla Model S [38] is the largest all wheels drive EV, the range of its 90 kWh battery is about 400 km. In practice, an EV travels an average of 53 km per day. Using simple math, if 1 kW costs 0.12 CAD, then the average day trip that consumes 10.3 kWh will cost 1.24 CAD. These numbers are important for two reasons. First, the operational cost of a EV is less than the operational cost of conventional vehicles, while the capital cost of EVs is higher than the capital cost of conventional vehicles. Second, the remaining of the battery capacity can be used to balance the electrical grid system.

2.3 EV Chargers, Charging Levels, and Battery Types

2.3.1 EV Chargers

Chargers can be classified into on-board and off-board chargers with unidirectional or bidirectional power flow [7]. If all charging equipment are installed on the vehicle, we call the charger on-board charger, in this case, the charger has limited size, weight, and extra cost is added. On the other hand, off-board charger system has no limited space and weight, and less cost [76]. Power flows in one direction on unidirectional chargers and both directions or bidirectional chargers. The unidirectional charger has fewer hardware requirements, simple interconnection, and low cost. Bidirectional chargers require more hardware and extra cost, but it supports the discharging operations [77]. In this thesis, we are interested in bidirectional chargers because we can use them for charging and discharging operations.

Bidirectional chargers have two stages the first stage has a bidirectional AC-DC converter that enforces power factor and the second stage is a bidirectional DC-DC converter that regulates battery current [76]. The most important feature of the bidirectional charger is the ability to work in charging and discharging modes. Therefore, it supports absorbing power from the grid, which is known as V2G operation and returning power to the grid, which is known as G2V operation. However, frequent charging and discharging processes caused battery aging problem. Also, the bidirectional charger has a metering issues and the necessity to upgrade the distribution grid [8].

Unidirectional chargers support G2V operation only, these chargers have one AC-DC stage, also components like AC-DC converter, diode bridge, and filter are used in manufacturing of this type. Unidirectional chargers have the advantage of low cost, lossless, high performance and simplicity in control and manage heavily loaded feeders due to multiple EVs [78].

2.3.2 Charging Levels

Charging levels are classified based on charging speed, charging voltage and used equipment into three levels (level 1, level 2 and fast charging). We will discuss these levels in this section. Charging levels have a direct connection with charging places, where each charging level might take place in one or more places. There are four suggested charging places home, work, commercial places, and supply stations. We will discuss these places later in this section.

2.3.2.1 Level 1 Charging

This level is the slowest charging level, it uses single-phase standard home power outlet with 120V. This charging level does not require further equipment, connections or special infrastructure. It can be used at home or work and can be used anytime [79]. The cost of Level 1 charging is minimum because no additional equipment is used. For many reasons, EV owners are recommended to charge their vehicles overnight. These reasons can be abstracted as following,

i) Reducing the cost of consumed power,

ii) EV owners have enough time to charge their vehicles until full,

iii) This is comfort charging option for the EV owners, and

iv) Encourage electrification (i.e. switching from conventional vehicles to EVs) [7].

However, level 1 charging is very slow; it takes 12-16 hours to fully charge the 24 kWh battery. The majority of EVs supported Level 1, where other EV supported other levels. To connect EV to the grid, SAE J1772 standard connector is used, which is shown in Figure 2-6 [8].

Figure 2-6: SAE's J1772 Combo Connector for AC or DC Level 1 and Level 2 [80]

2.3.2.2 Level 2 Charging

Level 2 charging can be used in private and public facilities [79]. On average, it takes 6-8 hours to fully charge the 24 kWh battery. Therefore, it has a moderate charging speed. Level 2 uses the outlets range from 208V to 240V, this outlet exists in houses and buildings in North America, in addition to the 120 V outlet, because houses use it for dryers, heaters, and Air-conditions [77].

Level 2 might be used in homes, in work or public places. However, extra equipment are required, such as special connections, and sockets [7]. Users prefer to use level 2 technology because it is fast and available. Although it costs higher than level 1. According to the connector, level 2 uses the SAE J1772 connector as in level 1 but with the addition of 2 pins on the connector to support the AC and DC currents [81]. The authors of [77] made a comparison between level 1 and level 2 using the Chevrolet Volt and they found that level 2 charging is more efficient than level 1 by 2.7% on average and up to 12.8% for shorter charge events that draw less than 2kWh from the grid.

2.3.2.3 Fast Charging

This level is the fastest, the most expensive, and the complex charging level. It takes 10-30 minutes to fully charge a 24 kWh battery [82]. Having fast charging rate requires extra equipment, special cables, and power sockets. Fast charging technology uses three phase power line, with 480V or higher which is twice as level 2. Moreover, additional space is required for this equipment. However, this technology cannot be used at homes or work, because of cost, space, and other connections so that it can be used only in supply stations [8]. Existing grid infrastructure in these areas cannot sufficiently fulfill burst in power demand for supply station services. Charger might be overloaded quickly based on the EV penetration ratio (P), where P is defined as the ratio of EVs to light vehicles, and schedule of charging and discharging. Power burst will cause losses in transformers, degradation in transformers lifetime, overload on generators, and overload on distribution lines. Additional investments will take place in lines, transformers, and generators [31].

2.3.3 Charging Places

EV may be charged at homes, at work places, at commercial places, and charging at supply stations. These places differ based on the level of charging and charger type [33]. To charge EV at home, at work or commercial places level 1 and level 2 might be used because of power line limitations. Fast chargers could be used on highways and supply stations. Moreover, fast charging could be used in commercial and residential areas if we embedded new coordination algorithms and additional enhancements to the current infrastructure [8].

2.3.4 EV Batteries and Motor Efficiency

The first EV was made after the invention of Lead Acid battery; this information reflect the strong relation between batteries and EV [83]. Moreover, batteries in the 19th and early 20th centuries had many disadvantages such as short trip times, long charging times, and poor durability. These factors slowed EVs evolution, and gave preference to ICE at those times [84]. Nowadays, the two major battery technologies are Nickel Metal Hydride (NiMH) and lithium ion (Li-ion) as shown in Table 2-2. Both technologies have negative and positive features such as handling high power, high-energy capacity, limited in weight and space, and have affordable costs.

NiMH is common in PHEV because of its mature technology and cooling system. However, it has short lifetime, and lower output power. On another hand, BEVs adopted Li-ion technology because of higher output power. But, Li-ion technologies should improve the cooling system and calendar life [36]. This short comparison leads to the conclusion that both technologies have advantages, but they also have disadvantages that need intensive effort to overcome.

Table 2-2: Battery Technology [85]

Company	Country	Vehicle Model	Battery Technology
GM	USA	Chevy Volt Saturn Vue Hybrid	Li-ion NiMH
Ford	USA	Escape, Fusion, MKZ HEV Escape PHEV	NiMH Li-ion
Toyota	Japan	Prius, Lexus	NiMH
Honda	Japan	Civic, Insight	NiMH
Hyundai	S. Korea	Sonata	Lithium polymer
Chrysler	USA	Chrysler 200C EV	Li-ion
BMW	Germany	X6, I3 Mini E (2012)	NiMH Li-ion
BYD	China	E6	Li-ion
Daimler Benz	Germany	ML450, S400 Smart EV (2010)	NiMH Li-ion
Mitsubishi	Japan	iMiEV (2010)	Li-ion
Nissan	Japan	Altima Leaf EV (2010)	NiMH Li-ion
Tesla	USA	Roadster (2009)	Li-ion
Think	Norway	Think EV	Li-ion, Sodium/ Metal Chloride

The developing race between battery technologies in addition to generous governmental grants, will influence batteries industry in the future. Moreover, any enhancement in battery technology will affect EV's future. Long charging time, limited space, limited weight, battery capacity, charging and discharging efficiency, charger cooling system and long lifetime. All these challenges will determine EV's future and battery technology's future [36].

In terms of efficiency, EV motor has a higher fuel efficiency than ICE. The fuel efficiency of the conventional vehicle is about 14% - 30% of the used fuel. On another hand, EV efficiency is up to 65% of the used power [72].

2.4 Vehicle to Home Standards and Algorithms

Based on power flow direction, power flow technologies between vehicle and grid, can be classified into two types: Vehicle to Grid (V2G) technologies and Grid to Vehicle (G2V) technologies. V2G and G2V technologies use three elements to transport power successfully, power connection, control unit, and metering system. The most important element is control unit that manages and controls other elements. In addition, it ensures the safety and security of charging and discharging processes. Control unit uses a number of algorithms and procedures to manage other elements. The third element measures the transported power quantities and battery SoC ratio, these quantities are the inputs of control unit element [32].

In the following sub-sections, we will review V2H standards specially V2H charging and discharging standards. In addition, we will review V2G algorithms and V2H algorithms. Finally, we will review pricing schemes.

2.4.1 V2H Charging Standards

V2H technology needs a group of standards that govern the hardware and software products compatibility. These standards guarantees that all users over the world will receive the same level of products or services. Many worldwide organizations, institutions, and commissions, such as IEEE, ISO, and International Electrotechnical Commission (IEC), The Society of Automotive Engineers (SAE), the Electric Drive Transport Association (EDTA), the European Standardization Commission (CEN), Japanese Industry Standards (JIS), and Japan EV Association Standards (JEVS), spent time and effort to set these standards [86]. We will review the charging (i.e. power flow) standards that guarantee the inter-operability between EV and Electric Vehicle Supply Equipment (EVSE).

IEEE 1547

This standard forms the interconnection of distributed resources with electric power systems. It provides the performance, the operation, the testing, and the safety requirements relevant to interconnection of distributed resources with electric power. These requirements shall be met before any power flow operation.

SAE J3072

This standard establishes interconnection requirements for EV interactive inverter system with power grid from EVSE. In addition, it defines required communication between EV and EVSE to authorize discharging at EVSE site, these requirements will be used in conjunction with IEEE 1547 standard for interconnecting distributed resources with electric power grids [80].

SAE J1772

This standard is the most known SAE standard. It provides the physical, electrical, functional, and performance requirements that facilitate conductive charging of EV. In addition, it defines the electrical interface of the charger between the EV and EVSE. Safety and performance are the targets of designing and implementing J1772 connector. Moreover, the J1772 connector is able to establish communications between the EV and EVSE without affecting power transportation processes [80].

2.4.2 V2G Algorithms

Algorithms related to V2G or G2V can be classified based on the nature of the algorithm into five types: coordination algorithms, scheduling algorithms, pricing algorithms, communication algorithms and admission control algorithms [32]. Moreover, improving algorithms in one or more of these types will improve the V2G technology, increase its reliability, and encourage people to adopt EVs [17]. Coordination and pricing are tied to each other because any charging or discharging process will reflect on the customer power bill. Therefore, we will review these two types of algorithms.

EV charging operations can be divided into two types, centralized charging and decentralized charging. In centralized charging, algorithms aimed to coordinate EV charging operations to reduce power demands at peak times, or to shift the peak demand from time to another. Decentralized algorithms aimed to reduce uncoordinated EV charging operations by finding new methods for charging EV batteries or using Battery Swap Stations (BSS) to swap batteries instead of charging them [87].

In this section, we will review centralized and decentralized algorithms. However, we will focus on centralized algorithms because we are convinced that we can use Smart Grid capabilities to run centralized algorithms. Moreover, decentralized option has many limitations, such as it serves a limited number of EVs, the cost of swapping battery is not defined, swapping time, a limited number of BSSs [88].

Present algorithms in V2G can be used in V2H and vice versa. However, additional constraints will be applied in some cases to keep the algorithms working correctly. In the following sub-sections, we will discuss scheduling algorithms in both V2G and V2H and pricing algorithms in the literature.

2.4.2.1 V2G Algorithms

In literature, we found that charging coordination algorithms are classified based on the purpose of coordination algorithm, peak shaving or peak shifting.

The authors of [65] proposed two heuristic algorithms to solve the coordination problem. They suggest a solution to reduce waiting time of vehicles at a charging station. However, they did not consider the power demands of the houses, and they did not discuss the relation between power prices and consumption. In [89], the authors proposed the use of incentive-based charging coordinating algorithm. They suggested Demand Side Management (DSM) approach to reduce power cost based on game theory. However, they did not consider the flexibility of user trips and the relation between the prices and power demands. The authors of [90], [91] used factors such as charging duration and charging rates of multiple EVs to coordinate and reduce consumed power from the grid. However, they ignored the role of pricing schemes, and incentives.

In [33], [92], the authors proposed coordination algorithm based on Markov Chain Monte Carlo model to predict departure probability based on real statistics from Portugal statistics and UK 2000 Time of Use Survey (TUS) respectively. Authors of [33] applied proposed algorithm in the period between (5:00 PM and 10:00 PM). In addition, they focused on the grid benefits than user benefits. However, they did not use their algorithm to solve the peak demand problem of whole peak time. The authors of [92] applied a case study and found that the integration of a large number of EV will not affect the robustness of the grid. However, they emphasized more on the health of distribution grid and referred to the EV battery as a part of the solution without describing coordination algorithm.

The authors of [1], [66] developed optimization strategy to manage and control household operations based on real-time price signal. They applied various algorithms based on the change in the price of electricity. In [66] the authors used the power price to encourage managing the use of appliances in the house. A home Energy Management System (EMS) is proposed in [1] to optimize the effect of using house appliances and EVs on the stability of the grid, they also used EV battery as ESS to balance the grid. However, both [1], [66] did not consider EV owner trip flexibility.

The authors of [18] suggested a bi-directional trading market between the user and the grid. In addition, they suggested the use of incentives and penalties to encourage the users to reduce their consumption during peak times. In [5], the authors used weather forecast to predict the amount of renewable power that can be used to support the grid. They also suggested using EV battery to store unused power form renewable resources. However, authors of [5], [18] did not consider a change in owner's trip schedule.

2.4.2.2 V2H Algorithms

V2H, which is a special case of V2G aimed to use the home as a point of contact between EV and Smart Grid. In addition, V2H technologies and algorithms might use the stored power in EV battery pack to balance the home power consumption instead of balancing power demands in the grid or micro grid [1]. In all cases, EV owners should know how to use and save their vehicle battery [21]. In this subsection, we will discuss these techniques and algorithms, which are designed and specialized for V2H operations.

The authors of [66] proposed the use of Demand Response (DR) to manage the charging and discharging operations. Also, stored power will be used to balance home power consumption in peak times. However, the proposal did not use the stored power in case of low house power consumption.

In [90], the authors proved that using stored power in EV battery through V2H and V2G operations will reduce the load interruption and increase the reliability of the classical distribution system, especially in terminal points that required a long time to repair faults in local transformers or distribution lines. However, they did not discuss power prices and flexibility in trips schedule of EV owners.

A stochastics optimization of DR management model for residential appliances based on real-time power price is proposed in [10]. The model divided home appliances into three categories based on the ability to interrupt and defer current operation to reduce consumed power during peak times. However, they ignored trip schedule changes. Authors of [93] proposed a centralized algorithm to schedule uses of EV and home appliances for the purpose of reducing consumed power at peak times. In addition, they proved proposed model using simulation and mathematical model. However, they ignored different pricing schemes and dynamic change of EV owner trip schedule. An Integer Linear Programming (ILP) optimization technique is proposed by authors of [94]. The proposed technique shaves the peak of houses power consumption using the power stored in the battery of EV. Moreover, simulation and mathematical model proved that ILP technique could be used in residential and common places. However, the authors did not use pricing schemes, and they ignored EV owner flexibility.

2.4.2.3 Pricing Schemes

In the literature, two pricing schemes were proposed to charge the customers for their electric consumption. The Time of Use (ToU) pricing scheme and the Real Time Pricing scheme (RTP). Coordination algorithms used these schemes to prove the correctness of their algorithms. Authors of [11] present a novel approach to find the optimal ToU price in the market. The proposed strategy aimed to change end user habits or change the operational hours to increase the customers benefit. In [95], the authors proposed new pricing model based on ToU scheme to encourage the customers to charge their vehicles during off-peak times. In addition, they proposed coordination model for charging and discharging EVs based on their pricing model to reduce the consumed power at peak times. Hierarchical clustering approach that converts the RTP to ToU without pre-knowledge of pricing blocks is proposed in [20]. They proposed dividing the RT period into half hour slot and then clustering the settlement periods in groups that have the least price rate difference. In addition, they applied the scheme for all seasons, and they found that customers with typical load would not be affected. However, companies will gain extra benefits.

The idea of RTP is to change the price of energy up or down at each time slot, in proportion to the price of fuel or power demands. The authors of [96], [97] uses this approach of pricing. They proposed a centralized algorithm that calculates the price of the next time slot based on the current price, the fuel price, the consumption expectations of the next time slot and demand history. The authors of [97] proposed an online real-time pricing algorithm based on Markov Chain Model. In addition, they initially assumed that the price is picked from the predefined finite set, and then the Markov Chain is used to produce real-time price. In [98], the authors suggested a new mechanism to generalize real-time pricing. They proposed the use of incentives for customers and suppliers if they change their pricing scheme to real-time scheme. Moreover, they present a guaranteed mechanism under moderate constraints to fulfill the demand of customers and safe operations of an electrical grid.

Chapter 3: System Model

This chapter discusses the system model of EV in terms of power and price. In addition, it presents the house load and the role of EV in reducing the overall load. This chapter consists of two sections. Section 1 discusses the house and EV power sub-models in addition to the relations that govern these models. Section 2 presents the FCD algorithm and its model for charging and discharging coordination.

3.1 House and EV Power Sub-models

3.1.1 House Sub-model

The system consists of a number of houses (H), each house has a number of appliances (N) these appliances consume amounts of power that are proportional to its operation hours. Time is divided into T equal time slots. Over any time slot, an appliance can be either operational or idle. The set of time slots over which the appliance is operational is denoted by ($\mathrm{O}_{\mathrm{T,n}}$). The total power consumed by the n^{th} appliance over a period of 24 hours where each appliance consumed amount of power in time slot (t) equals ($P_{C,n}$) can be written as

$$\mathrm{P}_{App,n} = \sum_{\mathrm{t=1}}^{\mathrm{T}} \mathrm{P}_{C,n} \, . \, A_{t,n} \, , \tag{3.1}$$

Where

$$A_{t,n} = \begin{cases} 1, & if\ t \in O_{T,n} \\ 0, & other\ wise \end{cases}$$

The total power consumed by the H^{th} house that has *N* appliances over 24 hours window can be written as

$$\mathrm{P}_{h\_Total} = \sum_{\mathrm{n=1}}^{\mathrm{N}} \mathrm{P}_{App,n}\ . \tag{3.2}$$

Using the previous equation we can calculate the total consumed power for all houses in the model using the following equation.

$$\mathrm{P}_{houses} = \sum_{\mathrm{h=1}}^{\mathrm{H}} \mathrm{P}_{h\_Total}\ . \tag{3.3}$$

3.1.2 EV Sub-model

The residents of H houses are assumed to have a total of V EVs. Of these vehicles $N_{EV\_ratio}(t)$ are participating in charging and discharging operations. The ratio of participant vehicles depends on the owner trip probability at each time slot ($P_{Trip}(t)$). In this thesis we assumed that the day is divided into two periods; peak period between 7:00 AM and 7:00 PM, and off peak period between 7:00 PM and 7:00 AM.

State of Charge (SoC) ratio is initially a uniform random value between (0% - 100%) for all vehicles. In addition, we assumed that all vehicles are able to charge during the off peak times. Therefore, at 7:00 AM most EVs are fully charged. SoC for V^{th} vehicle at the end of a trip is denoted by SoC_{After}. The distance travelled in a particular trip by the V^{th} vehicle is denoted by (D_t^v). The uniform random variable over the range [0, D_{Max}] is used to generate a distance vector of expected trips. D_{max} is the maximum distance that a vehicle can travel with a full charge for instance 160 km for Nissan Leaf, and 400 km for Tesla Model S. Using these distances, the SoC reduction at the end of a trip of V^{th} vehicle is denoted by SoC_{Trip}, can be written as

$$\mathrm{SoC}_{Trip} = \frac{D_t^v * \mathrm{SoC}_{Full}}{\varepsilon * D_{max}}. \tag{3.4}$$

Where ε is the driving efficiency factor, and it depends on EV driving efficiency, driving route, AC to DC inverter efficiency, and charging or discharging efficiency. Therefore, $\varepsilon = 1$, in case of ideal circumstances, $0 < \varepsilon < 1$, otherwise. SoC_{Full} is the full battery state of charge which can be used to drive the maximum distance D_{max}.

3.2 The Proposed FCD Algorithm

The proposed algorithm applies charging and discharging processes during peak times between 7:00 AM and 7:00 PM to help solving the power demand problem at peak time. We assume that the algorithm control lies at the aggregator side. The aggregator starts communication with each house and collect power consumption information about these houses through smart meters and surveys. Then, the aggregator will organize charging and discharging operations of his customer's vehicles. The communication between the aggregator and the houses is out of thesis scope. However, we assumed that a communication channel is available all the time between the aggregator and the houses. This channel will carry vehicle's SoC and the orders of charging and discharging. As shown in Figure 3-1, the aggregator uses the proposed algorithm to decide which EVs will charge and which EVs will discharge based on user trip probability, needed power for the trip, and time. The main two factors that affect the algorithm is trip schedule and SoC of each EV in the neighborhood. The algorithm aims to reduce power bill and shave peak demands without ignoring user's preferences.

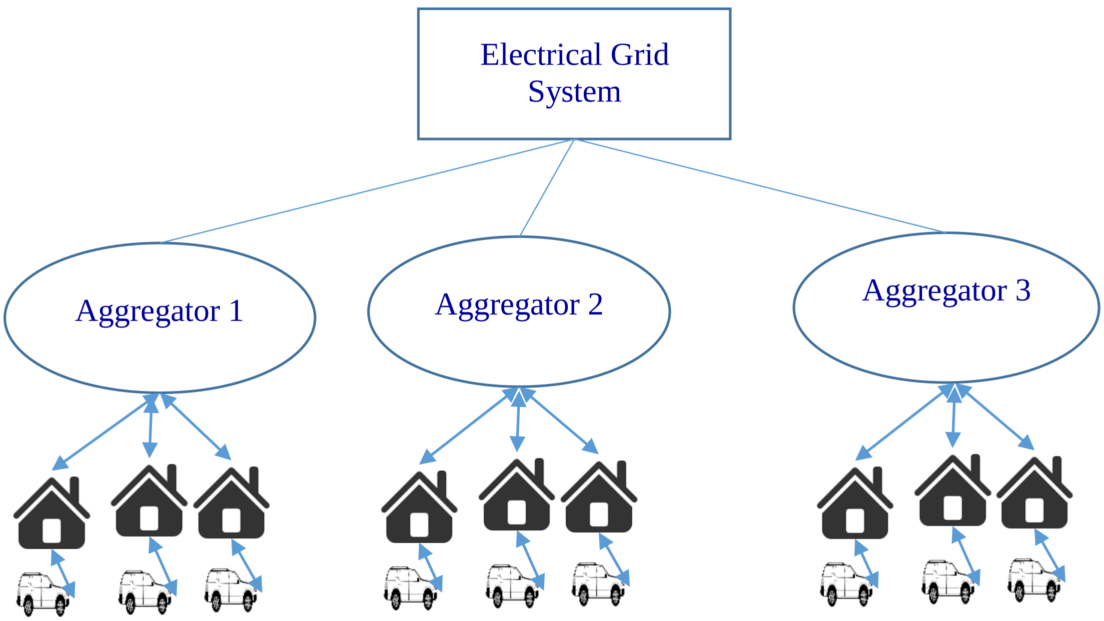

Figure 3-1: Aggregator Role in FCD Algorithm

In the purpose of increasing the reliability of our algorithm, we study four EVs classified into small, medium and large sizes. These EVs are classified based on three factors: the battery capacity, charging rate and charging efficiency. According to battery capacity, Tesla Model S has the largest capacity, followed by Toyota RAV 4 EV that has medium battery capacity and finally, BMW i3 and Nissan Leaf that have small capacity. Moreover, RAV4 EV has the highest charging rate followed by Tesla Model S and finally BMW-i3 and Leaf. BMW-i3 and Tesla Model S have the highest charging efficiency; also, Nissan Leaf and RAV4- EV have very close efficiencies. Table 3-1 present these factors and assigned values of each EV for each factor.

Table 3-1: EV's Specifications [38], [75], [99], [100]

EV Make	Battery Capacity kWh	Charging Rate L2 (average) kW	Charging Efficiency (average)
BMW i3	18.8	3.83	92.2%
Nissan Leaf	30	3.79	86%
Toyota RAV4	41.8	7.2	85.6%
Tesla Model S 2015	90	5.5	92%

3.2.1 Flexible Charging and Discharging Algorithm

The idea of our Flexible Charging and Discharging (FCD) algorithm is to shave power demands in peak times using stored power in EV battery. Charging process might happen at peak or off peak time based on the battery SoC and the required power for the trip. In addition, in case of emergency, when the vehicle leaves the house without sufficient SoC to meet the required power of the trip, owners can charge at charging station. However, discharging processes will take place during peak times between 7:00 AM and 7:00 PM. Peak time gained it's name from higher power demands. Therefore, the curve that represents consumed power will go up during this time. In addition, power prices increased at this time. For example, electricity prices jumped in Ontario from 8.3 cents/kWh at off peak to 12.8 cents/kWh at mid peak and reached 17.5 cents/kWh at peak times [101].

FCD algorithm is not mandatory for customers. However, the algorithm encouraged EV's owners to charge their vehicles at night during off peak time and low prices. Therefore, by 7:00 AM the EV battery will reach full charge even in the case of using level 1 chargers. In addition, EVs are ready to departure or remain at home based on the owner's trip plan. All stayed EVs might participate in FDC algorithm or not. If they participated, they could support the grid or the house during peak times.

Moreover, to give the EV owner higher degree of flexibility to change his travel plans, we consider two time slot scenarios: a 30-minute scenario and 10-minute scenario. Therefore, the owner may change his/her plan at any time slot. Such charges take place at the beginning of the following time slot.

As shown in Figure 3-2, the FCD algorithm calculates the required power for upcoming trip, and checks if the SoC in the battery is sufficient. If the SoC is not sufficient, the algorithm invokes EV charging until the power level is sufficient or departure time comes. In case that the EV driver has no planned trips, the FCD algorithm discharges the EV battery until SoC equal 20%. We consider the depletion threshold to be at 20% [36]. In other words, the battery efficiency will be harmed if we discharge the battery beneath this ratio. FCD algorithm updates the SoC for all participant EVs at the beginning of each time slot based on the scenario time. In addition, we studied four penetration ratios to show how the FCD algorithm works with large number of EVs.

For example, if a vehicle has a trip at 9:00 AM and it has a full battery charge at 7:00 AM, and it has 20 km trip distance. FCD algorithm calculates the required power to fulfill the trip from Equation 3.4 and subtracts this value from the total SoC in the battery and starts discharging while the vehicle has not departed or the required SoC reached.

Another example, if a vehicle has a 100 km trip at 5:00 PM and its SoC was 40% at 2:00 PM. The algorithm calculates the power needed to fulfill the trip, and since the SoC is not enough, the vehicle starts charging until the SoC is sufficient for the trip or the trip time is coming.

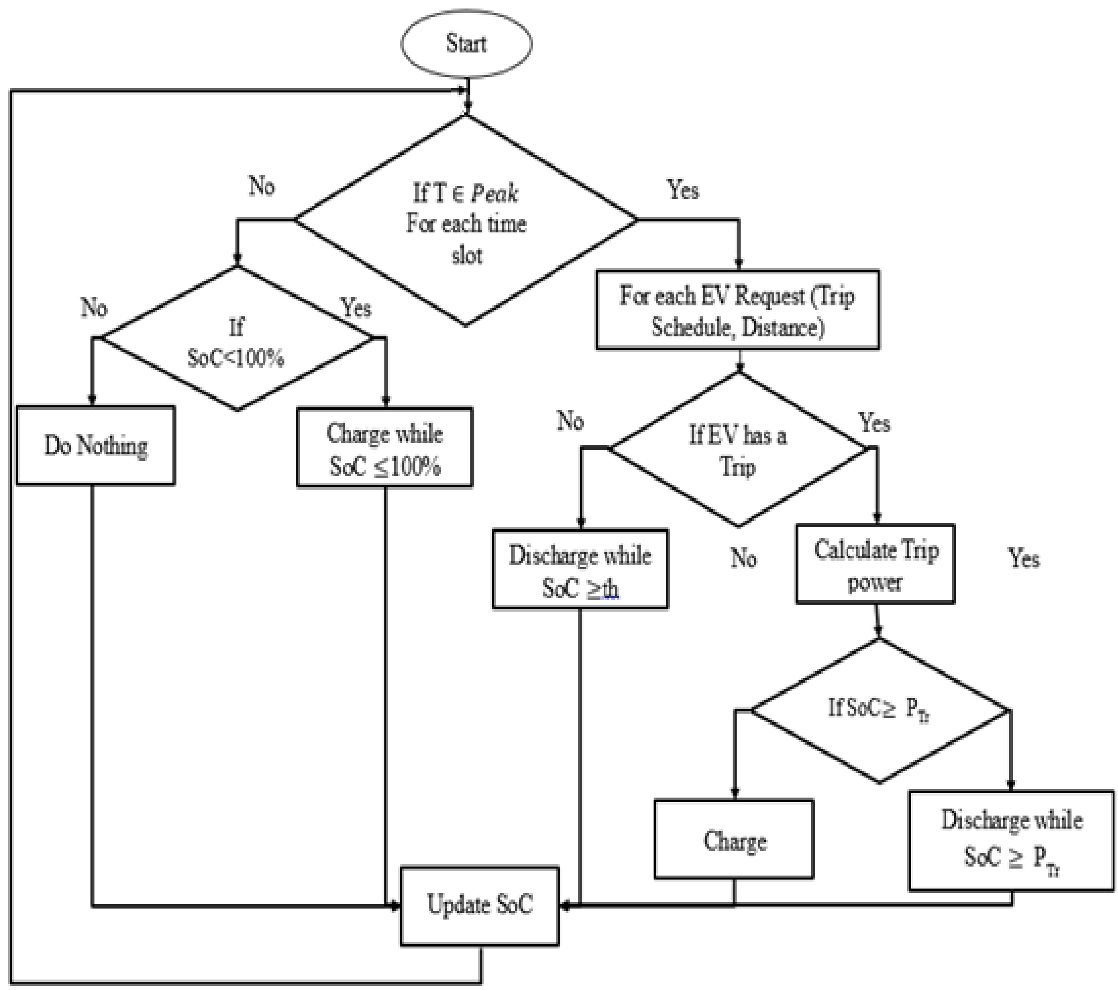

Figure 3-2: FCD Algorithm Flow Chart

3.2.2 Mathematical Formulas for FCD Algorithm

In general, FCD algorithm cares for three main points while it uses EV battery to shave peak of power demands: owner flexibility, battery health, and EV performance. Therefore, FCD algorithm uses a set of mathematical relations to guarantee these goals. In this section, we will present these relations and discuss each one of them.

At each time slot, each EV can be charged or discharged by the amount of power referred to as charge step (Ch_{step}) and discharge step ($DisCh_{step}$), respectively. We calculate the charging and discharging steps by multiplying charging efficiency (Ch_{eff}) and charging rate (Ch_{rate}) or discharging efficiency ($DisCh_{eff}$) and discharging rate ($Disch_{rate}$) by Time step (*S*). S is equal to the scenario time slot divided by 60 minutes. So, S is 0.5 for 30-minute scenario, and (1/6) for 10-minute scenario. Hence, Ch_{step} and $DisCh_{step}$ become as

$$Ch_{step} = Ch_{rate} * Ch_{eff} * S, \tag{3.5}$$

$$DisCh_{step} = DisCh_{rate} * DisCh_{eff} * S\ . \tag{3.6}$$

The exported power from Vth EV to the grid (SoC_{exp}) can be calculated as

$$SoC_{Exp}(EV, t) = 0.8 * SoC_{EV}(t) - SoC_{Trip}(t). \tag{3.7}$$

Where 0.8 is the result of subtracting battery depletion threshold (0.2) form the full SoC(SoC_{full}). On the other hand, the Vth EV consumed power (SoC_{Con}) is given as

$$SoC_{Con}(EV, t) = SoC_{Trip}(t) - 0.8 * SoC_{EV}(t). \tag{3.8}$$

Based on Equation 3.7 and Equation 3.8, we can calculate the total consumed power from the grid and total returned power to the grid for all EVs at all time slots by summing the SoC from Equation 3.7 and Equation 3.8. This yields

$$SoC_{Tot\_Dis} = \sum_{t=1}^{T} \sum_{EV=1}^{EV\_ratio} SoC_{Exp}(EV, t), \tag{3.9}$$

$$SoC_{Tot\_Ch} = \sum_{t=1}^{T} \sum_{EV=1}^{EV\_ratio} SoC_{Con}(EV, t). \tag{3.10}$$

Where T is 48 for 30-minute scenario and 144 for 10-minute scenario.

To calculate the total power consumed by any house, in addition to consumed power for EV charging, and exported power from EV to the grid, we use the following equation

$$P_H = P_{h\_Total}(t) + \sum_{t=1}^{T} [SoC_{Con}(t) - SoC_{Exp}(t)]. \tag{3.11}$$

The total power consumed by the neighborhood can be calculated from equation (3.12)

$$P_G = \sum_{h=1}^{H} P_H\,. \tag{3.12}$$

3.2.3 Cost Reduction Using FCD Algorithm

The second goal of the proposed algorithm is to minimize power bill of vehicle's owner. The difference between peak and off peak power prices guarantees a profit. This profit can be shared between the owners and electricity companies. To balance between the benefit of the owners and electricity companies, we should use part of the benefit to recompense EV owners or even the customers to encourage them to use the electricity in a wise way. In addition, electricity companies must have a share of benefit to help them to afford maintenance and other services expenses.

In this thesis, we used ToU pricing scheme to calculate profit amount of using FCD algorithm. Moreover, we derived a set of equations to calculate the profit of using FCD algorithm for the owners or electricity companies. In addition, we suggest to use the profit of power exchanging to reduce owners power bill.

The cost of consumed power and the cost of returned power can be written as in Equation (3.13) and Equation (3.14) respectively.

$$Cost_{Con}(t) = SoC_{Con}(t) * \; Price(t), \tag{3.13}$$

$$Cost_{Exp}(t) = SoC_{Exp}(t) * \; Price(t). \tag{3.14}$$

Where,

$$Price(t) = \begin{cases} 0.08, \; if \; t \in off \; peak \\ 0.12, \; if \; t \in on \; peak \end{cases}.$$

Using the previous equations we can calculate the total cost of consumed and returned power for all houses in the model using the following equation.

$$Cost_{Total}(t) = \sum_{t=1}^{T} Cost_{Con}(t) + \; Cost_{Exp}(t). \tag{3.15}$$

Chapter 4: Simulation Results

4.1 Introduction

In this chapter, we have three sections in addition to this introduction. Section 2 will discuss the performance metrics and confidence interval technique. In Section 3, we will mention simulation parameters. Finally, FCD algorithm results will be discusses.

4.2 Simulation Parameters

The first step in this thesis was building a simulator using Matlab, this simulator uses a predefined set of constants, variables, and relations (i.e. probability of parking vehicles at home on every time slot) and generate another set of random variables (i.e. initial SoC) to simulate the environment of electric vehicles in smart grid. The simulator deals with the power consumption of each house appliances as one number. This random number is generated to be around the average power consumption of the house. During the simulation, many parameters have been used to present the EVs and the Houses. These parameters help to show the results and to prove the validity of the proposed algorithms. Simulation parameters and their values are very important for those who intend to read the thesis and compare his/her with our work and results.

Some simulation parameters, such as (H) and (P), are chosen as shown in Table 4-1 to accurately compare proposed algorithm with other works in the literature. Simulation parameters can be divided into two tables, table of simulation parameters, and table of EV trip status parameters.

Table 4-1: Simulation Parameters

Parameter	**Value**
EV Types	Nissan Leaf, BMW i3, Tesla Model S, Toyota RAV 4 EV
Ch_{rate}	2.4, 3.7,5.5, 7.2
EV Charging Efficiency (%)	86,92
EV Battery Capacity (kWh)	18.8, 30, 41.8, 90
P	10%, 20%, 50%, 100%
EV Initial SoC	Uniform distribution Random number between 0%-100%
H	42

Table 4-2: EV Trip Status Parameters

Parameter	**Description**
SoC_{After}	Uniform distribution Random number between 20%-50% SoC_{EV} (i.e. SoC before trip)
$P_{Trip}(t)$	Probability of trip at time (t)
th	Battery Depletion Ratio =20%

4.3 Performance Metrics

4.3.1 Average Consumed Power

Average consumed power is used to measure the consumed power per time. This metric describes the domestic and EV power consumption at different times.

4.3.2 Power Loss

Inefficient chargers and connections cause Power loss. Which means that the absorbed power from the grid is larger than the stored power in the battery pack. One of our research goals is to determine the amount of power loss.

4.3.3 Power Cost

Cost factor is very important for all stakeholders: customers and electricity companies. Based on the costs and the profits stakeholders determine whether to adopt the algorithm or not. Therefore, to study the effect of using the FCD algorithms on the customers power cost this metric is used.

4.4 Simulation Results

In this section, we present FCD algorithm simulation results compared to two other works. The results will be divided based on the scenario and the performance metric. Figures and discussions show the validity and correctness of FCD algorithm in proportion to other works.We ran the simulation for a neighborhood of 42 houses, each house resident may have a EV. The number of participant EVs varied based on probability of trip for each resident.

Two scenarios have been used to study the effect of using EVs on the power demands. In addition, to use the EV battery as ESS, without affecting the performance of EV, the first scenario is based on the 10-minute time slot, and the second is based on the 30-minute time slot. The main differences between these scenarios are charging or discharging step, the required time to change trip schedule. In addition, 10-minute scenario divided the day into 144 time slots, at the beginning of each time slot, the FCD algorithm generated some random numbers. These random numbers in addition to other parameters have been used to calculate the various amounts, consumed and returned power, power loss, and power cost. In the 30-minute scenario, the day is divided into 48 time slots, and the algorithm works as well as in 10-minute scenario.

4.4.1 Average Consumed Power Results

4.4.1.1 10-minute Scenario

The following figure represents the total consumed and returned power in FCD algorithm, Berthold algorithm, and Wang algorithm. The figure represents the total consumed and returned power for all houses in the system. Figure 4-1 shows the superiority of FCD algorithm over both algorithm during the same period. The figure represent positive and negative values. The positive values represent that the EVs consumes power from the grid in this time slot. The negative values represent that EVs returned power is more than consumed power.

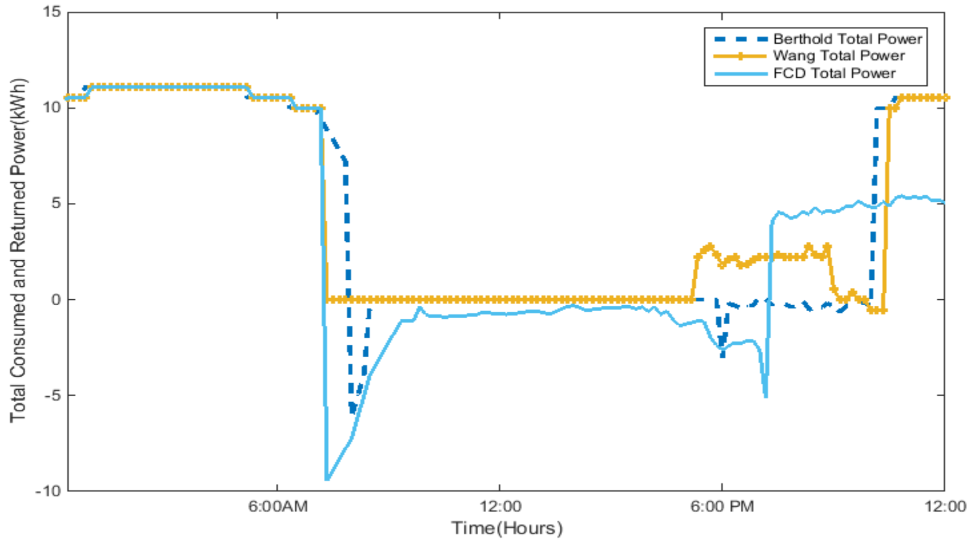

Figure 4-1: Total Consumed and Returned Power in FCD, Wang, and Berthold Algorithms, P=50% and Ch_{rate}=3.7

Figure 4-2 represents the average returned power in FCD, Wang, and Berthold algorithms. Between 7:00 AM and 7:00 PM FCD algorithm is the best on the average returned power.

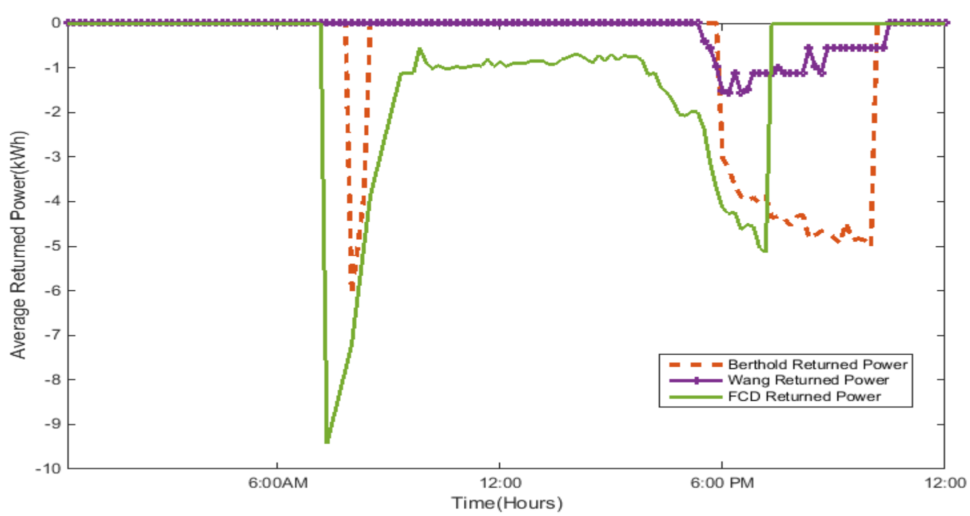

Figure 4-2: Average Returned Power in FCD, Wang and Berthold Algorithms, P=50% and Ch_{rate}=3.7

In Figure 4-3 and Figure 4-4, we studied the average returned power and the average consumed power under different levels of penetration. As shown in Figure 4-3 and Figure 4-4 any increase in the number of EVs will increase the average consumed power from the grid. In addition, we can infer from Figure 4-3, and Figure 4-4 that the use of FCD algorithm will reduce the peak of Average consumed power by returning the stored power to the grid. From Figure 4-3, we notice that the values from consumed power curves become closer to the normal consumption directly after start using FCD algorithm. Therefore, we can say that the FCD algorithm will keep the demands within acceptable ranges using the power stored in the EV batteries.

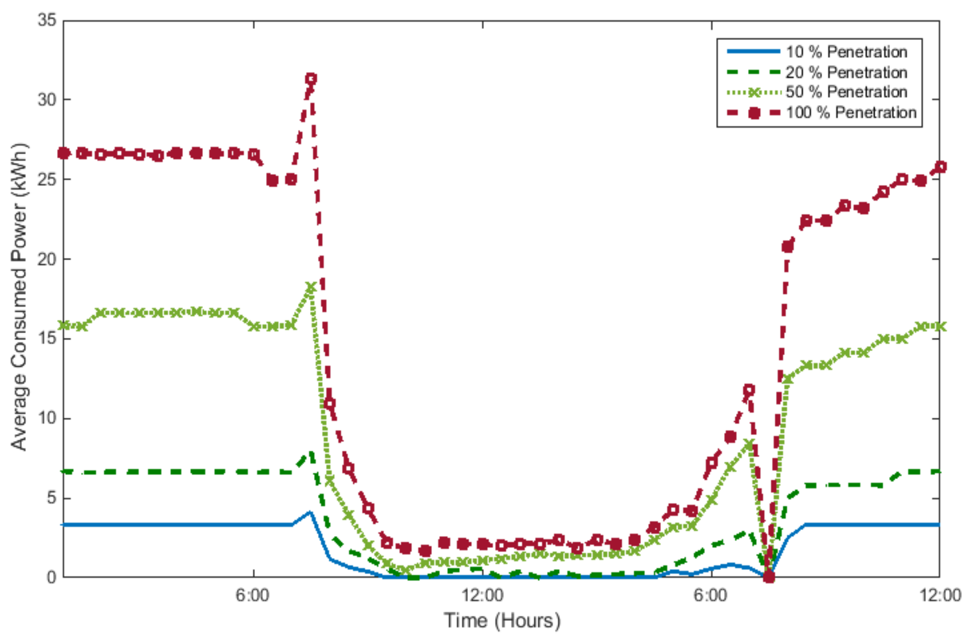

Figure 4-3: Average Consumed Power with Various Penetration Ratios,

Ch_{rate}=3.7

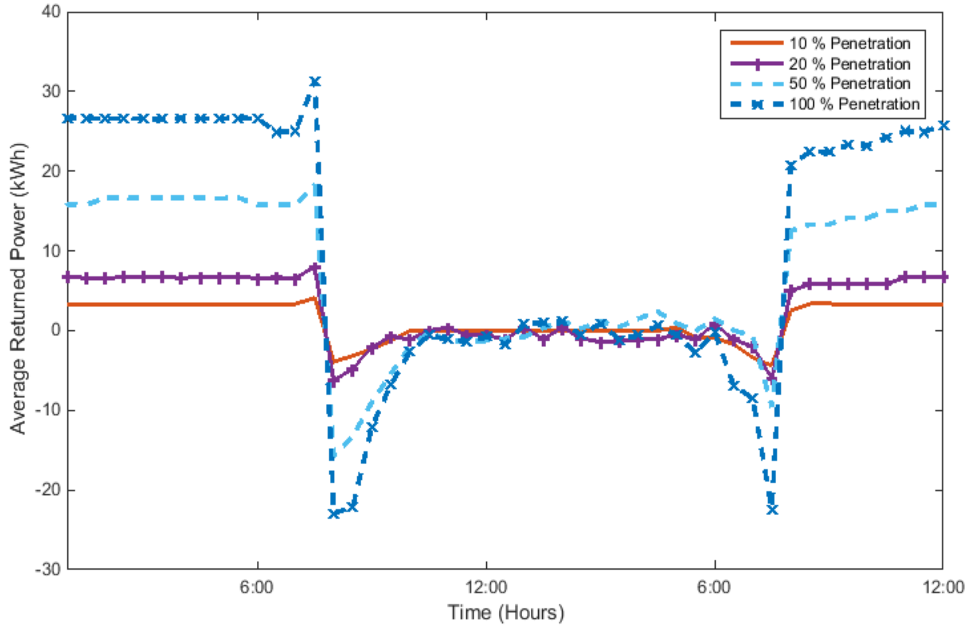

Figure 4-4: Average Returned Power with Various Penetration Ratios,
Ch_{rate}=3.7

4.4.1.2 30-minute Scenario

The following figures represent performance metrics based on 30-minute scenario. We notice that FCD algorithm works fine at both scenarios. In addition, 10-minute scenario gives more flexibility to the EV owner to change his trip plans.

In Figure 4-5, the total consumed and returned power for all algorithms are calculated using the 30-minute scenario. FCD algorithm still represent the dominant algorithm after working for 12 peak hours. Berthold algorithm represent a good choice. However, it is limited to evening hours.

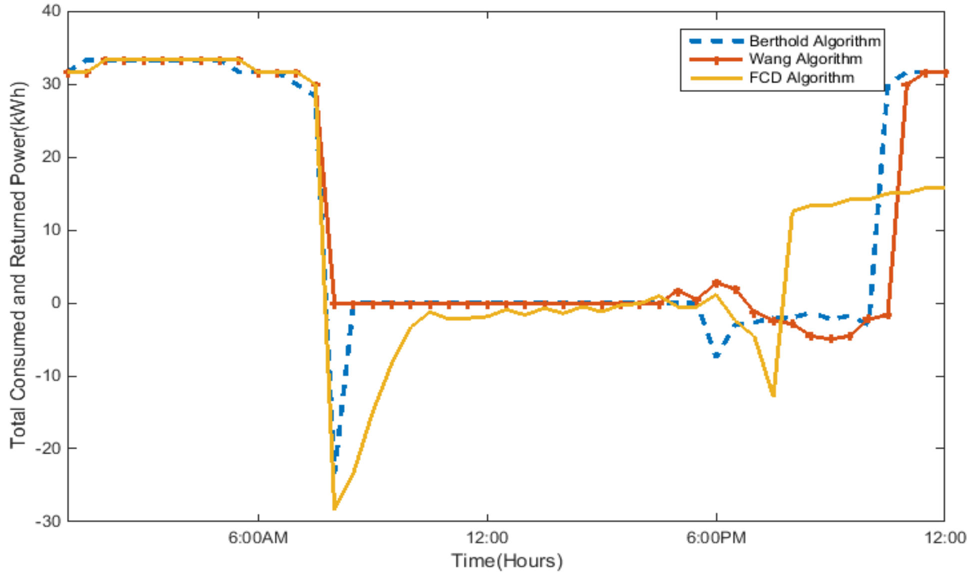

Figure 4-5: Total Consumed and Returned Power with P=50% and Ch_{rate}=3.7

In addition, Figure 4-6 shows the average returned power for all algorithms in case of R=3.7, P=50%, and 30-minute scenario. We can notice the improvement of FCD algorithm during the peak times. Berthold algorithm represent better returned power at 6:00 PM because most of returned EVs will start discharging at that time, and most of them have 60% of SoC while in FCD EVs have less power in their batteries to discharge.

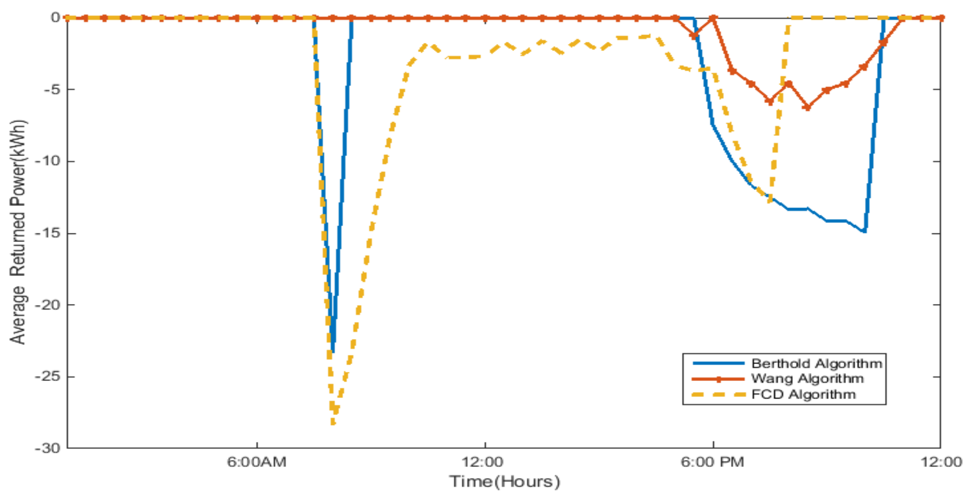

Figure 4-6: Average Returned Power with P=50% and Ch_{rate}=3.7

Figure 4-7, represent the performance of FCD under four various charging rates. We show the average consumed power for each charging rate. In addition, we use real charging efficiencies of four EVs as shown in Table 3-1 to calculate and draw the curves in the figure.

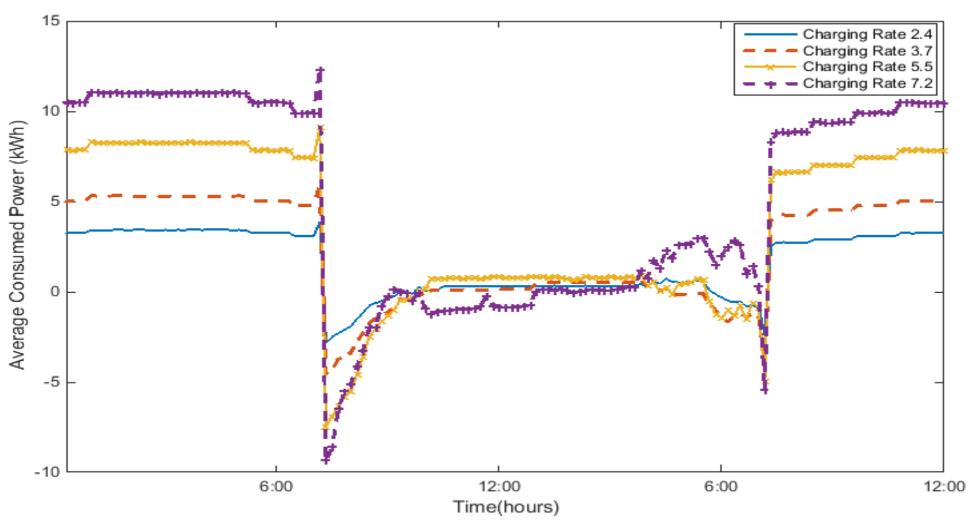

Figure 4-7: Average Consumed Power with Various Charging Rates and P=50%

4.4.2 Cost Reduction

In this section, we will study the effect of using FCD, Wang, and Berthold algorithms on reducing the customer power bill. Again, we study this crucial factor in lights of 30-minute and 10-minute scenarios. We will discuss the results and explain accompanied graphs. In this thesis, we used the Time of Use Price scheme (ToU) to calculate the cost of consumed and returned power to the grid.

4.4.2.1 10-minute Scenario

In Figure 4-8, we calculated the cost of the total consumed and returned power using FCD, Wang and Berthold algorithms. The curves reflect the amount of power consumed from the grid and/ or from the battery of EV. The solid curve represent the FCD algorithm, and it is clearly shows the superiority of FCD over other algorithms.

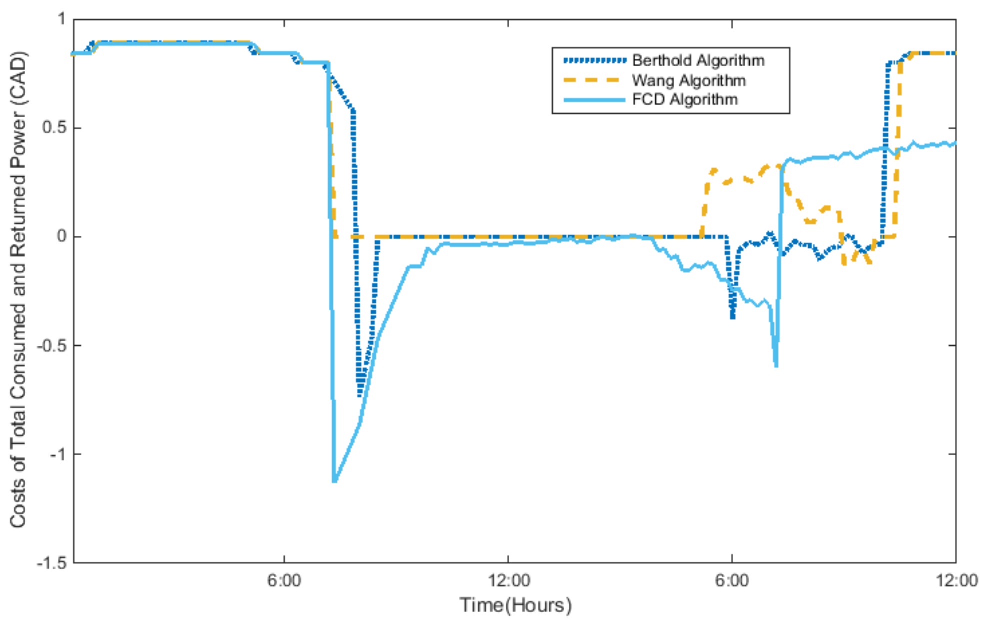

Figure 4-8: Costs of Total Consumed and Returned Power

In the following figure, we present the cost of returned power for each algorithm. FCD algorithm represents the best choice to reduce cost of consumed power by injecting power back to the grid in peak hours.

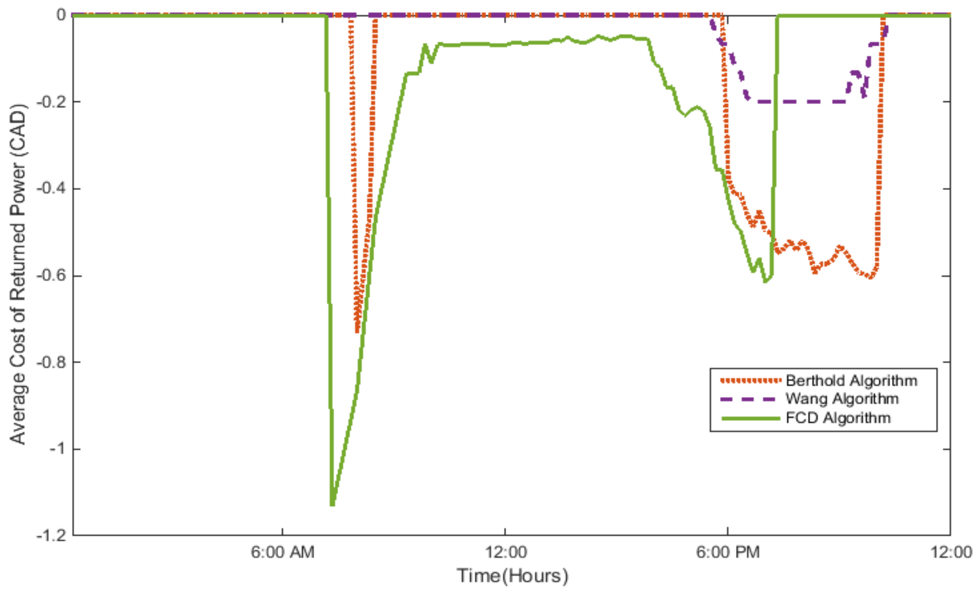

Figure 4-9: Average Cost of Returned Power

In Figure 4-10, we studied the relation between the cost of consumed power and the different levels of EV penetrations. From the figure, we find that the total cost of consumed power is proportion to penetration ratio.

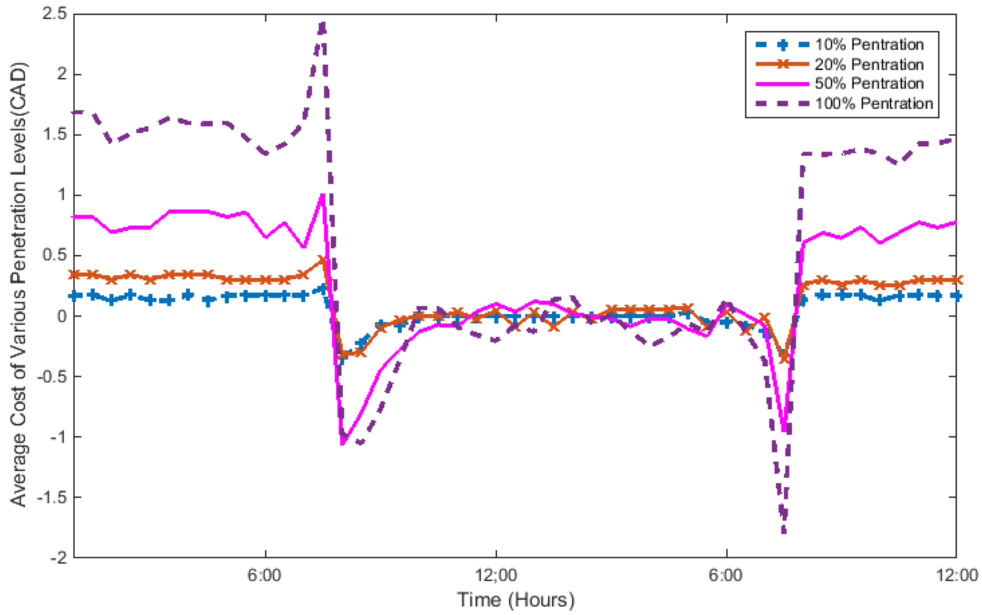

Figure 4-10: Cost of Consumed Power in Case of Various EV Penetration Ratios, Ch_{rate}=3.7

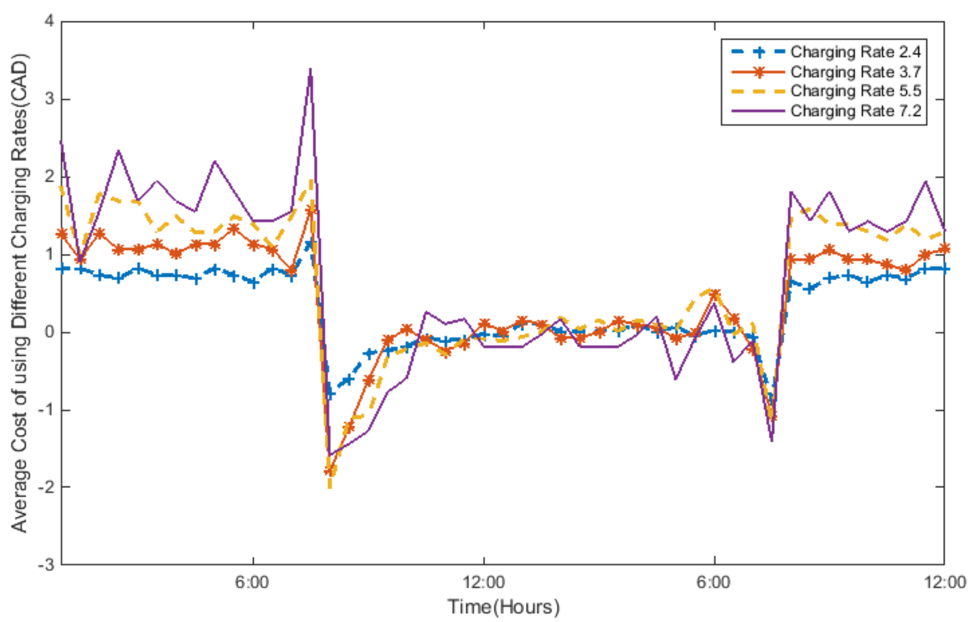

Figure 4-11: Cost of Consumed Power for Various Charging Rates, P=50%

The previous figure represent many charging rates, the positive values of each curve represent what we paid for consumed power, and the negative values of the curve represent what we gained from returning power to the grid. If we stored power during off peak time and sold it back during peak time.

4.4.2.2 30-minute Scenario

In this subsection, we will compare what we have done here with what we got previously in 30-minute scenario. In Figure 4-12, we studied the effect of using four penetration ratios in case of 10-minute scenario and 3.7 kW charging rate. We found that the FCD algorithm works fine under higher penetration ratios. However, the best performance of the algorithm was under the 50% penetration or less, where the consumed power is relatively small with the returned power.

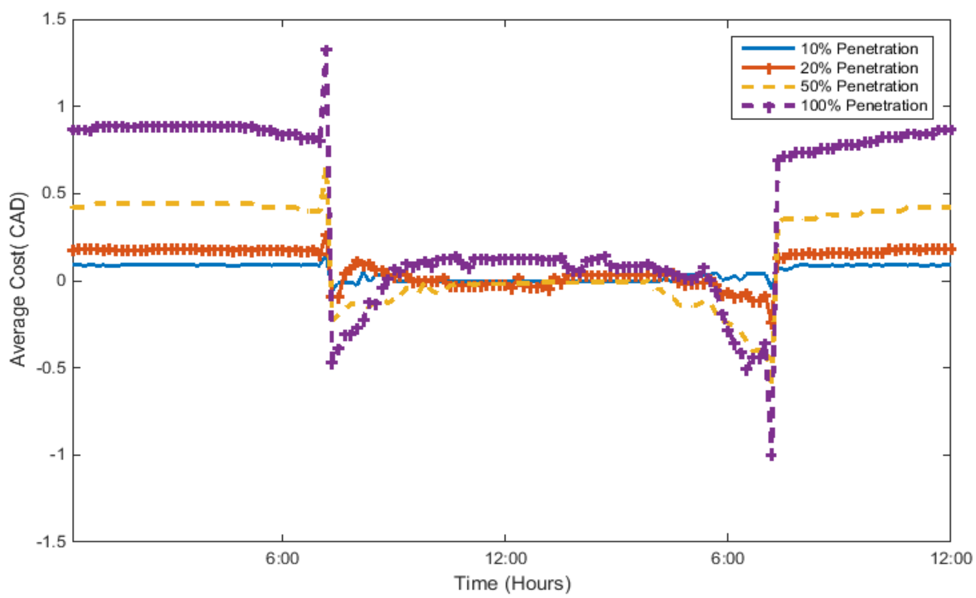

Figure 4-12: Average Cost of Consumed Power for Various Penetration Ratios, Ch_{rate}=3.7

Also, we study the effect of using four charging rates in case of 10-minute scenario and penetration ratio P=50%. As shown in Figure 4-13, we found that different charging rates have a proportional impact on the grid as the charging rate become larger. Therefore, the use of any charging rate has an impact on other factors in the process of charging and discharging. The impact of using higher charging rates in case of not using the FCD algorithm is the worst because these rates mean largely consumed power at any time without using new sources to fulfill the new power demands.

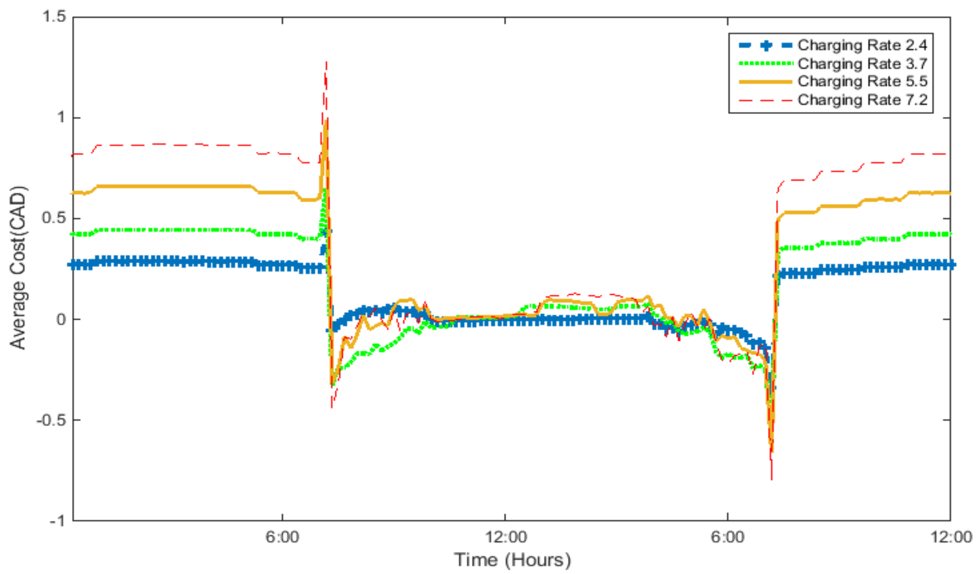

Figure 4-13: Average Cost of Consumed Power for Various Charging Rates, P=50%

4.4.3 Power Loss Results

In this section, we will discuss the graphs that show the amount of power loss that the current V2H system had. Two classes of figures have been presented, the power efficiency figures that discuss various charging efficiencies, and power loss figures that show the amount of lost power in charging and discharging processes.

4.4.3.1 Power Loss and Power Efficiency in 10-minute Scenario

As shown in Figure 4-14, the power loss in charging and discharging processes depends mainly on the efficiency of charging equipment. In Figure 4-14, we note that if we are able to increase the efficiency from 90% to 100%, the consumed power from the grid will be significantly reduced.

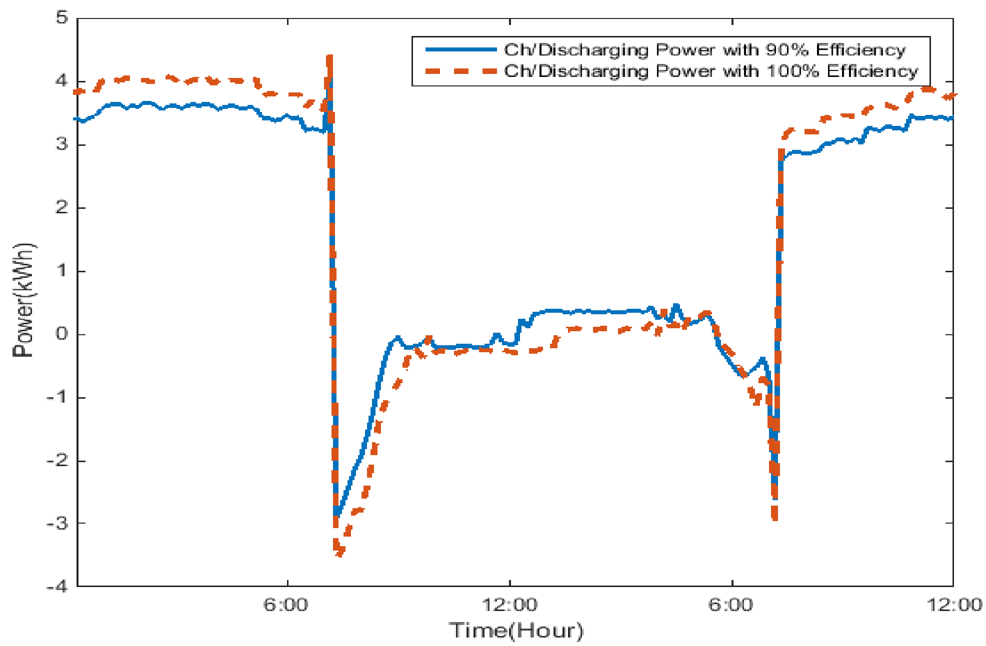

Figure 4-14: Effect of Different Efficiencies in 10-minute Scenario

In addition, from Figure 4-15 we can calculate the lost power in case of increasing the efficiency of charging system from 80% to 90%.

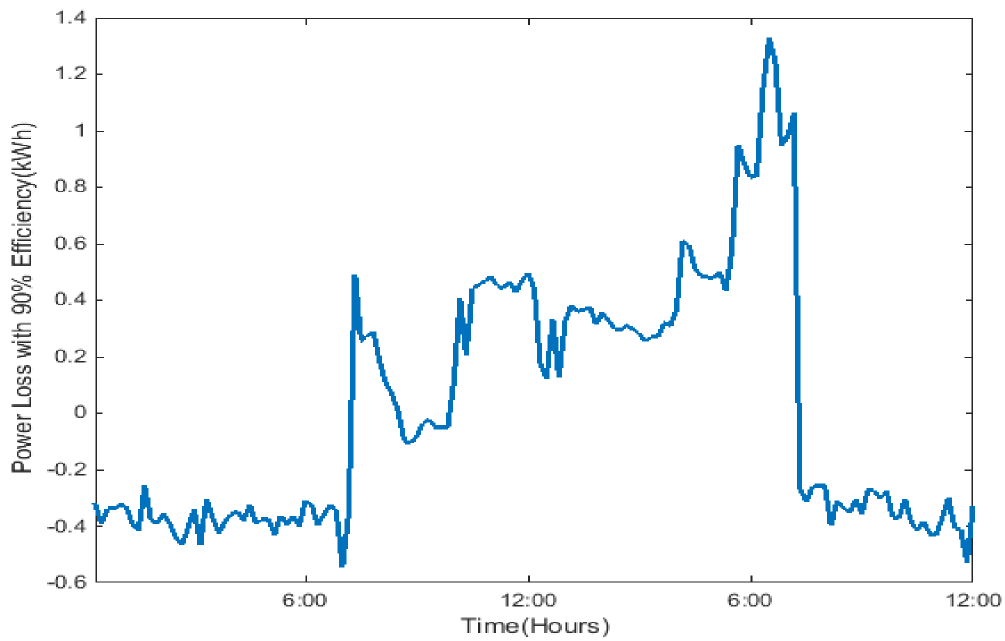

Figure 4-15: Power Loss with 90% Efficiency in 10-minute Scenario

4.4.3.2 Power Loss and Power Efficiency in 30-minute Scenario

The Figure 4-16 and Figure 4-17 represent the amount of lost power in case of using different efficiency values. In Figure 4-16, we compare the efficiency of some charging systems, which are around 80% with the expected full efficient charging system. The curves in the Figure 4-16 and Figure 4-17 show that a significant amount of power is lost because of using non-optimal charging system. These amounts of power cost the customers and the companies large amount of money.

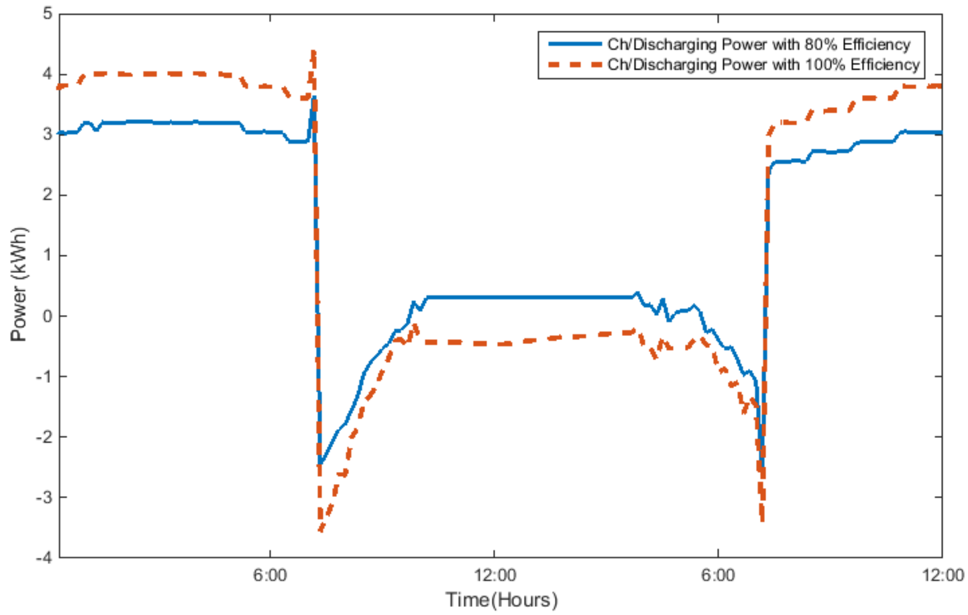

Figure 4-16: Power Loss for Different Efficiencies in 30-minute Scenario

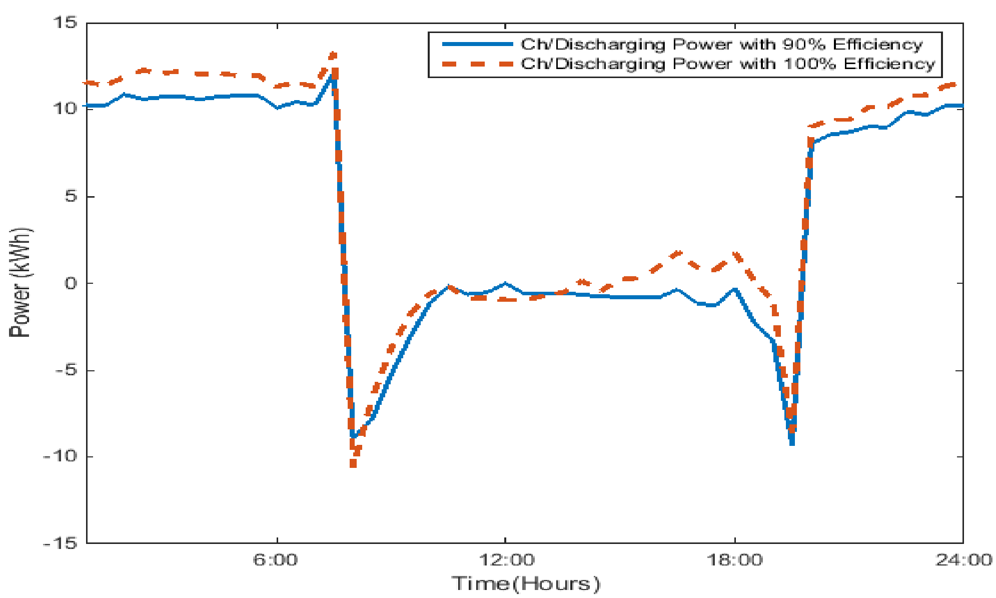

Figure 4-17: Effect of Different Efficiencies in 30-minute Scenario

Figure 4-18, and Figure 4-19 present the lost power during charging and discharging processes over the whole day. The curves have positive and negative values, the positive values represent lost power in kWh during the peak time, and the negative values represent the lost power during the off peak time. However, the total power lost is the absolute value of both peak and off peak times.

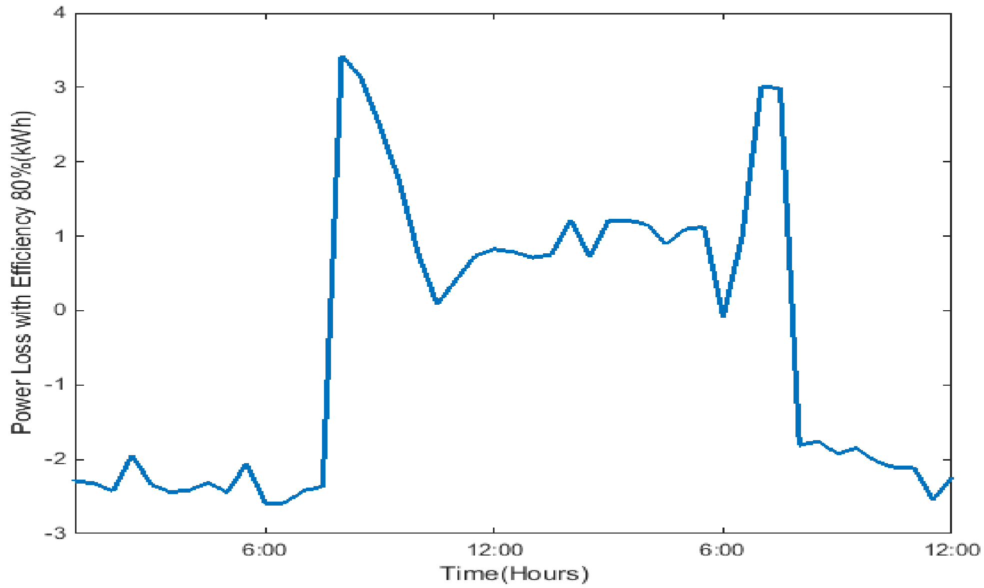

Figure 4-18: Power Loss with 80% Efficiency in 30-minute Scenario

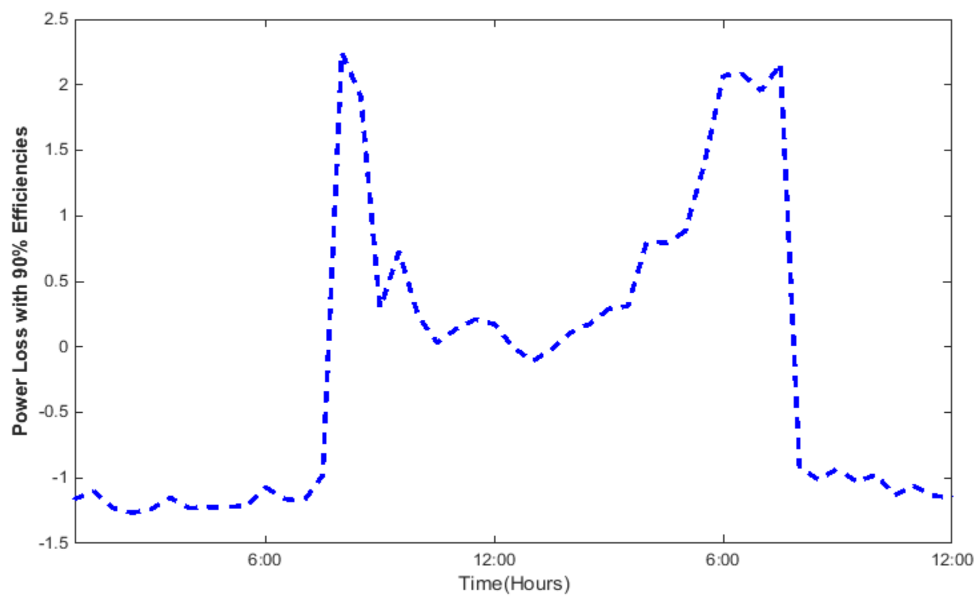

Figure 4-19: Power Loss with 90% Efficiency in 30-minute Scenario

4.4.4 Simulation Results Validation

To validate our proposed algorithm, we compare the results with other works, namely, [33] and [37], we will refer to these references in figures and discussions by the last name of the first author, Wang and Berthold respectively. In [33], the authors used the EV battery between 5:00 PM- 10:00 PM and they suggest that each vehicle should have 50% of battery's SoC before departure. The authors choose this period because the probability of departure after return in the evening is very small.

In [37], the authors suggest to use part of battery charge before departure between 8:00 AM - 8:30 AM and use whatever battery has after return to home in the evening at 6:00 PM. They suggest that returned vehicles have 60% of battery's SoC.

Confidence interval is a common mathematical tool that verifies and validates computer simulators. Confidence interval can be calculated by many methods. However, in our simulator, the population variance σ^2 is known, so the quantitative method to calculate the confidence interval has been used. Based on our simulations, we took a group of runs results. Then we apply confidence interval principle on the various performance metrics to determine whether the simulator passes the confidence interval test or not. We study these metrics in proportion to number of runs and we have the goal of $\alpha = 95\%$ as a confidence level. In addition the reliability factor $Z_{a/2}$ is equal 1.96.

Table 4-3: Consumed Power at Various Number of Runs

Number of Runs	Consumed Power at 7:00 AM	Consumed Power at 9:00 AM	Consumed Power at 11:00 AM	Consumed Power at 1:00 PM	Consumed Power at 3:00 PM	Consumed Power at 5:00 PM	Consumed Power at 7:00 PM
1000	6.235425	-0.3391	-0.30025	0.54834	0.55056	0.32301	-3.62304
5000	6.328776	-0.31147	0.536574	0.538128	0.520035	0.108336	-4.08424
10000	6.163941	-0.64763	-0.48696	0.026474	0.081308	0.014041	-4.38522
15000	6.084613	-0.77337	0.110445	0.497724	0.492137	0.095016	-4.75613
20000	6.240809	-0.42857	-0.57517	-0.43509	0.048923	-0.24506	-4.65975
25000	5.986496	-0.95857	0.099989	0.489843	0.151071	-0.73633	-4.26378
30000	6.182829	-0.98503	-0.74827	-0.56917	-0.02869	-0.86804	-4.23171
35000	6.170807	-0.94612	-0.41779	0.097077	0.504558	-0.62766	-4.99375
40000	5.992501	-0.8701	-0.71122	-0.5918	-0.44436	-0.71964	-5.09733
45000	6.307032	-0.78685	0.493013	0.536784	0.519492	-0.26094	-4.117
50000	6.019375	-0.9387	-0.57498	-0.36729	0.099667	-1.03063	-4.95405

Table 4-4: Confidence Interval Parameters for Consumed Power

Variable	7:00 AM	9:00 AM	11:00 AM	1:00 PM	3:00 PM	5:00 PM	7:00 PM
$\overline{X}$	6.155691	-0.72596	-0.23406	0.070093	0.226791	-0.3589	-4.46964
σ	0.120992	0.256462	0.466857	0.481719	0.318507	0.45894	0.46014
n	11	11	11	11	11	11	11
$\sqrt{n}$	3.316625	3.316625	3.316625	3.316625	3.316625	3.316625	3.316625
$Z_{a/2}$	1.96	1.96	1.96	1.96	1.96	1.96	1.96
CI	0.081283	0.172294	0.313639	0.323624	0.213976	0.30832	0.309126
Lower	6.074408	-0.89825	-0.5477	-0.25353	0.012815	-0.66722	-4.77876
Upper	6.236975	-0.55366	0.079582	0.393716	0.440767	-0.05058	-4.16051

The following Figures show two-sided confidence interval, where the Mean of each performance metric is bounded by the upper bound and lower bound. For each metric, a figure is plotted based on the table of values from the simulation. Figure 4-20 represents the confidence interval calculations based on cumulative method that we mentioned in the Appendix A.

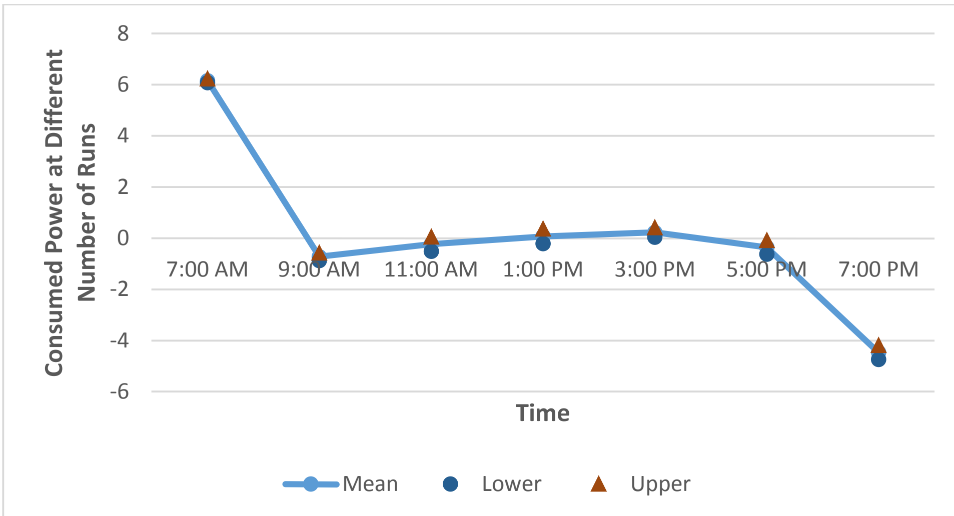

Figure 4-20: Confidence Interval of Consumed Power

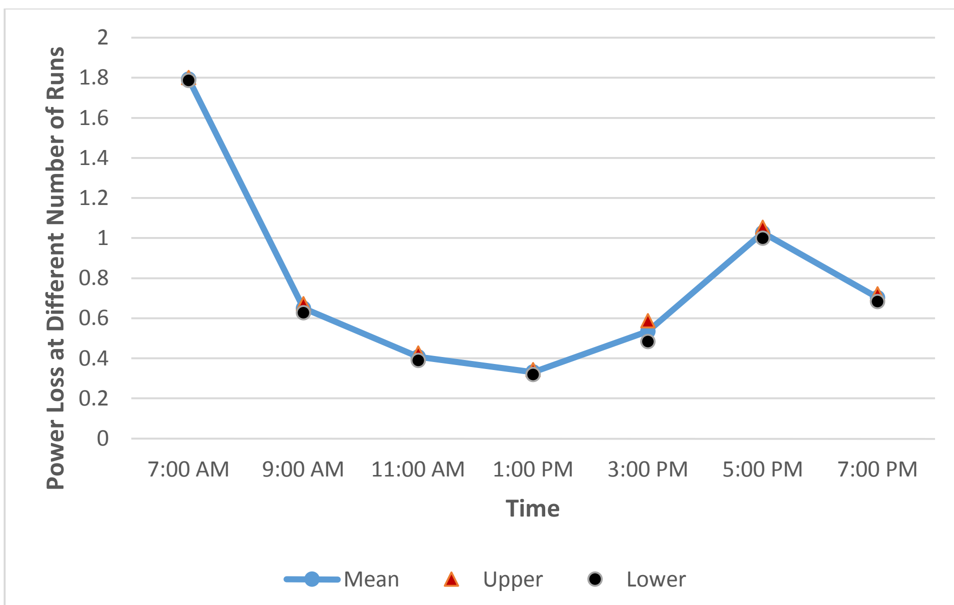

Figure 4-21: Confidence Interval of Power Loss

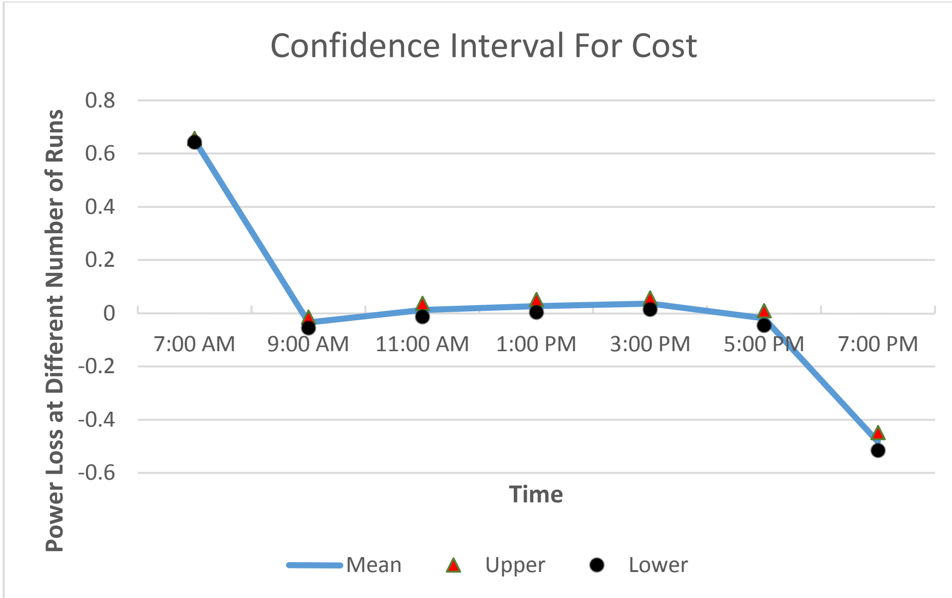

Figure 4-22: Confidence Interval of Cost

Chapter 5: Conclusions and Future Research

5.1 Concluding Remarks

In this thesis, we proposed a novel algorithm for charging and discharging EVs in a Smart Grid environment, namely FCD algorithm, that considers the power demands, the flexibility of user trip schedule, and the cost of consumed and lost power from the grid. The motivation behind this algorithm is to avail the EV battery as an ESS. The direct benefit of that algorithm is to reduce the power demands during peak times and to help the EV owner coordinate charging process to help the EV owners to afford the power bill.

We reach the following conclusions during our study of using EVs battery to store and retrieve power using charging and discharging operations in Smart Grid environment:

- Unorganized charging processes will explode the power demand problem at peak times.
- Unorganized Discharging processes will affect the performance of EV as a vehicle, which makes it unsuitable solution for future transportation.
- The FCD algorithm helps to reduce the power demand at peak times by organizing charging and discharging processes and use the excess power in EV's battery to balance the grid demands.

- A higher penetration ratio will seriously influence power system if we do not use all power resources, load shifting and peak shaving algorithms to meet the demands.

- Various types of EVs can be used to apply the FCD algorithm with different levels of reduce power demands at peak times.

5.2 Future Research

As an extension to the work developed in this thesis, we believe that some potential issues have not been addressed, and it represent future research, these issues can be summarized as following:

- Mobile ESS

  EVs are able to move from one place to another. Therefore, we can benefit from mobility by using the EV battery as mobile ESS. Mobile ESS will help us to provision electricity grid in any area. Also it could be used in disasters and afflicted areas where the whole infrastructure has been destroyed.

- Neighbours Power Grid

  We might extend this proposed approach in FCD algorithm to sell power to the neighbours, so a cooperative scheme for selling and transferring power should be implemented through the grid or directly by plug-in EV at the buyer home socket.

- Cooperative Electricity System

  In this thesis, we study the impact of using EV on the neighbourhood electricity grid (micro grid). Nevertheless, we still can balance the whole grid if we design a system that transfers power from micro grid to another micro grid. This system represents a crucial solution for high power demand in the grid.

- Charging Places

In chapter two, we mention that we have three main places to charge EVs are existed: at home, at work or commercial places, and at supply stations. In this thesis, we studied the performance of FCD algorithm in case that all EVs are charging and discharging at home. However, charging EVs in the future will not be limited to charging at home, so we recommended studying the impact of charging vehicles at other places on consumed power from micro-grid or the grid.

- Charging Levels

In this thesis, we mention that we have three charger types or charging levels, we discuss their specifications and power points of each one in chapter two. However, we mention that the fastest charger (level 3 charger) takes about thirty minutes to charge the EV battery until full, but this charger is very expensive and needs special equipment and connections. Therefore, an intensive research should be maintained in this area to make this type of chargers affordable and can be used in other places than the supply stations.

- Studying other EVs Specifications

In this thesis, we studied four EVs Nissan Leaf, BMW i3, Toyota RAV4 EV, and Tesla Model S. We used the specifications of these EVs as simulation parameters. However, there are many other EVs not mentioned in this thesis or other related works. Therefore, to generalize our algorithm it highly recommended to test the other EVs specification under the proposed model.

- Efficient Charging System

We studied the impact of using non-optimal charging systems in this thesis. Based on the results that we got, we recommended making intensive research on charging system components. That research should deals with the following components: the EV battery, the EVSE, charging level, and new cooling system for the charger.

- Redesign Electricity Grid

Current grids might not be able to meet the future power requirements as a consequent of every day population grows and increased EV numbers. Our algorithm is part of the solution because it is able to reduce the power demands. However the solution should include the design of new grids or, at least, redesign the current grids and new generators and transformers should be installed. In addition, the most important part of the solution is the use of renewable power resources.

- Renewable Power Resources

In this thesis, we mention that EV battery might be able to store power from the grid during off peak times and return this power in peak times. Never the less, these batteries are able also to store excess produced power by the renewable resources. These resources represent a promising option to fulfill the power demands in the future. However, research in this area does not perfectly covered. An intensive research on the efficiency of these power resources should be taken.

References

[1] O. Erdinc, N. G. Paterakis, T. D. P. Mendes, A. G. Bakirtzis and J. P. S. Catalao, "Smart Household Operation Considering Bi-Directional EV and ESS Utilization by Real-Time Pricing-Based DR", *IEEE Transactions on Smart Grid*, vol. 6, no. 3, pp. 1281–1291, May 2015.

[2] B. Zhu, X. She, Y. Huang and C. Tan, "A novel research on green electric vehicle battery replacement station", *in the Proceedings of the International Conference on Power System Technology (POWERCON)*, pp. 3129–3134, October 2014.

[3] N. Shidore, J. Kwon and A. Vyas, "Trade-off between PHEV fuel efficiency and estimated battery cycle life with cost analysis", *in the Proceedings of the IEEE Vehicle Power and Propulsion Conference (VPPC '09)*, pp. 669–677, Septmeber 2009.

[4] T. Morgan, "Smart grids and electric vehicles: made for each other?", *in the Proceedings of the International Transport Forum*, February 2012.

[5] H. N. T. Nguyen, C. Zhang and M. A. Mahmud, "Optimal Coordination of G2V and V2G to Support Power Grids With High Penetration of Renewable Energy", *IEEE Transactions on Transportation Electrification*, vol. 1, no. 2, pp. 188–195, August 2015.

[6] H. Turker, A. Hably and S. Bacha, "Housing peak shaving algorithm (HPSA) with plug-in hybrid electric vehicles (PHEVs): Vehicle-to-Home (V2H) and Vehicle-to-Grid (V2G) concepts", *in the Proceedings of the Fourth International*

Conference on Power Engineering, Energy and Electrical Drives (POWERENG), pp. 753–759, May 2013.

[7] M. Yilmaz and P. T. Krein, "Review of charging power levels and infrastructure for plug-in electric and hybrid vehicles", *in the Proceedings of the IEEE International Electric Vehicle Conference (IEVC)*, pp. 1–8, March 2012.

[8] M. Yilmaz and P. T. Krein, "Review of Battery Charger Topologies, Charging Power Levels and Infrastructure for Plug-In Electric and Hybrid Vehicles", *IEEE Transactions on Power Electronics*, vol. 28, no. 5, pp. 2151–2169, May 2013.

[9] S. Bahrami, M. Parniani and A. Vafaeimehr, "A modified approach for residential load scheduling using smart meters", *in the Proceedings of the 3rd IEEE PES International Conference and Exhibition on Innovative Smart Grid Technologies (ISGT Europe)*, pp. 1–8, October 2012.

[10] Z. Chen, L. Wu and Y. Fu, "Real-Time Price-Based Demand Response Management for Residential Appliances via Stochastic Optimization and Robust Optimization", *IEEE Transactions on Smart Grid*, vol. 3, no. 4, pp. 1822–1831, December 2012.

[11] S. Datchanamoorthy, S. Kumar, Y. Ozturk and G. Lee, "Optimal time-of-use pricing for residential load control", *in the Proceedings of the IEEE International Conference on Smart Grid Communications (SmartGridComm)*, pp. 375–380, October 2011.

[12] M. Erol-Kantarci and H. T. Mouftah, "Management of PHEV batteries in the smart grid: Towards a cyber-physical power infrastructure", *in the Proceedings of the 7th*

International Wireless Communications and Mobile Computing Conference (IWCMC), pp. 795–800, July 2011.

[13] J. K. Gruber and M. Prodanovic, "Residential Energy Load Profile Generation Using a Probabilistic Approach", *in the Proceedings of the Sixth UKSim/AMSS European Symposium on Computer Modeling and Simulation (EMS)*, pp. 317–322, November 2012.

[14] S. Han and S. Han, "Economics of V2G frequency regulation in consideration of the battery wear", *in the Proceedings of the 3rd IEEE PES International Conference and Exhibition on Innovative Smart Grid Technologies (ISGT Europe)*, pp. 1–8, October 2012.

[15] Y. He, B. Venkatesh and L. Guan, "Optimal Scheduling for Charging and Discharging of Electric Vehicles", *IEEE Transactions on Smart Grid*, vol. 3, no. 3, pp. 1095–1105, August 2012.

[16] S. Kaebisch, A. Schmitt, M. Winter and J. Heuer, "Interconnections and Communications of Electric Vehicles and Smart Grids", *in the Proceedings of the First IEEE International Conference on Smart Grid Communications (SmartGridComm)*, pp. 161–166, October 2010.

[17] W. Kempton and J. Tomia, "Vehicle-to-grid power implementation: From stabilizing the grid to supporting large-scale renewable energy", *Journal of Power Sources*, vol. 144, no. 1, pp. 280–294, June 2005.

[18] B.G. Kim, S. Ren, M. van der Schaar and J.W. Lee, "Bidirectional Energy Trading and Residential Load Scheduling with Electric Vehicles in the Smart Grid", *IEEE*

Journal on Selected Areas in Communications, vol. 31, no. 7, pp. 1219–1234, July 2013.

[19] Y. Lan, J. Wu and Z. Tang, “Generation of domestic load profiles using appliances’ activating moments”, *in the Proceedings of the IEEE PES Innovative Smart Grid Technologies Conference (ISGT)*, pp. 1–5, February 2014.

[20] R. Li, Z. Wang, S. L. Blond and F. Li, “Development of time-of-use price by clustering techniques”, *in the Proceedings of the IEEE PES General Meeting Conference Exposition*, pp. 1–5, July 2014.

[21] C. Liu, K. T. Chau, D. Wu and S. Gao, “Opportunities and Challenges of Vehicle-to-Home, Vehicle-to-Vehicle, and Vehicle-to-Grid Technologies”, *in the Proceedings of the IEEE*, vol. 101, no. 11, pp. 2409–2427, November 2013.

[22] Z. Wang and G. Zheng, “Residential Appliances Identification and Monitoring by a Nonintrusive Method”, *IEEE Transactions on Smart Grid*, vol. 3, no. 1, pp. 80–92, March 2012.

[23] K. Clement-Nyns, E. Haesen and J. Driesen, “The Impact of Charging Plug-In Hybrid Electric Vehicles on a Residential Distribution Grid”, *IEEE Transactions on Power Systems*, vol. 25, no. 1, pp. 371–380, February 2010.

[24] K. J. Dyke, N. Schofield and M. Barnes, “The Impact of Transport Electrification on Electrical Networks”, *IEEE Transactions on Industrial Electronics*, vol. 57, no. 12, pp. 3917–3926, December 2010.

[25] X. Gong, T. Lin and B. Su, "Survey on the impact of Electric Vehicles on power distribution grid", *in the Proceedings of the IEEE Power Engineering and Automation Conference (PEAM),* vol. 2, pp. 553–557, September 2011.

[26] S. Huang and D. Infield, "The impact of domestic Plug-in Hybrid Electric Vehicles on power distribution system loads", *in the Proceedings of International Conference on Power System Technology (POWERCON),* pp. 1–7, October 2010.

[27] P. Kadurek, C. Ioakimidis and P. Ferrao, "Electric Vehicles and their impact to the electric grid in isolated systems", *in the Proceedings of the International Conference on Power Engineering (POWERENG '09)*, pp. 49–54, March 2009.

[28] P. Stroehle, S. Becher, S. Lamparter, A. Schuller and C. Weinhardt, "The impact of charging strategies for electric vehicles on power distribution networks", *in the Proceedings of the 8th International Conference on the European Energy Market (EEM)*, pp. 51–56, May 2011.

[29] H. Wang, Q. Song, L. Zhang, F. Wen and J. Huang, "Load characteristics of electric vehicles in charging and discharging states and impacts on distribution systems", *in the Proceedings of International Conference on Sustainable Power Generation and Supply (SUPERGEN 2012)*, pp. 1–7, September 2012.

[30] J. Xiong, "Impact Assessment of Electric Vehicle Charging on Power Distribution Systems," Master Thesis, Carleton University, April 2013.

[31] K. J. Yunus, M. Reza, H. L. Parra and K. Srivastava, "Impacts of Stochastic Residential Plug-In Electric Vehicle Charging on Distribution Grid", *in the*

proceedings of the 2012 IEEE PES Innovative Smart Grid Technologies (ISGT), pp. 1–8, January 2012.

[32] S. Letendre and W. Kempton, *The V2G Concept: A New For Model Power?* Public Utilities Fortnightly, pp. 16–26, 2002.

[33] Y. Wang, S. Huang and D. Infield, "Investigation of the potential for electric vehicles to support the domestic peak load", *in the Proceedings of the IEEE International Electric Vehicle Conference (IEVC)*, pp. 1–8, December 2014.

[34] Ontario Ministry of Transportation, " Modernized Electric Vehicle Incentive Program (EVIP)". [Online]. Available: http://www.mto.gov.on.ca/english/vehicles/electric/electric-vehicle-incentive-program.shtml, (last access: 5 February 2015).

[35] C. Liu, K. T. Chau, D. Wu and S. Gao, "Opportunities and Challenges of Vehicle-to-Home, Vehicle-to-Vehicle, and Vehicle-to-Grid Technologies", *Proceedings of the IEEE*, vol. 101, no. 11, pp. 2409–2427, November 2013.

[36] K. Young, C. Wang, L. Wang and K. Strunz, "*Electric Vehicle Battery Technologies"*, Springer New York, pp. 15–56, 2013.

[37] F. Berthold, B. Blunier, D. Bouquain, S. Williamson and A. Miraoui, "PHEV control strategy including vehicle to home (V2H) and home to vehicle (H2V) functionalities", *in the Proceedings of the IEEE Vehicle Power and Propulsion Conference (VPPC)*, pp. 1–6, September 2011.

[38] Tesla Motors, “Tesla Model S Specifications". [Online]. Available: https://www.teslamotors.com/en_CA/support/model-s-specifications, (last access: 30 September 2015).

[39] C. Morrison, "30 electric cars companies ready to take over the road". [Online]. Available: http://venturebeat.com/2008/01/10/27-electric-cars-companies-ready-to-take-over-the-road/, (last access: 12 November 2015).

[40] H. Spongenberg, "EU states plug in to electric cars", Europe Observer Website. [Online]. Available: https://euobserver.com/transport/26594, (last access: 27 December 2015).

[41] “Smart Grid", wikipedia, https://en.wikipedia.org/wiki/Smart_grid. [Online]. Available: (last access: 28 September 2015).

[42] “Electric Vehicle Charging", Revision Energy Website. [Online]. Available: https://www.revisionenergy.com/at-home/electric-vehicle-charging/, (last access: 25 January2015).

[43] J. A. Peas Lopes, F. J. Soares and P. M. R. Almeida, “Identifying management procedures to deal with connection of Electric Vehicles in the grid”, *in the Proceedings of the IEEE Bucharest PowerTech.*, pp. 1–8, June 2009.

[44] “Visionary Graph of Smart Grid", 3M Energy Solutions Company. [Online]. Available: http://solutions.3m.com/wps/portal/3M, (last access: 14 December 2015).

[45] J. Zhou, R. Q. Hu and Y. Qian, “Scalable Distributed Communication Architectures to Support Advanced Metering Infrastructure in Smart Grid”, *IEEE*

Transactions on Parallel and Distributed Systems, vol. 23, no. 9, pp. 1632–1642, July 2012.

[46] A. Y. Saber and G. K. Venayagamoorthy, "Efficient Utilization of Renewable Energy Sources by Gridable Vehicles in Cyber-Physical Energy Systems", *IEEE Systems Journal*, vol. 4, no. 3, pp. 285–294, August 2010.

[47] "Electricity Grid Modernization", Federal Energy Regulatory Commission Assessment of Demand Response & Advanced Metering. [Online]. Available: http://www.ferc.gov/legal/staff-reports/2015/demand-response.pdf, (last access: 29 December 2015).

[48] Y. Yan, Y. Qian, H. Sharif and D. Tipper, "A Survey on Smart Grid Communication Infrastructures: Motivations, Requirements and Challenges", *IEEE Communications Surveys & Tutorials*, vol. 15, no. 1, pp. 5–20, February 2013.

[49] D. Zhaoyang, "Smart grid cyber security", *in the Proceedings of 13th International Conference on Control Automation Robotics Vision (ICARCV)*, pp. 1–2, December 2014.

[50] K. Yu, M. Arifuzzaman, Z. Wen, D. Zhang and T. Sato, "A Key Management Scheme for Secure Communications of Information Centric Advanced Metering Infrastructure in Smart Grid", *IEEE Transactions on Instrumentation and Measurement*, vol. 64, no. 8, pp. 2072–2085, August 2015.

[51] M. M. Farag, M. Azab and B. Mokhtar, "Cross-layer security framework for smart grid: Physical security layer", *in the Proceedings of the IEEE PES Innovative*

Smart Grid Technologies Conference Europe (ISGT-Europe), pp. 1–7, October 2014.

[52] Y. J. Kim, M. Thottan, V. Kolesnikov and W. Lee, "A secure decentralized data-centric information infrastructure for smart grid", *IEEE Communications Magazine*, vol. 48, no. 11, pp. 58–65, November 2010.

[53] N. Z. Xu and C. Y. Chung, "Reliability Evaluation of Distribution Systems Including Vehicle-to-Home and Vehicle-to-Grid", *IEEE Transactions on Power Systems*, vol. 31, no. 1, pp. 759–768, January 2016.

[54] A. I. Sarwat, A. Domijan, M. H. Amini, A. Damnjanovic and A. Moghadasi, "Smart Grid reliability assessment utilizing Boolean Driven Markov Process and variable weather conditions", *in the Proceedings of the IEEE North American Power Symposium (NAPS)*, pp. 1–6, October 2015.

[55] S. Al-imran, M. Fuad, T. Ahmed, M. Ali and M.Maruf, "Optimization of distributed energy resources to balance power supply and demand in a smart grid", *in the Proceedings of 3rd International Conference on Green Energy and Technology (ICGET)*, pp. 1–5, September 2015.

[56] S. S. R. Depuru, L. Wang, V. Devabhaktuni and N. Gudi, "Smart meters for power grid - Challenges, issues, advantages and status", *in the Proceedings of the IEEE Power Systems Conference and Exposition (PSCE)*, pp. 1–7, March 2011.

[57] S. Ahmad, "Smart metering and home automation solutions for the next decade", *in the Proceedings of International Conference on Emerging Trends in Networks and Computer Communications (ETNCC)*, pp. 200–204, April 2011.

[58] G. R. Barai, S. Krishnan and B. Venkatesh, "Smart metering and functionalities of smart meters in smart grid - a review", *in the Proceedings of the IEEE Electrical Power and Energy Conference (EPEC)*, pp. 138–145, October 2015.

[59] M. Zeifman, "Smart meter data analytics: Prediction of enrollment in residential energy efficiency programs", *in the Proceedings of the IEEE International Conference on Systems, Man and Cybernetics (SMC)*, pp. 413–416, October 2014.

[60] M. Uehara, "The Design of a Framework for Smart Appliances", *in the Proceedings of the IEEE 29th International Conference on Advanced Information Networking and Applications Workshops (WAINA)*, pp. 457–462, March 2015.

[61] B. Qi, X. F. Zhang, M. X. Wang and D. D. Wang, "Design of information interaction interface between electrical home appliances and smart grid", *in the Proceedings of China International Conference on Electricity Distribution (CICED)*, pp. 1–4, September 2012.

[62] X. Sun, Y. Chen, J. Liu and S. Huang, "A co-simulation platform for smart grid considering interaction between information and power systems", *in the Proceedings of the IEEE PES Innovative Smart Grid Technologies Conference (ISGT)*, pp. 1–6, February 2014.

[63] L. Gkatzikis, I. Koutsopoulos and T. Salonidis, "The Role of Aggregators in Smart Grid Demand Response Markets", *IEEE Journal on Selected Areas in Communications*, vol. 31, no. 7, pp. 1247–1257, July 2013.

[64] Q. Gong, S. Midlam-Mohler, V. Marano and G. Rizzoni, “Study of EV Charging on Residential Distribution Transformer Life”, *IEEE Transactions on Smart Grid*, vol. 3, no. 1, pp. 404–412, March 2012.

[65] B. Zhu, X. She, Y. Huang and C. Tan, “A novel research on green electric vehicle battery replacement station”, *in the Proceedings of the IEEE International Conference on Power System Technology (POWERCON)*, pp. 3129–3134, October 2014.

[66] K. M. Tsui and S. C. Chan, “Demand Response Optimization for Smart Home Scheduling Under Real-Time Pricing”, *IEEE Transactions on Smart Grid*, vol. 3, no. 4, pp. 1812–1821, December 2012.

[67] K. Ellegard, “A time-geographical approach to the study of everyday life of individuals - a challenge of complexity”, *GeoJournal*, vol. 48, no. 3, pp. 167–175, July 1999.

[68] L. Zhao and V. Aravinthan, “Strategies of residential peak shaving with integration of demand response and V2H”, *in the Proceedings of the IEEE PES Asia-Pacific Power and Energy Engineering Conference (APPEEC)*, pp. 1–5, December 2013.

[69] N. Chen, C.Tan and T. Quek, “Electric Vehicle Charging in Smart Grid: Optimality and Valley-Filling Algorithms”, *IEEE Journal of Selected Topics in Signal Processing*, vol. 8, no. 6, pp. 1073–1083, December 2014.

[70] J. Xu, X. Ai, H. Qin and Y. Zhu, “The management policy of regional electric vehicles considering peak load shifting”, *in the Proceedings of the IEEE Innovative Smart Grid Technologies - Asia (ISGT Asia)*, pp. 1–5, May 2012.

[71] "Energy Sources and Distribution", Natural Resources Canada. [Online]. Available: http://www.nrcan.gc.ca/energy/electricity-infrastructure/about-electricity/7359, (last access: 15 January 2016).

[72] "EV Energy Efficiency", US Department of Energy. [Online]. Available: https://www.fueleconomy.gov/feg/evtech.shtml, (last access: 15 January 2016).

[73] J. Widen and E. Wackelgard, "A high-resolution stochastic model of domestic activity patterns and electricity demand", *Applied Energy*, vol. 87, no. 6, pp. 1880–1892, June 2010.

[74] J. Widen, M. Lundh, I. Vassileva, E. Dahlquist, K. Ellegardrd and E. Wackelgard, "Constructing load profiles for household electricity and hot water from time-use data Modelling approach and validation", *Energy and Buildings*, vol. 41, no. 7, pp. 753–768, July 2009.

[75] "Steady State Vehicle Charging Fact Sheet: 2014 BMW i3", Idaho National Laboratory. [Online]. Available: http://avt.inl.gov/pdf/fsev/SteadyStateLoadCharacterization2014BMWi3.pdf, (last access: 22 December 2015).

[76] H. J. Chae, W. Y. Kim, S. Y. Yun, Y. S. Jeong, J. Y. Lee and H. T. Moon, "3.3kW on board charger for electric vehicle", *in the Proceedings of the IEEE 8th International Conference on Power Electronics and ECCE Asia (ICPE ECCE)*, pp. 2717–2719, May 2011.

[77] J. Maurio, L. Tallon, C. McClure and L. Hajnos, "Multiplexed electric vehicle charger provides affordable and flexible Level 2 charging", *in the Proceedings of*

the IEEE Transportation Electrification Conference and Expo (ITEC), pp. 1–7, June 2014.

[78] M. A. Fasugba and P. T. Krein, “Cost benefits and vehicle-to-grid regulation services of unidirectional charging of electric vehicles”, *in the Proceedings of the IEEE Energy Conversion Congress and Exposition (ECCE)*, pp. 827–834, September 2011.

[79] J. Sears, D. Roberts and K. Glitman, “A comparison of electric vehicle Level 1 and Level 2 charging efficiency”, *in the Proceedings of the IEEE Conference on Technologies for Sustainability (SusTech)*, pp. 255–258, July 2014.

[80] J. Pokrzywa and M. Reidy, " SAE's J1772 'combo connector' for ac and dc charging", Society of Automotive Engineers. [Online]. Available: http://articles.sae.org/10128, (last access: 3 March 2016).

[81] D. Aswani and B. Boyce, “Autonomous grid services through Electric Vehicles”, *in the Proceedings of the IEEE Power Energy Society General Meeting*, pp. 1–5, July 2015.

[82] M. Etezadi-Amoli, K. Choma and J. Stefani, “Rapid-Charge Electric-Vehicle Stations”, *IEEE Transactions on Power Delivery*, vol. 25, no. 3, pp. 1883–1887, July 2010.

[83] L. W. C. Wang K. Young and K. Strunz, “Electric Vehicle Battery Technologies,” Springer New York, pp. 15–56, 2013.

[84] D. Linden and T. Reddy, "Secondary Batteries Introduction", in Handbook of Batteries, McGraw-Hill Handbooks, 3rd Edition, pp. 22-3 to 22-11, 2010.

[85] T. Duong, “A review of lithium-ion battery properties of plug-in hybrid and electric vehicles in light of seminal assumptions on the viability of V2G”, *in the Proceedings of the IEEE PES Innovative Smart Grid Technologies (ISGT)*, pp. 1–1, January 2012.

[86] T. Bohn and H. Chaudhry, “Overview of SAE standards for plug-in electric vehicle”, *in the Proceedings of the IEEE PES Innovative Smart Grid Technologies (ISGT)*, pp. 1–7, January 2012.

[87] H. Xing, M. Fu, Z. Lin and Y. Mou, “Decentralized Optimal Scheduling for Charging and Discharging of Plug-In Electric Vehicles in Smart Grids”, *IEEE Transactions on Power Systems*, vol. 1, no. 99, pp. 1–10, December 2015.

[88] Q. Kang, J. Wang, M. Zhou and A. C. Ammari, “Centralized Charging Strategy and Scheduling Algorithm for Electric Vehicles Under a Battery Swapping Scenario”, *IEEE Transactions on Intelligent Transportation Systems*, vol. 17, no. 3, pp. 659–669, March 2016.

[89] A. H. Mohsenian-Rad, V. W. S. Wong, J. Jatskevich, R. Schober and A. Leon-Garcia, “Autonomous Demand-Side Management Based on Game-Theoretic Energy Consumption Scheduling for the Future Smart Grid”, *IEEE Transactions on Smart Grid*, vol. 1, no. 3, pp. 320–331, December 2010.

[90] P. Richardson, D. Flynn and A. Keane, “Local Versus Centralized Charging Strategies for Electric Vehicles in Low Voltage Distribution Systems”, *IEEE Transactions on Smart Grid*, vol. 3, no. 2, pp. 1020–1028, June 2012.

[91] M. Wang, M. Ismail, R. Zhang, X. S. Shen, E. Serpedin and K. Qaraqe, "A semi-distributed V2V fast charging strategy based on price control", *in the Proceedings of the IEEE Global Communications Conference (GLOBECOM)*, pp. 4550–4555, December 2014.

[92] F. J. Soares, J. A. Peas Lopes, P. M. R. Almeida and C. L. Moreira, "A stochastic model to simulate electric vehicles motion and quantify the energy required from the grid", *in the Proceedings of the Power Systems Computation Conference (PSCC), Stockholm, Sweden, 2011*, pp. 1–7, August 2011.

[93] M. H. K. Tushar, C. Assi, M. Maier and M. F. Uddin, "Smart Microgrids: Optimal Joint Scheduling for Electric Vehicles and Home Appliances", *IEEE Transactions on Smart Grid*, vol. 5, no. 1, pp. 239–250, January 2014.

[94] H. Sherif, Z. Zhu and S. Lambotharan, "An optimization framework for home demand side management incorporating electric vehicles", *in the Proceedings of the IEEE Innovative Smart Grid Technologies - Asia (ISGT Asia)*, pp. 57–61, May 2014.

[95] Y. Gao, C. Wang, Z. Wang and H. Liang, "Research on time-of-use price applying to electric vehicles charging", *in the Proceedings of the IEEE Innovative Smart Grid Technologies - Asia (ISGT Asia*, pp. 1–6, May 2012.

[96] K. Kobayashi and K. Hiraishi, "Algorithm for optimal real-time pricing based on switched Markov chain models", *in the Proceedings of the IEEE Power Energy Society Innovative Smart Grid Technologies Conference (ISGT)*, pp. 1–5, February 2015.

[97] M. Moghadam, R. Zhang and R. Ma, "Demand response for contingency management via real-time pricing in Smart Grids", *in the Proceedings of the IEEE International Conference on Smart Grid Communications (SmartGridComm)*, pp. 632–637, November 2014.

[98] T. Namerikawa, N. Okubo, R. Sato, Y. Okawa and M. Ono, "Real-Time Pricing Mechanism for Electricity Market With Built-In Incentive for Participation", *IEEE Transactions on Smart Grid*, vol. 6, no. 6, pp. 2714–2724, November 2015.

[99] "Rav4 EV Specifications", Online Forum for RAV4 EV. [Online]. Available: http://www.myrav4ev.com/rav4-ev-specs, (last access: 8 September 2015).

[100] "Nissan Leaf model S Specifications", Nissan Motors. [Online]. Available: http://www.nissan.ca/en/electric-cars/leaf/versions-specs, (last access: 23 November 2015).

[101] "Electricity Supply Information for Ontario Hydro Consumers", Ontario Hydro. [Online]. Available: http://www.ontario-hydro.com, (last access: 5 November 2015).

Appendix A: Confidence Interval Calculation

Confidence Interval (CI) is a common mathematical tool that verifies and validates computer simulators. CI can be calculated by many methods. However, in our simulator, the population variance σ^2 is known, so the quantitative method to calculate the CI has been used. Based on our simulations, we took a group of runs results. Then we apply CI principle on the various performance metrics to determine whether the simulator passes the CI test or not. We study these metrics in proportion to number of runs and we have the goal of $\alpha = 95\%$ as a confidence level.in addition the reliability factor $Z_{a/2}$ is equal 1.96.

The following tables and figures shows two-sided CI, where we bound the Mean of each performance metric by the upper and lower bounds.

The first step to calculate the CIs was to determine the Mean or the Average of all runs (x1,x2,…,x_i) at each point on X-axes using the following formula.

$$\overline{X} = \frac{\sum_{i=1}^{n} x_n}{n} \tag{A.1}$$

The population variance σ^2 is calculated from the following relation.

$$\sigma^2 = \frac{\sum_{i=1}^{n} (x_i - \overline{X})^2}{n} \tag{A.2}$$

Then, the standard deviation for each point has been calculated using the following relation.

$$\sigma = \sqrt{\frac{\sum_{i=1}^{n}(x_i - \bar{X})^2}{n}} \qquad (A.3)$$

Finally, the CI upper and lower bounds can be calculated using the previous relations as shown in the following relation.

$$CI = \bar{X} \mp Z_{a/2} * \frac{\sigma}{\sqrt{n}} \qquad (A.4)$$

Example: We will calculate the confidence interval for the Average consumed power metric in case of Penetration =50%, charging rate 3.7 kWh, charging efficiency =80%.

Number of Runs	**Consumed Power at 7:00 Am**	**Consumed Power at 9:00 Am**	**Consumed Power at 11:00 Am**	**Consumed Power at 1:00 Pm**	**Consumed Power at 3:00 Pm**	**Consumed Power at 5:00 Pm**	**Consumed Power at 7:00 Pm**
1000	6.235425	-0.3391	-0.30025	0.54834	0.55056	0.32301	-3.62304
5000	6.328776	-0.31147	0.536574	0.538128	0.520035	0.108336	-4.08424
10000	6.163941	-0.64763	-0.48696	0.026474	0.081308	0.014041	-4.38522
15000	6.084613	-0.77337	0.110445	0.497724	0.492137	0.095016	-4.75613
20000	6.240809	-0.42857	-0.57517	-0.43509	0.048923	-0.24506	-4.65975
25000	5.986496	-0.95857	0.099989	0.489843	0.151071	-0.73633	-4.26378
30000	6.182829	-0.98503	-0.74827	-0.56917	-0.02869	-0.86804	-4.23171
35000	6.170807	-0.94612	-0.41779	0.097077	0.504558	-0.62766	-4.99375
40000	5.992501	-0.8701	-0.71122	-0.5918	-0.44436	-0.71964	-5.09733
45000	6.307032	-0.78685	0.493013	0.536784	0.519492	-0.26094	-4.117
50000	6.019375	-0.9387	-0.57498	-0.36729	0.099667	-1.03063	-4.95405

Table A. 1: Consumed Power CI

The previous table represent average consumed power during different time slots and over different number of runs. We applied the previous equations, and we got the results that shown in the following table.

Variable	7:00 Am	9:00 Am	11:00 Am	1:00 Pm	3:00 Pm	5:00 Pm	7:00 Pm
$\bar{X}$	6.155691	-0.72596	-0.23406	0.070093	0.226791	-0.3589	-4.46964
σ	0.120992	0.256462	0.466857	0.481719	0.318507	0.45894	0.46014
n	11	11	11	11	11	11	11
$\sqrt{n}$	3.316625	3.316625	3.316625	3.316625	3.316625	3.316625	3.316625
$Z_{a/2}$	1.96	1.96	1.96	1.96	1.96	1.96	1.96
CI	0.081283	0.172294	0.313639	0.323624	0.213976	0.30832	0.309126
Lower	6.074408	-0.89825	-0.5477	-0.25353	0.012815	-0.66722	-4.77876
Upper	6.236975	-0.55366	0.079582	0.393716	0.440767	-0.05058	-4.16051

Table A. 2: Confidence Interval Variable Calculations

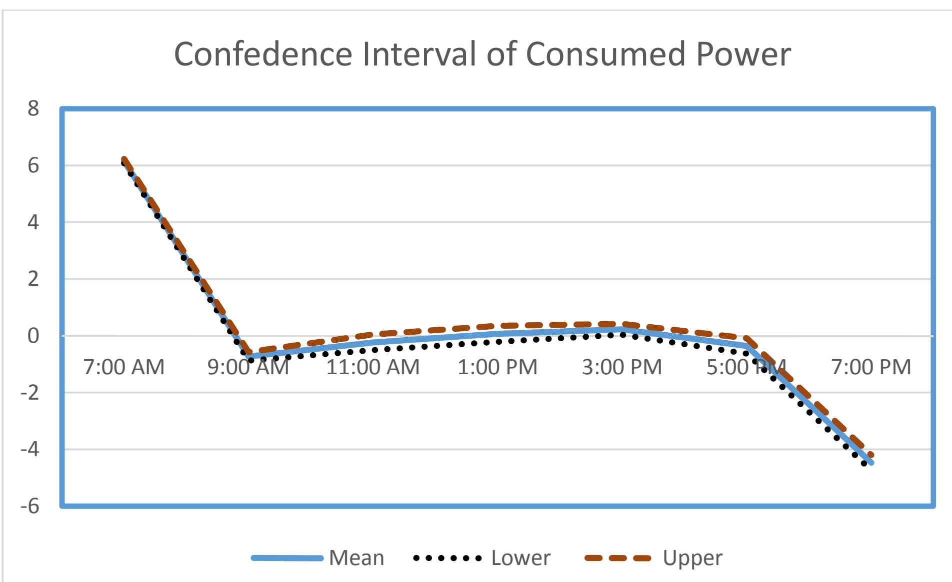

Figure 7-1: CI, Lower, and Upper bounds of Consumed Power Metric

The following tables are used to calculate the confidence interval for the power loss and price metrics.

Number of Runs	7:00 AM	9:00 AM	11:00 AM	1:00 PM	3:00 PM	5:00 PM	7:00 PM
5000	1.79016	0.603744	0.450016	0.351552	0.284816	1.082672	0.69072
10000	1.80056	0.718552	0.456152	0.375488	0.570672	1.051064	0.70328
15000	1.805749	0.622427	0.378987	0.328869	0.623003	0.974971	0.670757
20000	1.7799	0.671632	0.412184	0.316472	0.45018	1.056824	0.736176
25000	1.805894	0.622572	0.379132	0.329014	0.623148	0.975116	0.670902
30000	1.780045	0.671777	0.412329	0.316617	0.450325	1.056969	0.736321
35000	1.80604	0.622717	0.379277	0.32916	0.623293	0.975261	0.671048
40000	1.78019	0.671922	0.412474	0.316762	0.45047	1.057114	0.736466
45000	1.806185	0.622862	0.379422	0.329305	0.623438	0.975406	0.671193
50000	1.780335	0.672067	0.412619	0.316907	0.450615	1.057259	0.736611

Table A. 3: Power Loss at Various Number of Runs

Variable	7:00 AM	9:00 AM	11:00 AM	1:00 PM	3:00 PM	5:00 PM	7:00 PM
$\bar{X}$	1.793506	0.650027	0.407259	0.331015	0.534996	1.026266	0.702347
σ	0.012469	0.03612	0.028815	0.018961	0.084032	0.044748	0.031109
n	10	10	10	10	10	10	10
$\sqrt{n}$	3.162278	3.162278	3.162278	3.162278	3.162278	3.162278	3.162278
$Z_{a/2}$	1.96	1.96	1.96	1.96	1.96	1.96	1.96
CI	0.007728	0.022388	0.01786	0.011752	0.052084	0.027735	0.019281
Lower	1.785778	0.62764	0.389399	0.319263	0.482912	0.998531	0.683066
Upper	1.801234	0.672415	0.425119	0.342767	0.58708	1.054	0.721629

Table A. 4: Confidence Interval Parameters for Power Loss

Number of Runs	7:00 AM	9:00 AM	11:00 AM	1:00 PM	3:00 PM	5:00 PM	7:00 PM
1000	0.659451	-0.02284	0.053813	0.059807	0.065401	0.023643	-0.45148
5000	0.62291	0.020499	0.001265	0.008938	0.010496	-0.07684	-0.49387
10000	0.654511	-0.03755	0.015311	0.061605	0.064209	-0.01538	-0.56098
15000	0.64796	-0.09245	-0.04058	0.051362	0.063834	0.08749	-0.3545
20000	0.647964	-0.04509	0.062917	0.060493	0.064995	0.008914	-0.45094
25000	0.661159	-0.03927	0.061989	0.064972	0.063076	-0.04672	-0.56283
30000	0.654398	-0.0272	-0.00708	-0.00096	0.002129	-0.03593	-0.49516
35000	0.662593	-0.03118	0.058979	0.061674	0.064566	-0.07736	-0.52627
40000	0.655767	0.016369	0.014457	0.0068	0.018137	-0.05718	-0.44302
45000	0.633411	-0.08045	-0.04461	-0.03798	-0.04032	-0.09308	-0.58584
50000	0.646869	-0.04559	-0.04406	-0.03674	0.017705	0.079754	-0.38311

Table A. 5: Power Loss at Various Number of Runs

Variable	7:00 AM	9:00 AM	11:00 AM	1:00 PM	3:00 PM	5:00 PM	7:00 PM	7:00 AM
$\bar{X}$	0.422102	0.649727	-0.03498	0.012036	0.027271	0.035839	-0.01843	-0.48255
σ	11	11	11	11	11	11	11	11
n	3.316625	3.316625	3.316625	3.316625	3.316625	3.316625	3.316625	3.316625
$\sqrt{n}$	0.000958	0.012131	0.033982	0.043192	0.040537	0.036194	0.06201	0.074347
$Z_{a/2}$	1.96	1.96	1.96	1.96	1.96	1.96	1.96	1.96
CI	0.000566	0.007169	0.020082	0.025525	0.023956	0.021389	0.028045	0.033625
Lower	0.422668	0.656896	-0.0149	0.037561	0.051227	0.057229	0.009618	-0.44892
Upper	0.421536	0.642557	-0.05506	-0.01349	0.003315	0.01445	-0.04647	-0.51617

Table A. 6: Confidence Interval Parameters for Power Loss