THE ONTARIO FEED-IN TARIFF POLICY: AN ASSESSMENT

by Zakaria Nadir

(0300151471)

Major Paper presented to the
Department of Economics of the University of Ottawa
in partial fulfillment of the requirements of the M.A. Degree

Supervisor: Professor Gamal Atallah

ECO 6999

Ottawa, Ontario

August 2023

Table of Contents

Acknowledgement

I would like to express my sincere gratitude to my major research paper supervisor, Professor Gamal Atallah, for his unwavering guidance, invaluable insights, and continuous support throughout the course of my research. Your dedication to excellence and your commitment to nurturing a conducive learning environment have been instrumental in shaping the trajectory of my academic journey. Your mentorship has not only enriched my understanding of the subject matter but has also inspired me to strive for excellence in all aspects of my work. Thank you for your patience, encouragement, and belief in my capabilities.

I am equally thankful to Professor Aggey Simons, who served as the second reader of my research paper. Your constructive feedback and thoughtful suggestions have played a pivotal role in enhancing the quality and rigor of my research. Your expertise and discerning eye have challenged me to think critically and refine my ideas, ultimately contributing to the academic rigor of my work.

I extend my heartfelt appreciation to the former Chair of the Economics department, Professor Catherine Deri Armstrong. Your sense of empathy and visionary leadership have left an indelible mark on my academic experience. Your insistence on the importance of establishing strong mathematical foundations through the Math Bootcamp, which you personally supervised, has been immensely beneficial. The rigorous training not only equipped me with the necessary tools but also instilled in me a deeper appreciation for the quantitative aspects of economics. Thank you for your dedication to fostering a holistic learning environment that empowers students to excel.

I am indebted to Professor Louis Hotte for his remarkable efforts in initiating me into the art of writing an economics paper. Your guidance, mentorship, and systematic approach have demystified the intricacies of crafting a well-structured and impactful research paper. Your expertise has been a guiding light, and I am truly grateful for your patient guidance as I navigated the nuances of scholarly writing.

I would like to acknowledge Professor Leslie M. Shiell for his exceptional ability to elucidate abstract mathematical concepts in a creative and accessible manner. Your innovative teaching methods have made seemingly complex ideas comprehensible to a wide audience, and your

passion for teaching has been an inspiration. Thank you for imparting a deeper understanding of mathematical principles and for fostering a love for learning within me.

My gratitude extends to the dedicated department Officers, Alexie Morin-Fortin and Guilherme Queiroz, whose unwavering availability and cheerful willingness to assist have been a tremendous asset. Your prompt and helpful responses to my queries have eased my academic journey, and I am thankful for your constant support.

In conclusion, my academic pursuit has been shaped and enriched by the collective efforts and contributions of these remarkable individuals. Their guidance, wisdom, and encouragement have been pivotal in my growth as a scholar, and I am deeply appreciative of their role in my journey.

Abstract

Renewable energy technologies have reached an outstanding level of performance and have benefitted from economies of scales as they are increasingly integrated in energy systems around the world. Yet, they haven’t reached the level of technological maturity that guarantees a competitive return on investment in comparison with conventional fossil fuels technologies. Regulation was called for to correct the market’s inability (so far) to attract investors to renewables’ arena. In the power sector, feed-in tariffs have been a regulatory instrument to mitigate the risk associated with the uncertainty of renewables’ output by guaranteeing rates regardless of what the market price is. This violates the market efficiency principle and requires therefore an assessment. Our research shows that the viability of feed-in tariffs depends on the flexibility of the power system and therefore its ability to cost-effectively withstand renewables intermittency. Shedding light on Ontario’s experience with the policy, our research shows, through an empirical investigation, that between 2015 and 2018, the injection of wind power generation, up to 1,581 MWh, decreased electricity rates in the province by 0.0366 $ per MWh of wind energy on average but beyond that threshold 1 MWh of wind energy increased rates by 0.0120 $/MWh on average. Overall, the policy was, according to our conservative scenario, able to save on electricity rates, generating gains almost equal to feed-in tariff payments, in addition to preventing the emission of 5.8 M tons of CO2.

Introduction

The climate emergency has caught everyone by surprise. Suddenly, the business-as-usual way of doing things was no longer sustainable given how quickly our planet's temperature has been rising over the past decades. Many initiatives have been taken to cut down greenhouse gas emissions responsible for capturing more heat than necessary in the atmosphere, causing temperature to abnormally rise and therefore ecosystems to be disrupted. The power sector, which is one of the major CO2 emitters, has also been overwhelmed with a variety of measures that aim to increase the contribution of clean sources in the energy mix. After so many years since the Kyoto Agreement and other more binding agreements such as the Paris Accord, it is legitimate to question the effectiveness of these measures, not to vilify any of them, but to assess the way they were implemented. There is no question that some kind of regulation must be enacted to protect the environment because, if left without intervention, markets will inevitably fail to address the issue. In fact, profit maximization is not aligned with the inclination to use clean energy sources for a variety of reasons. First, although proven and performing very well, renewable energy technologies have an uncertain output. In a pure market, this means uncertain revenues putting profitability at stake. Most investors, even the least risk averse ones, would not take such a risk. Why would an investor commit colossal amounts of money in an uncertain venture when many alternatives guaranteeing decent returns on investment (ROI) are available? Secondly, the abundance of fossil fuels makes it hard, economically speaking, to simply give up on using them because doing so would cause an obvious opportunity cost that it never makes sense economically to bear. Thirdly, old investment paradigms are so established and rooted in the consciousness of many investors that they may simply pass on investing in renewable energy because it would make them nervous to venture in something relatively new.

Regarding the specific case of the power sector, what adds insult to injury is that the sector has already been cursed with a sluggish transition from vertical and state-owned systems to segmented and market ones. Unlike the airline and telecom sectors, for instance, that have succeeded to transition to fully functional markets requiring little to no regulation, the power sector continues to rely on heavy regulation to keep rates stable and supply secured. Adding the climate challenge to the picture, it would be almost impossible to rely on private sector initiatives in the absence of incentives imposed by regulators.

The feed-in tariff (FIT) policy is one of those measures that were put in place to mitigate renewable energy's uncertainty by guaranteeing a rate that investors will get no matter how low wholesale electricity market prices are. This is a significant incentive because investors, now, won't have to stress about potential revenues if they carefully select their sites and their technology providers. Furthermore, when compared to similar conventional power generation technologies in terms of capital expenditure such as combined cycles gas turbines (CCGT), investors would not find them particularly attractive because the latter will still get a market price since they have full control over the output while the former are now, thanks to FIT, unaffected by market price fluctuations.

The FIT mechanism does a great job at mitigating the risk associated with renewables and does attract investors in many instances, but since there is a cost incurred by society, it is necessary to assess its effectiveness. The goal of our research is to, first, determine the set of parameters that come into play when assessing how well a FIT policy was implemented through an economic analysis and secondly, shed light on Ontario's experience with the policy that lasted from 2009 to 2016[1] through an econometric analysis. The economic analysis provides a rigorous formulation of the problem of satisfying electricity demand at the least cost in the presence of renewables and provides a theoretical framework to assess potential gains, whereas the econometric analysis considers data about Ontario's wholesale market to investigate whether there was any effect of the policy on electricity rates and CO2 emissions over the period from 2015 to 2018. Performing both analyses helped us leverage insights from the economic analysis to guide the empirical investigation which endowed our research with some originality. In fact, we found, thanks to the economic analysis, that gains from renewables' integration in a power system are not unambiguous. More specifically, we found that gains from renewables depend on the level of the power system's flexibility, that is, its ability to ramp up and down production according to renewables' output. As renewables inject more power into the system, more flexibility will be required to ensure cost-effectiveness. This insight was then used in the empirical analysis by allowing regression results to vary depending on renewables' penetration rate.

---

[1] 2016 was the last year Ontario authorities accepted FIT applications, but existing FIT projects continued to be operated beyond that year according to FIT contracts' terms.

For our empirical analysis, we used data about Ontario's wholesale hourly electricity price known as the Hourly Ontario Energy Price (HOEP), hourly electricity demand and hourly power generation by technology all available on the Independent Electricity System Operator (IESO) website. These data were used to run regressions to uncover effects that wind power may have on electricity rates. As to the assessment of the FIT policy per se, we used, in addition, data about yearly FIT payments also available on IESO's website. Our econometric approach consists of viewing electricity rates as the instantaneous reflection of the energy mix state. In fact, electricity pricing, whether in pure markets or regulated ones is always cost-based as either competition or regulation will take care of exerting a downward pressure on prices. The novelty brought by our research is to allow any potential effect to vary depending on the level of renewables' penetration.

Within the context of the Ontario power system from 2015 to 2018, when wind production was lower than 1,581 MWh, we found that 1MWh of wind power reduces electricity rates by 0.0366 $/MWh on average. Beyond that wind penetration threshold, the effect switches sign as 1MWh of wind power now increases electricity rates by 0.0120 $/MWh on average. Both effects are statistically significant at the 1% and 10% significance levels respectively. Regarding CO2 emissions, we found that 1 MWh of wind power reduces the use of fossil fuel power plants by 0.487 MWh on average below the wind threshold and by 0.502 MWh on average beyond. Both effects are statistically significant at the 1% significance level. As to our assessment of Ontario's FIT policy, we found that, from 2015 to 2018, the policy generated a gain of $ 6 B and prevented the emissions of 5.8 M tons of CO2 while it costed $ 6.3 B according to our conservative scenario.

To conduct our research, we first review some of the literature that attempts to quantify the impact of FIT on electricity rates but also offers a critical assessment of the policy and others that are quantity-based such as Renewable Portfolio Standards (RPS) and Quota Obligations. We then analyze, on a fundamental level, the dynamics between renewable integration and power generation cost by formulating the optimization problems that arise from simulating a simplified power system, gaining insight as to how renewables interact with the rest of power plants. We then describe the data we use and explain the details of our empirical approach before we present and discuss our findings.

1. Literature review

1.1 Impact of RES on electricity rates

Given its intermittent nature, renewable energy has been hard to scale up without the need to impose a favourable regulatory framework for its development. In fact, investors were reluctant to engage in the risky business of investing in newly somewhat proven renewable energy sources (RES) technology whose output is not clearly identified. There is no question that RES technologies have gained a lot of maturity over the past years, requiring less and less capital expenditure and performing very well from a technical standpoint, but their intermittency has always been a serious concern for investors. Given the urgency of global warming and the consequences of climate change, policy makers have come up with a range of regulatory instruments to support the development of RES projects to cut greenhouse gas emissions which are a major externality of conventional power generation technologies. The underlying idea behind these instruments is the compensation of the risk associated with RES variability, so that they become more attractive to investors. Examples of these instruments include price-based ones such as FIT and the feed-in premium (FIP), and quantity-based ones such as RPS and Quota Obligations. Most of the research that studied the effectiveness of these instruments has only been conducted post-implementation after many stakeholders have noticed a sharp increase in electricity prices. Ritzenhofen et al. (2016) quantified, through a long-term capacity investment model, the effect of FIT and RPS on the Californian electricity market. The model was built in such a way to mimic the actual behavior of investors and consumers. In fact, they did not stop at the stage of finding an optimal unit commitment solution under each policy and then conclude as to what the renewable capacity is and what the retail electricity prices are but rather, they added iterations to illustrate a natural selection of projects whose net present values are positive or else they will be rejected. Sorting out power plants from the least to the most expensive one and using the selected projects they then constructed the supply curve and obtained electricity prices. They found that FIT is more cost-effective than RPS in terms of achieving renewables penetration and price reduction goals because with a flat rate discounted payment streams will be lower and lower in the future whereas with RPS there is still a chance for investors to get high payments. In terms of their impact on the reliability of supply, FIT does poorly in comparison with RPS because of the lack of incentives to contribute to meeting demand during peak hours.

Trujillo-Baute et al. (2017) studied the impact of a variety of instruments, including FIT, FIP, Quota Obligations and Tax Exemptions, on EU countries electricity retail prices. They found a positive and statistically significant effect though weak in magnitude. Their approach consists of explaining electricity prices in terms of the renewable energy promotion costs, taxes and levies controlling for electricity consumption and network costs.

Another effective, yet costly, tool available to mitigate renewables' intermittency and to overcome their non-storability is capacity payments which gives Transmission System Operators (TSO) the right to use a certain capacity in cases of emergency. Marques et al. (2019) cleverly investigated the impact of Spain's FIT and FIP considering capacity payments and they found that power producers tend to bid low on conventional power generation and high on RES in the spot market. Unsurprisingly, these producers maximize their revenue by maintaining nice money streams from FIT/FIP and from capacity payments. Using an autoregressive distributed lag approach, the authors calculated the effect of FIT and FIP on the amount of energy produced through wind and solar PV that turned out to be negative.

Intermittency is a major drawback of RES, but the technologies also have a negligeable variable cost. So, theoretically at least, they have the potential to decrease the electricity generation average cost. Gelabert et al. (2011) empirically investigated how the Spanish electricity energy mix evolved between 2005 and 2010 in the presence of an increasing RES integration, ultimately impacting electricity prices. They found that 1 GWh RES production resulted in a 4% electricity price cut. Though not explicitly accounted for, regulatory measures will inevitably be reflected on the prices especially in a competitive market environment like Spain's. Therefore, their finding also suggests the effectiveness of the overall cost of RES support.

It is no secret that electricity is a non-storable commodity. Handling its offer and demand adequacy can be challenging because shortages and excesses are not tolerated or tolerated within very narrow limits. Interconnections are a vital way to allow power exchanges when power is scarce in a system while it's abundant in adjacent ones. Paraschiv et al. (2014) concentrated their analysis on the impact of RES promotion on the European Energy Exchange (EEX) spot market and they found that while they decrease spot market prices, they do increase retail prices for German consumers (there is an interconnected power system in most of Europe). The authors adopted a dynamic fundamental approach that consists of, on the one hand, explaining the day ahead spot market electricity price in terms of fundamental variables such as the output of wind farms and fossil fuel power plants and fuels' prices and on the other hand allowing regression coefficients to change over time. They, in fact, found that the coefficients of wind output evolve in a negative range, which suggests RES (in this case wind) do decrease spot market prices.

The effect of RES integration on electricity prices stems from the changes that occur in the energy mix. In fact, in the presence of renewable energy, existing power plants will be involved in a different way now that a chunk of demand is satisfied through these renewables. It's unclear though whether this will result in an increase or decrease of the cost of electricity because power plants have technical limits. For instance, to satisfy residual demand, a power system operator may shut down a very expensive power plant which significantly decreases the marginal cost of electricity. However, the operator may also find it impossible to replace renewable energy production by ramping down production of other power plants in a short amount of time and so, they may have to shut down some power plants and start-up others (more expensive) that can ramp up production at the required speed. This effect is referred to as the merit order effect. Tveten et al. (2013) compared German market electricity prices of days of similar demand over the period from 2009 to 2011 and found that integration of PV led to a 7% decrease of prices on average, confirming a positive merit order effect.

The effect of FIT and more generally policies that accelerate the integration of renewables is not consensual in the literature. Nelson et al. (2012) were critical of the merit order effect, arguing that the effect is very small especially in the case of PV panels. Given that PV output is high during off-peak consumption hours, it is likely to replace an already low marginal cost and so, total benefits are not significant. On the other hand, PV investment cost is unambiguously higher than conventional power plants which means that gains can't offset PV investment cost. They added that even these small benefits are unlikely to be internalized by consumers because electricity rates are not flexible in that the reflection of any contraction of wholesale electricity prices on final retail prices is unlikely to happen. However, the study was conducted in 2012, the authors didn't consider the significant investment cost decrease that occurred in the PV industry especially over the past decade.

1.2 FIT structure and design

When implementing feed-in tariffs, policy makers are faced with the delicate question of remuneration. Offering a fixed rate or a premium on top of the market price? What distinguishes the two options is how market-independent the remuneration offered is. Couture and Gagnon (2010) have looked at the experience with both approaches and drew some interesting conclusions. Considering FIT as a representative of market-independent remuneration policies, they found that they provide greater financial assurance to investors as they significantly mitigate their investment risk. This in turn helps them access capital at competitive rates, lowering their financial cost and stimulating economic growth. On the other hand, rates can be ridiculously high when market price is very low as the FIT don't allow for any price adjustment. Plus, supply at a constant rate creates distortions in the demand response of other competitive power plants. In fact, renewable energy, having the priority, causes the output of other power plants to go down when demand is low which cripples the power generation system when demand increases again due to production ramp up limits. Choosing FIP as a representative of market-dependent remuneration policies, they found that the incentive of receiving the market price makes renewables output more aligned with demand fluctuations, limiting therefore demand response distortions. It was even found that the policy helped decrease the cost of meeting demand during peak hours. However, FIP provide much less financial assurance because it is hard to predict electricity prices over long periods (15 to 20 years). Their deployment depends on investors' risk appetite, and they may even not be suitable if the goal is to quickly achieve high renewable penetration rates. Another negative aspect of FIP is that although they are tied to market price, the premium component remains fixed. In case market price decreases, any consumption surplus is lost, which has pushed many countries to consider a sliding premium.

As is the case with any incentive, aiming for a right balance between overcompensating and undercompensating can be challenging. FIT rates are usually negotiated amid environment friendly policies which can give renewable project developers an upper hand pushing therefore for higher rates. Another issue that might arise is adverse selection as developers may not be truthful about their costs. These asymmetries in information and power can lead to market distortions and economic inefficiencies. Lesser and Su (2008) suggest a two-part FIT pricing to mitigate asymmetries between contracting authorities and developers. In fact, a first part consists of receiving capacity bids based on an annual lump sum payment developers will get in exchange of the renewable energy capacity they commit to build. Of course, penalties will be paid by developers if commitments are not honored. Furthermore, contracting authorities could adjust the annual lump sum payment in the bidding process if capacities received are higher or lower than renewable energy goals. This measure significantly increases efficiency and mitigates information asymmetry. The second part consists of the usual energy payments except it is not going to be a flat rate but rather a market price which further increases market efficiency.

FIT rates are usually negotiated or predetermined by policy makers. It’s hard, though, to find the logic behind their definition. They are mainly perceived as being arbitrarily fixed although there might be some vague rationale that may justify their level. At any rate, it’s rare to find clear methodologies that explain how FIT rates were set. Goodarzi et al. (2019) have developed a micro-founded model to find an optimal level of FIT rate that minimizes the cost of electricity. The rate is perceived as a trade-off between a too low price that will not attract investors and will therefore push the system operator to buy alternative expensive electricity, or too high that it would drive RES technology price upward, jeopardizing profitability for developers. Demand for RES technology was innovatively modeled as a function of consumers’ discount factor that reflects their willingness to invest and wait patiently for FIT payoffs. The capacity of RES technology purchased is examined in both a monopoly and competition. What’s interesting about this model is that it shows how variables interact with one another, giving a decision maker the opportunity to anticipate changes and proactively set or adjust FIT rates. For instance, as per the findings of the paper, the authors showed that the optimal level of FIT price is decreasing with respect to the capacity factor that reflects how much energy can be produced per unit of capacity. It follows that policy makers should proactively reduce rates when technology achieves higher performance levels. Likewise, policy makers may reduce FIT rates if they result in a too high demand for RES technology. As a matter of fact, as simple as it may seem, this no brainer piece of advice was not followed in many countries that implemented FIT aggressively such as Queensland, Australia, as reported by Nelson et al. (2012), and resulted in procyclical demand for RES technology, distorting the electricity market and creating a crisis in related industries such as PV installing.

Aiming for an efficient FIT rate, it would be interesting to view the problem as a sequential game with the policy maker as the leader and investors as followers. Farrell et al. (2017) adopted this game-theoretic approach to define the leader’s problem of minimizing the amount of FIT payments subject to a certain renewable generation target by incorporating, as an additional constraint, the follower's problem of deciding on capacity investment that maximizes their profit. In a micro-founded model, all variables were assumed to be deterministic except electricity market price that had to be considered as stochastic. The model finds optimal pricing of FIT under the most common approaches of a constant premium plus prevailing market price, price floor and price floor and cap. Depending on the pricing approach, exposure to market price risk would be allocated between the policy maker and investors accordingly.

Given long term commitments to reduce greenhouse emissions, policy makers seek to guarantee that the set of measures that they come up with trigger continuous benefits that go beyond the life cycle of a single or numbered projects. The concept is referred to as dynamic efficiency and is mainly focused on the policy's ability to induce technological improvement and cost reduction in existing technologies, facilitate the integration of emerging technologies and promote technological diversity. Del Rio (2012) assessed the dynamic efficiency of FIT by exploring the impact of its different design elements when implemented in different countries. FIT design elements are areas considered by policy makers when defining the clauses of the FIT. They include market price dependency, technology differentiation, caps & floors, degression, source and duration of support, capacity size thresholds and cost containment mechanisms. Different societal preferences will call for different FIT designs. Societies in favor of aggressive renewable energy integration tend to prioritize market independent and non-technology specific rates, less caps, more floors, and a taxpayer's support.

1.3 Social welfare under FIT

An important step in assessing the effectiveness of FIT is a careful account of its social cost. It could also be interesting to investigate whether the policy is equitable by exploring how this cost is allocated among consumers. Nelson et al. (2012) found that the FIT policy in Queensland, Australia led to a regressive taxation scheme because the high FIT rates are unequally paid back by bottom quintiles income households. In fact, when total electricity consumption by income bracket is considered, they found that electricity pricing resulted in a high weighted average cost among low incomes. This situation is equivalent to taxing low incomes at a 27% rate more while the top quintile is taxed at 8% only. Hence the regressive nature of the policy. Therefore, directly subsidizing renewables and maintaining electricity rates at their ex-ante renewables levels would have been a much more equitable way to finance FIT.

One of the main drivers of the social cost of FIT is the maturity of the technology and its ability to deliver high performance at a low capital expenditure. When they first emerged, PV panels used to be sold at outrageous prices and were inefficient. Their technology has quickly developed, offering high performing panels at competitive prices which should ultimately benefit consumers. Wand and Leuthold (2011) modeled the social welfare that arises from deploying panels as a net benefit from avoided fossil fuel cost and cut in PV panels investment cost on one hand and FIT subsidy cost on the other. Since the expected installed PV capacity, investment cost gains and the FIT payments all depend on the FIT subsidy, they calculated the specific level that maximizes social welfare. They found, within the German context, that the practiced levels of subsidy are above the optimal level. In addition, they found that FIT resulted in a net social welfare increase thanks to real investment costs and FIT rates degression. However, it is unclear whether these gains are due to the effectiveness of the FIT policy or the high electricity market prices that make it seem artificially competitive. It is worth mentioning that the German power system has known significant changes including the decommissioning of nuclear power plants which is likely to result in higher market prices.

The assessment of the social cost of FIT depends on the methodology followed to quantify costs and benefits. While the evaluation of direct costs can be relatively straightforward as it is basically the amount of subsidy paid to RES developers, the benefits can be tricky to uncover. Del Río and Gual (2007) adopted exogenous external cost estimates provided by the European Commission to evaluate the impact of each RES technology on avoided fossil fuel consumption among other externalities within the Spanish context. When the subsidy includes the capacity part (investment subsidy) as well as the energy part (FIT payments), they found that the benefits don’t offset the costs for all RES technologies. However, when the subsidy only includes FIT payments, they found that wind and small hydro projects were able to generate enough benefits to outweigh the costs. The authors don’t provide enough details about how the exogenous external cost estimates were calculated. This affects the soundness of their findings because, being unable to check the accuracy of these estimates, we are unable to check whether the considered benefits are grounded or not. Furthermore, on a fundamental level, the impact of any RES technology is closely related to intrinsic features of the power system in question, namely the shape of its load curve, technologies, interconnections, etc. While it is understandable that some policy makers may find standard estimates appealing thanks to their practicality, it's hard to accept such an approach within the context of a rigorous study.

FIT policy may have a boarder effect by stimulating the economy on top of impacting the power system. Behrens et al. (2016) were interested in quantifying the impact of FIT on greenhouse emissions but also on GDP growth and job creation. They compared their levels under FIT policy and their hypothetical values under a counterfactual situation where there would be no FIT. They considered three channels through which benefits can be achieved: operational, investment and opportunity costs. For example, under FIT, there could be operational savings from using less fossil fuel, an investment cost increase induced by the development of new RES projects and the opportunity cost of not paying the FIT subsidy; whereas under the counterfactual, there would be no fossil fuel savings, no RES capacity investment, and no greenhouse emissions reduction. To figure out the impact of FIT on each of the three mentioned components they relied on linear conversion rates taken from the calibration of a case of reference. The authors did not justify the relevance of these rates let alone justify why such a simplistic approach would make sense.

1.4 Concluding remarks

Based on the articles we reviewed, we note a tendency to adopt floppy approaches to quickly run into concluding that FIT policy has a positive net benefit and that they are welfare-increasing. In fact, we couldn't find a single paper that concluded that FIT is unambiguously welfare-improving through a granular examination of electricity markets that considers real impacts on the actual cost of electricity and on energy mixes. Conversely, reviewed articles that are skeptical about the FIT policy or acknowledge an insignificant positive net benefit were careful in adopting rigorous methodologies that avoided black box coefficients that remain meaningless in the absence of an explanation of their essence. As a matter of fact, these articles recognize the merit order impact for instance but rightly view it as insufficient in some cases to offset FIT subsidies. When many countries shifted to a degressive FIT policy decreasing rates and premiums, skeptical researchers had no problem with acknowledging a relative improvement of policy outcomes.

This is not to say that the FIT policy is an inferior policy or that supporting RES projects is not worthwhile altogether. Rather, this should remind us that being obsessed with protecting the environment should not make us prone to biased results that make us feel good about the current environmental policies. No approach is flawless, even the ones that claim to treat the issue fundamentally using rigorous mathematical models. However, a good investigation is one, in our opinion, that is interested in convincingly explaining the dynamics between a policy and its measurable outcomes rather than impulsively presenting void numbers.

Clearly, there is no consensus in the literature on the effectiveness of RES support including FIT. One argument in favor of such an outcome is that a regulatory measure can't be taken out of its context. In fact, each power system has very peculiar features such as the shape of the load curve, the energy mix, the market structure, and societal choices. Depending on electricity consumption behavior, power systems may have very different load curves that may put a variable amount of pressure on power generation and transmission in the presence of renewables. Likewise, energy mixes can make or break the ability of renewables to synergistically work with other power sources. Competitive markets versus vertically integrated power systems can make it easier for FIT to be more effective. Smart FIT designs can help achieve more market efficiency by leveraging investors' risk appetite. And finally, societies may make the deliberate choice of accepting the burden of RES promotion because they may derive a higher utility from CO2 emissions reduction in comparison with more affordable electricity prices.

2. Economic analysis

Whether in a competitive or a vertically integrated market, the goal of scheduling power generation is to increase consumers' surplus from consuming electricity which comes down to delivering it at the least possible cost. Markets tend to converge to a merit order logic that prioritizes cheaper power generation means when satisfying electricity demand either through a bid mechanism in competitive markets or through central power dispatching in vertically integrated ones. The merit order approach considers fundamental variables such as the start-up cost, the variable cost function of power generation by technology, technical features of power plants that describe their operability as well as energy balance requirements imposed by the very non-storable nature of electricity. The goal, then, is to minimize the total operating cost of generating electricity while making sure power plants operation constraints and electricity demand are satisfied. Within the context of FIT, we seek to understand whether the policy makes sense given the goal of cost minimization through an economic analysis.

2.1 Power generation variable cost functions

Unlike the start-up cost, which is a fixed cost that reflects the difficulty of starting up certain units compared to others, the variable cost function provides, by definition, a relationship between the level of output and the corresponding cost, bearing in mind that the relationship would not necessarily be linear. For thermal power plants, the variable cost comprises a variety of components such as maintenance and labor, but the most important component remains, by far, the fuel cost. As an analogy with economic production functions, we know that increasing returns to scale imply a concave cost function and decreasing returns to scale imply a convex cost function because, qualitatively speaking, decreasing returns, for instance, mean that, for an increase of inputs by the current amount, production will increase by less than the current level and therefore for the same additional cost less is produced. Hence the convexity of the cost function. In the realm of thermal engines, the role of a production function is fulfilled by the engine's efficiency which consists of a relationship that translates heat (the input) into power (production level) and that efficiency happens to be decreasing, for thermodynamic reasons, as production level increases. The cost function of a thermal power plant is therefore convex and is, more accurately, quadratic for the same thermodynamic reasons mentioned earlier. Thermodynamics provides the general form of the function, but exact coefficients of the polynomial are yet to be estimated based on historical performance data. Vanithasri et al. (2016) used a modified version of the radial optimization movement to estimate the coefficients of the cost function in the case of coal, oil, and natural gas. Depending on the type of the thermal power plant in question, the quadratic cost function will have different coefficients. For instance, steam turbines that run on coal or oil have lower efficiencies in comparison with open or combined cycle gas turbines (OCGT or CCGT) that run on natural gas. Therefore, we should expect the former to have a more convex cost function than the latter. Regarding nuclear power plants, they are hard to build, certainly costly as well in terms of capex, but once commissioned they deliver a large amount of power in a reliable and steady fashion, what's more, at a very low variable cost. As to renewable energy power plants, they also have a high capex and low variable cost although capex has been declining over the years as significant technical progress and high deployment rates have been achieved. Finally, hydro power plants that are usually thought of as run of river or reservoir plants, have very low variable costs as well, but their output depends on the availability of water just like renewables depend on the availability of the renewable resource (wind, sun radiations, …). For the last three power generation technologies whose operation is independent of any combustible fossil fuel, they don't have variable costs in functional forms. However, in practice, these variable costs can be quantified based on historical operation and maintenance expenses.

2.2 Power plants operability constraints

Let's recall that the basic problem we are facing is to satisfy demand at any moment using the combination of power plants that lead to the least total cost over the considered period. This optimization is usually run on a representative day where demand must be satisfied every hour or less than that, depending on the computational ability to solve the problem as going from an hour to 5 minutes for instance will multiply the number of decision variables by 12, which is significant.

The first requirement that we must deal with is to ensure that there will be enough capacity to satisfy demand which comes down to considering energy balance constraints at every unit of time. The amount of capacity available to satisfy demand is itself subject to the limits of each power plant. It is intuitive to think of a maximum capacity that must be considered but perhaps it is less intuitive to think of a minimum capacity that is different from zero for each power plant. This minimum is commonly called technical minimum and is considered in the case of thermal and nuclear power plants. The reason such a minimum exists is because, for technical reasons, to keep a power plant running, we shouldn’t go below a certain threshold so that its mechanical parts keep spinning. When there is an increase in demand, power plants can therefore, within a reasonable amount of time, increase production. However, if the power plant is totally shut down (which is equivalent to setting its output to zero), we will have to spend a considerable amount of money to start it up and the process will take a very long time. That said, the optimization process should not disregard the possibility of totally shutting down a power plant and then starting it up afterward if, given how demand changes, it is more cost-effective to do so or perhaps it is simply not possible to leave a unit spinning at a low production level because the market demand is very low. In fact, generating power at a level that is higher than demand is not tolerable because it has disastrous consequences such as blackouts, high voltage frequency, etc.

Talking about capacity limits, we mentioned that power plants should be able to vary their outputs. So, this is yet another constraint that must be considered as the capability of ramping up or down production depends on the type of technology. In fact, nuclear for instance is known for a slow change in output whereas combined cycles can modulate output very fast. This feature of power plants is very important as it provides power systems with the ability to respond quickly to changes in demand or in the output of other power plants.

Finally, thermal power plants are subject to thermodynamic and mechanical constraints that require a minimum amount of time for them to heat up or cool down. When a thermal power is started up/shut down it is expected to stay online/offline for a minimum amount of time.

2.3 Renewables intermittency

Apart from renewables, all other power generation technologies are 100 percent controllable in the sense that we can specify their outputs. Some technologies offer more capacity while others offer more flexibility but they all can be operated within their capabilities’ limits to produce at a certain level. However, renewables are not controllable in this sense because their output entirely depends on the availability of the resource. Going back to our optimization problem, we are faced with the impossibility of modeling the renewable capacity in the same way we did with conventional power plants. One accurate way to model them would be to come up with a stochastic representation of their output, shifting the problem from the minimization of a deterministic to an expected operational cost. However, this approach is time-consuming and would not lead to particularly useful results for the effort it requires. Instead, we can simply consider two scenarios of renewable production, high and low. For each scenario, we will have a plausible renewable output curve that we can subtract from demand as renewable energy is immediately dispatchable. The problem is, then, reduced to the satisfaction of an artificial residual demand using conventional power generation only.

2.4 Mathematical formulation

The goal of this section is to express, in mathematical terms, the problem of satisfying electricity demand at the least cost, not to solve it because that would be way beyond the scope of our research, but to show the parameters that dictate how the power system evolves at every moment to maintain balance between production and demand in the cheapest possible way. Given the constraints presented earlier and following Bechert and Kwatny (1972) who were the first to define the problem in its dynamic form, the problem can be formulated as follows:

Minimize the total cost:

$\sum_1^T \sum_1^N (GC_i(P_{i,t}).\, isON_{i,t} + S_{i,t}.\, (1 - isON_{i,(t-1)})\, .\, isON_{i,t} + SD_{i,t}.\, (1 - isON_{i,t}).\, isON_{i,(t-1)}$,

subject to the load balance requirement:

$\sum_{i=1}^N P_{i,t}.\, isON_{i,t} \geq D_t$,

the production range constraint:

$P_{i,Min}.\, isON_{i,t} \leq P_{i,t} \leq P_{i,Max}.\, isON_{i,t}$,

the ramp up/down capability:

$-Down_i \leq P_{i,t} - P_{i,(t-1)} \leq Up_i$,

and the operation time constraint that reflects how fast a unit can heat up or cool down:

$T_i^{ON} \geq T_{i,Min}^{ON}$ & $T_i^{OFF} \geq T_{i,Min}^{OFF}$.

$GC_i(P_{i,t})$ is the quadratic power generation cost function at the level of production $P_{i,t}$ of unit *i* at period *t*. $isON_{i,t}$ is a binary variable describing whether unit *i* is committed or not at period *t*. $S_{i,t}$ and $SD_{i,t}$ are respectively the start-up and shut down costs of unit *i* at period *t*. D_t is residual demand at period *t*. $P_{i,Min}$ and $P_{i,Max}$ are respectively the minimum and maximum power limiting the production range of unit *i* while it is online at any time period. $Down_i$ and Up_i are respectively the decrement and increment of power that unit *i* can perform between two consecutive periods of time. T_i^{ON} is the number of periods during which unit *i* remains online and $T_{i,Min}^{ON}$ is the minimum number of periods during which unit *i* must remain online. T_i^{OFF} is the number of periods during which unit *i* remains offline and $T_{i,Min}^{OFF}$ is the minimum number of periods during which unit *i* must remain offline.

Depending on the level of demand and the capabilities of the power generation system, the optimization process will commit, for each period *t*, the set of units that result in the least total cost. Within the context of a feed-in tariff policy that encourages the integration of renewable energy in the system, we seek to understand how the optimal solution will change when more renewable energy is integrated in the system, what are the ramifications in terms of the operational cost of producing electricity, whether there are any notable savings and most importantly whether they outweigh the financial support given to FIT beneficiaries. In fact, in the presence of a renewable generation, the optimisation problem will consider the residual demand that corresponds to total demand minus the amount of renewable energy produced. It is not clear whether the cost of generating electricity to satisfy the residual demand will necessarily go down given power plants operations constraints presented earlier that may cause some expensive units to be used more in comparison with the no-renewables scenario.

As stated earlier, we will not do this exercise in a general case. Rather, we will construct a simplified prototype of a power system and use our knowledge of the nature of the operational constraints presented previously to uncover the dynamics between renewables' integration, demand, and the rest of the power generation units through the simulation of typical scenarios.

2.5 Simulation of a simplified power system

Let's consider a power system that consists of the three power plants presented in table 1 with their main features. The simplified power system is ideal but highlights important aspects that are crucial to our understanding of its response to a demand or renewable output fluctuation. In fact, while hydro (reservoir type) really doesn't have any ramp up/down limit, CCGTs do have a high limit. Nonetheless, granted that we seek to create an instructive case, we can allow CCGT to freely ramp production up and down without loss of generality if we choose to capture the system's overall flexibility in ramp up/down limits of nuclear.

Table 1: Main technical and economic features of the installed capacity of a simplified power generation system

	Technology	Max (MW)	Technical minimum (MW)	Ramp-up/down (% / period)	Start-up/Shut-down cost ($)
PP1	Nuclear	1,000	400	20%	1,500
PP2	Hydro	500	0	No limit	0
PP3	CCGT	350	120	No limit	500

Source: Own calculations

Let's suppose that demand has the following profile:

- Period 1: 750 MWh
- Period 2: 950 MWh
- Period 3: 1,300 MWh
- Period 4: 1,700 MWh
- Period 5: 1,200 MWh
- Period 6: 900 MWh

The demand has the common humped curvature, peaking in period 4 at 1,700 MWh.

Let's suppose that PP1 and PP2 have a zero variable cost and that PP3 has the following quadratic variable cost function:

$$C_t = 0.05P_t^2 + 0.01P_t.$$

Initially PP1 is online. Demand will be satisfied during the first period by PP1. In the second period, as demand increases, we can ramp up PP1 by 20% to 900 MWh and start up PP2 and set it at 50 MWh. In the third period, demand continues to grow. So, to maintain balance, we ramp up PP1 to the maximum 1,000 MWh and PP2 to 300 MWh. In period 4, demand reaches a peak at 1,700 MWh. So, we ramp up PP2 to 500 MWh, but we will have to start up PP3 and set it at 200 MWh. In periods 5 and 6, demand decreases and so we can first shut down PP3 because that will immediately decrease the variable cost and then, ramp down PP1 and PP2, in a similar fashion as we did earlier, to maintain balance.

Let’s suppose that we integrated a 200 MW wind capacity in the system and explore how the system will adjust. Let’s recall that FIT payments are due upon injection of renewable energy in the system at a fixed unit price regardless of demand and supply dynamics. Let’s, then, explore two extreme scenarios depending on wind production profile. The first scenario, dubbed off-peak, corresponds to an abundant wind generation when demand is low and a scarce wind generation when demand is high. The second scenario, dubbed on-peak, corresponds to an abundant wind generation when demand is high and a scarce wind generation when demand is low. Both scenarios are depicted in table 2.

Wind power being supported by FIT and having a zero variable cost is prioritized in satisfying demand. So, to figure out the new optimum, we can start with the previous solution, worked out in the absence of renewables, and replace previous power production with available wind power, starting with the most expensive units and adjusting the output of existing power plants following the same algorithmic approach followed in the case without renewables.

Table 2: Wind power production profiles in two different scenarios

	Off-Peak Production Scenario (MWh)	On-Peak Production Scenario (MWh)
1	180	10
2	170	20
3	20	80
4	10	180
5	20	170
6	80	20

Source: Own calculations

Note that, counterintuitively, the “free” renewable energy did increase power generation variable cost by:

$$+(0.05 \times 205.04^2 + 0.01 \times 205.04) - (0.05 \times 200^2 + 0.01 \times 200) = \$ \;\; 823.32$$

as shown in table 3. In addition, PP3 produced 5.04 MWh more emitting therefore more CO2.

This result is explained by the importance of having flexible power plants in the system. In fact, nuclear (PP1), although cheap and having a large maximum output, has modest ramp up/down capabilities. Therefore, the integration of free wind power comes at the cost of a high usage of more flexible but also more expensive power plants (PP3).

Table 3: Optimal power dispatch in the off-peak wind generation scenario

	Demand (MWh)	Wind (MWh)	PP1 (MWh)	PP2 (MWh)	PP3 (MWh)	Variable cost change
1	750	180	570	0	0	0
2	950	170	684	96	0	0
3	1,300	20	820.8	459.2	0	0
4	1,700	10	984.96	500	205.04	$+(0.05 \times 205.04^2 + 0.01 \times 205.04) - (0.05 \times 200^2 + 0.01 \times 200)$
5	1,200	20	787.968	392.032	0	0
6	900	80	630.374	189.626	0	0

Source: Own calculations

Unlike the previous case, now wind integration is accompanied by a gain of:

$$(0.05 \times 200^2 + 0.01 \times 200) - (0.05 \times 120^2 + 0.01 \times 120) = \$1{,}280.80$$

as shown in table 4. In this scenario, PP3 generated 80 MWh less emitting therefore less CO2. This result is explained by the fact that wind, peaking in the same period as demand does, will relieve a power system that is being stretched to the limit by committing the last most expensive units.

In the previous scenarios, we didn't consider the operation time constraint. We can qualitatively see that adding it to the problem will increase the variable cost further, in the off-peak scenario, because once PP3 is started up in period 4 it must remain online for the next period too, at least if we assume a minimum of two-period operation time. In the on-peak scenario, this constraint will decrease the volume of gains.

Table 4: Optimal power dispatch in the on-peak wind generation scenario

	Demand (MWh)	Wind (MWh)	PP1 (MWh)	PP2 (MWh)	PP3 (MWh)	Variable cost change
1	750	10	740	0	0	0
2	950	20	888	42	0	0
3	1,300	80	1,000	220	0	0
4	1,700	180	1,000	400	120	$-(0.05 \times 200^2 + 0.01 \times 200) + (0.05 \times 120^2 + 0.01 \times 120)$
5	1,200	170	800	230	0	0
6	900	20	800	80	0	0

Source: Own calculations

In conclusion, although the wind capacity is producing the same exact amount of energy in the two scenarios (480 MWh), its integration to the power system led to two different outcomes. The first takeaway is that, contrary to popular belief, renewables are not synonymous of lower variable cost of generating electricity as this will depend on the variability of the resource and the flexibility of the power generation system. The second takeaway is that the negotiation of the FIT rates should consider the volume of gains (if any!). The third takeaway, and perhaps the most important one, is that granting FIT contracts should be done according to an optimal level of power generation system flexibility. If there is a societal choice that is in favor of increasing renewables, the electricity planning authority should proactively plan the optimal size and number of flexible units required to ensure that savings will outweigh FIT contracts' social cost.

Ma et al. (2013) suggest, to design the addition of new flexible units to the power generation system, the adoption of an objective function that differs from the one presented in our mathematical formulation by adding investment and operational costs of candidate flexible units. Depending on technological progress, different unit sizes with different capabilities, investment and O&M costs will be available for the system planner as candidate units. To find the optimal choice, the simulation should then be conducted in representative weeks to consider not only intraday variability but also weekly and seasonal variations of demand and renewable energy alike.

In a vertically integrated power system, the mentioned approach would be sufficient. However, in a market-based system, investors who will sponsor flexible power plants projects must make certain that they will be better-off investing which comes down to deriving a positive profit. Revenue streams, in a market-based system, are twofold: revenues from participating in the day-ahead market and revenues from the real-time balancing market. While the day ahead market is open to all generators, the real-time balancing one is only available to flexible units that can respond to a quick demand increase or renewable output decrease. A favorable investment decision will be made if these discounted net revenues offset the investment cost.

In the end, through proper planning, all stakeholders should be better-off. Flexible unit investors would profit because they would satisfy grounded energy but also flexibility capacity needs that generate a positive profit for them. Renewable energy investors will be able to integrate more energy as less curtailment is expected to occur, increasing therefore their revenues. Baseload generators, who are not well equipped to face renewable energy intermittency, won’t have to respond to quick demand changes and would be able to run smoothly as they should be. And finally, the regulator, who is at the end of the day the representative of consumers, would be able to increase consumption surplus by cost-effectively maximizing the benefit from renewable energy production.

3. Data

3.1 Market price of electricity

Ontario’s electricity wholesale market is an information platform that allows power generators and distributors to make bids to sell/buy electricity based on supply and demand constraints. The IESO oversees these transactions that take place every 5 minutes 24/7 to make sure electricity is continuously supplied at the least possible cost. The cost-effectiveness stems from the merit order that selects cheaper bids first until demand is fully satisfied every 5 minutes. Each hour, the weighted average of the 12 lowest bids represents the average wholesale electricity price also known as the HOEP. HOEP has been very variable over the years as it represents a mere reflection of market interaction between demand and supply. Just in 2022, the average weighted hourly price evolved between the extremes of 29 $/MWh and 60.6 $/MWh. Table 5 shows that, during our research period that lasts from 2015 to 2018, HOEP can have negative values. This is not surprising in electricity markets because offering a fee in exchange of injecting power in the grid enables producers to cost-effectively keep their units running at a low production level instead of going the costly way of shutting down a unit and then starting it up again when demand increases.

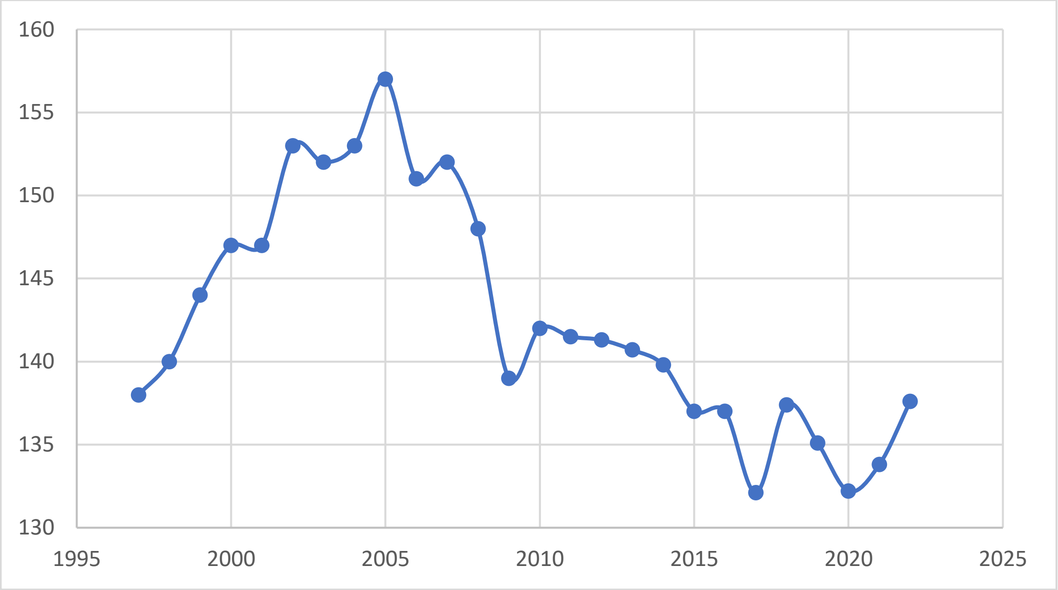
The HOEP only helps cover the power generation cost as other costs are yet to be incorporated in the final price through a separate component. In fact, the global adjustment refers to the cost of building new electricity infrastructures such as transmission grid reinforcements and the cost of regulated electricity rates such as FIT as well as energy efficiency and conservation programs. Large consumers contribute to the global adjustment based on their load’s percentage of the 5 highest peak loads. Once large consumers’ total contribution is worked out, the remainder of the global adjustment is passed on to consumers through their electricity bills. It is remarkable, though, that, since 2009, the global adjustment component started to increase significantly to the extent of surpassing HOEP since 2011. Finally, HOEP data was accessed through IESO’s website.

3.2 Electricity demand

As a power system operator, IESO has access to real time data describing the instantaneous state of Ontario’s power system. The sum of power at substations delivering electricity to distribution grids and losses over transmission lines corresponds to the province’s demand. Ontario’s electricity demand is different from the market demand as the latter includes, in addition, net electricity exports from Ontario to adjacent power systems.

In terms of energy, Ontario's electricity demand was 137.6 TWh in 2022. This is a significant decline from the 2005 level, for instance, where demand was as high as 157 TWh. Over the last 25 years, and as shown in figure 1, the province's demand has known mainly two distinct periods: one of growth that lasted from the late nineties up until the 2008 financial crisis where demand started shrinking steadily to reach the current level. According to Canada Energy Regulator (CER), this steady decline in energy demand is due to reduced industrial demand and increased energy efficiency.

Figure 1: Ontario's annual energy demand 1995-2022 (TWh)



Source: IESO database

In terms of power, all historical peak demands occurred during the sustained growth period mentioned above with the highest being 27,005 MW recorded in 2006. As far as analyzing the impact of wind integration on electricity rates, it makes more sense to use power demand as opposed to energy demand because the former gives a clear idea about how much power plants are being involved whereas the latter informs us of an energy balance over a certain period. Nonetheless, given that all our variables including demand are considered on an hourly level, energy and power will be synonymous. We are, therefore, going to be using Ontario's hourly energy demand as a factor that may cause prices to go up or down. Another demand worth considering, as far as market price fluctuations are concerned, is Ontario's market demand because it captures the opportunity of foreign bids and the limits of domestic power generation. This aspect will be accounted for by considering a power exchange variable which is simply the difference between the market and the province’s energy demands. Finally, electricity demand data was accessed through IESO’s website.

Table 5: Descriptive statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
hoep	35064	182.84	321.83	-670.8	18229.5
ontario demand	35064	15501.057	2327.27	10167	23240
nuclear	35064	10349.201	1012.842	6275	12505
hydro	35064	4075.422	802.011	2190	6379
natural gas generation (NG)	35064	1272.713	1141.747	49	6775
natural gas price	35064	12.972	1.97	9.623	16.29
wind	35064	1081.031	833.224	1	4028
solar	35071	86.649	8113.569	0	1519431
biofuel	35064	39.71	48.436	0	479
exchange	35064	2278.302	625.889	116	5090

Source: Own calculations based on IESO database

3.3 Power generation

Access to real time data at power plants' voltage elevating substations allows IESO to measure the output of every single power plant accurately and instantaneously. Data are then treated by the operator to aggregate it by power generation technology among other criteria. As of 2023, Ontario has a total installed capacity of 38,214 MW shared between nuclear (34%), gas (27%), hydro (24%), wind (13%), solar (1%) and biofuel (less than 1%). In terms of the 2021 energy mix, the bulk of the province's energy demand is satisfied by nuclear (58%) and hydro (24%). Nuclear has historically played a major role in satisfying the province's baseload given its compelling features of having larger unit sizes (around 1,000 MW each), cost-effectiveness and zero CO2 emissions, making this technology the best candidate to ensure a stable and reliable flow of energy almost around the clock. Hydro is the second most important power generation technology in the province and can satisfy demand at any moment, including peak hours, depending on reservoirs' filling rates. In fact, hydro has much better ramp up and ramp down capabilities in comparison with nuclear. The next technologies are power plants that run on natural gas and wind, satisfying respectively 9% and 8% of the province's demand. Let's note the similarity of these two technologies' contributions as they are expected to be synergistically operated to mitigate wind's intermittence on the one hand and natural gas high cost on the other. Wind power has a negligeable variable cost but is highly intermittent while some of the natural gas power plants are very flexible thanks to their superior ramp up and ramp down capabilities but are very expensive. This is a key observation that will be omnipresent throughout our research as it could explain the opportunity of integrating wind power in Ontario's power system. In fact, as shown in table 6, among all variables, the highest correlation of wind is with natural gas generation (NG), and it is indeed negative (-0.184). Otherwise, the rest of the technologies contributed with less than 1% individually which made us focus on the effect of wind and isolate it from other renewables. Finally, it is worth mentioning that IESO does not have access to power generation data at the distribution system level. Only transmission grid (high voltage) connected power plants are considered by IESO.

Table 6: Correlation matrix

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(1) hoep	1.000									
(2) ontario_demand	0.378	1.000								
(3) nuclear	0.033	0.346	1.000							
(4) hydro	0.297	0.624	0.028	1.000						
(5) NG	0.371	0.718	0.056	0.299	1.000					
(6) natural_gas_pr~e	0.024	0.001	0.089	0.118	-0.177	1.000				
(7) wind	-0.088	0.157	-0.005	-0.040	-0.184	0.055	1.000			
(8) solar	0.024	0.156	-0.057	0.138	0.095	-0.003	-0.129	1.000		
(9) biofuel	0.152	0.376	0.067	0.296	0.283	-0.034	-0.069	0.140	1.000	
(10) exchange	-0.138	-0.249	0.347	-0.181	-0.146	-0.035	0.239	-0.200	-0.152	1.000

Source: Own calculations based on IESO database

3.4 Feed-in tariff policy

Under the Ontario Green Act enacted in 2009, IESO was given the authority to sign agreements with renewable energy investors that commit to build renewable energy capacity and to connect it to the transmission network. In exchange, they can sell generated electricity on the spot market at a guaranteed FIT rate. They first receive a payment corresponding to the market price and then they receive the differential afterward if the market price is below the FIT agreed rate. FIT payments are one of the Global Adjustment's components as mentioned previously. In 2016, the province introduced the Large Renewable Procurement as an alternative to the FIT policy for capacities exceeding 500 KW by launching the execution of 454.9 MW in renewable energy contracts.

Despite our efforts, we were unable to find contractual FIT rates. However, we were able to find FIT payments made by the IESO to investors over the years of 2015, 2016, 2017 and 2018 on the operator's website which partly justifies the choice of our research period.

3.5 Natural gas price

Natural gas is approximatively the only fossil fuel used in power generation in Ontario[2]. Price changes will impact the variable cost of power plants that run on natural gas impacting in turn HOEP. We adopted commodity prices taken from the Ontario Energy Board website. We did not consider any natural gas price subsidy since our research is aimed at power generation and not retail use.

---

[2] There is also oil, but it is believed that the amount used is very small as IESO does not disclose data solely relating to oil.

4. Econometric analysis

4.1 Econometric approach

Data, whether it be electricity market prices, demand, or power generation, are highly sensitive to time. Therefore, it makes sense to set our empirical approach in a time series framework. Having explored the underlying reasons that explain how renewable energy and the power system's flexibility play out to determine the cost of generating electricity in the economic analysis section of this report, we now seek to check, through an econometric analysis, whether Ontario's power system data reveal any effect that wind penetration had on the province's electricity market during the period from 2015 to 2018. As a matter of fact, our research is interested in quantifying a possible effect that wind energy had on electricity prices as well as the use of fossil fuel.

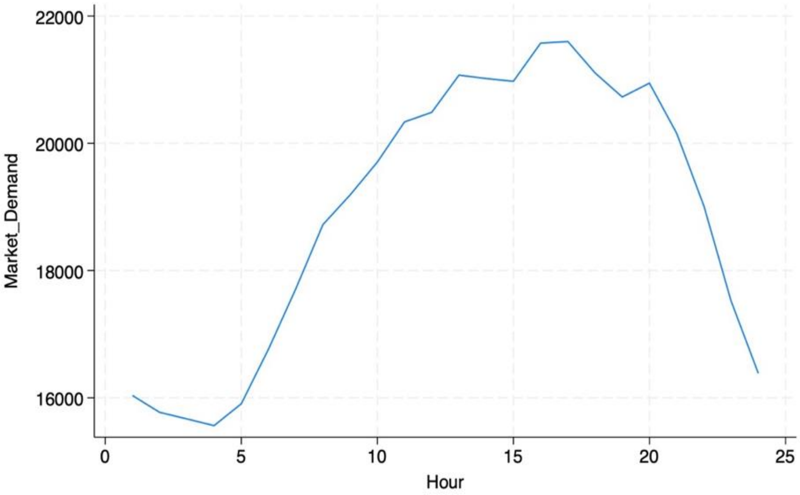
The econometric investigation can also further our understanding of the dynamics between electricity prices and wind integration because it, de facto, considers not only well-known theoretical principles such as the merit order for instance but also chaotic operational constraints such as wind intermittence, unforeseen demand shifts and curtailments that are hard, if not impossible, to examine on a theoretical level.

4.1.1 A close look at Ontario's demand, wind output and HOEP

- The demand

Electricity demand is rather typical in general though not necessarily the same across power systems because it is shaped based on socioeconomic features that may vary from one region to another. The common denominator remains the existence of some kind of variability but also seasonality translating patterns in the consumption behavior of residential, commercial, and industrial consumers. For interconnected systems, a chunk of the market demand reflects, in addition, energy exchanges with neighbouring power systems which is the case for Ontario as the province is interconnected to Quebec, Manitoba, New York, Minnesota and Michigan.

Figure 2: Ontario’s load curve on a typical summer day (MWh)



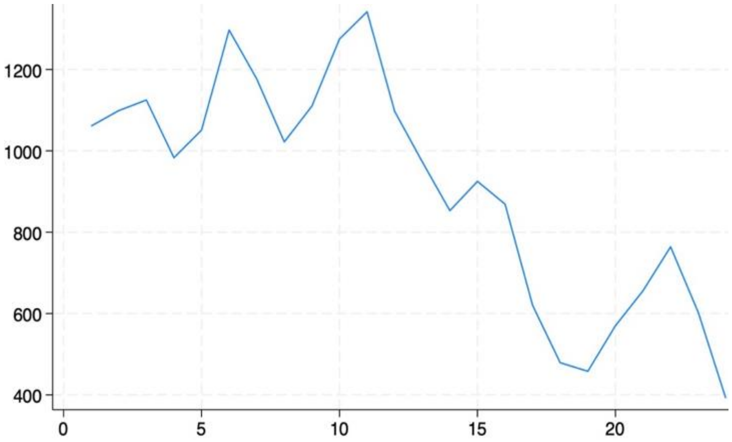
Source: IESO database

On the typical day shown in figure 2, demand went from 16,000 MW at 5am to 18,000 MW in a matter of less than 3 hours which is considerable and confirms the important variability of demand. This should also be seen as a constraint that requires power plants to quickly adapt by ramping up or down production in a timely manner.

- Wind power

Unlike demand, wind is random. It is therefore futile to assume any kind of seasonality when it comes to wind farms’ output.

Figure 3: Ontario’s wind output on a random day (MWh)



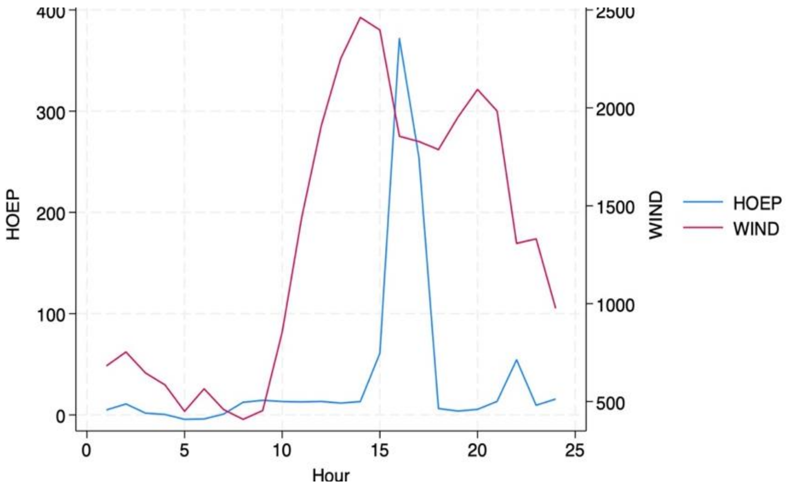
Source: IESO database

As shown in figure 3, we can appreciate how wind fluctuated between 400 MW and 1,350 MW during a randomly picked day in the province. Wind output is not only highly variable but also non-adjustable in the conventional fossil fuel power generation sense. Just like demand, it is a given parameter that is in addition random.

- HOEP

As pointed out earlier, HOEP is the average of the 12 cheapest bids which themselves, thanks to cost-based pricing, reflect the power generation technology cost. Ontario's energy mix is made up mainly of nuclear, hydro, natural gas, wind and solar. Nuclear and hydro's variable costs are stable because they don't rely on any fossil fuel. However, the cost of generating power at plants that run on natural gas will reflect the commodity price's volatility. Wind and solar have negligeable variable costs but the issue is that their outputs are highly volatile which requires spinning and non-spinning power generation backup that is flexible enough to take over when renewable power subsides. This backup is usually made up of CCGT and OCGT that run on natural gas. So, the more abundant and stable wind production is the less natural gas will be used and therefore the lower electricity prices will be and vice versa. In broad strokes, electricity prices would therefore reflect the variability of demand, wind availability and intermittence and natural gas commodity price.

Figure 4: Ontario's HOEP ($/MWh) and wind output (MWh)on a random day



Source: IESO database

So, clearly, HOEP is highly variable reflecting power generation constraints. Figure 4 tells us that, in addition to its variability, HOEP is sensitive to changes in wind output. At 3pm, as wind power decreased significantly there was a sharp increase in HOEP. Of course, this is an isolated remark regarding one randomly picked historical day and does not carry any statistical significance to infer any kind of general result. However, the goal of our empirical analysis is to statistically check the soundness of that claim.

4.1.2 The econometric relationships

Before getting into the econometric relationship per se, we made sure, given our time series framework, that there won't be any misleading spurious relationship stemming from non-stationarity. We, in fact, tested whether electricity prices, power generation output by technology and demand are stationary using the Dickey-Fuller test for unit roots and found 0 p-values which suggests that all variables are stationary. Our econometric models follow in essence Gelabert et al. (2011) who viewed electricity prices as a reflection of the amount of pressure put on the power system to satisfy demand. In fact, more pressure means the need to commit more expensive units, increasing therefore the cost of generating electricity and ultimately wholesale prices too. Having said that, to isolate an unbiased potential effect of wind energy on electricity price, we control for other variables that may influence electricity price too. Let's take, for example, demand. When it reaches peak levels, it puts a lot of pressure on power plants to maintain balance between load and generation. Given the merit order logic and the cost-based pricing approach of HOEP, more expensive power plants will be committed, increasing therefore the marginal cost and electricity rates. Therefore, demand is our first control variable. Among these expensive power plants, there are power plants that run on natural gas whose output influences electricity rates and is, therefore, controlled for too.

Being the only fossil fuel used in Ontario's energy mix, the next control variable is natural gas price as electricity rates could go up simply to allow the recovery of the extra cost imputable to natural gas price fluctuations. Wind not being the only renewable source, we also control for outputs of other renewables such as biofuel, solar and hydro. Ontario's power grid is interconnected to adjacent networks. We, therefore, control for power exchanges between the province and its neighbouring networks. The rationale behind this control is that when electricity is flowing to Ontario's grid, electricity price will reflect either the inability of domestic power plants to satisfy demand and therefore potentially higher bids from foreign generators, or the opportunity of satisfying demand at a lower cost through competitive bids from foreign generators. Finally, it is crucial to remark that, unlike any other power generation technology, nuclear is a baseload capacity whose output is mainly stable. In fact, electricity demand varies but conserves a baseload[3] that is satisfied by nuclear in the case of Ontario. When demand fluctuates during off-peak hours, it is likely satisfied by simply adjusting nuclear production level which leaves the marginal cost of electricity and therefore the price stable. This is different from what is expected to happen during on-peak hours. In fact, when demand is at its peak, ramping up nuclear is likely to be insufficient to satisfy demand, which pushes the system to commit more expensive units that now increase the marginal cost of electricity and therefore price as well. So, nuclear fluctuations are unlikely to impact electricity rates and therefore we choose not to control for them.

We are, therefore, interested in estimating the following relationship:

$$\begin{aligned} HOEP_t = {} & \beta_0 + \beta_1 Wind_t + \beta_2 Demand_t + \beta_3 NG_t + \beta_4 GasPrice_t + \beta_5 Solar_t + \beta_6 Biofuel_t \\ & + \beta_7 Hydro_t + \beta_8 Exchange_t + \varepsilon_t \qquad (1) \end{aligned}$$

where $HOEP_t$ is the HOEP at time *t*, $Wind_t$ is the amount of energy in MWh generated by Ontario's wind farms that are part of the feed-in tariff program at time *t*, $Demand_t$ is the amount of electricity in MWh consumed at time *t*, NG_t, $Solar_t$, $Biofuel_t$, and $Hydro_t$ are respectively natural gas', solar's, biofuel's and hydro's outputs at time *t*, $GasPrice_t$ is natural gas commodity price at time *t*, $Exchange_t$ is the amount of energy exchanged between Ontario's power system and adjacent networks and ε_t is an idiosyncratic error term.

Let's recall that our goal goes beyond evaluating the FIT policy in terms of its impact on electricity rates by examining the policy's ability to mitigate the CO2 emissions externality. So, we also explore the impact of wind output on the use of fossil fuels. A natural and straightforward candidate for the dependent variable would be carbon emissions but these are rarely directly measured and even if they were, it would be hard to check their accuracy given the sensitivity of the topic that might encourage a tendency to communicate lower values. Therefore, it is required to diligently examine carbon emissions at their source anyway. One way to do so is to consider the

---

[3] See figure 2 where market demand does not go below a value just below 16,000 MWh on that day. This amount of power can therefore be considered as a baseload.

amount of electricity generated at power plants that run on natural gas, being the only fossil fuel used to meet electricity demand, and then translate this amount, using power plants' efficiencies and conversion rates, into quantities of CO2 emissions. This choice is not only practical but also conserves the integrity and homogeneity of the analysis. The same amount of electricity generated at natural gas power plants, used to quantify CO2 emissions, is also used as a regressor in our first econometric relationship. Therefore, we are unlikely to face inconsistencies stemming from potentially incoherent carbon emissions with actual natural gas power plants' outputs. Therefore, our dependent variable can simply be the total output of natural gas power generation. We, then, control for demand for the same reasons we did in our first econometric relationship. Controlling for other renewables' outputs and power exchanges is coherent with the merit order logic that reflects a preference for cheaper options. Finally, natural gas being the only fossil fuel, its price fluctuations may encourage generating more power at power plants that run on this fuel if it's too cheap or may discourage its use if the full recovery of the cost is not possible when its price is too high. Our second relationship is therefore:

$$NG_t = \alpha_0 + \alpha_1 Wind_t + \alpha_2 Demand_t + \alpha_3 GasPrice_t + \alpha_4 Solar_t + \alpha_5 Biofuel_t + \alpha_6 Hydro_t + \alpha_7 Exchange_t + \delta_t \qquad (2)$$

4.2 Estimation approach

As a baseline case, we choose to first estimate our econometric relationships using OLS. In fact, under the assumptions outlined in the previous section, we expect the error terms of both relationships to be exogenous and therefore OLS estimates to be unbiased. However, we don't know for a fact whether error terms are homoscedastic. An efficiency issue might then arise using this estimation method. This can be concerning, given that one of the main goals of the estimation, beside pointing out an unbiased effect of wind generation, is to calculate predicted electricity prices and predicted natural gas power generation - both adjusted for zero wind generation - to build a counterfactual case where there would be no wind generation at all. Knowing price and natural gas generation in both cases will enable us to evaluate potential electricity rate savings and prevented CO2 emissions. Therefore, as far as our estimation goal, efficiency of estimates represents an important requirement that must be respected.

Threshold regressions remedy any potential inefficiency of OLS estimates by finding a non-linear -or linear-with-breaks- fit for data depending on the value of a regressor that we suspect may have different effects as it increases. This class of regressions has been applied to time series by considering time as a threshold variable. For example, when analyzing investment strategies, treating time as a threshold variable may provide valuable insights as to when there was a significant change in investment decisions, amounts invested being the dependent variable. The threshold variable can be any other regressor. For example, it is common in macroeconomic models to prefer models that predict a policy interest rate increase only when a certain threshold inflation level is reached. Under a threshold regression, coefficients estimates are worked out by finding the threshold that minimizes the sum of squared residuals to the left and to the right of the threshold. If the number of thresholds is not known information criteria such as AIC, BIC and HQIC can be used to find the number of thresholds that minimizes these information criteria.

The features of threshold regressions are very appealing within the scope of our research because they elegantly allow us to leverage the flexibility insight drawn from our economic analysis. In fact, by treating the amount of wind generation as a threshold variable we are acknowledging the amount of pressure that can be put on the flexibility of the power generation system. If the system's flexibility is solid, then we expect estimates to be similar for all wind generation ranges. On the other hand, estimates will be quite different if the flexibility becomes insufficient as wind generation reaches unsustainable levels. Moreover, threshold regression will result in more efficient estimates in comparison with OLS.

4.3 Results

The results were obtained by using an OLS regression first and then by running a threshold regression[4] where we assume that the effect of wind on electricity rates is not unique but rather changes depending on wind generation ranges. As expected, the threshold regression allowed us to find a better fit for our data given that we found that the error term, under OLS estimation, is heteroskedastic using the Breusch- Pagan-Godfrey test. We found a threshold of 1,581 MWh for wind generation. As shown in table 7, OLS estimation provides one unique effect as 1 MWh wind energy decreases price by 0.0247 $/MWh on average regardless of wind generation level.

---

[4] The threshold regression was conducted by running 28,051 regressions and evaluating the corresponding AIC, BIC and HQIC.

However, the threshold regression yields more granularity in its results by distinguishing between two effects that wind generation may have, depending on whether it is below or above 1,581 MWh. In fact, up to a 1,581 MWh wind generation, 1 MWh of wind energy decreases electricity price by 0.0366 $/MWh on average whereas beyond that threshold, 1 MWh of wind energy increases price by 0.0120 $/MWh on average.

Table 7: Electricity rates regressions results

VARIABLES	(1) HOEP	(2) Region1	(3) Region2
wind	-0.0247***	-0.0366***	0.0120*
	(0.00242)	(0.00462)	(0.00696)
ontario_demand	0.0200***	0.0263***	-0.00577
	(0.00155)	(0.00172)	(0.00359)
natural_gas_price	8.152***	5.825***	15.70***
	(0.818)	(0.916)	(1.829)
natural gas generation (NG)	0.0638***	0.0549***	0.0952***
	(0.00247)	(0.00276)	(0.00569)
hydro	0.0532***	0.0488***	0.0754***
	(0.00276)	(0.00306)	(0.00650)
biofuel	-0.0474	-0.105***	0.193**
	(0.0350)	(0.0389)	(0.0806)
solar	-0.237***	-0.255***	-0.196***
	(0.0222)	(0.0243)	(0.0547)
exchange	-0.0205***	-0.0165***	-0.0341***
	(0.00276)	(0.00320)	(0.00557)
Constant	-445.0***	-479.4***	-310.3***
	(19.72)	(22.56)	(43.95)
Observations	35,064	35,064	35,064
R-squared	0.188		

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Source: Own calculations

Similarly, as shown in table 8, OLS estimation provides one single effect of wind energy on the use of natural gas as 1 MWh wind energy decreases natural gas generation by 0.528 MWh on average irrespective of wind generation level. The threshold regression, on the other hand, considers the wind threshold by yielding two effects that are different in magnitude. In fact, below the wind integration threshold, 1 MWh wind energy decreases natural gas generation by 0.487 MWh on average and by 0.502 MWh on average beyond.

Table 8: Natural gas power plants' output regressions results

VARIABLES	(1) NG	(2) Region1	(3) Region2
wind	-0.528***	-0.487***	-0.502***
	(0.00439)	(0.0109)	(0.0117)
ontario_demand	0.494***	0.504***	0.440***
	(0.00204)	(0.00225)	(0.00497)
natural_gas_price	-68.16***	-75.01***	-48.91***
	(1.728)	(1.969)	(3.543)
hydro	-0.424***	-0.411***	-0.404***
	(0.00551)	(0.00626)	(0.0119)
biofuel	-0.294***	-0.513***	0.590***
	(0.0756)	(0.0861)	(0.155)
solar	-0.694***	-0.862***	-0.119
	(0.0477)	(0.0532)	(0.106)
exchange	0.236***	0.207***	0.310***
	(0.00583)	(0.00702)	(0.0104)
Constant	-3,704***	-3,751***	-3,462***
	(37.70)	(44.63)	(75.72)
Observations	35,064	35,064	35,064
R-squared	0.699		

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Source: Own calculations

4.4 Discussion

Wind power, having a negligeable variable cost, is immediately dispatchable given the merit order logic. The negative impact of wind power on electricity rates can, therefore, be explained by the fact that it reduces the pressure on conventional power generation technologies which in turn reduces the power system's needs for more expensive power generation means at the margin. The magnitude of the impact, on the other hand, will depend on whether this replacement occurs during peak or off-peak hours. In fact, during off-peak hours it is likely that the power system's marginal cost of power generation is that of nuclear or hydro which already have low variable costs, whereas during peak hours wind is likely to replace expensive power generation means, given that during these hours the system is stretched to the maximum by committing the last most expensive units not only because demand is high, but also because it changes more quickly which requires more expensive flexible units.

This scenario, though likely, does not provide a full picture of the dynamics between wind power and the rest of power generation technologies. As a matter of fact, no matter how impressive power generation ramp up and down capabilities are, it is unlikely to expect all expensive units to completely go offline because of the unpredictability of wind even though the latter may be abundantly available. Therefore, depending on the state of the power system, it may be economically more efficient to leave certain expensive units online even though they are not injecting that much power in the grid, just to avoid the costly start-up costs or the even more costly and catastrophic unmet power demand in case wind power goes suddenly to zero. The magnitude of the impact is, therefore, the sum of all these arbitrages that the dispatcher instantaneously makes, through market mechanisms, to navigate the foreseen demand but also the unpredictable wind output. The effect of wind power on electricity rates is, therefore, a net effect of the gains from decreasing the marginal cost and the extra cost of committing expensive flexible back up. If the latter outweighs the former when wind replaces an already low marginal cost or when it is so intermittent that many expensive flexible units must go online, we may end up with a positive net effect, increasing therefore electricity rates. In such a pessimistic scenario, wind power becomes rather a burden instead of an asset. That’s why beyond a 1,581 MWh wind power injection in the grid, existing flexible units may not be enough, or their sizes may not be economically optimal to deal with greater variability of wind power. The system may even be pushed to buy expensive electricity from foreign generators to overcome wind’s increased variability. Therefore, the benefits from integrating wind energy really rely on the level of preparedness of the rest of power plants which directly points to the vital role of planning.

The goal of planning future electric capacity is not to ensure that the total capacity matches the peak electricity demand. That would be a simplistic and even wrong way to think of the purpose of power generation strategic planning. As a matter of fact, our economic analysis showed that a power system should cost-effectively and holistically respond to a changing demand and, with the integration of RES, a changing renewable resource as well. Some of its elements will offer a large capacity but not enough flexibility while others may do the opposite. The bottom line is that when assessing security of supply, one should not stop at the stage of comparing total installed capacity, even by considering capacity factors, to peak demand but transcend this level by looking at the flexibility of the system. Power generation planners come up with optimal expansion plans by simulating long term scenarios of adding units of different kinds based on strategic choices to satisfy the operational goal of meeting demand at the least cost. The simulation uses, in essence, the equations presented in the mathematical formulation section of this report.

Within the context of Ontario's Green Act and Canada's Net-Zero more generally, we expect to see the reflection of strategic choices that support the development of clean sources of electricity such as the extension of nuclear and hydro, the integration of more RES projects and expanding flexible capacities such as OCGT and CCGT. In fact, we know now that lack of flexibility leads to a weak power system that can't cost-effectively withstand renewables' intermittence. So, it's legitimate to enquire about the flexibility of Ontario's power system during our study period. The rigorous way to do it is to simulate, using adequate software, how demand is met in a baseline scenario that uses existing power plants and to compare the cost to that of a hypothetical scenario that explores savings opportunities by adding a CCGT, for instance, to the installed capacity. Unfortunately, it is not always possible to access such a specialized software let alone the data required which is usually considered as confidential by power system operators.

Ma et al. (2013) acknowledged how cumbersome it would be to conduct such simulations each time we are interested in evaluating the flexibility of a certain power generation system. They suggested a metric that reflects an "offline" assessment of the flexibility by defining first a flexibility index with respect to a single generator:

$$flex(i) = \frac{\frac{1}{2}[P_{max} - P_{min}] + \frac{1}{2}[Ramp(i).\Delta t]}{P_{max}}$$

and then the metric that captures a certain system A's flexibility:

$$flex_A = \sum_{i \in A}[\frac{P_{max}(i)}{\sum_{i \in A} P_{min}(i)} \times flex(i)].$$

Through the terms P_{max} and P_{min}, a single generator's index reflects how much room is available to increase or decrease its output in response to a change in the residual demand, while the term $Ramp(i).\Delta t$ incorporates the actual ramp up and down capability. $Ramp(i)$ is expressed in MW/min. We, then, multiply times a time unit of our choice. So, the flexibility index is basically a normalized arithmetic average of these two aspects of a generator's flexibility. The whole system's flexibility is seen as the weighted average of generators' flexibility indices. The way weights were defined reports the significance of a generator in the whole system as the more important a generator is the higher its impact on the system's flexibility.

Within the context of Ontario's power system, we are going to use this metric to evaluate how it changed over the course of our study period in comparison with renewable capacity growth. In this period, the installed thermal and hydro capacity evolved according to table 9.

Table 9: Flexibility of power plants commissioned between 2015 and 2018 in Ontario

Year	**Power Plant**	**Capacity[5] (MW)**	P_{max} **(MW)**	P_{min} **(MW)**	$Ramp(i).\Delta t$ **(MW)**	$flex(i)$
2015	Thunder Bay Unit Converted to Burn Biomass	153	153	45.9	15.3	0.4
2015	Nuclear Upgrade at the Bruce Power Plant	31				0
2015	Thunder Bay Condensing Turbine Project	40	40	12	4	0.4
2015	Old Smoky Falls Units	-53	-53	0	-5.3	0.55
Total year flexibility index change						0.45
2016		0				0
Total year flexibility index change						0
2017	Peter Sutherland Senior Generating Station	29	29	8.7	2.9	0.4
2017	Greenfield South (Green Electron Power)	334	334	100.2	33.4	0.4
Total year flexibility index change						0.4
2018	Namewaminikan Hydro	10	10	0	0.5	0.525
2018	Thunder Bay Generating Station	-153	-153	-45.9	-15.3	0.4
2018	Fort Frances Unit	-47	-47	0	-2.35	-0.525
Total year flexibility index change						0.133

Source: Own calculations and IESO database

To keep calculations easy and meaningful, we assumed maximal power to be the same as the installed capacity, the technical minimum to be worth 30% of the installed capacity if it's thermal and 0 if it's hydro, and the ramp up/down capability to be worth 10% of the installed capacity per minute for all units. To further simplify without loss of coherence, we attribute equal weights of 1 to generators' flexibility indices to figure out the whole system's flexibility yearly change.

---

[5] Negative values for decommissioned units.

While renewable capacity significantly increased from 2015 to 2018 as illustrated in table 10, reaching a total added renewable capacity of 2,283.4 MW, the flexibility of Ontario's power system increased very modestly in magnitude and in a decreasing way as shown in table 9. This may suggest that there wasn't an adequate planning of flexible units that considers the significant increase of renewable projects, which in turn jeopardizes the power generations system's cost-effectiveness in meeting the residual demand.

Table 10: Renewable energy projects commissioned between 2015 and 2018 in Ontario

Year	Project	Capacity (MW)
2015	Grand Renewable Energy Park (Grand SF)	100
2015	Jericho Wind Energy Centre	150
2015	Adelaide Wind Power (Landon)	40
2015	Dufferin Wind Power (Shannon)	91.3
2015	Goshen Wind Energy Center	102
2015	Grand Renewable Energy Park (Grand WF)	149
2015	Goulais Wind Farm	25
2015	K2 Wind Project	270
2015	Bornish Wind Energy Centre	74
2015	Adelaide Wind Energy Centre	60
2015	Kingston Solar Project	100
Total year		**1,161.3**
2016	Grand Bend Wind Farm (Zurich)	99
2016	Northland Power Solar Empire	10
2016	Northland Power Solar Abitibi	10
2016	Northland Power Solar Martin's Meadow	10
2016	Northland Power Solar Long Lake	10
2016	Grand Valley Wind Farms (Phase 3)	40
2016	Armow Wind	180
2016	Cedar Point Wind Power Project Phase II	100
Total year		**459**
2017	Niagara Region Wind Farm	230
2017	South Gate Solar	50
2017	Windsor Solar	50
2017	Bow Lake Phase 1 and 2b	60
Total year		**390**
2018	Amherst Island Wind	74
2018	North Kent Wind 1	99.1
2018	Belle River Wind	100
Total year		**273.1**

Source: IESO database

The significant renewable capacity growth shouldn't really be a surprise given the legislative framework that incentivizes the integration of additional renewable capacity. From an institutional standpoint, IESO is responsible for planning both generation and transmission systems. It has all the prerogatives to anticipate the province's electricity needs. On the other hand, the planning of new power plants is one thing, their development is another. In fact, the tendering process is lengthy and tedious, plus a variety of permits are required to build a new power plant. While we acknowledge that building new power plants can be challenging, we also would like to point out the importance of coordination between green energy policies and difficulties on the ground. Pro-environment policy makers are often portrayed as being isolated from reality and unfortunately our analysis of Ontario's power generation system evolution between 2015 and 2018 may reveal an unhealthy mismatch between green energy goals and their implementation.

4.5 The policy's consequences

The first direct[6] benefit of the FIT policy consists of electricity price savings achieved through wind integration in the power system. These can be evaluated as the difference between actual prices and predicted prices adjusted for zero wind power production using the results from the previous electricity price regressions. The price differences being calculated for every single hour can then be multiplied times the amount of demand in each hour. We, then, sum the products over the study's period to obtain the total amount of savings as given by the following expression:

$$\sum_{i=1}^{35,064} (HOEP_i - \widehat{HOEP}_i \,|_{Wind_i=0}) Demand_i$$

35,064 corresponds to the number of observations which is the number of hours from 2015 to 2018 while $\widehat{HOEP}|_{Wind_i=0}$ is the predicted HOEP at hour i adjusted for zero wind production and represents, therefore, the wholesale electricity price in a counterfactual case where there would be no wind production.

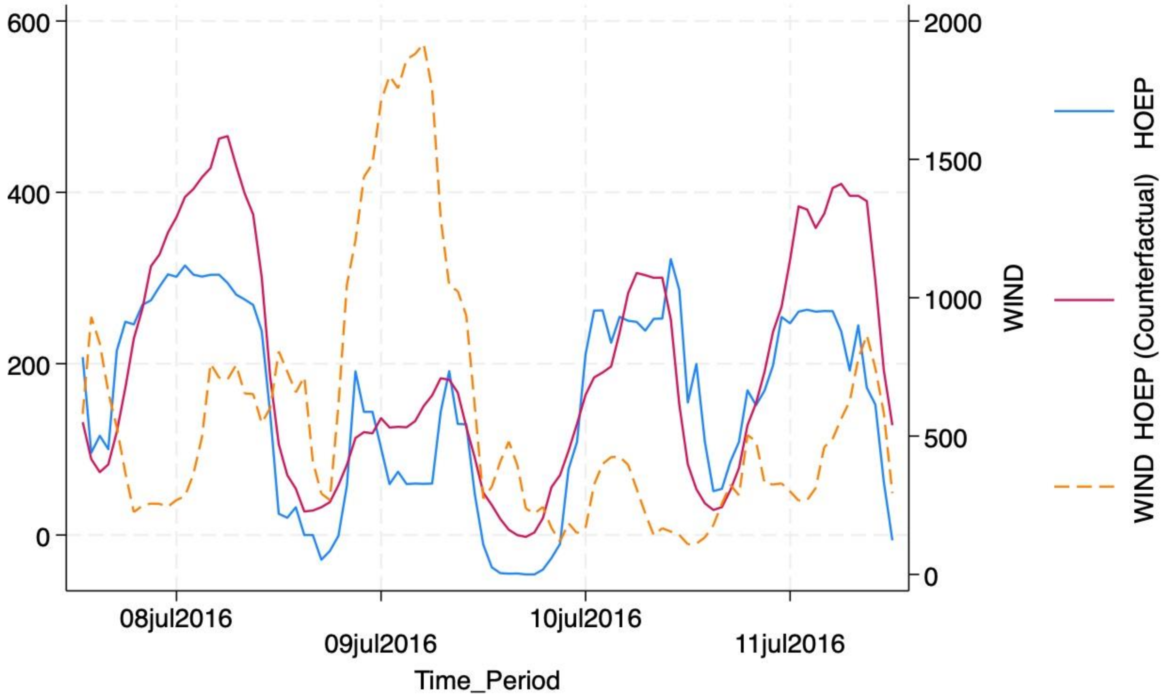
Depending on the model used to fit data, we calculated savings of as much as \$ 14,762,084,862 using the OLS estimation and as much as \$ 5,929,533,132 using the threshold regression. The

---

[6] There would be indirect benefits as well such as job creation and additional tax revenue, but they are beyond the scope of our research.

disparity between these two figures stems from the fact that the OLS estimation yields a single negative effect that accumulates net hourly savings which ultimately exaggerates total savings. On the other hand, the threshold regression yields two distinct effects that have opposite signs depending on whether wind production is above or below 1,581 MWh. Therefore, some of the savings accumulated during hours when wind is below 1,581 MWh are dissipated by losses accumulated during hours when wind is above 1,581 MWh resulting in a lower total savings figure.

Figure 5: Counterfactual HOEP Vs actual HOEP ($/MWh) during representative days from the study period (OLS estimation)

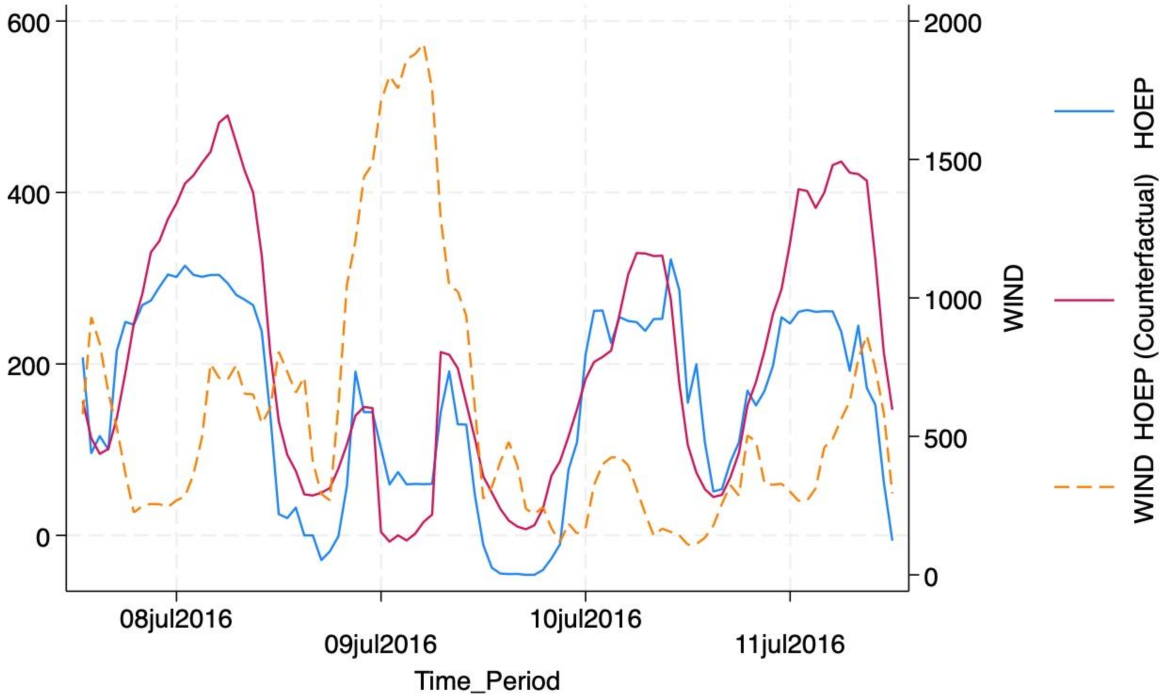


Source: IESO database and own calculations

This difference in treating counterfactual electricity prices by the threshold regression is depicted in figure 6 where the relative position of the counterfactual and actual electricity price curves is sensitive to wind production. During the days represented in figure 6, when wind is below 1,581 MWh, the counterfactual electricity price curve remains mostly above the actual price one which suggests that the power system is achieving savings thanks to a moderate amount of wind production. However, when wind exceeds 1,581 MWh in the evening of July 9th, 2016, the counterfactual electricity price curve goes immediately below the actual price one, which suggests that the power system is incurring losses because of an excessive amount of wind production.

On the other hand, OLS does not make such a distinction as shown in figure 5 as it yields a counterfactual electricity price curve that remains mostly above the actual price one irrespective of wind production.

Figure 6: Counterfactual HOEP Vs actual HOEP ($/MWh) during representative days from the study period (Threshold estimation)



Source: IESO database and own calculations

The second direct benefit of the policy corresponds to CO2 emissions prevented thanks to wind power that replaces natural gas. Using results from previous natural gas power plants' output regressions, we can evaluate the amount of prevented natural-gas-electricity as the difference between actual natural gas power plants' production and their predicted production adjusted for a zero-wind output for every single hour. Summing these differences over the study period yields the total amount of prevented natural-gas-electricity in MWh as given by the following expression:

$$\sum_{i=1}^{35,064} (NG_i - \widehat{NG}_i |_{Wind_i=0})$$

$\widehat{NG}|_{Wind_i=0}$ is natural gas power plants' predicted output at hour i adjusted for zero wind production.

Otherwise, natural gas is the only fossil fuel used in Ontario's energy mix according to the IESO. The efficiency of natural gas power plants ranges between 40% and 60% and can be expressed as:

$$\eta^{NG} = \frac{Electric\ energy\ in\ equivalent\ BTU}{NG\ heat\ rate\ in\ BTU}$$

while the amount of CO2 emissions per BTU of natural gas is 120 pounds per million BTU. So, given that $1KWh = 3{,}412.14\ BTU$, then avoiding a 1MWh of electricity from natural gas is equivalent to preventing between 682 and 1023 Pounds of CO2 emissions per MWh depending on efficiency.

Figure 7: Cost-Benefit Analysis (Optimistic Scenario).

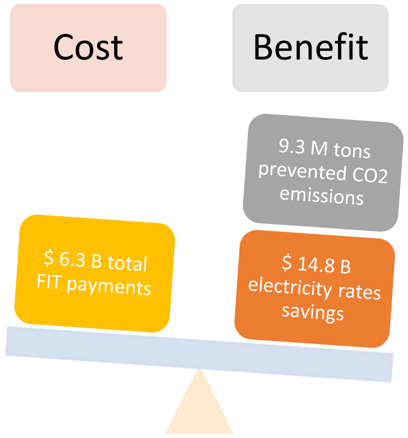
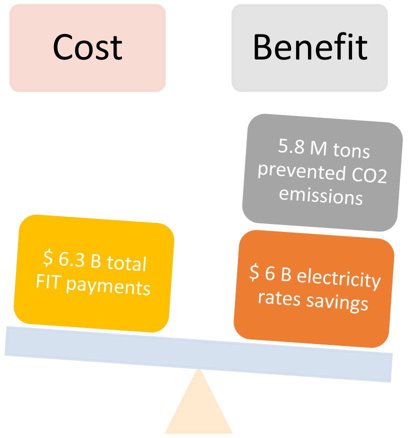


Figure 8: Cost-Benefit Analysis (Conservative Scenario).



Source: Own calculations

Depending on the estimation method, we calculated prevented CO2 emissions of 9,301,031, 7,440,824 and 6,200,687 tons corresponding to efficiencies of 40%, 50% and 60% respectively using the OLS estimation. However, using the threshold estimation, we calculated prevented CO2 emissions of 8,732,632, 6,986,105 and 5,821,754 tons for the same efficiencies respectively.

Invoking the same argument that explains the disparity between the two estimation methods in terms of savings on electricity price, we can see why OLS tends to overestimate prevented CO2 emissions too.

As to the cost of FIT, it is simply contractual payments made to investors to compensate them for the difference between the market price and the agreed FIT rates. Over the period of our study, FIT payments made to wind farms' owners amount to as much as $ 6,273,000,000 according to the IESO.

The threshold estimation is likely to provide better results that suggest that Ontarians are better-off overall considering especially prevented CO2 emissions, as savings on electricity price barely offset FIT payments. We discussed earlier how electricity price cuts would have been more significant had the province planned flexible power plants in a better way. This result shows that FIT as a policy is only one piece of the puzzle because other efforts in power system strategic planning are required to ensure the success of the policy. Other countries had mixed results after they implemented the policy. Spain for instance, one of the earliest countries to adopt the policy rather aggressively at the beginning at least, has achieved impressive renewable penetration rates but was forced in 2012 to revise its FIT rates amid the excessively high FIT payments that would inevitably cause a financial malaise either through electricity retail rates increases or budget cuts in other sectors if the government decides to bail out the regulator. Gelabert et al. (2011), who studied the Spanish power system from 2005 to 2009, found that renewable generation decreases electricity price whereas Marques et al. (2019), who studied the same exact Spanish system except now from 2010 to 2017, found the opposite. Both findings would be relevant and should motivate researchers and policy makers to investigate the extent to which power system planning was in line with the policy's goals and consequences on the ground. In fact, it was reported that the Spanish regulator, to face renewables' intermittency that was getting larger and larger because of their high penetration, had to allow many flexible generators to enter the capacity market which led to a significant electricity generation cost increase. Another aspect that would support the success of the policy is FIT contracts' design. Spain continued to guarantee high FIT rates even though the market was signaling that this choice was unsustainable. The market inefficiency was quickly reflected in retail prices, sparking criticism that in turn put pressure on policy makers to course-correct. Unfortunately, abrupt policy changes lead to procyclical demand for RES technologies, causing crises in the whole value chain as documented by Nelson et al. (2012) in their study of the FIT policy in Queensland, Australia.

This sudden loss of momentum happened in Ontario as well. FIT was first enacted in 2009 and then repealed in 2016 as if replacing FIT with another policy will magically get the province's power system efficiency back on track without addressing the underlying reasons that may cause FIT to be ineffective. We think this is a superficial treatment of the problem because, as demonstrated in our work, FIT is a tool that works in coordination with other important aspects of the power system, such as strategic planning, other stakeholders such as developers and their risk appetite, consumers and their willingness to support the policy, and of course the regulator and its ability to design and negotiate efficient FIT contracts.

At the end of the day, a cost must be borne to promote renewable energy as their technology has not reached the level of maturity that enables it to be autonomous and independent of any backup solution. FIT, as a policy, is an instrument that makes a lot of sense given this technological limitation. Regulators are right in adopting it if they commit to properly design it and support it through adequate strategic power system planning.

Otherwise, the question of the policy's social welfare should also consider its distributional effect on the population. That is, to check whether the policy's social cost is borne equitably by the population depending on their income. In most cases, the cost is passed on to consumers in their electricity bills. Winter and Schlesewsky (2019) investigated the German case by assessing the impact of the policy on widely used equality indices such Gini and Atkinson and found that the policy is regressive in nature as it doesn't distinguish between income brackets and leads to lowering disposable income of bottom quintiles more severely than that of top ones. In fact, qualitatively speaking, higher income households may have a higher consumption and may even pay a higher tiered electricity price but not high enough to reflect the income gap with lower income households. As a matter of fact, if FIT payments were recouped by the government by taxing income, lower income individuals would have paid the same tax rate as high income ones, which is not equitable.

In Ontario, FIT payments are recouped by adding them to the global adjustment component of electricity bills. This component is not exclusively dedicated to FIT payments as it also includes other wholesale rates regulation costs as well as the cost of reinforcing the province’s transmission network among other rubrics. It is worth noting, though, that the global adjustment component used to be much lower than HOEP, but sine 2009 it has started to increase consistently to surpass it in 2011 and then to be worth more than the double, triple, and quadruple of HOEP since then. As mentioned earlier, this component does not contain FIT payments only. So, we can’t draw any conclusion as to what role the policy plays in inflating it. However, we would like to point out that, since the global adjustment incorporates costs of subsidies and investments that benefit all Ontarians, there might be a distributional effect issue here as well. IESO does treat commercial consumers differently by billing them the global adjustment separately, but residential consumers are billed in the same way regardless of their income.

Finally, one important additional social welfare benefit that can be derived from the FIT policy can arguably be stimulating the market and driving innovation. It is easy to see that incentives do attract firms to compete to offer superior goods through innovation. However, innovation can also be motivated by a firm’s interest in being a first mover in a niche industry to reap maximum benefits. So, the link between FIT and innovation can be hard to establish. Böhringer et al. (2017) studied the evolution of the number of renewable energy patents in Germany between 1990 and 2015 knowing that this period contains two important renewable energy policy milestones. 1991 is the year when the German government enacted FIT for the first time before it was amended in 2000, granting beneficiaries even more benefits. To isolate a plausible effect that the policy may have on innovation, the authors controlled for potential effects of government spending on research and development. Another aspect that might interfere with the pure effect of the policy has to do with experience where technology providers learn by doing from existing projects. To account for any innovation that may be achieved through experience, the authors controlled for renewable energy capacity at the country level as well as at the OECD one. The effect on innovation might also be disturbed by a spillover effect from international research. So, the number of global renewable energy patents was controlled for as well. A positive effect of the policy was found though not as important as the global research effect in magnitude. However, the authors didn’t find any additional benefit from the policy amendment in 2000 which reminds us of the importance of FIT design discussed earlier in this report. In fact, this interesting result is explained by the fact that, depending on FIT structure and design, the policy could either signal expansion or disruption. FIT subsidy may be generous to induce renewable energy expansion but not generous enough to outweigh the risk of embarking on brand new technological paths. In addition, the way FIT payment is calculated as a function of the average cost of the technology does not encourage developers to radically change the technology to seek lower costs.

The main takeaway from the German experience is that FIT should be thought of as a long-term policy that certainly has operational goals of cutting greenhouse emissions and making electricity more affordable but has also strategic goals of fostering the development of renewable energy technologies that, although they have come a long way, still struggle with achieving the level of maturity that makes them attractive without any regulatory intervention. Therefore, judging the policy by its operational performance solely may be unwise. Ontario's experience with the policy lasted from 2009 to 2016. It's hard to say that enough time was given to reap the benefits. Even the regulator itself was not given enough time to learn from experience to progressively design better FIT structures. The fact that a policy may have some hiccups would not be a reliable measure of its effectiveness. In fact, any policy is expected to be less effective than desired during the early stages of its adoption. When it comes to FIT, effects found in our research may not be particularly exciting but, when put in a strategic perspective, we can see that the results were decent for a beginning bearing in mind that the policy seeks long-term benefits including innovation. Unfortunately, abruptly ending the policy may suggest that the goal behind the policy was speculative in nature. That is, to have immediate results as far as electricity price and CO2 emissions, disregarding long-term goals of inducing innovation, creating industry ecosystems that support the local production of renewable energy technologies, building a thorough knowledge base of implementing large scale renewable energy projects and acquiring a proven experience in managing renewable energy intermittency.

Conclusion

The main takeaway from our research is that feed-in tariffs are neither an attractive nor a poor choice to mitigate CO2 emissions as they remain a tool among others whose effectiveness depends on the way policy makers use it. We showed in our economic analysis that the cost-effectiveness of injecting renewables in a power system is closely related to the wind production profile and the flexibility of the other power plants. While there isn't much one can do about optimizing wind power production profiles except by selecting the best possible sites, there is a lot to do to design the level of flexibility required to achieve meaningful gains from wind integration. Any negotiation of FIT agreements should only occur after a careful assessment of the strengths and weaknesses of the power system in terms of its ability to withstand renewables intermittency. If the system is too weak, then decision makers should refrain from offering any FIT contract and engage, instead, in reinforcing the power system by optimally adding and expanding the right units. Conversely, if the system is strong enough then, negotiation of rates among other important clauses should seek to make the transaction as efficient as possible now that a clearer idea of the gains that are likely to be achieved is available.

Feed-in tariffs are a regulatory instrument that artificially embellishes renewable energy investments by interfering with market preferences. But we can still make these investments not entirely inefficient through proper power system planning and FIT contracts design. As well, depending on societal preferences, prevented CO2 emissions can also help mitigate market inefficiency because consumers would pay an extra for what they perceive as a real value of living in a clean environment.

In the case of Ontario, our research found that wind integration up to 1,581 MWh did cause electricity rates to decrease at a rate of 0.0366 $/MWh on average for every MWh of wind energy. However, beyond that threshold, wind integration increased rates by 0.0120 $/MWh on average for every MWh of wind energy. This is an indication that, perhaps, there wasn't an optimal planning of the extension of combined cycle steam turbines or other flexible units as FIT contracts were being signed. Even with such results, we found that gains from electricity rates alone were almost the same as FIT payments over the period from 2015 to 2018. If we add gains from prevented CO2 emissions, then clearly there is a positive net benefit from the policy although there was room to do better.

In 2016, the province scrapped the feed-in tariffs and put in place an alternative program. We haven’t found any study conducted by any party, that justifies the decision. We would like to warn against making decisions that feed on popular beliefs that either praise or vilify feed-in tariffs. Having said that though, it is perfectly legitimate to seek more efficient policies. However, we would like to draw attention to the importance of incorporating the capabilities of the power system when enacting green energy policies. Through an honest assessment of its strengths and weaknesses, policy makers would be able to decide on the timing of the policy and more importantly on the roadmap that should be embraced to ensure its success.

Otherwise, we acknowledge that the question of assessing feed-in tariffs’ effectiveness is challenging and is indeed a quite complicated one if we were to add all relevant variables. For instance, our research did not consider power transmission at all although it represents an important part of the problem, especially considering renewables’ intermittency. As a matter of fact, grid congestion can potentially lead power system operators to curtail wind farms’ outputs for instance or even totally disconnect them because they may have significant power spikes, triggering power transit overflows which can undermine their full benefit.

References

Bechert, T. E. and H. G. Kwatny (1972) "On the Optimal Dynamic Dispatch of Real Power." *IEEE Transactions on Power Apparatus and Systems*, vol. PAS-91, no. 3, pp. 889-898

Behrens, Paul, João F.D. Rodrigues, Tiago Brás and Carlos Silva (2016) "Environmental, economic, and social impacts of feed-in tariffs: A Portuguese perspective 2000–2010." *Applied Energy*, Volume 173, Pages 309-319

Böhringer, Christoph, Alexander Cuntz, Dietmar Harhoff and Emmanuel Asane-Otoo (2017) "The impact of the German feed-in tariff scheme on innovation: Evidence based on patent filings in renewable energy technologies." *Energy Economics*, Volume 67, Pages 545-553

Couture, Toby and Yves Gagnon (2010) "An analysis of feed-in tariff remuneration models: Implications for renewable energy investment." *Energy Policy*, Volume 38, Issue 2, Pages 955-965

Del Río, Pablo (2012) "The dynamic efficiency of feed-in tariffs: The impact of different design elements." *Energy Policy*, Volume 41, Pages 139-151

Del Río, Pablo and Miguel A. Gual (2007) "An integrated assessment of the feed-in tariff system in Spain." *Energy Policy*, Volume 35, Issue 2, Pages 994-1012

Farrell, Niall, Mel T. Devine, William T. Lee, James P. Gleeson, and Sean Lyons (2017) "Specifying an Efficient Renewable Energy Feed-in Tariff." *Energy Journal*, Vol. 38, Pages 53-75

Gelabert, Liliana, Xavier Labandeira and Pedro Linares (2011) "An ex-post analysis of the effect of renewables and cogeneration on Spanish electricity prices." *Energy Economics*, Volume 33, Supplement 1, Pages S59-S65

Goodarzi, S., S. Aflaki, and A. Masini, (2019) "Optimal Feed-In Tariff Policies: The Impact of Market Structure and Technology Characteristics." *Production and Operations Management*, Volume 28, Issue 5, Pages 1108-1128

Lesser, Jonathan A. and Xuejuan Su (2008) “Design of an economically efficient feed-in tariff structure for renewable energy development.” *Energy Policy*, Volume 36, Issue 3, Pages 981-990

Ma, J., V. Silva, R. Belhomme, D. S. Kirschen and L. F. Ochoa (2013) “Evaluating and planning flexibility in sustainable power systems.” *IEEE Power & Energy Society General Meeting*, Vancouver, BC, Canada, pp. 1-11

Marques, António Cardoso, Fuinhas, José Alberto and Macedoa, Daniela Pereira (2019) “The impact of feed-in and capacity policies on electricity generation from renewable energy sources in Spain.” *Utilities Policy*, Volume 56, Pages 159-168

Nelson, Tim, Paul Simshauser and James Nelson (2012) “Queensland Solar Feed-In Tariffs and the Merit-Order Effect: Economic Benefit, or Regressive Taxation and Wealth Transfers?” *Economic Analysis and Policy*, Volume 42, Issue 3, Pages 277-301

Paraschiv, Florentina, Erni, David and Pietsch, Ralf (2014) “The impact of renewable energies on EEX day-ahead electricity prices.” *Energy Policy*, Volume 73, Pages 196-210

Ritzenhofen, Ingmar, John R. Birge and Stefan Spinler (2016) “The structural impact of renewable portfolio standards and feed-in tariffs on electricity markets.” *European Journal of Operational Research*, Volume 255, Issue 1, Pages 224-242

Trujillo-Baute, Elisa, Pablo del Río, and Pere Mir-Artigues (2017) “Analysing the impact of renewable energy regulation on retail electricity prices.” *Energy Policy*, Volume 114, Pages 153-164

Tveten, Åsa Grytli, Torjus Folsland Bolkesjø, Thomas Martinsen and Håvard Hvarnes (2013) “Solar feed-in tariffs and the merit order effect: A study of the German electricity market.” *Energy Policy*, Volume 61, Pages 761-770

Vanithasri, M., R. Balamurugan, L. Lakshminarasimman (2016) “Modified radial movement optimization (MRMO) technique for estimating the parameters of fuel cost function in thermal power plants.” *Engineering Science and Technology*, Volume 19, Issue 4, Pages 2035-2042

Wand, Robert and Florian Leuthold (2011) “Feed-in tariffs for photovoltaics: Learning by doing in Germany?” *Applied Energy*, Volume 88, Issue 12, Pages 4387-4399

Winter, Simon and Lisa Schlesewsky (2019) “The German feed-in tariff revisited - an empirical investigation on its distributional effects.” *Energy Policy*, Volume 132, Pages 344-356