Optimization of the Renewable Power Grid:

Calibration and Application

by

Jun (Jon) Duan
B.A, East China Normal University, 1998
M.A, University of Victoria, 2015

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We acknowledge with respect the Lekwungen peoples on whose traditional territory the university stands and the Songhees, Esquimalt and W̱SÁNEĆ peoples whose historical relationships with the land continue to this day.

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ABSTRACT

The goal of this study is to determine the economic implications of incorporating intermittent renewable energy into current power systems. The study also considers how to achieve an optimal mix of generating assets with renewable power, as well as the costs and advantages of using renewable energy sources to reduce CO2 emissions. Furthermore, this study examines how renewable energy exacerbates the "missing money" problem, which is a critical problem in electricity market design. The last part of this research is devoted to the calibration of the hybrid electricity grid model. We adopt positive mathematical programming (PMP) to calibrate the quadratic cost function for fossil fuel power plants. The calibrated model enables us to better analyze the impact of renewable energy on the electricity market.

We find that due to the intermittency of wind and solar power, renewable energy could replace part of the peak load capacity like gas turbines but is not able to replace most of the base load capacity like coal capacities. The unintended consequences are that to eliminate the coal base load capacity, other forms of baseload capacities such as nuclear or hydropower capacity are necessary to incorporate the intermittent renewable power. Moreover, the capacity factors of remained peak load capacities and newly built base load capacities declined. Further support policies for maintaining the capacity adequacy standard are necessary for a reliable hybrid electricity market.

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This dissertation could not have been written without the support and guidance of my supervisor, Dr. van Kooten. I also want to acknowledge the members of my graduate committee for their helpful comments and suggestions.

DEDICATION

To my parents for their unwavering support and optimism.

To my wife, without question, who is always in my corner.

Chapter 1 INTRODUCTION

In most of the world, the most important sector accounting for CO_2 emissions is electricity and heat. The importance of coal-fired power globally cannot be overemphasized – about 70% of China's, 60% of Australia's and 75% of India's power was generated by coal in 2015 (World Bank, 2021). In 2021, China, India, Indonesia, Japan, and Vietnam have plans to build more than 600 coal power units in the next ten years (Ambrose, 2021). Although hydroelectricity accounts for 67 percent of total energy generation in Canada, coal, natural gas, and petroleum are used to generate the majority of electricity in Alberta, Saskatchewan, Nova Scotia, and Nunavut in 2019 (CER, 2022). Even though many coal-fired power plants have been phased out or converted to gas-fueled power plants recently, coal still represents over 60% of Canada's electricity sector emissions while providing only 7% of the country's electricity in 2018 (NRCan, 2021).

To combat climate change, more countries have moved away from fossil fuels, which requires investment in alternative energy sources. For example, in 2012, with regulations on emissions from the coal-fired electricity sector, Canada became the first major coal user to ban the construction of traditional coal-fired power stations.[1] On the pathway to decarbonization, many countries have put their faith in renewables. In 2015, in Paris at the United Nations Climate Change Conference, nearly 50 countries agreed to make their energy production 100 percent renewable by 2050 (Payton, 2016). In Canada, Alberta's NDP government planned to phase out all coal-fired electricity generation facilities by 2030 and replace two-thirds of the lost electricity production with renewables (Government of Alberta, 2016). This timeline may have changed under the United

[1] In 2012, the Canadian federal government approved the Reduction of Carbon Dioxide Emissions from Coal-fired Generation of Electricity Regulations. The regulation requires that coal-fired generation units meet a GHG emissions intensity target once it reaches the end of life (Government of Canada, 2018).

Conservative Party government.

Decarbonization comes with a cost. First, even if costs are falling over time, most renewables, such as wind and solar, are still more expensive than fossil fuels over their life cycle (Lazard, 2016). Replacing fossil fuels with renewables appears to lead to rising electricity bills for final consumers.

Second, a stumbling block in the development of modern renewable energy globally is the intermittent nature of renewable energy, specifically solar and wind power. The wind is not always blowing, and the sun is not always shining. They are not dispatchable like gas or coal power. When we need power, we can push the throttle to increase power output or quickly start another gas generation unit, but we cannot make the wind blow. Because of its intermittency, wind and solar cannot be considered reliable as either baseload sources of electricity or suitable for addressing peak demand (van Kooten, 2016a), and thus the integration of renewable energy into the grid has proven problematic for many countries (Timilsina et al., 2013). For instance, since 2015, Hawaii's local utility company has slowed down the connection of a new rooftop solar system to the grid due to safety concerns and questions about the overall stability of the grid (Merchant, 2019). At the beginning of 2017, the South Australian blackout was blamed on wind generation failures (Murphy & Knaus, 2017). At the end of 2021, the European power price surged due to the low wind output (Gillespie & Starn, 2021). Overall, the intermittency in wind (and solar) power output is unavoidable, and so are the related possible damages to the short-term reliability of the electricity grid. Consequently, the gaps result in large costs of ramping existing generating assets or investing in new assets to compensate for this intermittency (van Kooten et al., 2016). Accordingly, the opportunity cost of introducing renewables is much higher than the explicit accounting cost.

Nowadays, three approaches can be considered to overcome the intermittency problem of renewables. The first is on the supply side: We can expand the power grid's connectivity. By locating wind and solar sources of renewable energy across a large landscape, intermittency can be alleviated to some extent, depending upon the correlations among wind sites and between wind and solar. The wind may stop blowing in one place, but it might be blowing in other places. Therefore, entrepreneurs in China, South Korea, Russia and Japan have signed a Memorandum of Understanding that seeks to create the Asia Super Grid (Hanley, 2016). In the same way, it might be possible to connect European and African grids or construct a North American power pool that is connected by much more transmission interties than now exist. In many cases, however, such huge interconnection projects are unrealistic from a political and even physical standpoint, and they are too expensive to undertake. Further, there is no guarantee that when the wind is not blowing in one region it is blowing hard enough in another region to cover any shortfall. In a much more restricted region, such as western Canada, the wind power from Alberta and hydro energy from British Columbia might be able to work together to provide reliable, clean and sustainable electricity.

The second potential method for overcoming intermittency is storage. Electricity can be stored in a reservoir behind a hydroelectric dam or in a battery, or compressed air can be used to store energy. One alternative receiving a great deal of attention recently is a form of chemical storage, as occurs when electricity is used to create hydrogen from water (H_2O) or natural gas (CH_4). Energy storage is likely going to play an important role in any future power system.

The third approach to dealing with intermittency takes place on the demand side. With new technologies, the electricity demand (known as load) is getting more forecastable and controllable.

Demand-side management (load management) can “reduce energy consumption, and improve overall electricity usage efficiency, through the implementation of policies and methods that control electricity demand” (Hallberg et al., 2011). With the development of new technologies, such as smart grids and net meters, demand response can make use of “incentive payments designed to induce lower electricity use at times of high wholesale market prices or when system reliability is jeopardized” (Nwulu & Gbadamosi, 2021). The volatility and uncertainty of the load can be alleviated by better forecasting and other demand-side management measures. In the future, to better balance the demand and supply of electricity, we will likely see demand-side management become a core part of the power system. However, smart technologies serve more to redistribute load (thereby reducing pressure on generating assets at peak times) than to reduce energy use.

The third aspect of decarbonization cost is that wind and solar power disrupt electrical systems. Under the current power system, wind and solar energy have almost zero marginal production cost, so in the bidding competitions they can drive other generation units out when wind and solar are available. The economic return to conventional generation assets falls and the incentive to invest in conventional assets is reduced (The Economist, 2017). Without conventional assets as a backup when wind or solar is not available, power disruptions and blackouts can occur. If we cannot give enough economic incentive to invest and maintain the necessary conventional backup capacity, we are going to face long-term reliability problems. Current power systems must be able to balance the contributions from conventional energy and renewables. The problem is that the original power system is not designed for variable and distributed power resources like wind and solar energy. In the current conventional system, generation is centralized, the transmission is unidirectional, and distribution is passive. Electricity is generated in one place and is transmitted from upstream generators to downstream users. All power generated must be distributed instantaneously to users (Bakke, 2017). To build an electric power system that integrates renewable sources of energy, we need to redesign the power system by reforming the pricing mechanism, improving regulations, and changing the business model (Lund, 2005). Ideally, in the future, with the incorporation of intermittent (variable) renewables, distributed generators such as rooftop photovoltaics grow, and power flows can be bidirectional between different microgrids. The distributed generation sources are getting more active based on the smart grid control system. More microgrid systems are needed to manage various energy sources and coordinate controllable demand loads with power supply sources (Huang et al., 2008).

In short, we still need to rely on conventional, fossil-fuel power sources as a backup to provide a reliable energy supply. For example, when wind generating capacity is increased, nearly an equivalent amount of fast-gas capacity is required as backup (van Kooten, 2016a). However, the grid operator needs to provide capacity payments to developers of such assets because wind and solar power reduce wholesale electricity prices and the operating capacity of gas plants. The capacity payments then lead to higher retail prices as grid operators need to recover such outlays (van Kooten et al. 2016; van Kooten, 2017; van Kooten & Mokhtarzadeh, 2019). Nonetheless, integrating renewable energy sources into an electricity grid, whether an existing grid or one that is optimally designed, results in indirect costs imposed on non-renewable assets, costs that are often ignored when considering the costs of integrating renewables into an existing or even new grid structure (van Kooten, 2016b).

The development of the electricity grid needs government support and regulations. Governments have been exploring different policy tools to provide incentives for firms to develop and operate renewable generating assets. For example, in Canada, on October 3, 2016, the Canadian federal government announced that, unless provinces were more aggressive in their policies to reduce CO_2 emissions, it would implement a carbon tax that would start at $10 per tonne of carbon dioxide (tCO_2) beginning in 2017 and increase annually by $10/$tCO_2$ until it reached $50/$tCO_2$ in 2021. Moreover, the Government of Canada introduced a price on carbon pollution across Canada in 2019. The price is scheduled to rise in steps until 2030 to reach $170 per tonne (Government of Canada, 2022).

Some provinces set up their own policies. For example, in 2009, Ontario provided a feed-in tariff (FIT) for medium- and small-scale renewable energy providers, known as microFIT. It also offers renewable procurement processes for large renewable energy providers, which is one of North America's first comprehensive guaranteed pricing structures for renewable electricity production, offering stable prices in long term. In 2016, Ontario stopped accepting applications for its FIT program. In 2016, Ontario adopted a cap-and-trade system for facilities producing over 25,000 tCO_2 annually. Ontario cancelled the cap-and-trade regulation and wound down the large renewable procurement contracts in 2018 (IESO, 2018). The Alberta government chose to implement an economy-wide carbon tax of $20/$tCO_2$ beginning in 2017 and increased it to $30/$tCO_2$ in 2018. At the same time, the government provides subsidies to encourage renewable energy and capped emissions from oil sands developments at 100 megatons of CO_2 (Government of Alberta, 2016). But because the new United Conservative government cancelled the carbon tax in 2019, Alberta switched to implementing a carbon tax under the Federal fuel charge in 2020, and the Federal Carbon Tax is $50 per tonne of CO_2 emission in 2022 (Government of Canada, 2022). It is worth noting that the previous discussion regarding renewables intermittency, the electricity supply reliability, and the implicit costs of integrating renewables into grids show that certain public policies are needed to support the required backup capacity. However, in reality, this type of policy is not adequate.

Given the above background, the goal of the research presented here is to investigate the economic consequences of integrating renewable energy into existing power systems, the implementation of well-designed policies to achieve an optimal mix of generating assets to reduce carbon dioxide (CO_2) emissions, and the reliability of power systems with renewable energy sources. To be specific, the following three aspects are studied using a carbon-constrained jurisdiction such as Alberta: (1) the optimal generation mix in which a carbon tax is used to incentivize removals of fossil fuel generation and investment in wind turbines and nuclear power; and (2) the effect of flexible storage of electricity on a power system with wind and solar sources, (3) The methods used to calibrate a grid optimization model are examined; the calibrated model is then used to analyze climate policy impacts on the integration of renewable generating assets into a fossil-fuel-dominated electricity grid.

To facilitate the analysis of the economic impacts of integrating renewables into power systems, the next chapter will introduce the related economic theory of power markets, especially how to model the demand and supply of electricity. Further, the chapter illustrates the implications of integrating renewables into the electricity system and then provides a brief overview of the models implemented in the dissertation. In Chapter 3, we adopt a grid optimization model to determine the optimal generation mix in Alberta with a climate change target. With the assumption of rational expectations of the grid operator (and asset owners) and interties between adjacent jurisdictions, we assume the grid operator optimizes load across assets in each hour. Then we can calculate the optimal tax or subsidy required to introduce renewables into the grid and to achieve a climate change target.

Storage can alleviate the volatility and uncertainty of renewables, and enable coal plants to operate more efficiently, thereby saving fuel and potentially reducing CO_2 emissions. The development of modern battery technology makes it possible to have a utility-scale battery to improve the integration of renewables. Hence, Chapter 4 examines whether battery storage could alleviate the intermittency issue of renewables and even help to solve a long-term asset investment mystery: the “missing money” problem.

To examine the performance of a grid, we need accurate economic cost evaluations for generation technologies. These cost evaluations need to take explicit and implicit costs into account. Chapter 5 applies the positive mathematical programming (PMP) method first introduced by Howitt (1995) in a farm management context to calibrate the economic costs of generation technologies. Then the impacts of the cost of electricity and two policy scenarios — a carbon tax and an emissions reduction target — on the generating mix are discussed using the calibrated model. Summary and conclusions are provided in Chapter 6.

GAMS is used to solve the constrained optimization problems found in this study (GAMS Development Corporation, 2012). In particular, the CPLEX solver is used for the linear programming (LP) models in Chapters 3 and 4, and also in Chapter 5 to solve quadratic programming models (Cplex, 2009).

Chapter 2 ECONOMIC THEORY OF POWER MARKETS

2.1 Introduction

Electricity is a special commodity. It is a special good because it is transportable and can be sold instantly from one place to another place where it is needed. It is also a service because it is intangible, and consumers benefit from the services such as heating and lighting that electricity produces. Given the particularities of electricity, the demand and supply of electricity have their own characteristics. Generally speaking, since we lack grid-scale storage when electricity is generated (produced), it must be consumed at the same time. Suppliers must forecast the demand and make good production plans; otherwise, excess supply will have to be curtailed or wasted.

On the demand side, consumers use electricity continuously, but do not know the electricity price immediately due to a lack of real-time metering. Consumers usually pay a fixed rate based on a contract, so they are less responsive to changes in supply; even if prices change hourly, most consumers are unable to monitor price changes. Only a few large firms are subjected to variable wholesale market prices and have the ability to take action to respond to the change in the market price. That means the electricity demand is inelastic, and consumers are not able to and do not have an incentive to adjust their behaviour immediately when the market supply and wholesale market price change.

Electricity is important and the cost of supply interruption is very high, so sometimes consumers may be willing to pay much higher prices, or even extremely high prices in limited cases, to secure electricity supply. The value of lost load (VOLL) is broadly used to indicate the cost of power supply interruptions, or to indicate how valuable the security of energy supply is in theory and practice. Generators and governments use VOLL as a benchmark when evaluating the operating conditions of the current electricity generation capacity and making decisions about generation capacity investments or related electricity market price regulations. Researchers have been using revealed preferences, stated preferences, and proxy methods to estimate VOLL (van der Welle & van der Zwaan, 2007). After estimating VOLL, the aggregate value of (in)security of electricity supply can be represented by multiplying VOLL by the probability of supply disruptions, which is measured by the disruption intensity, frequency, and length. The application and the limitations of VOLL will be further discussed in section 2.4.

The ways that electricity is generated and distributed add more complexity to the demand and supply analysis of the power market with renewables. First, the electricity from wind or solar renewable energy sources is intermittent. Hence, it is not manageable or dispatchable; producers cannot precisely control the amount and the timing of electricity production. Second, after generation, electricity relies on the transmission and distribution network to reach consumers. When the network has a glitch that lowers the quality and/or frequency of the electricity, or even worse, there is a blackout, electricity still cannot be used by consumers. Third, the producers provide not only electricity but also ancillary services such as frequency stabilization, while supply must be continually adjusted as consumption/load fluctuates from one minute or even a second to the next. At the same time, payments that producers get change over time with changes in the market.

Historically, the supply of electricity was monopolized. As a result, electric utilities were government-owned entities or regulated, with retail prices set by the public regulator; investor-owned firms were vertically integrated, with utilities providing bundled generation, transmission and distribution services. In the last couple of decades, electricity markets have become deregulated and less centralized in many countries and areas. In some areas, transmission and distribution systems are still controlled by monopolies and are subject to government oversight.

In many electricity systems, the generation of electricity has been transformed into free and competitive markets at the wholesale level. Suppliers compete in a pool, and prices are determined by the various levels of competition. For example, wholesale electricity competition was deregulated in Norway, Denmark, Britain, Texas and much of the east coast of the United States; and there was the infamous California deregulation exercise (Bushnell et al., 2017). In Canada, different provinces have different approaches. For instance, Alberta has fully deregulated its wholesale power market—the generation mix is investor-driven although guided by government policy; but the electricity system in British Columbia is characterized as a near-monopoly on the selling side and a monopsony concerning electricity purchases (Christian et al., 2020).

Given the above characteristics of the electricity market, section 2.2 will briefly explain the electricity demand pattern. Section 2.3 elaborates on one classical approach for modelling the demand and supply of electricity in the long run. Section 2.5 focuses on a traditional short-run model for determining the generation mix. Sections 2.5 and 2.6 discuss the challenge to the electricity system for integrating renewables and then provide a brief introduction of the model to be used in subsequent chapters for determining the optimal investment in various types of generating capacity.

2.2 Demand Pattern for electricity

Electricity demand or load has strong seasonal patterns, both daily and annually. Hourly peak loads, as shown in Figure 2.1, typically occur in the evenings, with loads falling thereafter and reaching their lowest point around midnight or slightly later. Monthly peak loads are typically experienced during the winter as a result of heating demand, though in warmer regions, peak loads are experienced during the summer as a result of cooling demand (see Figure 2.2).

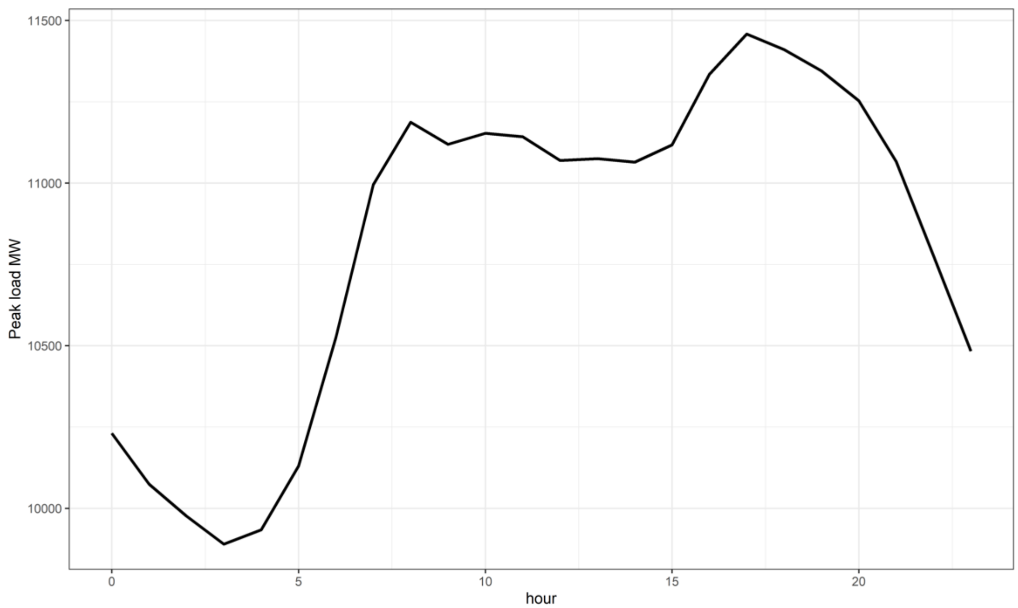

Figure 2.1: Hourly Daily Load Demonstrating Peak Hours (2005-2016) Alberta

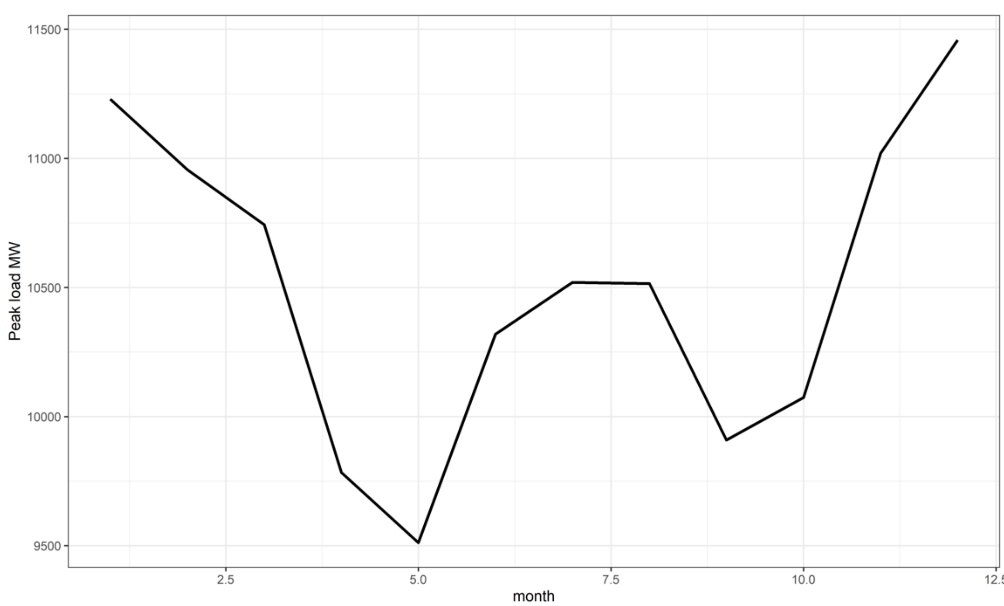

Figure 2.2: Peak Load Demand by Month (2005-2016) Alberta

2.3 Load Duration and Screening Curve

The classical load-duration/screening curve method (Joskow, 2006; Stoft, 2002) provides a means for choosing the best mix of generation assets and ensuring that the market provides adequate incentives for efficient long-term investment (Cramton, 2017).

2.3.1 Load duration

The electricity demand function can be represented by a load duration curve, in which the hourly demand data for a given year are arranged in descending order of magnitude, with the highest hourly (peak) load on the left side of the graph. Figure 2.3 provides an example of a load duration curve for Ontario for 2021.

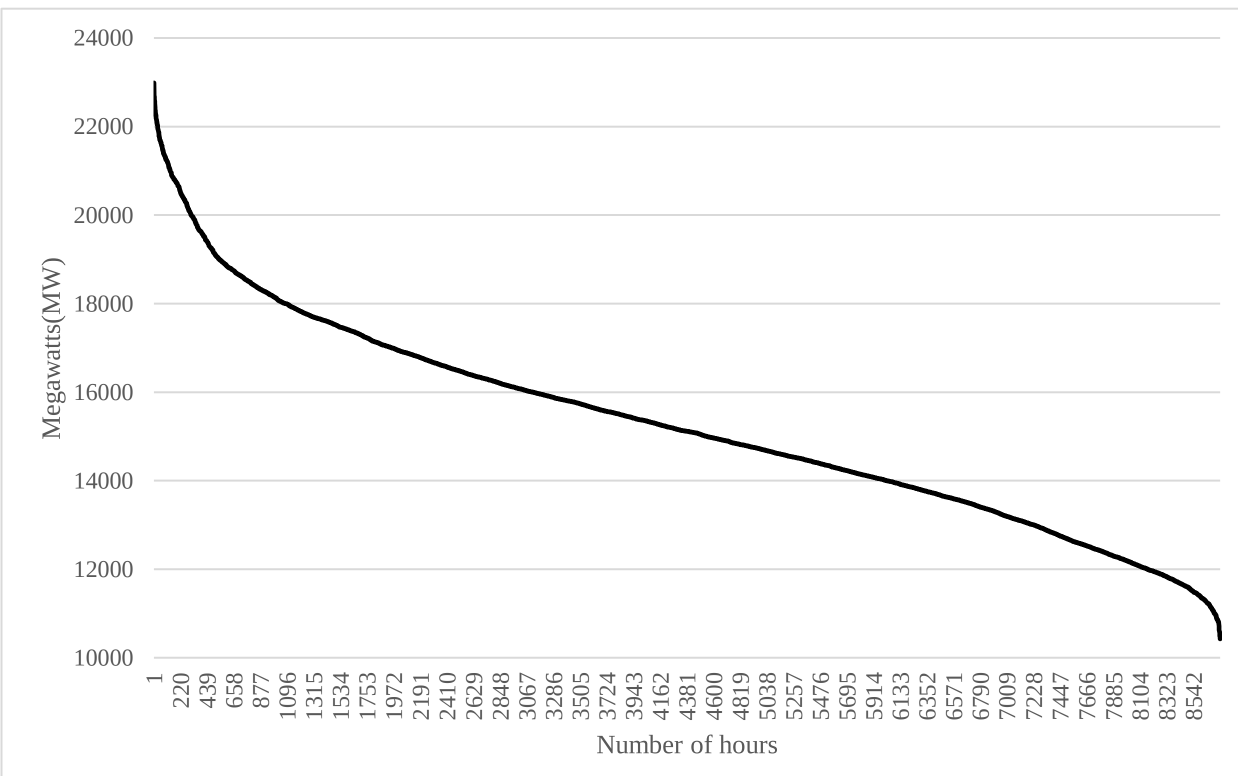

Figure 2.3: Ontario Load Duration Curve, 2021(IESO, 2022)

The area under the load duration curve for any given hour represents the energy required to meet the load. The peak load of around 22,000 megawatt-hours (MWh) only lasts a few hours, as shown in Figure 2.3; the most frequent loads are between 1800 MWh and 10,000 MWh. The minimum point corresponds to the jurisdiction's baseload, which is the minimum amount of generation that must be produced continuously throughout the year.

The load duration curve can be used to investigate capacity investment decisions at power plants. The three types of power requirements are peak load, intermediate load, and baseload. Baseload generators are highly efficient and reliable, and they operate continuously, meaning that one or more generators are always capable of supplying this minimum level of power. Peak load generators are less efficient but respond quickly and can be activated immediately to provide electricity. The intermediate load capacity is the capacity that exists between the peak load and baseload generators and includes “load following” generation which refers to the increased power produced by a baseload plant as demand increases.

2.3.2 Screening curves

While the load duration curve describes demand, a screening curve can be used to depict the supply of electricity. Traditionally, a screening curve plots the "average cost of using a unit of capacity as a function of capacity factor" (Stoft, 2002). The generator's capacity factor (CF) is its percentage usage – the actual output during a particular period (measured in terms of MWh) divided by the asset’s rated capacity (MW) multiplied by the number of hours in that period. The CF is affected by the duration of the load. The total cost of a unit of capacity utilization is divided into two parts: fixed cost and variable cost. The fixed cost could be calculated using the annualized overnight cost, [2] also known as annualized capital cost, while the variable cost could be calculated as the fuel cost plus variable operation and maintenance (O&M) costs per unit output. The unit of the cost of using capacity is usually \$/MW; it is converted to an energy cost (\$/MWh) using a presumed CF.

The equation of a screening curve is given by a fixed cost (annual cost for the year expressed in \$/MW, which is similar to a rental cost of capacity with a time unit) component, denoted *fc*, and a variable cost (\$/MWh) component, denoted *vc*:

$$C(h) = fc + vc \times h, \tag{2.1}$$

where C refers to the total cost of operating one unit (MW) of the asset for one year at a given capacity factor; *h* denotes the number of hours of electricity produced by the asset in question through the year, which is equivalent to the 8760 multiples capacity factor. For example, the annual utilization cost of one MW capacity of the coal power plant is *fc* if it does not get used at all (h =0), and when it gets used for 3000 hours, the C(h) will be $fc + vc \times 3000$. The fixed cost component consists of the overnight construction cost plus the fixed O&M costs, with the fixed costs then annualized. The screening curve provides the cost as a function of the hours the asset operates. The hours of operation are then determined from the load duration curve and by the intersection with other screening curves, which is illustrated in the next section.

[2] The annualized cost of an overnight cost is the cost that would give the same net present cost as the actual cash flow sequence associated with that overnight cost if it occurred evenly in every year of the project lifetime. The overnight cost of a power plant is the cost of constructing the power plant overnight. Because a plant cannot be built in one night, this is a hypothetical scenario, but it calculates the cost of a plant if it were built today at current pricing. The annualized overnight cost gives us a reference of the cost that we need to pay if we could pay for a plant by the year.

2.3.3 Application of load duration and screen curves

Here we use linear screening functions for three broad generation technologies and a linear load duration curve as an example to show how the optimal generation mix is determined. The approach is similar to the one used by Joskow (2006). The screening curve data are provided in Table 2.1, with an example of a screening curve provided in Figure 2.4. The screening curve demonstrates that when an asset is only used for less than 1000 hours per year, the peaking asset has the lowest average cost. When an asset runs for more than 6000 hours per year, the baseload asset has the lowest average cost.

Table 2.1: Assumed Values for the Screening Curves

Generation Technology	Annualized Fix Costs ($/MW per year)	Variable Costs ($/MWh)
Baseload	$200,000	$4.5
Intermediate/load following	$90,000	$26.0
Peaking	$55,000	$45.2
Wind	$240,000	$0.0

Source: Author's calculations

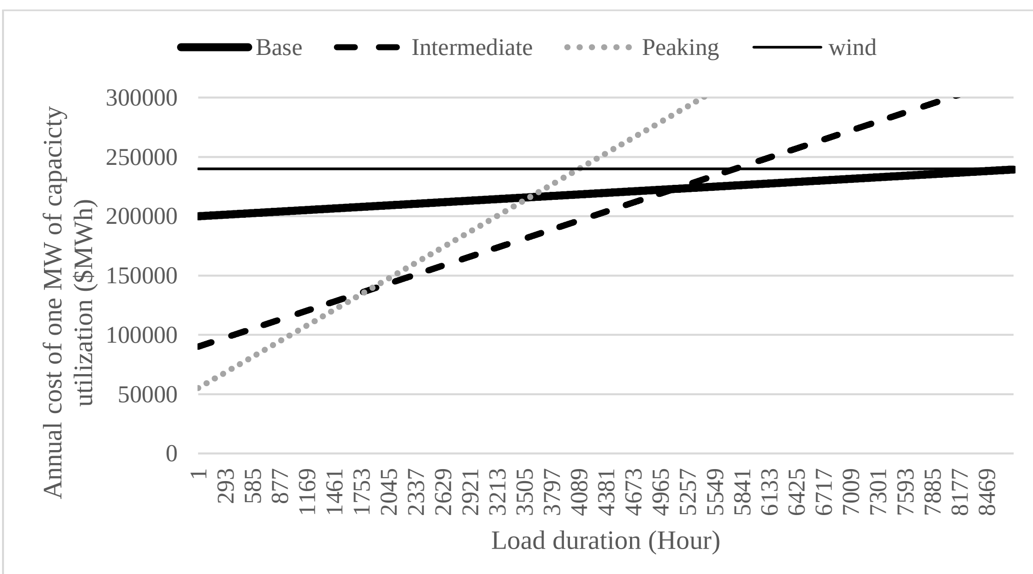

Figure 2.4: Screening Curves

The load duration curve is assumed to be given by the following equation:

$$D(h) = 24{,}000 - 1.484\, h,\ 0 \leq h \leq 8760 \qquad (2.2)$$

where D refers to the system load (MW), h is the number of hours the asset operates, and there are 8760 hours in the year. To determine the running time of each asset, we find the intersections of the screening curves for the base and intermediate assets, and the intermediate and peaking assets. Finally, the optimal capacities of each asset type are then found from the load duration curve. These values are also provided in Table 2.2 and Figure 2.5. The fixed component of costs is simply given by the optimal capacity for the asset multiplied by the annualized capital cost.

Table 2.2: Least Cost Mix of Generating Technologies, Running Times and Costs

Generation Technology	Capacity (MW)	Running hours[a]	Total Costs ($ billions) Fixed	Variable	TOTAL
Baseload	16,408	5116 – 8760	$3.282	$0.602	$3.884
Intermediate	4,887	1823 – 5116	$0.440	$0.441	$0.881
Peaking	2,705	1 – 1823	$0.149	$0.111	$0.260
Total	24,000	–	$3.871	$1.154	$5.025

[a] Hours not needed to service baseload (i.e., load following and peaking hours)
Source: Author’s calculations

The load duration curve is then used in conjunction with the screening curves to determine the optimal generation mix for meeting the load profile for a specific electricity system. Figure 2.5 shows how to do this. To calculate the operating costs, we must first determine how many megawatt-hours the asset is expected to operate during the year. This is represented by the area beneath the load duration curve in Figure 2.5's bottom panel. For baseload, it is given by area (a+b+c+d+e+f) and for the peaking asset by area k. This gives 133.881 TWh of baseload output during the year and 2.466 TWh of peaking output. The total cost of operating this hypothetical system for one year is about $5.025 billion.

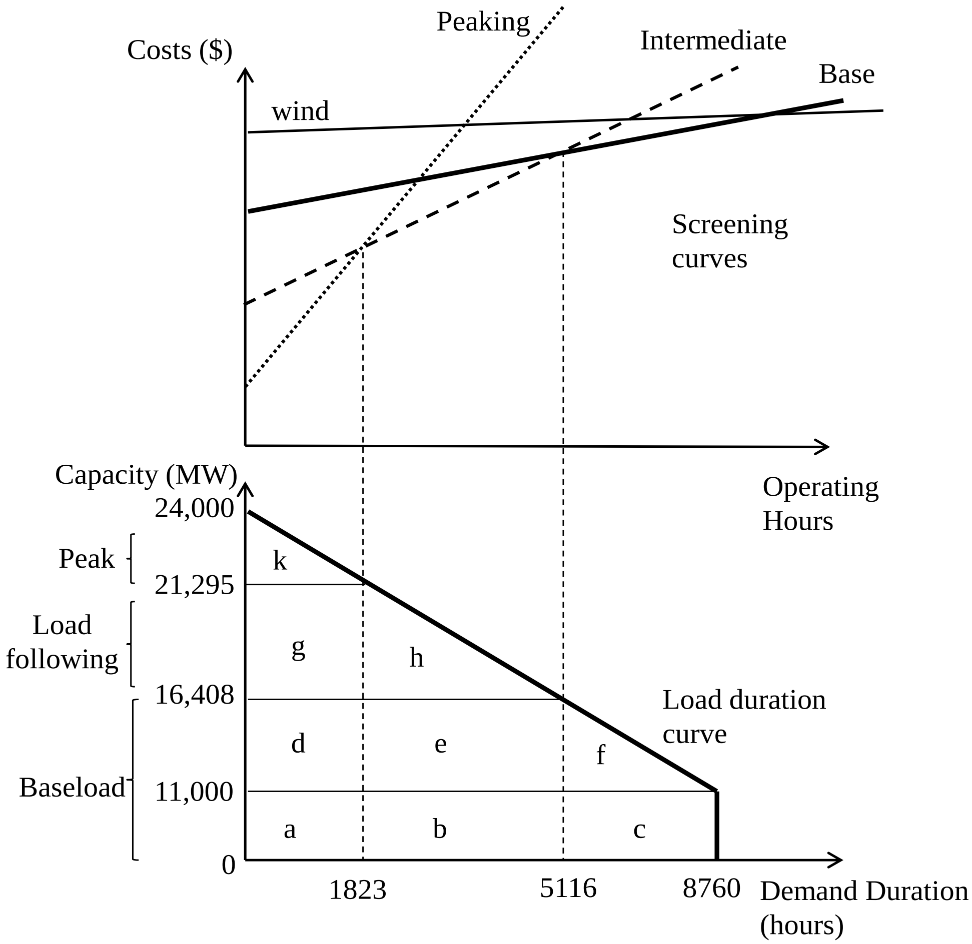

Figure 2.5: Load Duration, Screening Curves and the Choice of Optimal Capacity of Generating Assets

Wind energy was too expensive in the preceding analysis when compared to fossil fuel energy sources. However, the picture changes when governments intervene to reduce CO2 emissions through a carbon tax or a feed-in tariff (FIT) to encourage investment in renewable resources, in this case, wind-generated electricity. Figure 2.6 depicts the situation in which a carbon tax is used, whereas Figure 2.7 depicts the situation in which a FIT is used.

Table 2.3: Assumed Values for the Screening Curves under a Carbon Tax

Generation Technology	Annualized Fix Costs ($/MW per year)	Variable Costs including tax ($/MWh)
Baseload	$200,000	$30.0
Intermediate/load following	$90,000	$39.5
Peaking	$55,000	$63.2
Wind	$240,000	$0.0

Source: Author's calculations

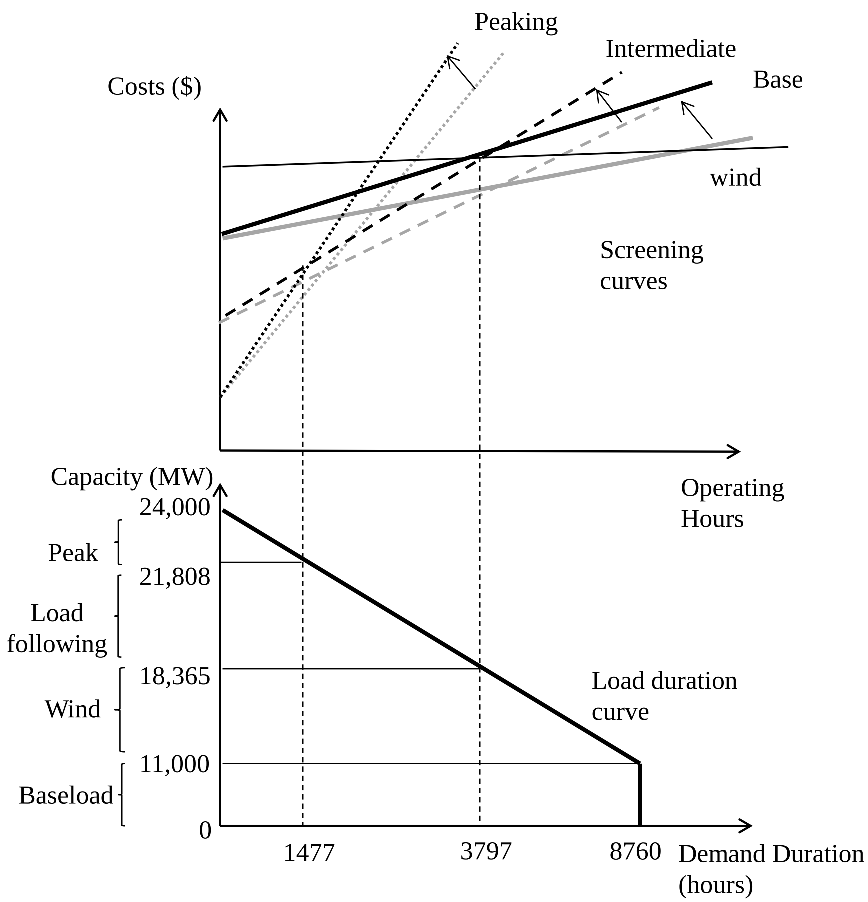

Figure 2.6: Least Cost Generating Mix under a Carbon Tax

Peaking facilities are assumed to emit 0.60 tonnes of CO_2 (tCO_2) per MWh, intermediate assets 0.45 tCO_2/MWh, and baseload plants 0.85 tCO_2/MWh. Then, as shown in Table 2.3, a $30/$tCO_2$ carbon tax raises the operating costs of various technologies. Using this data, we discover that the least expensive mix eliminates baseload (fossil fuel/coal) generating capacity.

However, due to the unreliability of wind energy, wind cannot be used to replace baseload capacity. According to Figure 2.6, it is prudent to continue using the baseload facility while wind provides load-following services. Even so, reserve capacity would need to be increased to backstop wind resources. Wind energy is not dispatchable, and when and how much energy it produces are decided by the wind resource and weather conditions. To simplify our example, we assume that the intermediate capacity could respond quickly to a decline in wind generation. Furthermore, we also assume that the capacity factor for wind is 40%. Therefore, the cost of wind capacity is $3.167 billion.

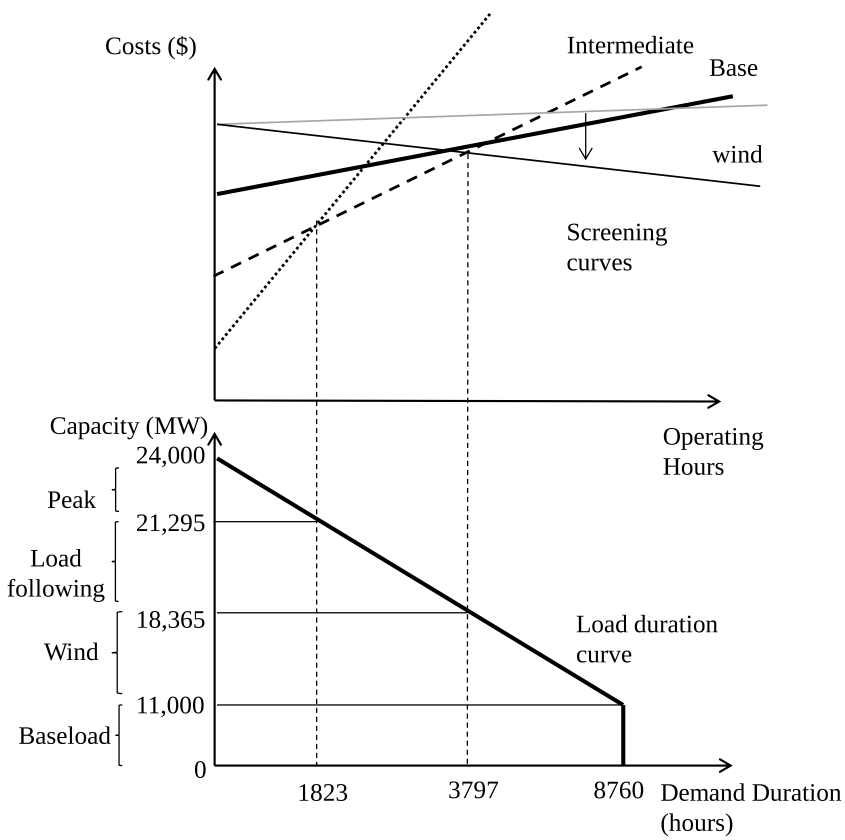

Figure 2.7: Least Cost Generating Mix under a Feed-in Tariff for Wind Energy

In the case of a carbon tax, we can calculate the costs associated with the least-cost generating mix. In Table 2.4, the same method as in Table 2.2 is used. The costs of operating the minimum cost technology mix now total $9.194 billion, of which $2.653 billion is a tax transfer from fossil fuel producers to government/taxpayers. Not surprisingly, the true annual costs have risen to $6.541 billion (fixed and variable total cost), $1.516 billion higher than the $5.025 billion it would have cost to generate the same amount of electricity without government intervention.

Table 2.4: Least Cost Mix of Generating Technologies, Running Times and Costs with Carbon Tax

Generation Technology	Capacity (MW)	Running hours[a]	Total Costs ($ billions) Fixed	Variable	Tax	Total
Baseload	11,000	8760	$2.200	$0.434	$2.457	$5.091
Intermediate	3,443	1477 – 3797	$0.310	$0.236	$0.123	$0.669
Peaking	2,192	1 – 1477	$0.121	$0.073	$0.029	$0.223
Wind	13,197	3797 – 8760	$3.167	$0.000	$0.000	$3.167
Total	**29,832**	**–**	**$5.798**	**$0.743**	**$2.653**	**$9.194**

[a] Not including any hours needed to service baseload (i.e., load following and peaking hours)
Source: Author's calculations

Finally, the case of a wind energy feed-in tariff (FIT) is considered. A feed-in tariff is a renewable energy payments mechanism that offers long-term contracts to renewable energy producers. A FIT could provide price certainty and help finance renewable energy investments. In our case, the FIT only affects the screening curve for wind energy and does not affect the screening curves for other generation technologies. Initially, it was assumed that wind energy had no variable cost, implying that the wind screening curve was flat. The screening curve for wind with a FIT has a negative slope, which is determined by the difference in each hour between the FIT and the realized wholesale spot price. The subsidy ($/MWh) would vary in practice, but because the screening curve-load duration method assumes demand is fixed in each hour, we simply assume a fixed subsidy rate, which produces the same result as the carbon tax. This outcome results in a subsidy of $13.505/MWh. Figure 2.7 depicts the situation in the case of a FIT, while Table 2.5 shows the associated least-cost generation mix, running times, and costs.

Table 2.5: Least Cost Mix of Generating Technologies, Running Times and Costs with FIT

Generation	Capacity	Running	Total Costs ($ billions)			
Technology	(MW)	hours[a]	Fixed	Variable	Subsidy[b]	Total
Baseload	11,000	9760	$2.200	$0.434	n.a.	$2.634
Intermediate	3,443	1477 – 3797	$0.310	$0.236	n.a.	$0.546
Peaking	2,192	1 – 1477	$0.121	$0.073	n.a.	$0.194
Wind	13,197	3797 – 8760	$3.167	$0.000	$0.624	$3.791
Total	**29,832**	**–**	**$5.798**	**$0.743**	**$0.624**	**$7.165**

[a] Not including any hours needed to service baseload (i.e., load following and peaking hours)
[b] n.a. = not applicable
Source: Author's calculations

The total cost of generation is now $7.165 billion, of which a $0.624 billion reduction is a subsidy paid by taxpayers/ratepayers or some combination of the two. The true cost of meeting the annual load to society is again $6.541 billion(fixed and variable total cost), which is the same as the cost with a carbon tax case and higher than the cost without government intervention.

2.4 Merit Order and Supply Stack

In contrast to the load duration/screening curve method, the merit order and supply stack model is a short-run demand and supply model. Its goal is to achieve short-run efficiency or make the best use of the existing resources (Cramton, 2017). The supply stack ranks available sources of electrical generation, based on an ascending order of prices that reflects the costs of producing electricity. Once the supply stack is established, the system operator will choose to permit assets to generate electricity based on the ranking of costs — the merit order.

To be specific, the assets with the lowest bid price, and presumably the lowest marginal costs, are the first ones to be brought online to meet load in that hour. Consequently, the assets with the highest marginal costs are the last to be brought online and the last unit that is brought online is called the marginal unit. Allocating the generation resources according to their marginal costs is also recognized as allocating assets in merit order. Correspondingly, the lower marginal cost assets have greater merit and always get dispatched before higher marginal cost assets with less merit. Overall, the process of dispatching generation as above is known as economic dispatch, which results in minimizing the cost of producing electricity and maximizing profit. Figure 2.8 shows one example to explain how the merit order and supply stack model works under normal market conditions in theory. The horizontal axis represents the generation from different assets, whose unit is MWh. The vertical axis represents the marginal generation costs of various assets.

Suppose that demand is perfectly inelastic at the level of 90 MWh. The gas plant is the marginal unit with its marginal cost at $40 per MWh, which is also the equilibrium price. Due to the perfect inelasticity of demand, the wholesale market is prone to market power. Further, we assume the wholesale market is deregulated. Then individual generators are price takers. Each generator's production decision will not change the market price and each generator bids to supply electricity based on its own marginal costs of producing power. Accordingly, the competitive equilibrium price will be the marginal cost of a marginal unit, i.e., the last unit of the generator that gets dispatched. And non-marginal units can get the quasi rent (supply surplus).

When electricity demand exceeds supply, there will be a blackout and the market price could be exceedingly high. In a competitive market, the market price would be set at the VOLL (indicated by the horizontal line at $70 MWh) and scarcity rents kick in (see Figure 2.9). Now non-marginal units can get compensation for their fixed overnight investment cost and fixed operation and maintenance costs from both the quasi rent (supply surplus) and the scarcity rents (van Kooten, 2016d). But the marginal unit only gets the scarcity rent. Hence, scarcity rents are important and necessary because peaking generators need them to recover their fixed costs.

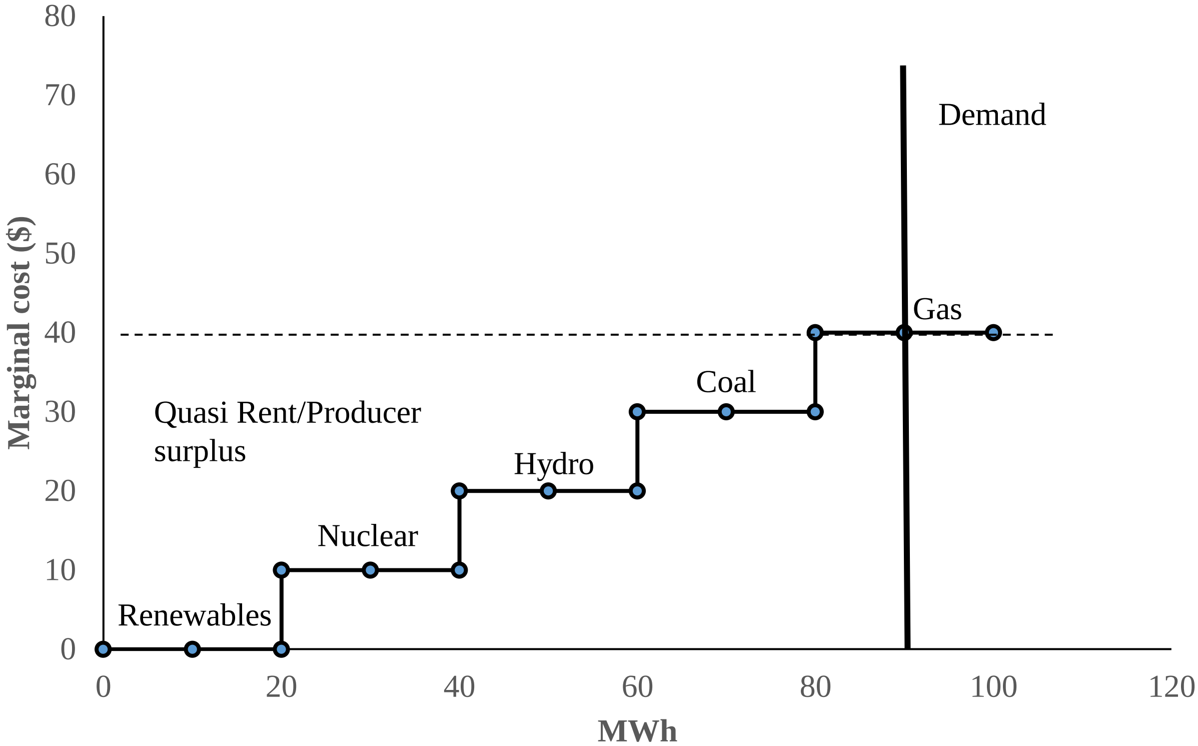

Figure 2.8: Supply Stack

As previously stated, power users are less sensitive to changes in the wholesale market. Plus it is impossible to get consumers all in one place whenever excess demand exists. We cannot find the accurate VOLL value. Therefore, in theory, we approximate it using surveys and other approaches. Then the projected VOLL should be used by regulators to create policies that ensure peaking load capacity recovers its fixed cost.

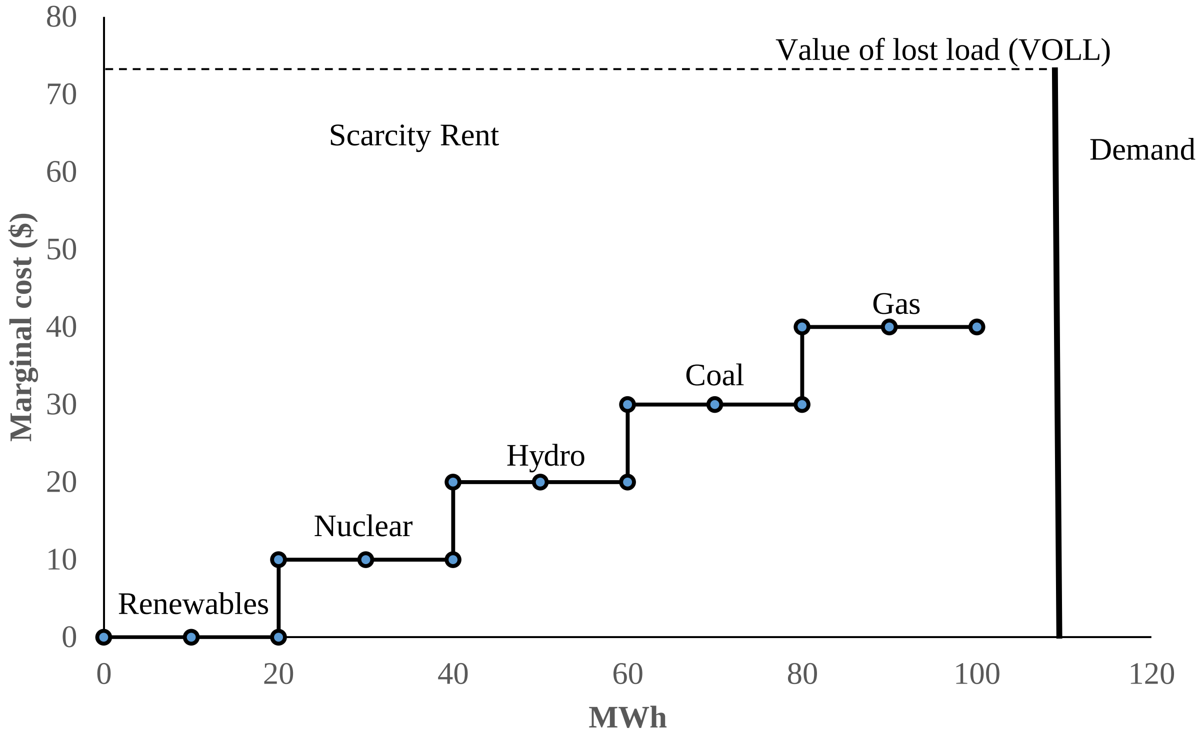

Figure 2.9: Merid Order and Scarcity Rent

However, in reality, some authorities establish a price cap for electricity to safeguard consumers for different reasons. When the price cap is far below the actual VOLL, there will be unintended consequences. Because if the peaking prices are too low, the generators will not get adequate revenue (scarcity rents) to recover the costs and investors will have fewer incentives to invest in peak capacities such as open-cycle gas turbines (OCGT). The net revenue gap, or the phenomenon of missing money, has been coined to describe this lost producer surplus (Joskow, 2006). As a result, assets with high operating costs are less lucrative to operate; OCGT plants are cheap to build but more expensive to operate. Thus, they are for peak purposes. If they operate fewer hours and if there is a cap on the highest price that they can earn, they get insufficient producer surplus to cover the fixed costs, and no one will invest in OCGT capacity. Maintaining capacity sufficiency becomes difficult (Milligan, 2015). For example, in Texas, the price cap was $1,000/MWh at the beginning, then it was gradually raised to $3,000/MWh in 2012, to $5,000/MWh in 2013, to $7,000/MWh in 2014, and to $9,000/MWh in mid-2015. The increase in price caps was due to the situation that the earlier price caps were triggered repeatedly and the Electric Reliability Council of Texas (ERCOT) intended to encourage the needed electricity generation investment to satisfy the demand and reliability needs for electricity (ERCOT, 2015). However, in 2021, the February's Winter Storm caused an energy emergency. After that, the regulator in Texas decided to cut the wholesale electricity price cap back to $5,000/MWh in order to ensure that prices remain affordable during scarcity events (Reuters, 2021). With the lower price cap, the missing money problem may again be a problem in Texas. The authority needs to be creative about its policies to alleviate the issue.

2.5 The implication of Renewables

The merit order and supply stack model encounter greater challenges when massive renewables enter the power production market. The marginal costs of renewables are close to zero. In a system with merit orders, the renewables are brought online right before other energy sources, which eventually crowd out high-cost energy sources such as OCGT, etc. In the end, the market reaches a new equilibrium with lower prices due to the entry of low-cost suppliers.

As Figure 2.10 illustrates, when more renewable power penetrates the generation mix, gas is forced out of the supply stack. Then coal becomes the marginal unit, and its marginal cost sets the market equilibrium price. This effect has been called the merit order effect (MOE) of renewables electricity generation. It has been observed in Italian, German and Denmark power markets (Cludius et al., 2014; Clò et al. 2015; Sensfuß et al. 2008; Sorknæs et al., 2019).

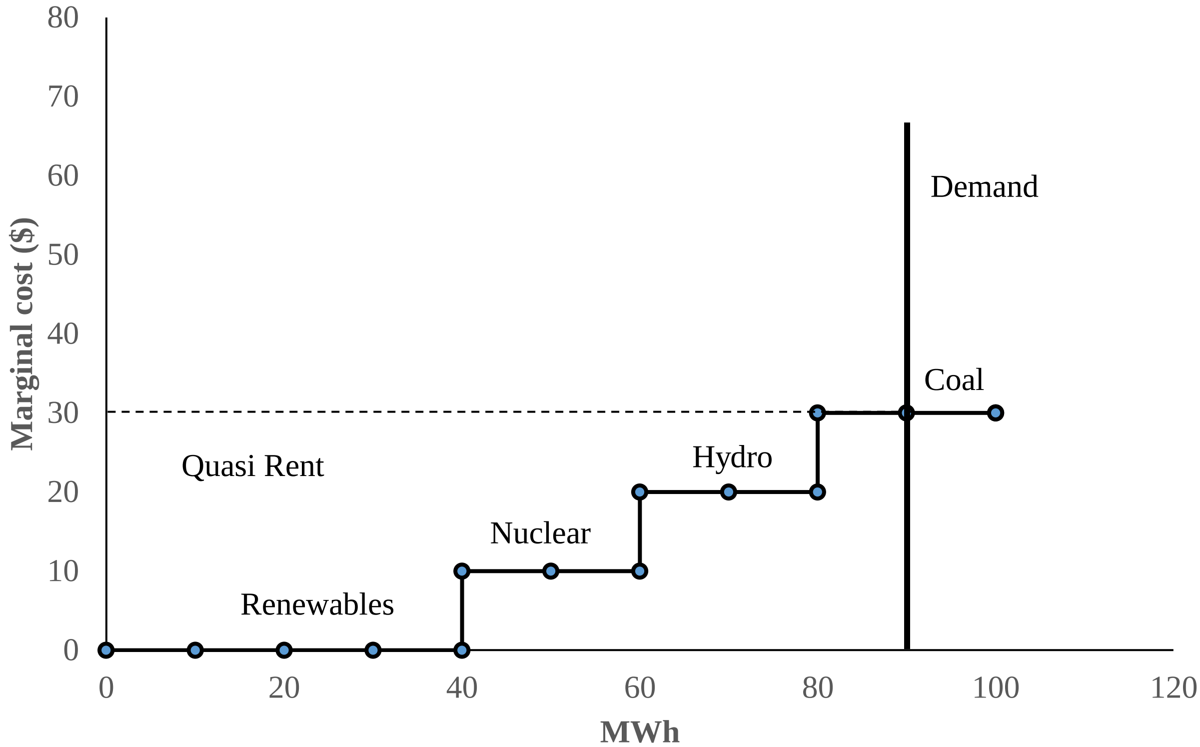

Figure 2.10: Merit Order Effect of Renewables

According to the MOE, renewables not only lower wholesale market prices, but also eliminate the requirement for traditional dispatchable power. This appears to be exactly what we want: customers gain from the low cost, while polluting power plants are replaced. However, the MOE tells us only part of the story. In reality, due to the reasons discussed below, the generators may behave differently from what the MOE predicts, and the market prices of electricity may increase, instead of decreasing, with a higher penetration rate of wind and solar energy. Also, some researchers found that with growing wind penetration levels, power price volatility rises even as electricity prices fall (Martinez-Anido et al., 2016).

First, the MOE only considers the direct costs in the short run and ignores the indirect costs in the long term. As represented in the famous California duck curve, which is replicated in Figure 2.11, the interrupted supply stack may not be able to produce consistent and reliable electricity.

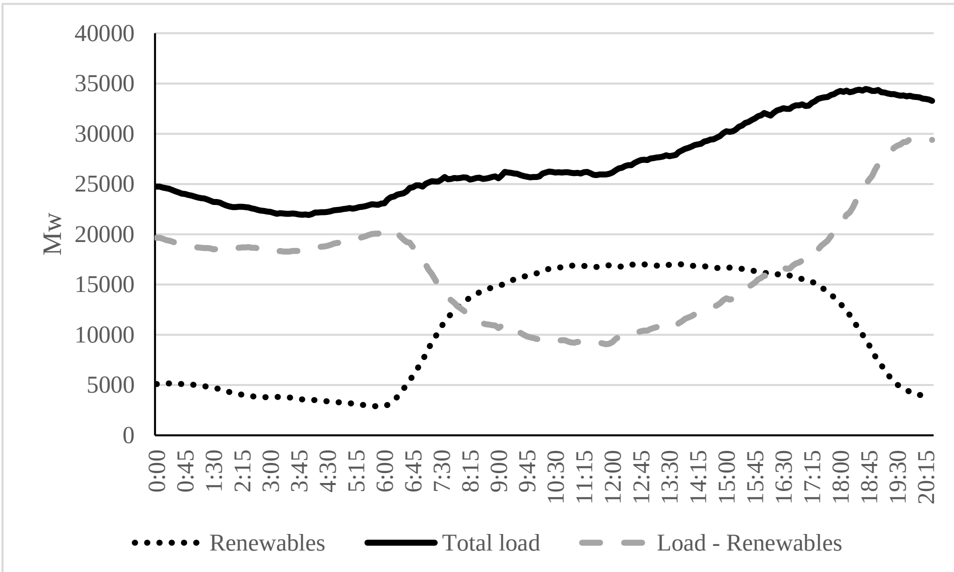

Figure 2.11: An Example of Electrical Demand "Duck Curve" Using Data from California

In Figure 2.11, the bold black curve represents the total demand for electrical power. The dotted curve indicates the supply of solar electrical power. And the gray dashed curve (the duck curve) represents the supply of electrical power from dispatchable sources (i.e., the gray dashed curve represents residual demand/load that equals total demand minus supply from solar and wind energy). As the sun sets, the gray dashed curve rises steeply from 17:00 to 18:00, indicating around 10 gigawatts of dispatchable producing capacity need to come online within one hour to meet the electricity demand in the evening when people are back at home.[3]

The duck curve created by rising solar power generation poses various challenges to the

[3] Graph of California hourly electric load vs. load less solar and wind (the Duck curve) along with renewables output. Data are for May 24, 2022, obtained from California Independent System Operator (CAISO, 2022).

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electrical system. A significant increase in demand for generation flexibility is one example. At midday, dispatchable power plants must reduce their output to allow solar power to be used. In the evening, the dispatchable power capacity such as gas turbines must ramp up in a short amount of time. The low cost of renewable energy lowers wholesale electricity prices when they are available, but the intermittency of renewables leads to higher ramping costs in the baseload component of the electrical system.

In addition to the added cost of ramping, renewables have a large influence on the missing money problem. With the cheaper renewables with subsidies, the meaning of missing money has lately been broadened to include the price consequences of subsidized or mandatory renewable energy generation. Generally speaking, in the long run, the utilization rate of the conventional generation assets declines when the output from renewables increases. For example, wind and solar are driving down wholesale rates in California, New York, and many other states, making the ongoing operation of some nuclear and fossil fuel power plants unprofitable (Borenstein, 2017). Hence, renewable energy integration does not solve the "missing money" problem; instead, it makes it worse.

The increasing explicit and implicit costs in electricity generation after integrating renewable energy sources must be addressed through effective electricity market design so that a consistent and reliable electricity supply can exist. Chapters 3 and 4 will discuss the questions related to the market design for addressing the above problem. However, all those market interventions also come with a cost. For example, with a capacity market and capacity payment, the overall cost of operating the system will increase so that, even if the wholesale price is lowered, the retail price will need to be raised to cover the capacity payments. The retail price also increases because_most wind and solar power projects are heavily subsidized, so either ratepayers or taxpayers must cover this cost; for example, the system operator usually pays the transmission and distribution system for the wind and solar projects. Finally, intermittent wind and solar power impose higher costs on existing assets, which will need to be considered when new investments need to be made. All those costs are not reflected in the wholesale market price, but they are eventually imposed on the final electricity consumers. Therefore, in some countries that have a high penetration rate of wind and solar power, the wholesale market prices/generation marginal costs fall, but the retail market price rises (Murray, 2019). Those unintended consequences are not anticipated by the MOE.

Second, the MOE does not consider generators' strategic behavior. Under certain circumstances, the bids can be lower than the true short-run marginal costs of production. For example, in a particular hour, a coal-fired power plant will bid in lower than its anticipated marginal cost of production for that hour to ensure that it can continue to produce because it would be too costly to shut down only to restart again one or two hours later. In this case, the coal plant will bid in at or near $0/MWh, knowing full well that the final price will be higher because coal-generated power is unlikely to be the marginal unit and other assets will bid in at higher marginal costs, thus leading to a higher price.

In other cases, generators might halt production and bid at a price that is higher than the competitive price. For instance, in an oligopolistic energy market, thermal generators with a varied energy portfolio and control over some or all renewable supplies might use this strategy. They can compensate for the price drops caused by the MOE by lowering their traditional fossil fuel energy supply. This offer strategy is called economic withholding. For example, as Figure 2.12 depicts, the producers could hold back their low-cost dispatchable supply and bid at a higher price which could equal the marginal cost of a gas plant, rather than that of a coal plant. Then, the market price will go back to the same level as shown in Figure 2.8. In reality, when regulators suspect electricity suppliers of conspiring to raise costs and profits, they will open investigations that could result in fines or other penalties (Alberta Utilities Commission (AUC), 2022).

The MOE could be completely neutralized in the extreme case when all renewable supply is controlled by thermal power providers, and renewables have no impact on wholesale market prices. Researchers also argue that neutralization of the merit order effect could result in higher markups and reduce social welfare (Acemoglu et al., 2017).

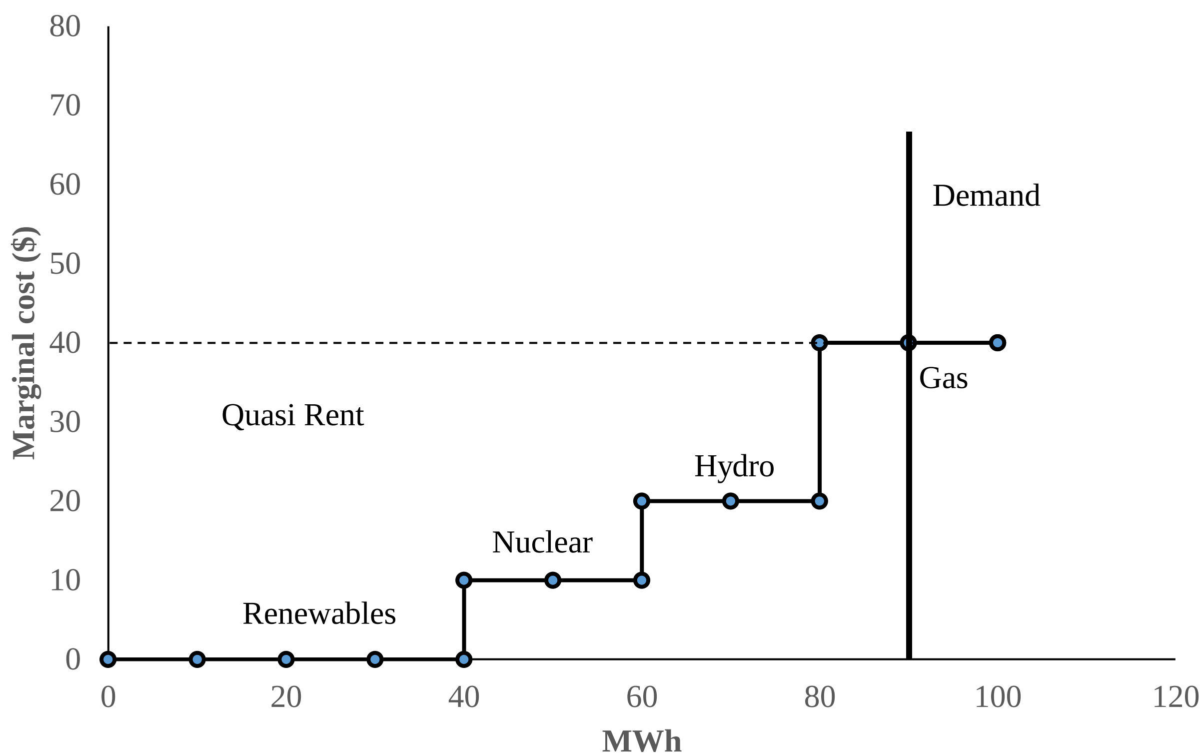

Figure 2.12: An Example in which the Merit Order Effect Is Completely Neutralized

2.6 A grid optimization model for renewable integration

The previous discussion demonstrates that the classical screen-duration-curve model and merit-order model are simple and elegant. Both models require minimal technical data to account for the different cost structures of the generation mix, with some assets having high capital costs and low fuel costs, and other assets having the opposite. However, both models have limitations in terms of the optimization of the short-run operation or long-run capital investment. First, the methods are static and do not account for the dynamic features of the electricity grid, such as changes in asset mix and variations in wind speed. Second, they are deterministic approaches which cannot account for the stochastic events such as uncertainty in demand and renewables supply, and start-up/ramp-up constraints. Third, they are good for analysis for conventional dispatchable power plants, but not ideal for intermittent wind or solar power whose production is much hard to predict (Güner, 2018).

Because of these and other shortcomings, a grid optimization model will be employed in the dissertation to study the impacts of integrating renewable into a power grid on CO_2 emissions reduction and the missing money problem. The model is a modified version of the screening curve model that takes into account the different cost structures of generation assets, ramping constraints, and other physical and economic factors. It essentially is a mathematical optimization model in which the system operator minimizes the costs of generating power to meet hourly load (Lamont 2008; van Kooten et al. 2016b). The details about the model setup and application will be explained in the following chapters.

Chapter 3 Substitution Effect Of Renewables: Role Of Nuclear Energy In Reducing CO_2 Emissions[4]

3.1. Introduction

The NDP Government of Alberta promised to make the province a world leader in renewable energy. To achieve this, all coal-fired electricity generation facilities are to be phased out by 2030, with two-thirds of the lost electricity production to be replaced by renewables, primarily wind and solar power, with natural gas to be used for generating baseload power (and as a backup to intermittent energy sources). To encourage a speedy transition, the government implemented an economy-wide carbon tax of \$20 per tonne of CO_2 (tCO_2) beginning in 2017 and increased it to \$30/tCO_2 in 2018; committed to producing 30% of electricity from renewables by 2030; provided subsidies to encourage renewable energy; and capped emissions from oil sands developments at 100 megatons of CO_2 (Government of Alberta, 2018).

The purpose of the current chapter is to investigate whether it would be possible for Alberta to reduce its CO_2 emissions by 30% or more, replacing two-thirds of the lost coal-fired power with wind-generated electricity. To do so, a grid optimization model that enables investment and disinvestment in generating facilities is developed. The objective is to investigate whether there might be sufficient wind at any given time by employing uncorrelated wind regimes from various sites throughout the province. The analysis is at a macro scale since the objective is to guide policy related to climate change rather than prescribe actual investment decisions regarding generating assets or transmission requirements.

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[4] The material in this chapter is based on van Kooten, G. C., Duan, J., & Lynch, R. (2016). Is There a Future for Nuclear Power? Wind and Emission Reduction Targets in Fossil-Fuel Alberta. *PLOS ONE*, *11*(11), e0165822. https://doi.org/10.1371/journal.pone.0165822

We begin the next section by examining the characteristics of the Alberta electricity system, followed by a discussion of the costs of producing electricity. Then we describe our model and the origins of the wind power data that we employ. This is followed by our results and a concluding discussion. Our results indicate that, for Alberta to reduce CO_2 emissions from the production of electricity by 30% or more will likely require something more than investments in wind energy, with nuclear energy looking most promising despite its high costs.

3.2 Background

The costs of developing and operating renewable (wind- or solar-powered) generating assets can be substantial and may only be viable for firms when governments provide subsidies or other inducements. An indirect but important cost of these renewables is associated with the high variability of wind patterns and inconsistent availability of solar energy (due to lack of sunlight). Intermittency in wind (and solar) power output is unavoidable, often resulting in large costs of ramping existing generating assets or investing in new assets to compensate for this intermittency (van Kooten 2016a).[5] Nonetheless, there are also significant benefits to society of transitioning away from fossil fuels, primarily from reduced greenhouse gas (GHG) emissions as measured in terms of CO_2. The benefits to society relate mainly to the substitution of clean energy for fossil fuels, especially coal-fired power.

To measure the degree to which intermittent energy can substitute for coal-fired power will be determined in this chapter by first collecting hourly wind data from various locations across

[5] We focus only on wind power because potential solar photovoltaic (PV) electricity output is more difficult to model and beyond the scope of the current study. However, the inherent intermittency we model using wind is likely little affected by adding solar power. For example, Monahan and van Kooten (2010) found that adding a predictable tidal power output profile to a wind profile had no impact on the management of a power grid on Haida Gwaii off the Northwest coast of British Columbia.

Alberta. We then assume the establishment of sufficient wind generating capacity to meet half of the province's peak load, with wind farms spread across the province to reduce the potential intermittency in supply as wind speeds vary across the landscape. We simulate the wind power that could have been generated every hour for the period 2006 through 2015 using wind-turbine power curves and the data on wind speeds. Hourly wind power output is then subtracted from demand to obtain the load that must be met by the various fossil-fuel and other generating assets comprising the Alberta electricity system.

Our objective is to examine the case where the Alberta government seeks to eliminate coal, using both a carbon tax and regulation. To determine how generation is allocated across assets in each hour, we use an existing grid model for Alberta that optimizes load across assets (van Kooten et al., 2013). The grid allocation model is annual with an hourly time step and assumes rational expectations on the part of the grid operator/asset owner. Any excess power remaining when intermittent wind power is subtracted from the load is assumed to be exported to British Columbia, which has the ability to store power behind hydroelectric dams, or to Saskatchewan or the United States via transmission interties. Excess power is assumed to be sold at a price of zero – Alberta receives no remuneration, nor does it have to pay (negative price) to dump the excess power. Costs are determined in the analysis using the Levelized cost of electricity (LCOE) when power is generated from various facilities as determined by the grid allocation model, although an investor is assumed to incur an annualized cost of construction. The optimal allocation of output across assets is also used to determine CO_2 emissions.

Our analysis seeks to determine if the benefits to society from changing to wind and solar energy will outweigh the costs, and whether imposing strong restrictions on fossil fuels is economically feasible. We can calculate the costs and benefits of reducing CO_2 emissions from Alberta's electricity sector; in doing so, we rely on assumed values of the social cost of carbon or the price of carbon (see Nordhaus, 2014; Tol, 2014). Depending on the results, it may be necessary to examine the optimal subsidies required by governments to facilitate the construction of renewable generating facilities as well as the compensation for firms that had earlier been encouraged to invest in new coal-fired generating capacity.

3.3 Alberta Electricity Grid

The Alberta electricity grid is characterized by industrial consumers and three main types of generation – coal, natural gas and co-generation. The 2015 load duration curve shown in Figure 3.1 is indicative of the province's industrial base; the peak load of 11,229 MW is only 56% greater than the baseload of 7,203 MW, and baseload demand (63.10 TWh) accounts for 78.6% of total generation of 80.26 TWh. In contrast, for example, the peak loads of British Columbia and Ontario are more than double those of baseload. Alberta's generation mix is dominated by fossil fuels (Table 3.1) despite recent efforts to increase the use of biomass and wind (there is no solar in the mix), and recovery of waste heat. As indicated in Figure 3.2, installed wind capacity has increased by 1,445 MW since 2000, while co-generation capacity increased by 2,951 MW (most of which relies on natural gas and not biomass), natural gas plant capacity by 1,372 MW, and coal-fired capacity by 556 MW, although overall investment in coal capacity has been greater since over 500 MW was decommissioned during the same period.

Costs of Producing Electricity

A study by Stacy and Taylor (2015) examined the costs of generating electricity in the U.S. by three types of assets: baseload assets capable of dispatching electricity at any time and for very long periods (coal, combined-cycle natural gas, nuclear and hydro), dispatchable peak resources (gas turbines), and intermittent resources (wind). The authors compared U.S. EIA (2010) estimates of the LCOE based on information from existing plants, estimates of what it would cost to produce electricity from new plants with the latest technology, and estimates for new construction but revised to take into account observed capacity factors (CFs) rather than assumed CFs.[6] Their calculations are provided in Table 3.2, along with more recent estimates from U.S. EIA (2015).

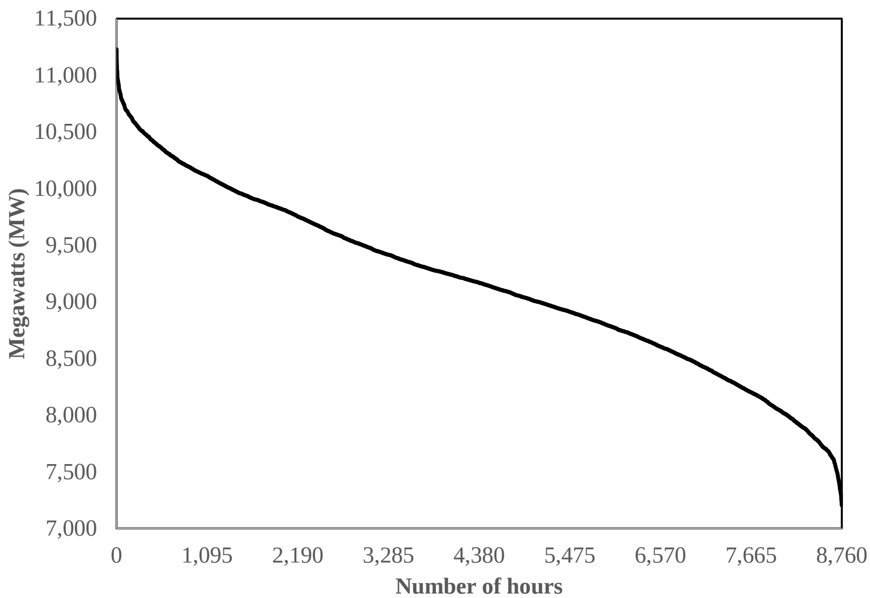


Figure 3.1: Alberta Load Duration Curve, 2015

[6] A generating asset's capacity factor is given by the ratio of the annual electricity generated by the asset divided by the asset's capacity multiplied by 8760 hours (8784 hours in a leap year).

Table 3.1: Capacity and Generation, Alberta Electric System, 2014

	Capacity		Generation	
Fuel Source	MW	Share	GWh	Share
Coal	6,258	38.5%	44,442	55.0%
Natural Gas	7,080	43.6%	28,136	35.0%
Hydro	900	5.5%	1,861	2.0%
Wind	1,459	9.0%	3,471	4.0%
Biomass[a]	447	2.8%	2,060	3.0%
Other[b]	98	0.6%	373	0.0%
Total	**16,242**	**100.0%**	**80,343**	**100.0%**

[a] Co-gen biomass accounts for 158.0 MW of capacity, biogas for 8.8 MW and other biomass for the remainder.
[b] Includes fuel oil and waste heat, which is a by-product of existing industrial operations with the heat otherwise escaping from an exhaust pipe.
Source: Alberta Utilities Commission (AUC) and Alberta Electric System Operator (AESO, 2016).

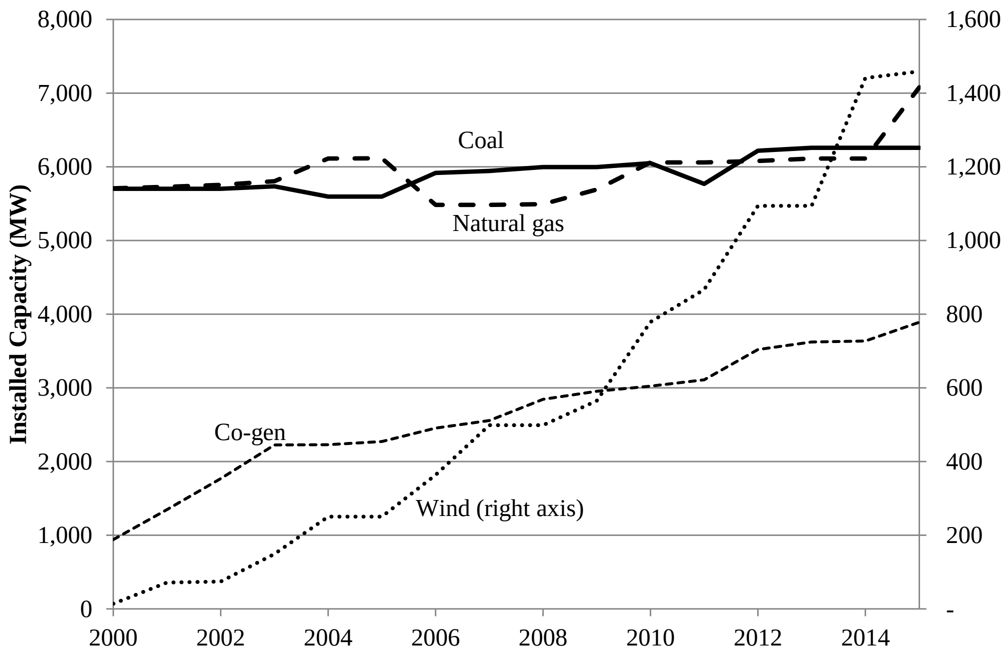


Figure 3.2: Installed Generating Capacity by Type, Alberta, 2000-2015

The results in Table 3.2 indicate that current costs of producing electricity (Existing column) are much lower than those of new construction. This is primarily because the construction costs of many assets have been paid off. Decision-makers need to consider this when they implement policies that result in the premature closure of existing generators, because doing so might lead to higher-than-expected overall electricity costs. Next, estimates of the LCOEs for new construction indicate that, despite recent advances in technology, wind remains at a cost disadvantage relative to fossil fuels, and more so if costs of additional transmission are taken into account. Finally, if the observed as opposed to estimated CF is used to calculate Levelized costs, the LCOE for new construction will turn out to be higher than expected by the U.S. EIA (2010, 2015), thereby reinforcing the preference for keeping current assets longer.

Table 3.2: Estimates of the Levelized Costs of Electricity (LCOE) for Existing Plants, New Construction with Optimistic Capacity Factors and New Construction based on Observed Capacity Factors, and Latest Estimates, Three Generating Asset Types ($US 2012/MWh)

Generator Type	Existing[a]	Optimistic[a]	Observed[a]	Latest[b]
Dispatchable full-time capable resources (baseload)				
Conventional coal	38.4	80.0	97.7	93.7
Conventional combined cycle gas (CC gas)	48.9	66.3	73.4	74.1
Nuclear	29.6	96.1	92.7	93.8
Hydro (seasonal)	34.2	84.5	116.8	82.2
Dispatchable peaking resources				
Conventional combustion turbine (CT gas)	142.8	128.4	362.1	139.4
Non-dispatchable intermittent resources as used in practice				
Wind	Not available	96.2	112.8	72.5

[a] Source: Stacy and Taylor (2015). The ‘Existing’ column is based on their own calculations. Data in the ‘Optimistic’ and ‘Observed’ columns are based on U.S. EIA (2010).
[b] Source: U.S. EIA (2015). Values for plants entering service in 2020; $2013 values deflated to $2012 using an inflation rate of 1.5%. Capacity factors for wind (36%) and solar (25%) are the best observed in the U.S., so LCOEs for intermittent resources are likely higher than reported here.

There are two caveats to consider. First, the use of LCOE to select renewable energy projects (or otherwise make investment choices) can be misleading because the value of power changes over time and space, as does the production of power from various assets, especially intermittent ones. Second, LCOE estimates exclude externality costs, except perhaps in the case of nuclear power, where recent cost overruns to address evolving environmental regulations have resulted in construction delays and higher costs (Lovering et al. , 2016). This issue is best addressed by employing an annualized cost (or penalty) for investing in new generating capacity, which could be over and above the carbon tax used to incentivize both investment and generation.[7] Finally, a (quite) small penalty is imposed to incentivize the removal of assets that fail to produce power during the year.

Overnight construction costs are difficult to determine. In the current analysis, we use data from surveys conducted at various times by the International Energy Agency (IEA) and U.S. Energy Information Administration (U.S. EIA). It should be noted, however, that our results are robust regarding capital costs.[8] We assume overnight costs of wind are $2,700 per kW, while those of coal, conventional combustion turbine (CT) gas (which we assume to be the same as for co-gen), combined cycle (CC) gas, and nuclear power plants are $2,600, $1,900, $1,600 and $6,000 per kW of installed capacity, respectively. Capital costs are annualized using a 5% discount rate and the estimated length of time taken to build the facility, which is taken to be 7 years for nuclear power plants, 4 years for coal assets, 2 years of CT gas, and 3 years for co-gen/CC gas facilities.

Wind power is less expensive on a LCOE basis than CT gas and seasonal hydro, but more expensive than electricity generated from CC gas, nuclear and coal. Overall, available data indicate that traditional fossil fuel technologies are clearly preferred to wind power on a cost basis, unless externality costs are considered.

[7] In the current application, this is done by assuming that the lifetimes of all generating assets are the same (30 years). This disadvantages investments in nuclear and coal compared to other assets, because the construction cost is spread over fewer years. In the case of coal, however, the carbon tax ensures that no further capacity is added.
[8] See, e.g., http://www.eia.gov/oiaf/beck_plantcosts/index.html [Accessed September 8, 2016].

3.4. Alberta Model

The Alberta grid allocation model is described in various places; here we provide a brief description as found in van Kooten et al. (2013). The Alberta Electric System Operator (AESO) is considered to be the decision maker, so the AESO's profit function can be written as:[9]

$$\Pi = \sum_{t=1}^{T}\left[P_{A,t}D_t - \sum_i \left(OM_i + b_i + \tau\varphi_i\right)Q_{i,t} + \sum_k \left[\left(P_{k,t} - \delta\right)X_{k,t} - \left(P_{k,t} + \delta\right)M_{k,t}\right]\right] - \sum_i (a_i - d_i)\Delta C_i,\ k \in \{BC, MID, SK\}, \tag{3.1}$$

where Π is profit ($); i refers to the generation source (coal, CT gas, wind, etc.); T is the number of hours in the one-year time horizon (8760); D_t refers to the load (demand) that has to be met in hour t (MW); $Q_{i,t}$ is the amount of electricity produced by generator i in hour t (MW); OM_i is operating and maintenance cost of generator i ($/MWh); and b_i is the variable fuel cost of producing electricity from i ($/MWh), which does not change with output (i.e., there are no economies of scale). We define $P_{j,t}$ to be the price ($/MWh) of electricity in each hour, with j∈{AB, BC, MID, SK} referring to Alberta, British Columbia, MidC and Saskatchewan, respectively. While Alberta and MidC prices vary hourly, the BC and Saskatchewan prices are fixed at $75 and $56 per MWh, respectively. $M_{k,t}$ refers to the amount imported by Alberta from region k∈{BC, MID, SK} at t, while $X_{k,t}$ refers to the amount exported from Alberta to region k; δ is the transmission cost ($/MWh).

The first term in square brackets is simply the gross revenue earned by selling electricity

[9] It is more appropriate to refer to this as a 'gross margin' function, because equation (3.1) excludes many costs, such as ancillary services, that are required to operate a grid. We use the term 'profit' simply because it is more familiar.

to meet the Alberta load, while the second term refers to the overall costs of internal power generation. Costs are summed across all of the generators; for each generator, it is simply the variable operating & maintenance cost plus fuel cost multiplied by the generator output over the year. In addition, the carbon tax paid by each generator is treated as a cost. The carbon tax ($ per tCO_2) is denoted by τ and is used to incentivize the removal of fossil fuel capacity and entry of renewable or nuclear capacity, while φ_i is the CO_2 emitted when producing an MWh of electricity from generation source i (and depends on the fuel source). Then the third term in square brackets refers to the revenue from the sale of exports minus the cost of buying imports, with net exports accounting for the difference between load and internal generation in any hour. The terms in square brackets are then summed over the 8760 hours in the year to which the model is calibrated.

The final term in (1) permits the addition or removal of generating assets, where a_i and d_i refer to the annualized cost of adding or decommissioning assets ($/MW), C_i refers to the capacity of generating source i (MW), and ΔC_i is the capacity added or removed. For wind assets, ΔC_W is measured in terms of the number of wind turbines that are added (no reduction in numbers is permitted), each with a capacity of 3.5 MW (as discussed below). Given that wind energy is non-dispatchable ('must run'), storage is assumed to be available in each period in neighboring jurisdictions via transmission interties; excess energy can be directed or retrieved if the Alberta system cannot respond quickly enough because of extreme variability in wind power output from one period to the next. Further, R_i is the proportion of the capacity of generator type i that can to ramped in a given hour; given that the Alberta system can ramp 600 MW of production in any hour, we assume ramp rates of 0.04 for coal and co-gen plants, 0.02 for nuclear plants, and 1.0 for GT gas (peak) plants. Transmission between Alberta and BC, and Alberta and MidC, is constrained depending on whether power is exported or imported; the import and export constraints are denoted TRM_{kt} and TRX_{kt}, respectively, with k defined above and capacity changing over time for reasons discussed below.

The objective function (1) is maximized subject to the following constraints:

Demand is met every hour:	$\sum_i Q_{i,t} + \sum_k \left(M_{k,t} - X_{k,t}\right) \geq D_t, \forall t = 1,\ldots,T$; $k \in$ {BC, MID, SK}	(3.2)
Ramping-up constraint:	$Q_{i,t} - Q_{i,(t-1)} \leq C_i \times R_i, \forall\ i,t=2,\ldots,T$	(3.3)
Ramping-down constraint:	$Q_{i,t} - Q_{i,(t-1)} \geq -C_i \times R_i, \forall\ i,t=2,\ldots,T$	(3.4)
Capacity constraints:	$Q_{i,t} \leq C_i, \ \forall\ t,i$	(3.5)
Import trans constraint:	$M_{k,t} \leq TRM_{k,t}, \forall\ k,t$	(3.6)
Export trans constraint:	$X_{k,t} \leq TRK_{k,t}, \forall\ k,t$	(3.7)
Non-negativity:	$Q_{i,t}, M_{k,t}, X_{k,t} \geq 0, \forall\ t,i,k$	(3.8)

In any given hour, electricity can only flow in one direction along a transmission intertie. To model this constraint requires the use of a binary variable for each intertie in the model. To avoid such a nonlinear constraint, we assume that the import and export capacities at any time are equal, and that they equal the total capacity of the line at that time ($TRM_{k,t} = TRX_{k,t} = TCAP_{k,t}$, $\forall k,t$), although this applies only to the Alberta-BC intertie where the capacity varies in each period due to internal transmission constraints. These constraints relate, for example, to internal operations that could prevent imported electricity from being delivered to where it is needed. We then employ the following linear constraint to limit the flow of electricity to one direction:

$$X_{k,t} + M_{k,t} \leq TCAP_{k,t}, \forall\ k,t. \quad (3.9)$$

3.4.1 Wind Data

Hourly wind speed data for 17 locations scattered throughout Alberta were collected from Environment Canada for the decade 2006 through 2015. The location with the highest average wind speed (8.58 m/s) over the period was Pincher Creek in southwestern Alberta, which is about 85 km southwest of Lethbridge, the main center in southern Alberta; Barnwell, which is about 45 km east and somewhat north of Lethbridge, came a distant second with an average wind speed of 4.71 m/s, followed by Raymond (due east of Pincher Creek and about 35 km southeast of Lethbridge), Lethbridge and Killam as the only five sites with average wind speeds above 4.0 m/s. Only Killam is not in southern Alberta as it is located 400 km directly north of Lethbridge.

The power generated by the wind depends not only on wind speed but also on the height of the turbine hub. To determine the actual power available from a wind turbine, the measured wind velocity must be adjusted to obtain wind speed at the turbine hub height. This is done using the following relationship:

$$V_{hub} = V_{data} \times \left(\frac{H_{hub}}{H_{data}} \right)^{\alpha}, \tag{3.10}$$

where V_{hub} is the wind velocity (m/s) at the turbine hub height, V_{data} is the measured wind velocity (m/s), H_{hub} is the height of the wind turbine hub (m), H_{data} is the height (m) at which the data was measured, and α is the site shear component that is dependent on the type of ground surface on which the wind turbine is built. Empirical evidence suggests that $\alpha = 0.06$ for open water, $\alpha = 0.10$ for short grasses, $\alpha = 0.14$ the most common value, $\alpha = 0.18$ for low vegetation, $\alpha = 0.22$ for forested regions, and $\alpha = 0.26$ for obstructed flows. We use this information to set values of α

depending on our knowledge of the terrain in the vicinity of the 17 towns in the dataset.[10] The wind velocity at our sites was measured at 10 m height.

Wind power is related to wind speed as follows:

$$p = ½ \rho v^3 \pi r^2, \tag{3.11}$$

where p is the power of the wind measured in watts, v is wind speed measured in m/s, r is the radius of the rotor measured in meters, and ρ is the density of dry air parameter (assumed equal to 0.94) measured in kg/m^3. This formula is generally quite useful, but it neglects information on the turbine, particularly the wind speed at which power production begins as well as the cut-out speed where the rotator blade must be turned to avoid damage.

Conversion of the available mechanical energy (wind speed) to electricity is based on the above relations and the technical specifications for a 3.5-MW capacity Enercon E-101 wind turbine. Then, by weighting each location equally, but Pincher Creek at four times the weight of the other locations, we aggregated the potential power production at each location into a single wind power profile for an Alberta-wide, 3.5 MW turbine. The capacity factor of Alberta's wind regime averaged 28.7% over the 12 years reaching a high of 33.4% in 2013 and a low of 23.3% in 2010; for Pincher Creek, the CF averaged an incredible 55.5%, ranging from 33.9% (2010) to 79.8% (2013).[11]

[10] Information on average wind speeds, shear factors employed, and the average power output for the 17 sites is found in Appendix Table 3A.1; a correlation matrix of wind speeds is found in Table 3A.2. The power curve for the wind turbine that is used to convert wind speed to power output is also provided in the Appendix. See also www.enercon.de for technical information.

[11] It is important to note, however, that these numbers are potential and not actual CFs. For 2014, our calculations based on wind speed data indicate a CF of 32.7% while the realized CF was 35.6%, although, not surprisingly, most wind farms currently active in Alberta are located in the Pincher Creek region.

As indicated in Figure 3.3, even if Alberta were to build wind farms across a vast area, about 60% of the time the power produced would be less than one-quarter of the installed capacity. Worse yet, about 96% of the time, wind power would be below half of the rated capacity, and there are only for 17 hours per year on average when the potential electricity available from wind exceeded 75% of capacity. On average, there would be no wind output whatsoever for 5.2 hours during the year, ranging from one hour in 2006 to 13 hours in 2011. No matter how much wind capacity is installed in Alberta, or where it is located, there are times when no wind power is available and many, many times when the wind power output is inadequate. In the model, we assume a cap on the number of wind turbines that can be installed of 3500 to avoid potential adverse public reaction related to visual and other dis-amenities and because this would result in installed capacity of 12,250 MW that exceeds peak load.

3.4.2 Generating Assets

To keep the analysis simple, we ignore marginal generation, such as run-of-river hydro that one subtracts from load in any event, and small amounts of electricity generated from biomass, biogas and flare gas. As evident from Table 3.1, hydro accounts for 2% and biomass for about 3% of Alberta's requirements, while other clean energy sources account for negligible power output. Thus, we focus only on coal, natural gas, wind and potentially nuclear energy. Between them, coal and natural gas account for all of the baseload generation, or 63.072 TWh (= 7200 MW × 8760 hours / 1 million), while the remaining 17.19 TWh of electricity is produced by baseload plants, CT gas, wind and imports. Coal plants account for 6258 MW of capacity and co-gen plants for 3892 MW (more than 90% of co-gen plants burn natural gas). For simplicity, we assume that these two sources constitute Alberta's total baseload capacity (10,150 MW), while remaining capacity consists of 7080 MW of CT gas and 1459 MW of wind (or 417 turbines of 3.5 MW capacity).

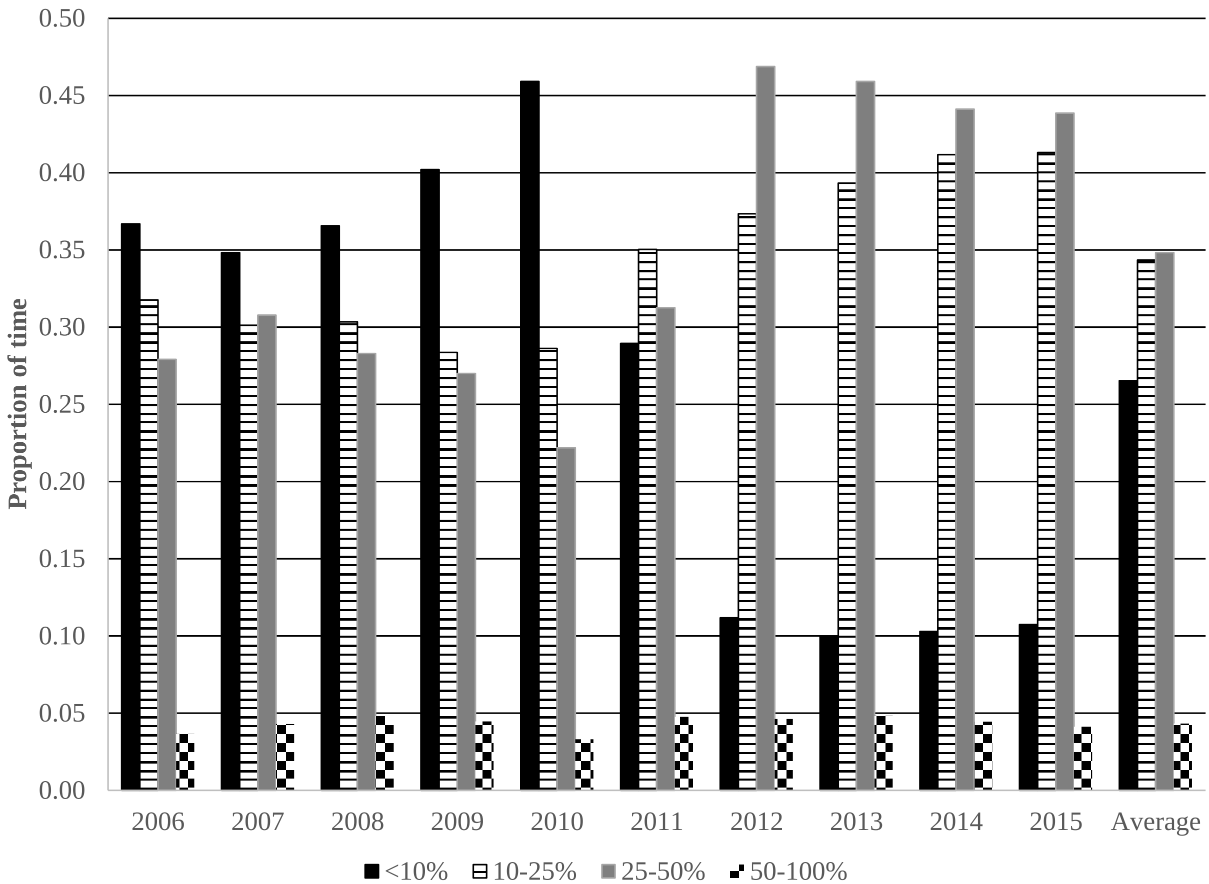


Figure 3.3: Wind Power Output as a Proportion of Capacity, Alberta, 2006-2015

3.5 Results

The model is parameterized for 2015 – the generation mix, the load and price profiles, and transmission intertie capacities are based on 2015 data from the AESO. However, rather than employing the existing wind profile (see van Kooten, et al., 2016), we employ each of the ten wind profiles that we developed in the previous section. That is, each run of the model provides outcomes for each of the ten wind profiles. We assume that 417 wind turbines are already in place (with a total capacity of 1460 MW), although their wind power profile is different from that of the existing wind farms that have the same capacity. We also note that wind speeds are higher for the period 2012-2015 than for the preceding six years, which turns out to make a large difference as indicated below. We begin by considering the wind speed profile for 2015 only.

In Table 3.3, we provide the results for the 2015 wind speed profile and several carbon taxes, two levels of the BC-Alberta intertie capacity (storage potential), and whether or not nuclear power is permitted. In the case of the 2015 wind profile, 3226 wind turbines are installed even when there is no carbon tax; that is, the wind profile is such that it pays to install wind power, although, for wind profiles associated with years 2006 through 2011, it is not worthwhile installing any new wind turbines beyond those already in place (417). That is, because the variable costs of wind are effectively zero, whenever there is sufficient wind so that the savings in the variable costs of wind versus other generating assets exceeds the annualized cost of investing in wind then wind will be brought into the generation mix. This occurs for 2012-2015, but not in earlier years.

With a carbon tax and the 2015 wind profile, the optimal number of turbines to install reaches its maximum of 3500. Again, this is not the case for other wind profiles; indeed, only if the carbon tax is \$100/tCO_2 is it worthwhile to increase turbines from 417 to 3500. In particular, for the 2010 wind profile, it is only worthwhile to invest in wind energy if the carbon price is \$100; for the \$50/tCO_2 scenario, the number of turbines remains at 417. This has implications as well for the scenario where investment in nuclear power is permitted.

Table 3.3: Wind versus Nuclear Power in a Carbon Constrained World, Results for the Alberta Electricity Grid, 2015 Wind Profile

Carbon tax ($/t$CO_2$)	Total emissions Mt CO_2	Emission reduction	Trade along intertie (GWh) Import from BC	Export to BC	Optimal installed capacity (MW)[a] Coal	Co-gen	Gas	Nuclear
Base Case Scenario								
$0	32.74		4,819	54	6,258	3,292	4,184	0
Current transmission capacity: No nuclear								
$30	29.05	11.3%	4,829	57	6,258	3,292	6,077	0
$50	29.03	11.3%	4,862	50	0	3,292	6,320	0
$100	28.80	12.0%	4,878	34	0	3,759	6,306	0
Double transmission capacity: No nuclear								
$50	25.46	22.2%	9,707	40	0	3,292	7,278	0
$100	25.41	22.4%	9,796	28	0	3,292	6,319	0
Current transmission capacity: With nuclear								
$100	8.25	74.8%	4,312	221	0	3,292	4,220	3,728
Double transmission capacity: With nuclear								
$100	8.16	75.1%	8,870	232	0	3,292	4,413	3,182

[a] Under the base case scenario, 2809 additional wind turbines are installed for a total of 3226 turbines (11,291 MW capacity); in all no-nuclear scenarios 3083 additional turbines are installed, for a total of 3500 (12,250 MW). When nuclear power plants are permitted, the existing 417 turbines (1460 MW) remain with no new turbines built.

Because our model utilizes all available capacity on the BC-Alberta transmission intertie, wind is encouraged even when there is no carbon tax. Given that imports are the cheapest source of power whenever the internal Alberta price exceeds the fixed BC price, Alberta imports much more along the intertie than it exports. By increasing the variable costs of producing electricity from fossil fuels, the carbon tax exacerbates the import effect because imports are considered to be carbon free.[12] Hence, as the carbon tax increases in the base scenarios, we see an increase in imports and a reduction in exports (which are taxed when produced by fossil fuel assets).

Now consider the impact of the various wind, carbon tax and nuclear energy scenarios on

[12] We employ this assumption because the BC government does not levy its carbon tax on electricity despite that power consumed at night likely comes from Alberta coal plants, and even imports from the U.S. could originate from fossil fuel plants.

CO_2 emissions. Emissions are provided in Table 3.4 only for the case of the existing capacity constraints on transmission interties. As indicated in the first column, the better wind scenarios (2012-2015) lead to greater investments in wind turbines and lower CO_2 emissions in order to meet the Alberta 2015 load. With a carbon tax of \$30/tCO_2 there is a significant reduction in emissions, ranging from 6.0% in 2013 (when the wind regime was sufficient to warrant building the maximum 3500 turbines) to 38.0% in 2011 (when no investment in wind energy occurred without incentives). As the carbon tax increases from \$30 to \$50 and then to \$100 per tCO_2, emission reductions were much smaller reflecting either weak wind regimes or no further potential to add more turbines. Compared to maximum annual emissions of 54.85 Mt CO_2 (under the weak 2010 wind regime), the best emissions that could be accomplished with a maximum investment in wind energy would occur in 2013, namely, 28.25 Mt CO_2 – a reduction of 48.5% compared to 2010 baseline emissions. This comparison is invalid, however, since it compares results under different wind regimes. More appropriately, if we look at average annual emissions over the decade, we find that they fell from 45.27 to 31.73 Mt CO_2, or by only 30%.

Table 3.4: Greenhouse Gas Emissions for Ten Wind Profiles, Various Carbon Taxes, With and Without Nuclear Energy, Mt CO2[a]

	Base	No Nuclear			With Nuclear
Year	$0/t$CO_2$	$30	$50	$100	$100
2006	54.58	45.12	38.65	33.95	4.86
2007	54.44	43.70	33.64	33.29	5.77
2008	54.49	45.05	34.00	33.58	5.42
2009	54.59	45.13	40.63	34.16	4.92
2010	54.85	45.32	45.23	35.52	4.80
2011	54.30	33.67	32.82	32.53	6.89
2012	30.59	28.70	28.67	28.51	8.89
2013	30.26	28.46	28.43	28.25	8.83
2014	31.84	28.94	28.91	28.68	8.40
2015	32.74	29.05	29.03	28.80	8.45
Average	**45.27**	**37.31**	**34.00**	**31.73**	**6.72**

[a] Carbon taxes are $/t$CO_2$.

The potential for including nuclear energy into the generation mix changes everything. Now average annual emissions fall from 45.27 to 6.72 Mt CO_2, or by slightly more than 85%. It also turns out that the average costs of reducing carbon emissions is lower under the nuclear option than it is under all of the other options (see Table 3.5). There are wind regimes and carbon tax scenarios where the cost of reducing emissions is negative, indicating that the tax revenue exceeds the returns to the generators, so it is socially beneficial to reduce emissions by investing in wind energy but not privately beneficial.[13] However, costs vary greatly by wind regime and the level of the carbon tax. Therefore, it is necessary to look at the average costs over the decade, which are provided in the last row of Table 3.5. These indicate that average costs are greater than $800/t$CO_2$. In comparison, average costs of reducing CO_2 emissions under a nuclear option never exceed $500/t$CO_2$ and average about $270/t$CO_2$.

[13] The net present value of the base scenario is subtracted from the NPV for each scenario (minus the associated tax revenue) and then divided by the change in emissions.

Table 3.5: Average Costs of Reducing Greenhouse Gas Emissions for Ten Wind Profiles, Various Carbon Taxes, With and Without Nuclear Energy, $/tCO$_2$[a]

	No Nuclear			With Nuclear
Year	$30	$50	$100	$100
2006	$ 742.79	$ 465.74	$ 481.89	$ 190.58
2007	$ 607.88	–$ 64.44	$ 408.25	$ 186.58
2008	$ 89.99	–$ 56.82	$ 436.87	$ 189.13
2009	$ 1,364.39	$ 532.75	$ 754.75	$ 314.53
2010	$ 72.38	$ 906.03	$ 521.85	$ 195.56
2011	$ 167.21	$ 211.08	$ 366.71	$ 167.80
2012	$ 3,606.35	$ 4,125.51	$ 5,233.49	$ 333.36
2013	$ 346.51	$ 901.77	$ 5,512.62	$ 478.38
2014	$ 2,296.96	$ 532.11	$ 3,526.26	$ 428.89
2015	–$ 28.12	$ 1,906.09	$ 2,527.56	$ 390.16
Average	**$845.12**	**$864.53**	**$1,806.39**	**$270.45**

[a] Values are calculated relative to emissions and net returns in the base case. Negative values indicate that, for the scenario, costs are lower than in the base case.

Surprisingly, compared to other studies (van Kooten et al., 2016; van Kooten et al., 2013), the model results indicate that wind and nuclear energy can coexist, but not in all cases. For the 2011-2015 wind regimes, it would pay to invest in the full complement of 3500 turbines along with an average of about 3600 MW of nuclear power compared to an average of nearly 6500 MW of nuclear capacity for the period 2006-2011 when wind speed regimes led to lower levels of wind power and smaller investments in wind turbines. Indeed, using the 2010 wind regime, it is not worthwhile to invest in new wind capacity while nuclear capacity tops out at 7120 MW.

3.6 Conclusions

To mitigate climate change, it is necessary to reduce CO_2 emissions. Given the importance of electricity to industrial economies, and because of increasing emphasis on using battery-powered, hybrid and/or fuel-cell vehicles that require electricity, there has been a great deal of interest in promoting wind energy. In this study, we examined the potential to replace coal-fired power in

Alberta with wind energy. The model used in the analysis is primarily meant to be a policy tool for shedding light on the integration of renewables into electricity grids, and the potential impact on emissions of removing coal-fired power from the generation mix, rather than as a recipe for restructuring the power grid.

Since wind regimes play a very important role, we used wind speed data from locations scattered widely across the province (in some cases a thousand or more kilometers apart) to develop wind power regimes for the decade 2006-2015. Then, using 2015 load and infrastructure data for Alberta, we examined the potential for wind energy to reduce CO_2 emissions. Our findings indicate that the variability of wind speeds from one hour to the next and from one year to the next is likely to have a great impact on the viability of investments in wind energy. For some wind regimes, investments in wind power make sense without further incentives; indeed, we found this to be the case for the winds that characterize southwestern Alberta, especially around Pincher Creek where most of Alberta's existing wind farms are located. For other wind regimes, incentives are likely needed to induce investment in wind power. With the exception of certain locations such as Pincher Creek, the variability in wind regimes militates against investment in wind turbines.

We also considered solar power in Alberta but found that, based on the available data, solar power was sufficiently inadequate during winter and night times to warrant consideration at this time. If better data on solar radiation and photovoltaic conversion become available, this will need to be considered further. However, since solar only accounts for some 2% of total renewable capacity and has been shown to have a capacity factor of only 11% in Germany, it is unlikely that solar PV can overcome the problems identified here, particularly the high costs of implementing wind power in areas outside of a small region in southwestern Alberta.

Finally, if politicians in Alberta are serious about reducing greenhouse gas emissions by 30% or more and, at the same time, continue to develop the oil sands despite a cap on annual emissions of 100 Mt CO_2, it is unlikely this can be achieved without purchasing carbon offsets outside the province or investing in nuclear power. Given that prices of carbon offsets are likely to rise exorbitantly in the future as more and more jurisdictions look to carbon offsets to meet emission reduction targets, and as developing countries are brought into an effective emission-reduction agreement, the most realistic option might well be a nuclear one.

APPENDIX: Summary of Alberta Wind Data

Table 3A: Summary of Wind Speed (m/s), Wind Shear Multiplier and Power Output (MW)

Location	Average Wind Speed (m/s)	Wind Shear Multiplier (α)	Average Power Output (MW)
Barnwell	4.71	0.10	0.74
Beaverlodge	3.02	0.18	0.50
Brooks	3.50	0.10	0.39
Fort Vermillion	1.82	0.22	0.12
Grand Prairie	3.35	0.10	0.31
Killam	4.01	0.14	0.61
Lethbridge	4.49	0.10	0.70
Lindbergh	3.13	0.14	0.30
Medicine Hat	3.52	0.14	0.49
Peace River	2.95	0.20	0.49
Pincher Creek	8.58	0.14	1.85
Prentiss	3.95	0.20	0.73
Raymond	4.56	0.10	0.71
Valleyview	3.90	0.22	0.80
Vegreville	3.72	0.14	0.28
Violet Grove	2.99	0.10	0.43
Whitecourt	2.66	0.22	0.45

The analysis employs an ENERCON E-101 turbine with a nameplate capacity of 3.5 MW. The hub height is 99 m, while the rotor diameter is 101 m (50.5 m radius), with a swept area of 8,012 m^2. The turbine has three blades and variable rotation speed between 4 and 14.5 rpm, and built-in lightning protection. The power curve is given in Figure 3A.

Correlation between sites is important to guarantee at least some level of wind output at any time. The wind-speed correlation matrix across sites is provided in Table 3B. There are many instances where the correlations of wind speeds across locations exceed 0.60, which confirms that lack of wind is likely to occur at more than one location at the same time. Pincher Creek wind speeds are essentially uncorrelated with the other locations, as are those of Grande Prairie.

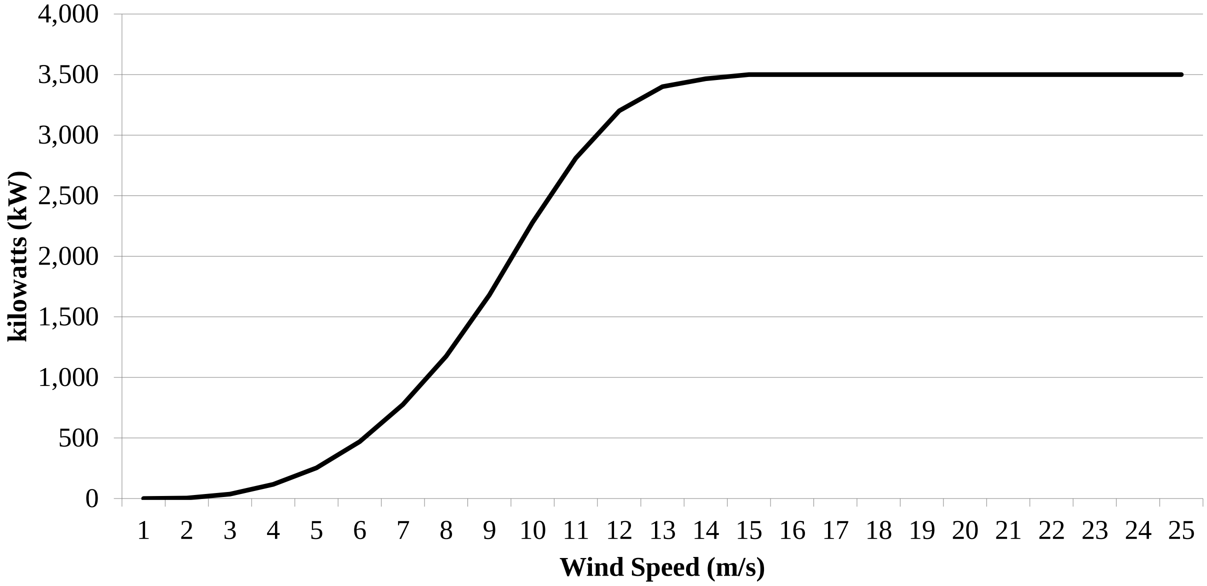


Figure 3A: Power Curve for ENERCON-101, 3.5 MW Capacity Turbine

Table 3B: Correlation Matrix of Wind Speeds[a]

	Barn-well	Beaver-lodge	Brooks	Ft. Vermillion	Grande Prairie	Killam	Leth-bridge	Lind-bergh	Medicine Hat	Peace River	Prentiss	Pincher Creek	Ray-mond	Valley-view	Vegre-ville	Violet Grove	White-court
Barnwell	1.000																
Beaverlodge	0.241	1.000															
Brooks	0.468	0.137	1.000														
Ft. Vermillion	0.133	0.196	0.140	1.000													
Grande Prairie	0.107	0.292	0.072	0.121	1.000												
Killam	0.263	0.202	0.462	0.264	0.121	1.000											
Lethbridge	0.756	0.267	0.333	0.132	0.123	0.185	1.000										
Lindbergh	0.206	0.237	0.288	0.317	0.134	0.584	0.172	1.000									
Medicine Hat	0.528	0.209	0.518	0.129	0.101	0.284	0.471	0.228	1.000								
Peace River	0.195	0.450	0.149	0.260	0.086	0.235	0.202	0.267	0.181	1.000							
Prentiss	0.283	0.152	0.422	0.195	0.081	0.532	0.210	0.324	0.299	0.185	1.000						
Pincher Creek	0.190	0.117	0.044	0.067	0.082	0.039	0.226	0.052	0.134	0.047	0.063	1.000					
Raymond	0.684	0.276	0.367	0.149	0.136	0.249	0.754	0.219	0.465	0.215	0.253	0.224	1.000				
Valleyview	0.215	0.420	0.142	0.249	0.191	0.252	0.226	0.270	0.187	0.387	0.263	0.102	0.240	1.000			
Vegreville	0.247	0.239	0.410	0.300	0.146	0.790	0.192	0.635	0.262	0.272	0.504	0.042	0.247	0.293	1.000		
Violet Grove	0.236	0.237	0.326	0.285	0.125	0.458	0.209	0.355	0.241	0.255	0.483	0.055	0.248	0.327	0.479	1.000	
Whitecourt	0.215	0.307	0.278	0.323	0.175	0.460	0.189	0.381	0.202	0.308	0.398	0.068	0.237	0.367	0.493	0.584	1.000

[a] Shaded areas indicate correlation exceeds 0.5.

Chapter 4 THE NEED FOR AND ROLE OF BATTERY STORAGE IN RENEWABLE ENERGY GRIDS[1]

4.1 Introduction

To reduce carbon dioxide emissions, many jurisdictions have looked to large-scale wind and solar energy for generating electricity. Renewables have little to near zero CO_2 emissions and low marginal costs, but suffer from intermittency that exacerbates a traditional problem in electricity wholesale markets – the so-called 'missing money' problem (Milligan, 2014). Because the introduction of renewables into an electricity grid reduces the wholesale price of electricity, extant generating assets with high marginal costs do not earn enough revenue to cover their fixed (investment) and even operating costs (Jenkin et al., 2016). This could result in premature retirement of assets, but, more importantly, disincentivizes investment in new thermal generating assets, particularly fast-responding, peak generators. Yet, intermittent renewable generation requires flexible capacity as a backup. If there is insufficient fast-responding capacity, grid stability could be at risk. As a result, various market designs, including the use of capacity markets, have developed to ensure resource adequacy (Söder et al., 2019). In this paper, we investigate whether battery storage is a feasible alternative for addressing this problem.

To our knowledge, this is the first paper to explore the impacts of battery storage on the 'missing money' problem. To do so, we employ ten years of data from Alberta, Canada, to simulate the effects of integrating wind and solar renewable energy, and a storage battery, into an optimal generating mix. We chose Alberta because its mix of generating assets is in the transition from a high fossil-fuel grid to one with a lower emissions profile. In 2019, coal and gas respectively accounted for 38.6% and 44.3% of Alberta's total generating capacity (Table 4.1), yet 62% of

[1] The material in this chapter is based on Duan, J., van Kooten, G. C., & Liu, X. (2020). Renewable electricity grids, battery storage and missing money. *Resources, Conservation and Recycling*, *161*, 105001.

Alberta's power was generated by coal, with coal setting the system marginal price in 79% of hours (Alberta Electric System Operator [AESO], 2020a).[2] Appendix 4A provides additional details regarding Alberta's electricity system including its generation mix.

Alberta has committed to shutting down all of its coal plants by 2030 and replace two-thirds of coal-generating capacity with renewable energy (Alberta Government, 2016). Alberta also elected to return to an energy-only wholesale electricity market after exploring the use of a capacity market (Alberta Energy, 2019a). Generators offer to sell electricity to the power pool (or spot market) in Alberta's wholesale electricity market, and retailers bid to buy power. Alberta had investigated alternatives such as shortage pricing to ensure grid stability (AESO, 2019b). In this chapter, we examine an alternative option that relies on battery storage to mitigate the intermittency problem. Our application to Alberta illustrates the impact of renewables and battery storage on supply patterns, supply variability, the missing money problem, and CO_2 emissions.

The impacts of intermittency on the electricity market have been well studied. Some studies exam the reliability of wind and solar, finding that the renewables cannot be relied upon as a baseload source of electricity or for addressing peak demand (van Kooten, et al., 2016; van Kooten & Mokhtarzadeh, 2019); indeed, the integration of renewables into extant grids has proven to be problematic in many countries (Timilsina et al., 2013). Some studies explore the possibility to store intermittent power behind hydroelectric dams or, if such storage is unavailable, in grid-scale batteries (Weitemeyeret al., 2015; Budischak et al., 2013). We employ a cost-minimization model

[2] Since baseload coal plants cannot adjust output quickly enough to follow changes in demand, they will bid to sell power at a very low price. As more renewables enter the grid, the wholesale price will drop, and coal will set the system marginal price more frequently. Because wind power tends to substitute for natural gas more often than for coal (see results below), natural gas sets the system marginal cost less frequently as a result.

that is similar to Budischak's model, but instead of only looking at the feasibility of adding renewable sources of power generation, we use our model to evaluate the impact of battery storage on the missing money problem associated with the use of renewable energy.

Table 4.1: Current and Anticipated Changes in Generating Capacity, Alberta Electric System (MW)

All regions	Existing 2019[a]	2024	2030	2034	2039
Peak Load	12,062	12,828	13,455	13,879	14,404
Coal-fired/Coal-to-gas	5,723	5,430	4,890	1,729	0
Cogeneration	4,043	5,319	5,499	5,589	5,679
Combined-cycle (CC gas)	1,748	1,748	2,227	6,059	8,454
Simple-cycle gas (GT gas)	905	1,136	1,833	2,298	2,901
Hydroelectric	894	894	894	894	894
Wind	1,781	2,904	3,854	4,272	3,931
Solar[b]	15	131	231	481	481
Other (primarily biomass)	423	423	423	473	473
Total Generating Capacity	16,532	17,985	19,851	21,795	22,813

[a] Cogen refers to cogeneration which is used primarily in industrial plants; CC gas provides baseload power; GT refers to fast-responding (peak) gas turbines; solar refers to PV solar plants.
[b] Refers mainly to solar photovoltaic and excludes rooftop solar that is included via load adjustments.
Source: (AESO, 2019a); the existing capacity in 2019 is from (AESO, 2020a)

The missing money problem is an economic consequence of the greater integration of renewable energy (RE) sources (Joskow, 2013). The marginal costs associated with renewables are very low, and greater penetration of renewables lowers the market price of electricity so that conventional fossil-fuel assets, such as coal and gas plants, lose market share and can no longer recover fixed costs, especially when there is a cap on market prices, such as the $999.99/MWh cap that exists in Alberta (Pérez-Arriaga, 2013). When investors cannot recover fixed costs, they have no incentive to invest in fossil-fuel assets that are necessary as a backup in situations where the output from renewables is insufficient to meet demand. Thus, there is growing concern over resource adequacy, with reserve margins shrinking as renewable capacity increases (e.g., see Kleit

& Michaels, 2013).

Scarcity (shortage) pricing and capacity markets are two well-established market designs to overcome the missing money problem (Joskow, 2019). Scarcity pricing refers to the absence of limits on wholesale prices (Hogan, 2013), which implies that scarcity pricing is not practiced in the Alberta electricity system. Conversely, capacity markets provide "revenue to owners of power plants who in return agree to stand ready to supply power when needed" (APPA, 2015). Capacity payments enable owners to recuperate capital and other costs that are not recoverable through electricity sales in wholesale markets. Since a capacity market would operate in addition to an energy market, this may not be the most efficient approach; for example, evidence from Britain indicates that capacity payments could lead to excessive procurement (Newbery, 2016). In this chapter, we investigate the potential to use energy from wind and solar sources with battery storage to meet Alberta's goal of eliminating coal plants, while alleviating the missing money problem without implementing a capacity payment or shortage pricing.

4.2. Methods

We begin by assuming that the independent AESO makes decisions regarding investments in electrical generating capacity, and then allocates generation in each hour in least-cost fashion to meet a pre-determined load. The operator's objective is to minimize total cost such that exogenous demand (D_t) is met in each period:

$$\mathrm{TC} = \sum_{\mathrm{r} \in \{\mathrm{w,\ s}\}} \left[f_r K_r + \sum_{t=1}^{T} v_r K_r P_{r,t} \right] + \sum_{\mathrm{j} \in \{\mathrm{GT,\ CC}\}} \left[f_j K_j + \sum_{t=1}^{T} (\tau \varphi_j + v_j) P_{j,t} \right] + f_b K_b + \sum_{t=1}^{T} v_b b_t^{-}, \qquad (4.1)$$

where TC refers to the total cost of the hybrid RE system; T is the number of hours in one year (8,760); v_i and f_i (i=w, s, GT, CC, b) refer to the variable and fixed costs of obtaining power from wind (w), solar (s), simple-cycle gas turbines (GT), combined-cycle (CC) gas plants, and battery storage (b), respectively; K_w and K_s refer to the capacities of wind turbines and solar modules to be installed; $P_{r,t}$ refers to the electricity produced by each MW capacity of renewable asset K_r, $r \in \{w, s\}$;[3] K_j refers to the capacity of natural gas facilities (MW); $P_{j,t}$, $j \in \{GT, CC\}$, refers to the power produced by a gas source; K_b refers to the capacity of the battery, which is measured in power (MW) and energy (MWh) terms;[4] τ refers to the carbon tax used as an incentive to remove fossil-fuel capacity and invest in renewables and a battery; φ_j is the amount of CO_2 emitted (tonnes) when producing one MWh of electricity from energy source j; and b_t^- refers to the power provided out of battery storage.

Costs are determined exogenously for each energy source, while the energy provided each hour by one unit of wind or solar capacity is exogenously determined by the wind profile and solar intensities (Appendix 4D). The AESO decision-maker chooses the number of wind turbines and solar panels to install, which is equivalent to determining the power levels of wind and solar generation assets. It also selects the size of the Li-ion battery, both in terms of power output at any moment and the energy that is stored, as well as the flow of energy into and out of the battery in each hour. The system operator is also assumed to choose the overall capacity of gas generation to be installed, and the hourly production of electricity from natural gas. These choices are naturally affected by the constraints facing the decision-maker.

[3] The total wind or solar capacity that is installed in the model is a product of the numbers of wind turbines or solar modules, respectively, multiplied by their capacities. The actual electricity output $P_{r,t}$ per turbine or solar module at any time is determined from historical weather data.

[4] Fixed operation and maintenance costs are incorporated into the annualized capital cost. Battery capacity is measured in terms of the maximum power available at any instant (MW) and total available energy (MWh).

The system constraints are as follows:

(4.2)	$\sum_{r\in\{w,s\}} K_r P_{r,t} + \sum_{j\in\{GT,CC\}} P_{j,t} + b_t^- \geq D_t + b_t^+$	Demand is met every hour[5]
(4.3)	$V_t = V_{t-1} + \delta b_{t-1}^+ - b_{t-1}^-$	Battery operating equation
(4.4)	$V_t \leq d_b K_b$	Energy stored in the battery cannot exceed the capacity of the battery
(4.5)	$b_t^+ \leq d_b K_b$	Charge to the battery cannot exceed the capacity of the battery
(4.6)	$b_t^- \leq K_b$	Discharge from the battery cannot exceed the power rating of the battery
(4.7)	$P_{j,t} \leq K_j, \forall j$	The power produced by a gas source j cannot exceed available (endogenously- determined) capacity
(4.8)	$P_{j,t} \leq P_{j,t-1} + r_j \times K_j, \forall j$	Ramping up constraints for all j
(4.9)	$P_{j,t} \geq P_{j,t-1} - r_j \times K_j, \forall j$	Ramping down constraints for all j
(4.10)	$K_j,\ b_t^-,\ b_t^+,\ V_t,\ P_{j,t} \geq 0$	Non-negativity constraints

In constraint (4.2), b_t^- denotes the discharge from the battery at time t to meet demand and b_t^+ denotes the flow of energy into the battery (charge) at t if there is excess power available to the grid – the Alberta load must be met in each hour. Constraint (4.3) is a dynamic equation that indicates the available energy in the battery at time t (V_t), where $\delta = 0.86$ is the roundtrip efficiency of the battery (Lazard, 2017). The energy available in period t equals that of the previous period plus any loss or gain in charge, with gains in energy multiplied by the roundtrip efficiency (loss due to the operation of the battery). The battery cannot charge and discharge at the same time,

[5] The model permits output to exceed load (demand), therefore there may occasionally be some wasted electricity.

which is satisfied via constraints (4.2) and (4.3). The variables in constraint (4.3) are all non-negative, which guarantees that discharge b_t^- from the battery cannot exceed the current energy V_t available in the battery. Constraints (4.4), (4.5) and (4.6) concern the battery's power rating and capacity (power rating times duration), where K_b is the power rating in MW, d_b is the battery's duration which is assumed to be four hours (U.S. Energy Information Administration (U.S. EIA), 2020). The term $d_b K_b$ is the battery's energy capacity in MWh.

In constraints (4.8) and (4.9), r_j is the ramping rate for fossil fuel generators. Advanced GT are peak-load plants that can ramp to their full capacity within an hour, while CC gas facilities more like baseload plants (with a boiler) and are assumed to ramp up to 40% capacity per hour (Gonzalez-Salazar et al., 2018). It is assumed that generators ramp up and down by the same absolute amounts.

By solving the mathematical program given by equations (4.1) through (4.10), we find the optimal combination of wind turbines and solar modules to construct, the capacities of GT and CC gas facilities to install, and the size of the battery, given the exogenously determined parameters and data. Now consider the data we employ.

4.3. Data

The capacities of wind turbines and solar panels vary by location. Therefore, we divided the province into three wind profile regions (southwest, southeast and north) to reflect different average wind speeds, and three solar regions (south, central and north) to reflect different latitudes.[6] Optimal capacities of wind and solar to install are chosen for each of the respective

[6] The northern regions for wind and solar are not identical.

regions, while the choice of GT (peak) gas and CC (baseload) gas facility capacities are not location dependent.

The decisions are determined for each year over the period 2006-2015 as they depend on the observed load and actual wind profile and solar intensities for each year. Thus, optimal capacities, system costs and CO_2 output are determined for every year separately over the decade for which we have data. The ten years of data and ten separate model runs allow us to test various scenarios; however, since renewable energy availability and energy demand change across years, the 'worst' case investment scenarios are the obvious ones of greatest interest.

4.3.1 Load

The total Alberta internal load (AIL) has risen by nearly 1.6% annually between 2006 and 2015. About a third of total AIL can be attributed to the industrial sector and a fifth to commercial activity, with the remainder to residential and farm customers.[7] Annual peak demand usually occurs during winter, even though most space heating employs natural gas. Load data for 2006 through 2015 indicate peaks of about 11,500 MW occurring in December. During a given day, demand is highest in early evening hours and then falls into the night, rising again to a lower peak in the early morning. However, demand does not fluctuate as dramatically as in other regions because of Alberta's high industrial demand, which remains more or less constant throughout the day. Average hourly demands during daytime hover between 8,700 to 9,000 MW (AESO, 2017a). Additional details regarding the AIL are found in Appendix 4A.

[7] Average AIL decreased slightly between 2015 and 2016, but winter peak load set a record at 11,458 MW. Slowing load growth since 2014 can be attributed to mild winter weather and decreased industrial activity throughout Alberta, particularly in the oil sands (AESO, 2017b).

4.3.2 Costs

In our model, we use overnight construction costs and fixed and variable O&M costs to compute the total costs of the power system. In the current analysis, we use cost data from the AESO (2019c), and battery data from the U.S., with this information found in Table 4.2. Overnight costs are converted to annualized fixed capital costs using the 8.5 percent discount rate employed by the system operator (AESO, 2018). Annualized fixed capital costs and fixed O&M costs are combined into an overall annual fixed cost.

Alberta has also raised its carbon tax to $30/t$CO_2$, which, under its Carbon Competitiveness Incentive Regulation (Government of Alberta, 2018), requires a generating asset to pay for the difference between its CO_2 emissions and those of the cleanest gas plant (Howie et al., 2017). However, for simplicity and in anticipation of a more general carbon tax, we assume that the $30/t$CO_2$ carbon tax (roughly US$23/t$CO_2$ using 2019 exchange rates) is directly imposed on any CO_2 emissions, thereby raising the variable cost of the fossil fuel generators. Consequently, we can examine how changes in carbon taxes influence the optimal generation mix.

Table 4.2: Cost of Electricity Estimates for GT, CC Gas, Solar and Wind (C$)

Assumptions	GT gas[a]	CC gas	Wind	Solar	Li-ion battery[b]
Overnight Capital Cost ($/kW)	1,075	1,344	1,924	1,898	1,482
Fixed O&M Costs ($/kW per year)	43.25	52.84	36.34	33.67	25.00
Variable O&M Costs ($/MWh)	4.51	2.65	—	—	0
Capacity factor (%)	34.0	81.0	42.5	21.0	—
Heat Rate (GJ/MWh)	9.68	7.03	—	—	—
Natural Gas Price Range ($/GJ)	1.58-3.54	1.58-3.54	—	—	—
Economic life (years)	15	15	15	15	10

Source: Data from AESO (2019a) with noted exceptions

[a] The overnight capital cost and fixed operation & maintenance (O&M) costs for GT gas are the average costs of Aeroderivative combustion turbine (CT) and Frame CT (AESO 2018).

[b] Cost data from Appendix Table 4B.2, adjusted for an exchange rate of $US1.0=$C1.3269 in 2019.

4.3.3 Solar data

Despite Alberta's high latitude (which usually does not bode well for solar power potential), its sunny summers and cold (but also sunny) winters are conducive to solar cell performance (Eisenmenger, 2011). Alberta's solar potential could be harnessed under a new renewable energy scheme. Indeed, the potential of total concentrating solar power in Alberta is about 9,177 TWh/year (terawatt-hours per year) on land with slopes of less than four percent (Djebbar et al., 2013).[8]

We employ data from the Canadian Weather Energy and Engineering Datasets (CWEEDS), which provides annual data on a range of meteorological elements, recorded hourly at about 10 km grid spacing (Government of Canada, 2021a).[9] Based on this data, we determined the potential power output from a single Canadian Solar CS5P-220M Panel with 220W capacity for the north, central and southern Alberta; this is provided in Figure 4.1 for each of the years in our time horizon (see Appendix Table 4B.1). The choice of a solar panel type is expected to play a minor role in determining the optimal generating mix in the current study.[10] The highest potential solar output occurs in southern Alberta, where the average hourly CF in 2014 was about 90% over the five to six hours of average daily sunlight.

4.3.4 Wind data

Alberta has a long history of utilizing wind as an energy source. In 2019, Alberta had the third-

[8] It would of course be unreasonable to expect all this land to be covered by solar panels. A large PV farm has a capacity-weighted average land use of 7.9 acres per MWAC (denoting nominal power output converted from DC to AC using an inverter and assuming no loss of power in doing so) and a generation-weighted average land use of 3.4 acres per GWh per year (Ong et al., 2013).
[9] Given the slight mismatch with our data on load and wind (2006-2015), we use actual solar data for 2006-2014 but, for 2015, we use the 2005 solar irradiation profile.
[10] The module we chose may not be the best choice as it is relatively conservative, but it was chosen to account for other factors that will affect performance, such as shading and transmission loss.

largest wind market in Canada, with an estimated 1,781 MW of installed capacity (AESO, 2019c). For our purposes, wind speed data were collected from 17 locations in Alberta (Government of Canada, 2017b), and an average was taken across three regions (southwest, southeast and north) over a ten-year period from 2006 to 2015. Conversion of the available mechanical energy (wind speed) to electricity is based on the technical specifications for a 3.5-MW capacity Enercon E-101 wind turbine (van Kooten et al., 2016; see Appendix 4B for details). Modelled values of wind power from a 3.5 MW turbine demonstrate that the average CF over the ten years of observed data was roughly 32%. To put that in perspective, the average CF of wind in California is about 20% (Rosenbloom, 2016).

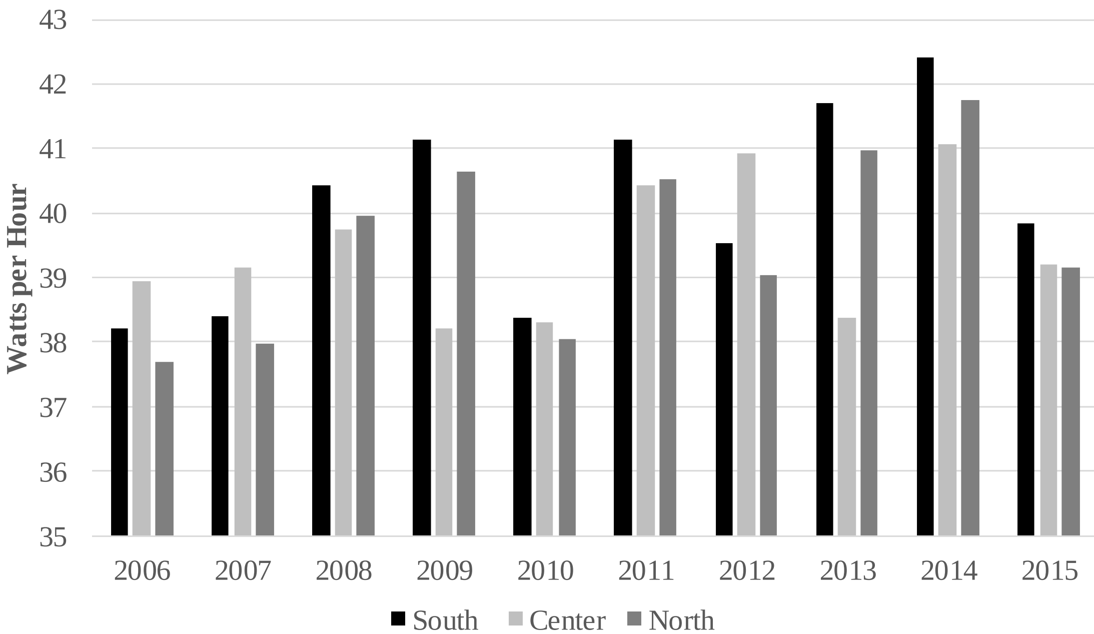


Figure 4.1: Potential Average Hourly Energy (Wh) Output of a 220W Capacity Solar Panel

The average hourly energy outputs for each of the ten years in our time horizon and each region are provided in Figure 4.2. Potential wind generation was higher in 2013 than in any other year. Data also indicate that southwestern Alberta has the best wind profiles, with CFs almost double than those anywhere else in the province.

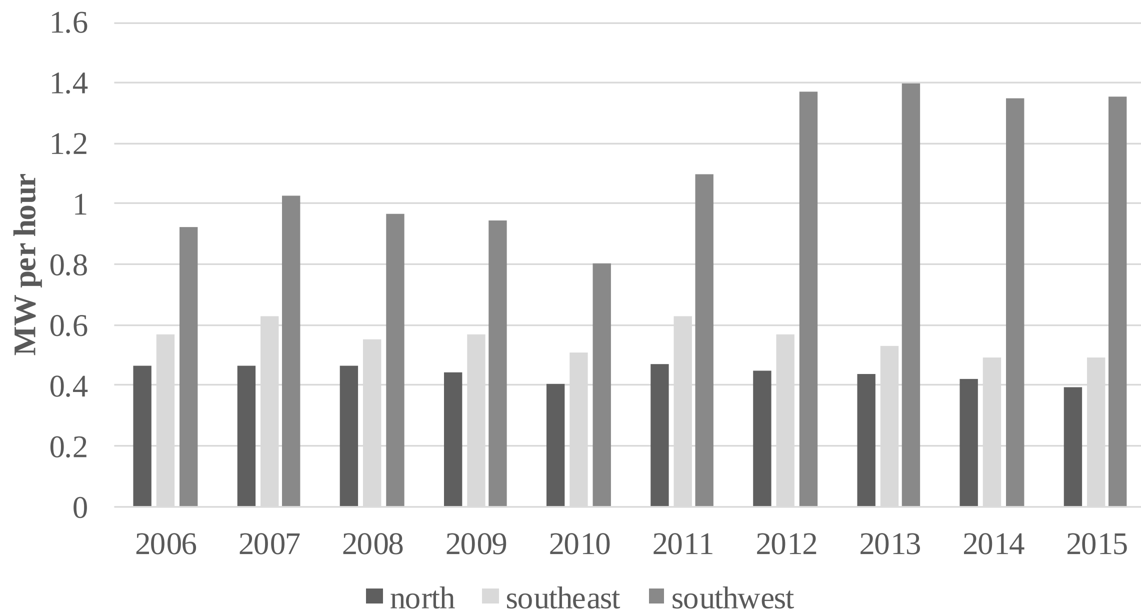


Figure 4.2: Potential Average Hourly Energy Output (MWh) for a 3.5MW Capacity Wind Turbine

4.3.5 Energy storage

Various types of energy storage technology exist today. For instance, pumped-hydroelectric storage works through the gravitational potential energy of water; it has existed for many years, there is significant installed capacity globally, and it is the best option for storing electricity in terms of efficiency and cost. However, there are limits to this option due to the availability of adequate sites (see Benitez et al., 2008). For our purposes, we focus on battery (electrochemical) storage technologies. In this study, we consider the extent to which batteries might back up renewable energy sources in place of conventional GT. We assume a series of Li-ion batteries that are known to be smaller, more advanced, and more efficient than many other types of conventional batteries (including lead-acid batteries). The parameters associated with Li-ion batteries designed to fulfill the aforementioned applications are found in Lazard (2017).

According to the U.S. EIA, the capital cost of a typical 50 MW battery has declined to $C 1482/kW of installed capacity, while the duration (operation at peak capacity) has increased from 4 to 8 hours (U.S. EIA, 2020). Additionally, the price of utility-scale Li-ion batteries is forecasted to fall by as much as fifty percent in the near future (Lazard, 2017). Finally, the cost of recharging a battery is included in the round-trip efficiency rating of the battery, which we assume to be 70%.

4.4 Results

We begin by assuming that Alberta eliminates its coal-generating capacity while imposing a \$30/tCO_2 carbon tax. The carbon tax on coal would be much higher than it is for natural gas (see Appendix 4B; Schlomer et al., 2014). We then explore what happens to Alberta's optimal generation mix as the carbon tax is increased; the rising carbon tax is used to incentivize disinvestment in fossil fuels, but investment in solar and wind energy and battery capacity. We simulate the effect of the tax over the ten-year period for which we have exogenous solar, wind and load information, while ignoring how changes in solar cycles, wind regimes, and differences in load from a previous year might affect other years. Capital costs are annualized at a discount rate of 8.5%. The economic life of a battery is assumed to be 10 years, it is assumed to be 15 years for wind and solar assets, and 20 years for fossil fuel assets (AESO, 2019a).

4.4.1 Current carbon tax

Our results are provided in Tables 4.3 and 4.4. We find that the current carbon tax of \$30/tCO_2 is not high enough to encourage the integration of RE capacity, as only natural gas assets are included in the optimal generation mix. In a ten-year period, 8,885 MW of CC gas capacity and 2,562 MW of GT gas capacity are needed to be built. These values are the maximum values in the ten-year simulation. The maximum values are taken as planned capacities to ensure that, even in what might be considered a bad year for wind and/or solar availability, there is sufficient generation capacity in the system to meet the electrical load. However, average values are provided for capacity factors, total costs and CO_2 emissions (Table 4.3). As expected, for a \$30/tCO_2 tax, the capacity factor for CC (baseload) gas averages 98%, while it averages 19.4% for GT (peak) gas. Reliance on fossil fuels results in annual CO_2 emissions that average 25.5 Mt CO_2 under a \$30/tCO_2 tax (Table 4.4).

Table 4.3: Configuration with Current Battery Cost[a]

Tax (\$/tCO_2)	*Wind capacity (MW)*	*Wind CF*	*Battery capacity (MW)*	*Battery CF*	*GT gas capacity (MW)*	*GT gas CF*	*CC gas capacity (MW)*	*CC gas CF*
30	–	–	–	–	2,562	19.4%	8,885	97.8%
60	–	–	–	–	2,023	9.8%	9,426	94.9%
90	7	39.9%	–	–	1,769	6.5%	9,726	93.3%
120	7	39.9%	–	–	1,646	4.9%	9,884	92.2%
150	7	39.9%	–	–	1,569	4.0%	9,980	91.5%
180	704	39.6%	–	–	1,506	3.5%	9,866	90.9%
210	3,956	39.5%	–	–	2,268	2.9%	9,932	89.5%
240	9,887	39.0%	116	20.3%	2,814	3.7%	9,268	79.4%

Source: Authors' calculations

[a] Capacities are maximum values over ten years. Capacity factors (CF) are based on aggregated performance over ten years. CFs for wind will decline as more turbines are built because better wind sites are initially exploited followed by poorer sites. The capacity factor of the battery is determined as the ratio of discharge divided by capacity.

Table 4.4: Generation share, Cost and Emission with Current Battery Cost[a]

Tax (\$/tCO_2)	*CC share*	*GT share*	*Renewables share*	*Total cost (\$ mil)*	*Emissions (MtCO_2)*
30	94.8%	5.2%	–	2,897	25.5
60	98.0%	2.0%	–	3,656	25.1
90	98.8%	1.2%	0.0%	4,408	25.0
120	99.2%	0.8%	0.0%	5,159	25.0
150	99.4%	0.6%	0.0%	5,908	25.0
180	98.9%	0.5%	0.6%	6,655	24.8
210	96.3%	0.4%	3.3%	7,394	24.1
240	81.3%	0.7%	18.0%	8,050	20.5

Source: Authors' calculations.

[a] Shares are based on aggregated production for ten years, while the other variables are averaged over ten years.

4.4.2 Increased carbon taxes

To investigate how carbon taxes can incentivize investment in renewable energy and battery storage, we increase the carbon tax in the model by increments of \$30/tCO_2 to a maximum of

\$240/tCO_2. Neither wind capacity nor battery storage enters the system at low carbon taxes (Table 4.3). When the carbon tax reaches \$180/tCO_2, a wind capacity of 704 MW enters the system and renewables account for 0.6% of power generation. However, system-wide emissions are only reduced by 0.7 Mt CO_2 and much of this reduction occurs mainly because more efficient CC gas replaces GT gas.

Another 0.7 Mt CO_2 is saved when the carbon tax reaches \$210/tCO_2 as a significant wind capacity of some 4,000 MW is added, which replaces part of the baseload CC capacity (Table 4.3). Finally, under a carbon tax of \$240/tCO_2, nearly 10,000 MW of wind capacity is added to the grid, and the share of RE in power generation increases to 18% (Table 4.4). Emissions are reduced by 5.0 Mt CO_2 compared to what they are under a \$30/tCO_2 tax. At that point, the share of intermittent RE is sufficiently high that a battery of more than 100 MW capacity is also worth installing. Finally, the model never chooses to install solar panels due to their high cost and low efficiency.

An increase in the carbon tax has some negative effects, however; the average total costs of electricity production are higher, partly because fossil fuel assets operate at lower average efficiencies. For example, when the carbon tax increases to \$240/tCO_2, the CF of CC gas falls from 98% to 79%. Meanwhile, the average total cost (including the cost of the carbon tax) is nearly trebled from \$2,897 million to \$8,050 million, which will lead to a significant increase in the retail price of electricity. Even after subtracting the tax revenue, the social cost still increases by 50%, from \$2,131 million to \$3,125 million.

More importantly, the missing money problem is not alleviated with an increase in the carbon tax; rather, it is exacerbated. On one hand, more peak-load GT gas capacity is required to mitigate the intermittency of renewables and maintain system reliability as more renewables are integrated into the grid. As Table 4.3 shows, with the $240/t$CO_2$ carbon tax, the GT gas capacity exceeds the capacity level with the current carbon tax. On the other hand, the CF for GT gas drops to 3.7% from 19.4% and the production share for GT gas declines to 0.7% from 5.0% (Tables 4.3 and 4.4). It will become more difficult to incentivize further investment in GT gas capacity.

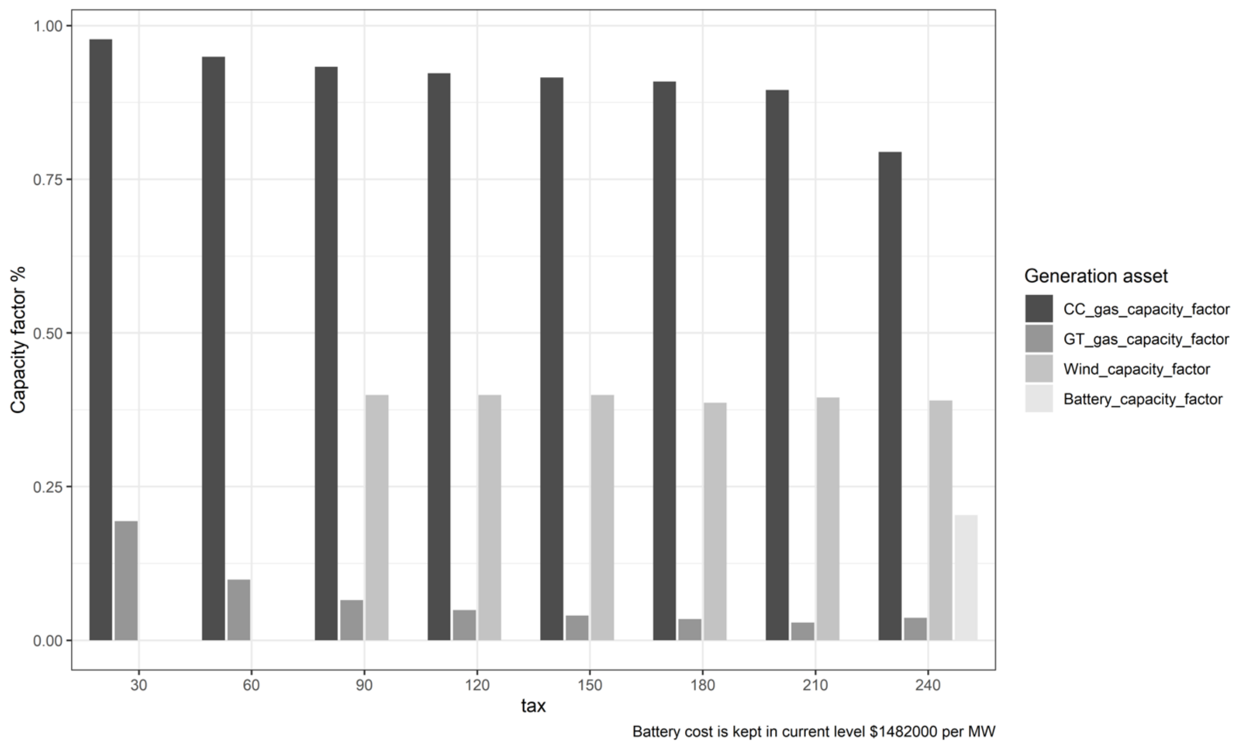


Figure 4.3: Capacity factors for generation assets with an increasing carbon tax

Battery storage does not play an important role in the baseline configuration. When the carbon tax approaches $240/t$CO_2$, 116 MW of battery capacity is integrated into the optimal generation mix (Table 4.3). The battery responds quickly to fluctuations in load and displace some of the peak GT gas generation capacity. In the absence of battery storage, more GT gas generation will be needed when the carbon tax reaches $240/t$CO_2$ because much more wind capacity is integrated. However, compared to the case where the carbon tax is $210/t$CO_2$ in Table 4.3 and Figure 4.3, we find that required GT gas capacity is reduced while GT (peak) gas operates at a higher capacity factor (3.7% versus 2.9%) when the battery is first integrated into the generation mix. In this regard, battery storage mitigates the missing money problem to some extent.

In the following section, we further examine the changes in the optimal generation mix and the impacts of battery storage on the missing money problem if the battery cost can be lowered and more battery storage is integrated.

4.4.3 Decreased battery storage costs

We gradually decrease the battery cost to 30% of its current level in eight increments. Along with eight levels of carbon taxes, we have 64 scenarios in total. We report the outcomes of the scenarios for the high carbon tax of \$240/tCO_2 in Tables 4.5 and 4.6. We examine the high carbon tax because it is then easier to identify the pattern of impacts, although the same pattern exists with the lower carbon tax scenarios.

As anticipated, a reduction in battery cost has a positive effect on reducing CO_2 emissions and the integration of renewables into the grid (Table 4.6). Both CO_2 emissions and the capacity and production share of fossil fuels declines with the decline in battery cost, while RE capacity and production shares grow. Another positive impact of a lower battery cost is the alleviation of the missing money problem. When the battery cost falls, more battery storage will be integrated into the generation mix; less peak-load capacity is required to maintain grid reliability. For example, peak GT gas capacity declines by 26% to 2,100 MW when the battery cost is reduced by 60% or more (Table 4.5).

With a larger battery, two things happen: first, battery output will replace GT (peak) gas output, leading to a reduction in GT capacity. Second, CC (baseload) capacity can take advantage of battery storage by operating at a level exceeding baseload, with the difference sent to the battery to be employed during peak times, which is reflected by the increase in CC capacity factor. This latter effect is also seen in the reduction in GT capacity relative to CC capacity – the ratio fell from 30.4% in the first row of values in Table 4.5 to 22.8% in the bottom row. The system relies less on GT gas's fast-responding service, which alleviates the missing money problem.

Table 4.5: Configuration with Varying Battery Cost and a Carbon Tax of $240/tCO_2$[a]

Battery cost ($/kW)	Wind capacity (MW)	Wind CF	Battery capacity (MW)	Battery CF	GT gas capacity (MW)	GT gas CF	CC gas capacity (MW)	CC gas CF
1,482	9,887	39.0%	116	20.3%	2,814	3.7%	9,268	79.4%
1,334	10,114	39.0%	295	17.8%	2,829	3.4%	9,268	79.6%
1,186	10,685	39.0%	773	15.4%	2,796	3.1%	9,268	80.1%
1,037	11,734	39.0%	2,291	13.3%	2,217	2.6%	9,268	81.8%
889	12,179	39.0%	3,055	9.9%	2,100	2.7%	9,165	83.0%
741	12,356	39.0%	3,078	10.0%	2,098	2.7%	9,165	82.9%
593	12,527	39.0%	3,099	10.1%	2,098	2.7%	9,165	82.8%
445	12,917	39.0%	3,145	10.2%	2,096	2.7%	9,165	82.8%

Source: Authors' calculations
[a] See footnotes in Table 4.3.

Table 4.6: Generation Share, Cost and Carbon Emissions with Varying Battery Cost and a Carbon Tax of $240/tCO2

Battery cost ($/kW)	*Fossil fuel generation CC share*	*Fossil fuel generation GT share*	*Renewables generation share*	*Net cost ($ mil)*	*Carbon emissions ($MtCO_2$)*	*Tax revenue ($mil)*
1,482	81.3%	0.7%	18.0%	8,050	20.52	4,925
1,334	80.9%	0.7%	18.4%	8,049	20.42	4,900
1,186	80.2%	0.6%	19.2%	8,046	20.22	4,852
1,037	78.6%	0.5%	20.9%	8,037	19.81	4,754
889	78.1%	0.4%	21.5%	8,017	19.64	4,715
741	78.0%	0.4%	21.7%	7,990	19.62	4,708
593	77.8%	0.4%	21.8%	7,962	19.58	4,699
445	77.6%	0.4%	22.1%	7,935	19.53	4,686

Source: Authors' calculations. See footnotes in Table 4.4.

Some negative issues related to a large battery could potentially undermine its positive effects. The greater battery capacity tends to reduce the GT gas capacity factor – from 3.7% to 2.7%

in our simulation (Table 4.5); this decreases the revenue accruing to GT generators, which could aggravate the missing money problem. Further, the capacity factor/utilization rate of the battery itself diminishes, which could cause a new missing money problem due to the less profitable battery.

We can summarize the impact of the battery on the missing money problem as having a substitution effect and utilization effect. First, when the cost of the battery declines, a larger battery replaces fast-responding GT assets. Less investment in GT assets is needed, thereby alleviating the missing money problem. Second, the capacity factor/utilization rate of remaining GT assets falls as such assets are needed less often – remaining GT assets have greater difficulty recovering their investment costs. The overall effect that the battery has on the missing money problem depends on the trade-off between the substitution and utilization effects. In our model for Alberta, the investment in GT assets declines by 718 MW (from 2,814 MW of capacity to 2,096 MW) and the GT capacity factor decreases by one percentage point (3.7% to 2.7%). Since the magnitude of change in the investment of GT assets is larger than the change in the capacity factor, the substitution effect dominates the utilization effect. We conclude, therefore, that the battery has a positive impact on alleviating the missing money problem. As the cost of the battery continues to decline, this positive effect will become more profound.

4.5 Concluding Discussion

Our findings suggest that renewable energy in the form of wind power can displace baseload electricity generation and capacity to some extent, but that GT (peak) gas generators are still required to back up intermittent wind and solar sources of energy. Indeed, as indicated in this study, large-scale integration of renewables into a grid exacerbates the missing money problem – those investments in peak-load, fast-responding gas assets fail to generate sufficient revenues to cover capital costs when intermittent power enters the system. With greater intermittent renewable energy, more peak-load GT gas capacity is needed; but, despite the greater GT capacity, the hours that such capacity is called upon is reduced, thereby lowering its capacity factor and earnings. As more intermittent capacity enters the grid, the less efficient but necessary GT gas capacity becomes. Although required to cover shortfalls in wind (or solar) output, GT gas plants tend to operate less frequently, while wholesale prices are lower as a result of more renewable energy.

What else is going on here? The purpose of our research was to determine how we might be able to mitigate the missing money problem. In our baseline scenarios, the introduction of battery storage occurs only when the carbon tax exceeds $200/MWh, but it occurs sooner if the capital cost of the battery is significantly reduced from our baseline of $1,482/kW. Adding lower-cost battery storage to the generation mix can partially displace GT (peak) gas capacity, which alleviates the missing money problem as long as GT's capacity factor does not decrease too rapidly when capacity is reduced – so the substitution effect dominates the utilization effect – and prices are sufficient to maintain or increase revenue.

The integration of renewable energy and battery storage into a fossil-fuel electricity system does reduce CO_2 emissions, as expected. However, once coal-fired power plants are replaced by natural gas, the extent to which intermittent renewables and storage can reduce emissions is greatly constrained. Without some kind of storage, we find that, for the Alberta load profile, investments in wind and solar reduce CO_2 emissions by less than three percent; with battery storage, emissions can be reduced by some 20%. However, serious reductions in emissions, say by 50% or more, may require reliance on other sources such as nuclear power (van Kooten, 2017). Further, the social cost of mitigating emissions is high. Without battery storage, the cost is more than \$1,000/tCO_2, but with storage, it falls to some \$182/tCO_2.

Our modelling exercise is quite robust with respect to costs. What is important is the ratio of the costs of the various generating assets to each other, not the actual level of the costs. We employed cost estimates from the Alberta Electricity System Operator, which fall within the ranges employed by the U.S. Energy Information Administration. The U.S. EIA derives cost estimates based on surveys of energy providers, and these vary significantly across similar generating assets and can change significantly from one year to the next. Further, some of our data are derived from U.S. EIA estimates, especially those related to the costs of battery storage, which are quite variable. We address the issue of battery costs by examining a variety of cost scenarios. However, because it is the ratio of costs among assets that is important, our findings are also applicable to jurisdictions other than Alberta.

Several caveats need to be addressed. In the model, the impacts of the changes in the marginal costs of fossil fuel and renewable energy sources due to economies of scale and/or availability of energy supply (e.g., wind and solar profiles, nearness of coal or gas deposits) are not considered. Alberta has huge coal and natural gas reserves. While the marginal cost of accessing and removing these fossil fuels will eventually increase, it is unlikely to affect the results of our analysis because coal was eliminated in our model for political reasons, leaving only natural gas as an option. We did not consider biomass because it cannot be considered carbon neutral (Johnston & van Kooten, 2017) nor did we consider nuclear power due to the stigma attached to it. Meanwhile, the marginal cost of generating electricity from wind is likely to rise, perhaps sharply, as the best available sites are exploited first. Current wind farms in Alberta are in the southwest corner of the province, where capacity factors range from some 40 to over 70 percent. As soon as one moves north and east, capacity factors drop rapidly. With minor exceptions, capacity factors throughout the rest of the province are 25% and less. Further, as one moves from the southwest corner, the value of farmland increases. If land rents are appropriately considered, the marginal cost of renewables also rises, and the cost of wind and solar energy may not be able to compete with coal, natural gas and petroleum in the southwest corner.

Additionally, it would be difficult to model the demand side, partly because demand-side management is more about shifting electricity use from one hour to another. Alberta's demand for electricity is quite different from that in other jurisdictions. First, the load is essentially industrial, dependent primarily on oilsands development. This demand cannot be shifted to another period – it is highly inelastic, as is commercial demand. Residential demand is somewhat more flexible, but, because homes are heated using natural gas rather than electricity, there is less opportunity to shift load across time. Hence, our current model can do little to address demand response. If the potential benefit of demand-side management is considered, we could shift electricity consumption to the time when low-cost renewable energy is supplied; at the same time, more renewable capacity will likely lead to greater storage capacity. Furthermore, on the demand side, when more electric cars get into the market, car batteries could be used to mitigate the missing money problem. In this sense, our estimates of the effect that battery storage has on the missing money problem are underestimated.

Government intervention could impose more restrictions and constraints on the electricity market. As discussed earlier, the Alberta government decided to phase out coal power, which is why we excluded coal in our generation mix without considering its economic feasibility. We considered only GT gas, CC gas, wind, solar and battery storage for reducing CO_2 emissions. We concluded that (1) it would be impossible to remove natural gas from an optimal generation mix. (2) By investing in renewable sources of power generation, wholesale electricity prices decline but fast-responding gas assets are still needed to support intermittent power from renewables. However, these two factors reduce the revenue available to the fast-responding assets, leading to a missing money problem. (3) It is also difficult to reduce CO_2 emissions without an ability to store intermittent electricity and doing so could be quite costly. (4) With high shares of renewable assets in an electricity grid, battery storage can play an important role, especially in alleviating the missing money problem – a role that our model likely underestimates. Although our focus was on the Alberta electricity system, these conclusions apply more broadly to other grids as well.

APPENDIX 4A: Additional Information on Alberta's Load (2006-2015)

Table 4A.1: Monthly Averaged Peak Loads, 2006-2015

Month	Peak/MW	Month	Peak/MW
January	11,229	July	10,520
February	10,956	August	10,515
March	10,743	September	9,909
April	9,783	October	10,074
May	9,512	November	11,020
June	10,319	December	11,458

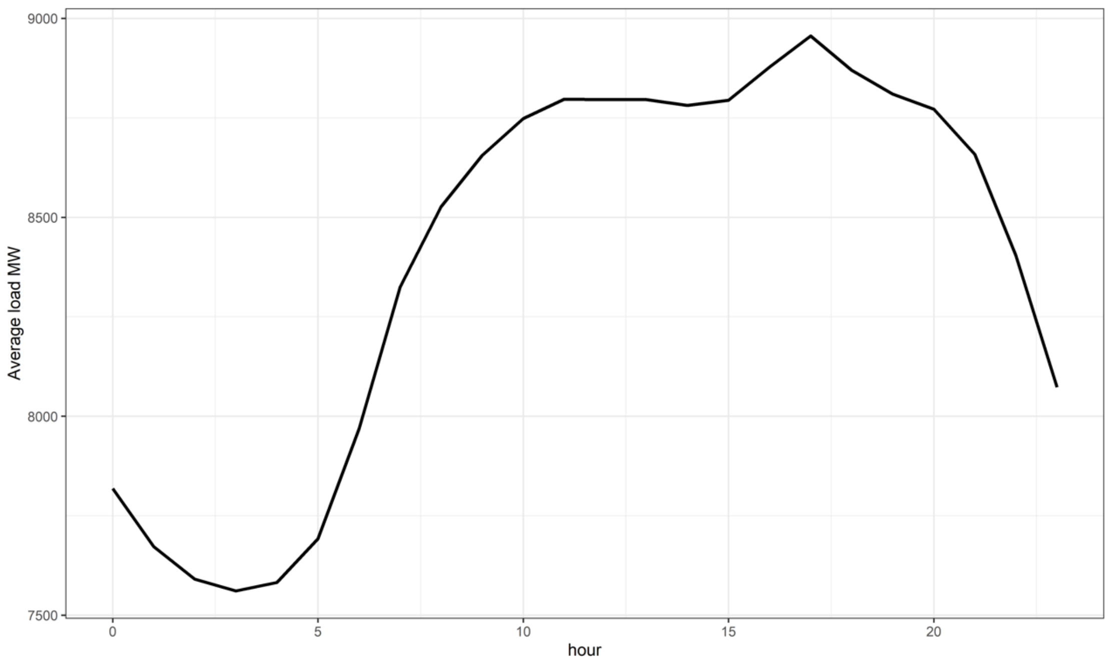


Figure 4A.1 Average load by hour over the day (2005-2016)

APPENDIX 4B: Alberta's Carbon Dioxide Emissions

During the 21st Conference of the Parties (COP 21) in 2015, Canada's Prime Minister Justin Trudeau highlighted the key role that provincial and territorial governments would have in enabling Canada to achieve its carbon emissions targets over the coming years (Environment and Climate Change Canada, 2015). While most Canadian provinces and territories have kept their greenhouse gas (GHG) emissions in check. Over the past 25 years, Alberta's emissions had risen to 262.9 megatons (Mt) of carbon dioxide (CO_2) equivalent as of 2016 – an increase of roughly 51% since 1990 (Canada Energy Regulator, 2019). This now comprises some 37.3% of Canada's overall emissions. For Canada to meet its Paris commitment will require significant CO_2 reductions from Alberta.

The bulk of Alberta's emissions come from its oil and gas industry, with more minor contributions from sectors such as agriculture and transportation. The oil and gas sector contribute some 48% of the province's CO_2 emissions. Although Alberta's natural resource sectors are large carbon emitters, much of their activity is designated as trade-exposed under international regulations. This means that policies aimed at reducing emissions in these industries may only serve to locate them elsewhere, resulting in continued CO_2 emissions at the cost of local economies. Emissions reduction efforts in these sectors may prove to be ineffective or, at the very least, unpopular. In 2016, the electricity sector accounted for 17% of Alberta's total GHG emissions, with most coming from coal-fired electricity generation.

APPENDIX 4C: Alberta Generation Mix

In recent years, capacity additions in Alberta were dominated by natural gas-fired facilities and wind turbines. Gas facilities that generate heat and use waste steam to generate electricity, which is referred to as cogeneration or combined heat and power (CHP), have been built to support expansion in Alberta's oil sands (AESO, 2017a). Conversely, only six percent of Alberta's electricity currently originates from wind sources. Despite the relatively low level of installed capacity, Alberta has a long history of utilizing wind energy to generate electricity. The planned decommissioning of coal-fired power plants in Alberta presents an opportunity to further invest in wind power. The Canadian Wind Energy Association (CanWEA, 2017) notes that, while Alberta currently has an installed capacity of 1,445 megawatts (MW) of wind generation, at least 4,000 MW of new wind generating capacity will be needed to compensate for the anticipated loss in coal capacity (CanWEA, 2017). The AESO anticipates that the removal of coal-fired capacity will lead to some 4,000 MW of new wind capacity (Table 4.1).

The solar photovoltaic (or solar PV) energy market in Alberta is not as well developed, with an installed capacity of roughly 15 MW in 2019 (Table 4.1). However, solar PV has great potential in Alberta – a study undertaken by the Pembina Institute notes that solar irradiance levels in some parts of Alberta are as high as the sunniest parts of the United States (Hastings-Simon, 2016). Initially, the AESO did not anticipate significant increases in solar generating capacity to replace decommissioned coal plants, but its most recent studies foresee nearly 500 MW of installed solar PV capacity within two decades, compared with 4,000 MW of wind capacity (Table 4.1). From Table 4.1, combined cycle (CC) gas and wind will see the greatest increase in capacity over the next 20 years.

APPENDIX 4D: Calculating the Output of Solar and Wind Energy

Solar power

The choice of the solar panel may play a large role in determining the final cost and efficacy of solar plants. Crystalline silicon (mono- or poly-crystalline; the difference in efficiency is often negligible) panels are common in many solar applications. Thin-film solar panels, on the other hand, are very diverse in scope. Modules made of such materials often perform better in times of lower irradiance, and their temperature coefficients are lower (Sunbeam Communications, 2014). These particular advantages may be useful for applications in Alberta but are left for future research. The solar energy outputs were calculated by using the PVLIB package in Python, developed by Sandia National Laboratories (Holmgren et al., 2015).[11]

Table 4D.1: Technical Specifications for Canadian Solar CS5P-220M (220W) Solar Panel

Nominal maximum power (W/NOCT)[a]	Module efficiency (η_m)	Size (m^2)	Temperature coefficient (%/K)	NOCT (°C)
220	0.1294	1.919	-0.45	45

[a] Under Standard Test Conditions: an irradiance of 1000 W/m^2, module temperatures of 25°C, wind speeds of 1 m/s, and an air mass of 1.5. Then, the nominal maximum power is calculated as: $E = \eta_m \times A$, where E denotes electrical power in kWp (kilowatt-peak) and A denotes area of the panel in m^2. NOCT denotes Nominal Operating Cell Temperature.

Wind power

Wind velocity (m/s) is a function of wind speed and turbine height (van Kooten et al., 2016):

$$V_{hub} = V_{data} \times (\frac{H_{hub}}{H_{data}})^{\alpha}, \qquad (4.11)$$

where V_{hub} is the wind velocity at the turbine hub; V_{data} is the observed wind velocity; H_{hub} is the height of the hub; H_{data} is the height at which the data was collected, and α is a wind shear

[11] PVLIB Python is a community-supported tool that provides a set of functions and classes for simulating the performance of photovoltaic energy systems. PVLIB Python was originally imported from the PVLIB MATLAB toolbox developed at Sandia National Laboratories.

component. We use our knowledge of the regions in the dataset to set values of α, which assume different values based on the type of terrain upon which the turbines are built. Wind power is a function of wind speeds, as represented by the following equation:

$$P_w = ½\beta v^3 \pi r^2, \qquad (4.12)$$

where P_w is wind power (measured in watts); β is the density of dry air (assumed to be equal to 0.94, measured in kg/m^2); v is wind velocity (measured in m/s), and r is the radius of the rotor (measured in meters).

Costs of producing electricity

Bodies such as the U.S. Energy Information Agency (U.S. EIA) are continuously updating the cost estimations of new utility-scale plants. Some estimates are provided in Table 4D.2.

Table 4D.2: U.S. Cost of Electricity Estimates for GT (Peak) Gas, CC (Baseload) Gas, Solar, Wind and Battery Power (US$2020 per MWh)

Type[a]	Overnight Capital Cost ($/kW)	Fixed O&M ($/kW/yr)	Variable O&M ($/MWh)	Emissions[b] (tCO_2/MWh)	Facility Life (years)
Coal	3,676	40.58	7.08	0.807	30
GT (peak) gas	944	11.65	4.60	0.505	20
CC (baseload) gas	1,021	13.15	2.21	0.340	20
Solar	1,313	15.25	0	0	15
Wind	1,471	30.74	0	0	15
Nuclear	6,116	108.32	2.69	0	30
Li-ion battery[c]	1,117	18.85	0	0	10

[a] For coal, GT gas, CC gas, nuclear, solar, and wind power sources, values are the average of the data provided in Table 4D.2 of U.S. EIA (2020).
[b] Emissions are converted to emissions by: 0.000453593 × heat rates [Btu/kWh] × CO_2 emissions [lbs/MMBtu] to get CO_2 emissions [kg CO_2/MWh], and then dividing by 1,000 to get tCO_2/MWh.
[c] Capital cost of a battery with capacity given by 50MW/200MWh is $1,389/kW or $347/kWh; for a battery rated 50MW/100MWh, costs are $845/kW and $423/kWh. Associated fixed O&M costs are $24.80/kW and $12.9/kW, respectively. Average values are given in the table.
Source: U.S. EIA (2020)

Chapter 5 CALIBRATION OF ELECTRICITY GENERATION COST FUNCTIONS: A POSITIVE MATHEMATICAL PROGRAMMING APPROACH

5.1 Introduction

The integration of renewables into electricity grids has resulted in energy supply problems because the intermittency of wind and solar power results in a less stable supply of electricity—wind and solar power outputs are too variable. When power generated from wind and solar suddenly drops, traditional coal, gas and other thermal generators need to ramp up quickly, or even have to be 'cold started' to meet load. This leads to inefficient thermal generation and greater CO_2 emissions than might otherwise be the case. At the same time, the low cost associated with wind and solar generation makes investments in traditional thermal generation less profitable, because their near-zero marginal costs reduce the wholesale market price of electricity. When the share of power generated by renewables rises, the capacity factors of traditional thermal generators fall to the extent that those assets may not make enough revenue to recover their capital costs.

Wind and solar power potentially have a negative impact on the entire economy, resulting in 'green inflation' for example. This occurs when generation from renewables is lower than anticipated and fossil fuel prices are simultaneously high—electricity prices surge and the whole economy suffers from higher energy costs, leading to inflation (IEA, 2021). This happened in Europe and Asia. In Europe, lower than expected wind regimes affected many countries during 2021 and into 2022, thereby requiring increased output from traditional fossil-fuel generators. Gas prices in Europe spiked as a result of reduced domestic gas production and lower imports from Russia and competition for LNG from Asia (PA Media, 2021). As a result, coal-fired power was less costly to produce, even though coal plants had to purchase carbon offset credits. Electricity prices rose dramatically, while the overall increase in energy prices led to inflation. Large increases in electricity prices could occur in any jurisdiction where an electricity grid heavily relies on intermittent, renewable generation. To gain a better understanding of the potential seriousness of this phenomenon, it is important to model the impact that renewables can have on an existing electricity grid.

The modelling of electricity systems is fraught with complexities related to regulatory and political developments (e.g., command-and-control versus unregulated/privatized decision making), technological developments, market prices for primary energy carriers, weather factors (e.g., related to wind and solar output), and even the calibration and solution methods used to solve constrained optimization problems (Ahmed, 2016). The complexity of the mathematical programming (MP) problem poses many challenges, with a major one related to the costs of operating power plants at various levels of capacity. Information on costs is difficult to find—cost data and (quite sophisticated) decision models used by system operators and asset owners are often proprietary. Further, even if costs are available for individual generators, models often aggregate several or all generators of a particular fuel type. In that case, engineering costs are no longer relevant for modelling purposes as costs need to reflect how various generators operate in tandem and how external factors, including the operation of other generator types under changing load conditions, affect operating costs. Models must then be calibrated to actual operating levels, and this requires the discovery of the parameters of economic cost functions.

Given that calibration of MP models of electricity grids is not common in the literature, a major contribution of the current research is to demonstrate how one or more calibration methods can be used to develop economic cost functions for grid optimization modelling. As an application, we calibrate the cost functions for fossil fuel generators using data on generation by assets and related prices for a grid characterized by a mix of generating assets but dominated by coal-fired power and various types of natural gas sources (e.g., baseload and peaking gas plants and co-generation assets) and increasing wind capacity. Price data are required for calibrating a grid optimization model; however, when simulating the effect of climate policies on generation, prices are no longer available (as they are determined by the mix of assets and generation decisions) so it is necessary to minimize costs rather than maximize revenue.

5.2 Background: Calibrating Mathematical Programming Models

Before grid optimization models can be used for policy purposes, it is important to calibrate the parameters used to represent various aspects of the grid so that it is most representative of the actual grid (Paris, 2011). A well-calibrated MP model should be able to reproduce observed historical data—a model should be calibrated so that it provides a realistic approximation of what happens in the real world (Vanni et al., 2011). In an MP model, calibration constraints use data on inputs and outputs (for a base year, say) to discover the parameters of a postulated objective functional form so that, once the calibration constraints are removed, the model with the adjusted objective function replicates the observed outcomes (Howitt, 1995; Heckelei, 2002; Heckelei & Britz, 2005). The calibrated models can then be used for policy analysis.

A most promising approach that directly enables one to find the parameters of an economic cost function is positive mathematical programming (PMP). PMP has been used to calibrate models in agricultural and resource economics but has yet to be applied to the estimation of cost functions in the operation of electricity grids. The method was first developed by Howitt (1995), who derived cost functions based on positive inferences from the base year data, rather than normative assumptions. PMP uses information about the dual variables associated with the calibration constraints to adjust the objective function so that the calibrated model duplicates observed outcomes. The most common application begins by specifying a linear objective function in the calibration stage but replaces it with a nonlinear (often quadratic) objective function once the model is calibrated. The method was initially applied to policy analysis in agriculture (e.g., Röhm & Dabbert, 2003; Liu et al., 2020), but has increasingly been implemented in trade models and models related to resource management (Weintraub et al., 2007; Paris, 2011; Heckelei et al., 2012; Johnston & van Kooten, 2017).

As noted, the standard PMP approach involves two stages to calibrate a linear cost function to obtain an upward sloping supply (marginal cost) function. Define the optimization problem as:

$$\underset{\boldsymbol{x}}{Maximize}\ \mathbf{R}(\boldsymbol{x}) - \mathbf{c}(\boldsymbol{x}) \tag{5.1}$$

$$\text{Subject to: } \mathbf{A}\boldsymbol{x} \leq \mathbf{b} \tag{5.2}$$

where $\mathbf{R}(\boldsymbol{x})$ and $\mathbf{c}(\boldsymbol{x})$ are revenue and cost functions, respectively. The vector $\boldsymbol{x}$ is $k \times 1$, representing k activities with non-negative values; vector $\mathbf{b}$ is $m \times 1$, signifying the m resource constraints. In practice, $\mathbf{c}(\boldsymbol{x})$ represents the average variable costs rather than marginal costs (supply functions) that vary with $\boldsymbol{x}$.

In general, a linear programming (LP) model is specified in the first stage of the PMP process along with calibration constraints that bind the LP problem to the observed activity levels:

$$\underset{\boldsymbol{x}}{Maximize}\quad \boldsymbol{Z} = \mathbf{p}'\boldsymbol{x} - \mathbf{c}'\boldsymbol{x} \tag{5.3}$$

$$\text{Subject to: }\ \mathbf{A}\boldsymbol{x} \leq \mathbf{b} \qquad [\boldsymbol{\lambda}] \tag{5.4}$$

$$\boldsymbol{x} \leq \mathbf{x^0} + \mathbf{e} \quad [\boldsymbol{\rho}] \tag{5.5}$$

$$\boldsymbol{x} \geq \mathbf{0} \tag{5.6}$$

where $\mathbf{x}^0$ is a k×1 vector representing the observed activity levels in the base year. The elements of the vector $\boldsymbol{e}$ are small positive numbers added to the observed levels to prevent degeneracy of the solution due to the relationship between constraints (5.5) and (5.4), and $\boldsymbol{\rho}$ are dual variables associated with the calibration constraints. The associated Karush-Kuhn-Tucker conditions are:

$$\mathbf{p} - \mathbf{c} - \mathbf{A'}\boldsymbol{\lambda} - \boldsymbol{\rho} = \mathbf{0} \Rightarrow \mathbf{c} + \boldsymbol{\rho} = \mathbf{p} - \mathbf{A'}\boldsymbol{\lambda} \tag{5.7}$$

Given the calibration constraints, the optimal solution will exactly reproduce the observed base-year activity levels $\mathbf{x}^0$. The left-hand side (LHS) of second equation in (5.7) represents the marginal costs of production, while the RHS represents the value of the marginal product (marginal product of the input multiplied by the output price).

In the second stage, a quadratic variable cost function is specified, and a quadratic MP problem defined as follows:

$$\underset{\boldsymbol{x}}{Maximize} \quad \boldsymbol{Z} = \mathbf{p'}\,\boldsymbol{x} - \mathbf{d'}\,\boldsymbol{x} - \frac{1}{2}\boldsymbol{x}'\,\mathbf{Q}\,\boldsymbol{x} \tag{5.8}$$

$$\text{Subject to:} \quad \mathbf{A}\,\boldsymbol{x} \leq \mathbf{b} \tag{5.9}$$

$$\boldsymbol{x} \geq \mathbf{0} \tag{5.10}$$

In the model, the cost functions are $C(\boldsymbol{x}) = \mathbf{d}'\boldsymbol{x} + \frac{1}{2}\boldsymbol{x}'\boldsymbol{Q}$, where $\boldsymbol{d}$ is the vector of parameters associated with the linear terms and $\boldsymbol{Q}$ is a symmetric, positive semi-definite matrix of parameters associated with the quadratic terms. Because the observed levels of activities are assumed to be optimal, the marginal costs of these activities are set equal to the prices at the base-year activity levels $\mathbf{x}^0$ and all activities have a marginal profit that equals the opportunity cost of the resources. Hence, the marginal cost functions can be derived as (Howitt, 2005):

$$\boldsymbol{MC} = \frac{\partial \boldsymbol{C}}{\partial \boldsymbol{x}} = \boldsymbol{d} + \boldsymbol{Q}\mathbf{x}^0 = \mathbf{c} + \boldsymbol{\rho} \tag{5.11}$$

For parameters that satisfy equation (5.11), the variable cost functions have the right curvature (convex in activity levels) and the resulting quadratic (nonlinear) programming problem defined by equations (5.8) to (5.10) will have a solution that matches the base-year level $\boldsymbol{x}^0$ **(**Heckelei, 2002).

Two sets of unknown parameters need to be estimated in equation (5.11), which causes an underdetermined specification problem. To be specific, an infinite number of parameter sets could satisfy condition (5.11) and lead to a perfectly calibrated model. However, each set could imply a different response behavior to changing economic policies. A couple of methods were introduced to specify parameter sets to avoid an arbitrary simulation of behavior. An early specification rule was to set $\boldsymbol{d} = \boldsymbol{c}$ and all the off-diagonal elements of $\boldsymbol{Q}$ to be 0. Then the diagonal elements of $\boldsymbol{Q}$ are computed as follows:

$$q_{ii} = \rho_i / x_i^0 \tag{5.12}$$

Another approach proposed by Paris and Howitt (1988) sets both the linear cost function parameters $\boldsymbol{d}$ and the off-diagonal elements of $\boldsymbol{Q}$ to zero. Then the diagonal elements are calculated as:

$$q_{ii}=c_i+\rho_i/x_i^0. \tag{5.13}$$

The following section elaborates on the importance of calibrating cost functions for generating electricity, and how to calibrate the parameters of the cost functions.

5.3 Calibration of Power Generation Cost Function in Theory

The levelized costs of electricity (LCOE) have been used broadly to compare the costs of intermittent and dispatchable generating technologies. Many factors that influence the cost of electricity are likely omitted due to measurement errors, selection bias or technological difficulties. However, using a systematic calibration approach, we can identify a cost or production function for generating electricity that then simulates the observed output and, thereby, the behavior of the assets' operators. In this way, our model better captures the way generating assets operate in the real world, while remaining flexible enough to predict system responses to future policy changes. In other words, the calibrated model provides a baseline model that facilitates policy analysis.

PMP is especially suited for estimating cost functions for groups of generators for several reasons: (1) PMP enables us completely to recover the base-year observations without adding constraints. (2) It takes into consideration not only the operating and maintenance costs of generating power from a particular source (e.g., an aggregation of several thermal power plants or generators), but also explicitly accounts for the costs associated with planned and unplanned shutdowns, other nuances specific to existing assets (e.g., varying ages of generators), et cetera. (3) PMP allows systems continuously to react to policy changes. In what follows, we calibrate the cost functions for Alberta's generation mix using PMP, and then, in the next section, use the calibrated model to conduct policy analysis to examine how the optimal generation mix changes with changes in the carbon tax, and identify the potential costs of greater reliance on renewable energy.

5.3.1 Calibration Constraints

It is assumed that, in a wholesale electricity market, the system operator works as a social planner to maximize the total net revenue of the grid subject to a set of technical and economic constraints. To calibrate the model, we treat renewable wind, solar and run-of-river hydro as must-run (non-dispatchable) assets whose production is subtracted from total system load. Hence, the system operator can only control the output from fossil fuel generators. Flexible quadratic cost functions are calibrated only for fossil fuel generators and hydropower stations with reservoirs. The first stage of the model is defined as follows:

$$\underset{G_{it}}{Maximize} \quad \mathrm{Z_{AB}} = \sum_{t=1}^{T}\left[\mathrm{P_t}\Sigma_i \mathrm{G_{it}} - \sum_i \mathrm{c_i G_{it}}\right], \tag{5.14}$$

where Z_{AB} is net revenue ($); *i* refers to the generator fuel type (coal, natural gas, biomass, wind, hydro, solar, etc.); T is the total number of hours (t) in a one-year time horizon (8760 hours); P_t are observed Alberta prices of electricity in each hour ($/MWh); G_{it} are observed electricity production by generator *i* in hour *t* (MWh); and c_i is the variable fuel cost plus other variable costs of producing electricity from generator *i* ($/MWh).

The constraints are as follows:

$$G_{i,t} \leq \mathrm{K_i} \ \forall t = 1, \ldots, \mathrm{T}; \forall i \qquad [\lambda_{i,t}] \tag{5.15}$$

$$\sum_i G_{i,t} \geq D_t - M_{k,t} + X_{k,t},\ \forall t = 1, \ldots, T \quad [\eta_t] \tag{5.16}$$

where K_i is the capacity of generator i; D_t is the hourly load (MWh); $M_{k,t}$ refers to Alberta imports from region $k \in$ {BC, SK, US} at t; $X_{k,t}$ equals exports from Alberta to region k at t; $\lambda_{i,t}$ refers to the shadow prices (dual variables) related to the capacity constraints; and η_t represents the shadow prices related to the load each hour.[1]

The first step of the PMP procedure is to use a set of calibration constraints to recover the base-year energy use and estimate shadow prices for each generation fuel type:

$$G_{i,t} \leq G_{i,t}^{obs} + \epsilon \qquad [\rho_{i,t}] \tag{5.17}$$

where ϵ is a small perturbation needed to prevent degeneracy and $\rho_{i,t}$ refers to the dual variables associated with calibration constraints (5.17). Other technical constraints are ignored.

The first-order conditions for this optimization problem in terms of $G_{i,t}$ are:

$$c_i + \rho_{i,t} = P_t - \lambda_{i,t} + \eta_t \quad \forall t = 1, \ldots, T;\ \forall i \tag{5.18}$$

In equation (5.18), the LHS represents the marginal costs of producing electricity by asset-type i, including the cost of allocating generation across assets that use the same fuel type. The RHS represents the marginal revenue that accrues to asset i when it generates one more unit of electricity given that nothing else in the grid changes. Finally, η_t represents the change in revenue that occurs if system generation increases by one unit to meet a marginal increase in load.

[1]For simplicity, $M_{k,t}$ and $X_{k,t}$ are fixed at the 2019 observed values; therefore, the costs and revenues associated with imports and exports are not included in the objective function.

After solving the net revenue maximization problem, the solution $G_{i,t}$ recovers observed generation, $G_{i,t}^{\text{obs}}$, and the dual variables $\rho_{i,t}$ associated with the calibration constraints are used to calibrate the parameters of the quadratic cost functions and, thereby, the non-linear objective function. The dual variables are interpreted as "capturing any type of model misspecification, data errors, aggregate bias, risk behavior and price expectations" (de Frahan et al., 2007).

5.3.2 Calibrated Model

When we use the forgoing calibration method to discover the parameters of a nonlinear increasing cost function, the dual variables $\rho_{i,t}$ are the differences between the accounting cost vector, **c**, and the actual variable marginal cost of supplying the observed allocation of electricity across asset types. Typically, a quadratic cost function is specified as:

$$C(G_{i,t}) = (d_{i,t} + \tfrac{1}{2}\, q_{i,t} \times G_{i,t})G_{i,t}\ , \forall i, t, \tag{5.19}$$

with corresponding linear marginal cost functions:

$$MC_{i,t} = d_{i,t} + q_{i,t} \times G_{i,t}\ , \forall i, t, \tag{5.20}$$

where $d_{i,t}$ is the intercept of the marginal cost function and $q_{i,t}$ is its slope.

For simplicity, we focus on calibrating the variable cost functions of the major fossil-fuel generating assets such as coal/gas assets and hydroelectric reservoirs. The reason is that fossil fuel generators and non run-of-river hydropower are dispatchable, while wind, solar, biomass, and cogeneration power stations are less flexible or non-dispatchable. For example, wind speed at any time decides how much output a wind turbine produces, but thermal generation must be capable of ramping up or down to facilitate the entry of wind power into the grid. Likewise, biomass and cogeneration output are often treated as must run, although their output is not intermittent as that from wind and solar sources. Biomass generation is limited, with much of the power used 'behind-the-fence' or on-site in a local sawmill or pulp mill, with only extra power delivered to the grid. Cogeneration occurs as a result of burning gas for heating purposes or injecting steam into oilsands to make heavy petroleum viscous for extraction purposes, with exhaust heat used to produce electricity (AESO, 2021b); such power production is, by its nature, less responsive to gas and electricity prices. For calibration purposes only, we treat their output as exogenous and subtract it from the system load. Likewise, net imports are subtracted from the load for ease of analysis. We do not calibrate the cost function for battery storage since battery storage has not been broadly used in electricity grids, and most of time the battery is used for ancillary service—it is difficult to obtain data for battery operations.

The nonlinear objective function is now specified as:

$$\underset{G_{it}}{Maximize} \quad R = \sum_{t=1}^{T} \left[\mathrm{P_t}\ \Sigma_{\mathrm{i}} G_{\mathrm{I,t}} - \sum_{\mathrm{f}} (d_{\mathrm{f,t}} + \tfrac{1}{2} q_{\mathrm{f,t}} \times G_{\mathrm{f,t}}) - \sum_{\mathrm{r}} \mathrm{c_{r,t}} \times G_{\mathrm{r,t}} \right] \tag{5.21}$$

where *f* refers to dispatchable assets, including coal, natural gas and non-run-of-river assets, and *r* refers to non-dispatchable assets (biomass, cogeneration, wind, solar, and run-of-river hydro). The second term in square brackets is the average cost function. We solve objective function (5.21) subject to constraints (5.15) and (5.16), but no longer retain the calibration constraint (5.17). As noted, it is assumed that the calibrated quadratic cost functions capture information from other technical constraints, including the ramping up/down constraints.[2]

The first-order conditions for the resulting constrained optimization problem with respect to $G_{f,t}$ are:

$$d_{f,t} + q_{f,t} \times G_{f,t} = P_t - \lambda_{f,t} + \eta_t, \forall f, t. \tag{5.22}$$

Again, the LHS of equation (5.22) is interpreted as marginal cost and the RHS as marginal revenue.

Assuming that the observed $G^{obs}_{f,t}$ are optimal solutions for the given hourly prices in the base year, equations (5.18) and (5.20) should be reconciled. Therefore, the variable marginal cost functions, MC_i, could be set equal to the sum of the average costs c_i and the differential marginal cost $\rho_{i,t}$ as follows:

$$d_{f,t} + q_{f,t} \times G^{obs}_{f,t} = c_f + \rho_{f,t}, \ \forall t = 1, \dots, T \tag{5.23}$$

where $f \subset i$ refers to generators that use fossil fuels. This is an under-determined system, but several strategies can be employed to solve this problem.

One strategy, [S1], is to assume $d_i = 0$, $\forall i$, which leads to:

[S1] $$q_{f,t} = (c_f + \rho_{f,t})/G^{obs}_{f,t} \text{ and } d_{f,t} = 0, \ \forall t = 1, \dots, T. \tag{5.24}$$

The second strategy, [S2], assumes that d_i equals the average variable cost c_i, so

[2] Huisman et al. (2014) note that dispatchable hydroelectric output should also be represented by a nonlinear cost function. They further indicate that "similar scenarios apply for solar and wind power, the only difference with hydropower is that the input-water can be stored in reservoirs. This storability creates indirect costs, namely opportunity costs, as the decision needs to be made to either produce hydropower now or generate electricity in the future against a possible better price" (p.156).

[S2] $q_{f,t} = \rho_{f,t} / G^{obs}_{f,t}$ and $d_{f,t} = c_f \quad \forall t = 1, \ldots, T.$ (5.25)

A final strategy, [S3], assumes the average cost c_f equals $d_{f,t} + \frac{1}{2} q_{f,t} \times G_{f,t}$. Therefore,

[S3] $q_{f,t} = (2\times \rho_{f,t})\, G^{obs}_{f,t}$ and $d_{f,t} = c_f - \rho_{f,t} \quad \forall t = 1, \ldots, T.$ (5.26)

In all these approaches, the calibrated parameters q_i and d_i could be used in equation (5.19), with the calibrated parameters enabling us to recover the observed generation $G^{obs}_{f,t}$. However, different strategies for calibrating the model could lead to different simulation responses to the policy changes (de Frahan et al., 2007).

5.4 Application to the Alberta Grid

As an application of our approach, we examine the Alberta electricity market because it is carbon-intensive, with about 45% of generated electricity coming from coal and about the same from natural gas. Indeed, "Alberta's electricity sector produces more GHG emissions than any other province because of its size and reliance on coal-fired generation. In 2017, Alberta's power sector generated 60% of total Canadian GHG emissions from power generation" (Government of Canada, 2021c). The task of decarbonizing the Alberta grid poses a challenge because oilsands development is a key to Canada's economy and its clean energy future. At the same time, Alberta has excellent wind and solar resources: south-western Alberta, around the town of Pincher Creek, is a particularly beneficial place to site wind farms (McWilliam et al., 2012). Further, the Alberta Electric System Operator (AESO) provides information on hourly prices, load, and generation by asset type on an hourly basis.

We employ each of the three approaches to calibrate the parameters of quadratic cost functions for the Alberta electricity grid using observed data for 2019. This section starts with the background information employed in our model, including the capacities of generating assets by fuel type and purpose, costs of generating electricity in Alberta, and a description of the representative generators used in our simulation. Then the PMP calibration results are presented, followed by a discussion of the policy impacts.

5.4.1 Description of the Alberta Electricity Grid

Electricity demand in Alberta has increased over the past several years, although load has remained relatively stable within a given year because more than half of the demand comes from industrial and commercial activities. Specifically, about one-third of the total Alberta internal load (AIL) is from the industrial sector; one-fifth comes from commercial activities and the remainder is contributed by residential and farm customers (AESO, 2017a). A load duration curve rearranges the hourly load (demand) throughout a year from highest to lowest, with the lowest load to be met by baseload generators—thermal assets, such as coal, nuclear or combined-cycle gas turbines (CCGT), or a hydroelectric facility with reservoir. Alberta's load duration curve for 2019 is provided in Figure 5.1; the highest load was 8854 MW, while the baseload was 5747 MW. In our study, we ignore any generation used to self-supply behind-the-fence load and consider only the system load that is external to the generating assets.[3]

[3] The Alberta internal load represents the system load plus load served by on-site generating units, including those within an industrial system and the City of Medicine Hat (AESO, 2020b).

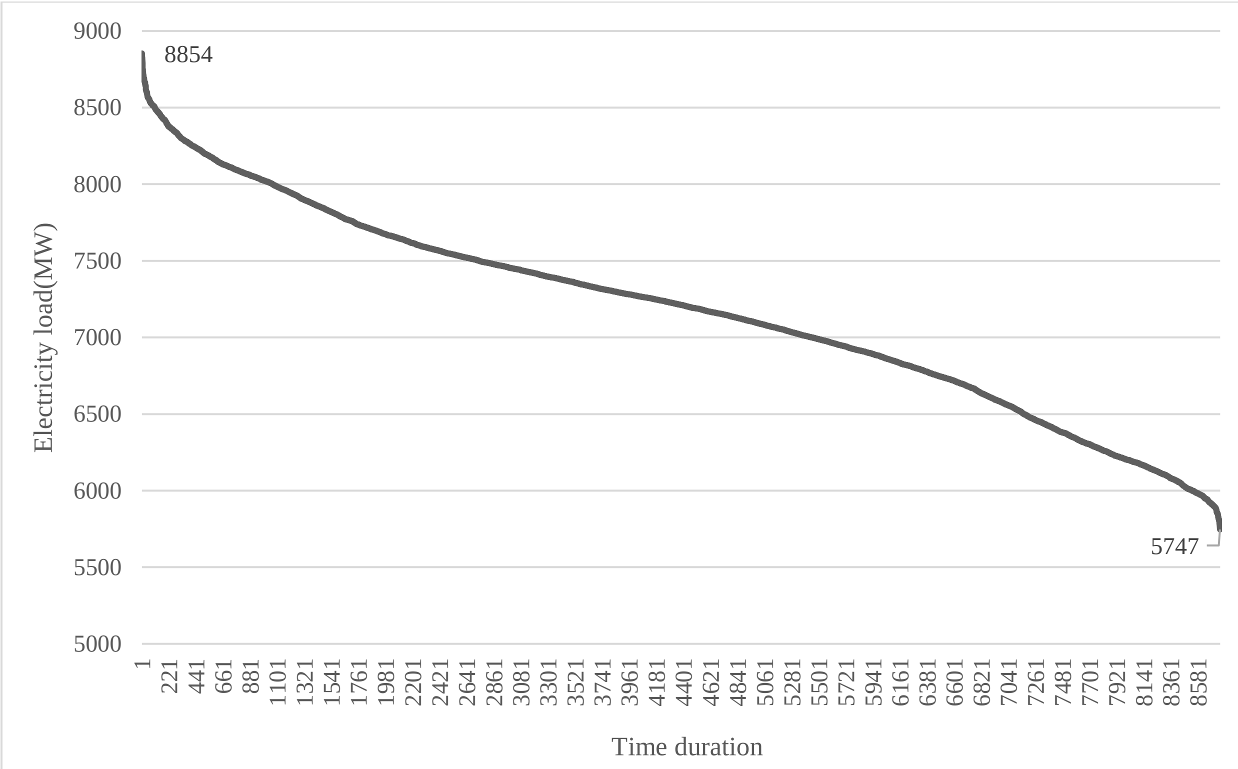


Figure 5.1: Load Duration Curve, Alberta, 2019

In Alberta, electricity is generated from multiple sources. Table 5.1 shows the composition of Alberta's generating capacity in 2019. These capacity data are used as the base case scenario for calibration purposes. Thermal generators still dominate the mix, with coal and gas accounting for 80% of total system capacity; as a result, there is great potential to introduce more renewable electricity generation. In 2019, Alberta did not rely on utility-scale battery storage, but, by 2021 two new battery storage stations had been built along with wind farms (AESO, 2021a).

Table 5.1: Alberta Electric System Generating Capacity in 2019 (MW)

Year	Coal	Cogen[a]	CCGT gas[b]	OCGT gas[c]	Biomass	Hydro	Wind	Solar	Total
2019	5,723	4,937	1,748	921	420	894	1,781	15	16,439

[a] Cogen refers to cogeneration which is used primarily in industrial plants
[b] Combined-cycle gas turbin (CCGT) provides baseload power
[c] Open-cycle gas turbine (OCGT) refers to fast-responding (peak load) gas turbines.
Source: AESO (2020b)

Cost information is from the AESO, U.S. Energy Information Administration (EIA), and various other sources, as indicated in Table 5.2. All monetary values are converted to Canadian dollars. In recent years, the cost of renewables fell significantly (EIA, 2021). We use scenario analysis to investigate how the Alberta electricity generation mix responds to different assumptions about costs. For example, we simulate changes in the generation mix resulting from a 50% reduction in the costs of renewables.

Table 5.2: Cost of Electricity Estimates for GT, CC Gas, Solar, Wind and Battery Power (CAN$2019 per MWh)[a]

Type	Overnight Capital Cost ($/kW)	Fixed O&M ($/kW/yr)	Fuel Cost ($/MWh)	Variable O&M ($/MWh)	Emissions (tCO_2/MWh)	Facility Life (years)
Coal		53	21.6	5.9	0.63	
OCGT	1159	57.3	16.5	4.6	0.17	25
CCGT	1667	53.9	11.9	2.7	0.023	30
Cogeneration		53.9	23.6	2.7	0.022	
Biomass	2501	164.3	56.5	6.31	0.965	
Run of River		54.6	2.56	13.62	0.024	
Brazeau & Bighorn Reservoirs		54.6	2.56	13.62	0.024	
Solar	1643	19.9	0	0	0.048	25
Wind	1586	32.5	0	0	0.012	25
Li-ion battery	1515	32.4	0	0	0.3	10

[a] Authors' calculations based on data from AESO (2019a, 2021b), EIA (2021), Lovering et al, (2016) , Rapier (2021), and Schlomer et al. (2014) and Sönnichsen(2021).

Alberta has excellent potential to deploy renewable resources to generate electricity for two reasons. First, Alberta has abundant wind and solar resources, with wind power especially high during winter and in June, while solar output is high in summer but low in winter (Climenhaga, 2021). During the day, solar power is highest at noon and wind power is at its peak at night. In essence, wind and solar power are complementary, but solar power is more valuable than wind power because solar is available at a time when demand and prices are greatest. A second reason why Alberta is a good place to invest in renewables relates to its electricity market, which is deregulated so electricity companies can make asset investment decisions independently. Thus, the market is quite resilient to economic shocks and responsive to policy incentives, such as carbon taxes.

To estimate potential generation capacity from wind and solar, we modeled two representative generators. We used the 2019 wind speed profile for Pincher Creek from Environment and Climate Change Canada (Government of Canada, 2021b) and an ENERCON E-126 7.58 MW wind turbine to estimate electricity output (see Figure 5.2).[4] Wind generation was stronger in 2020 than in 2019, resulting in an increase in the average capacity factor from 30% to 39%; the capacity factor was also 15-20% higher in winter than in summer (AESO, 2020b). In our simulations, the average annual capacity factors reach around 35%. In addition to high wind profiles, southern Alberta has one of Canada's highest solar potentials, which explains why one of the largest solar farms in North America was developed in Vulcan County in 2021(Government of Alberta, 2021). We used solar radiation and temperature information for Pincher Creek in 2017 from Canadian Weather Energy and Engineering Datasets (CWEEDS),[5] and a Canadian Solar CS6X_300P panel to calculate potential solar power output (see Figure 5.3).

[4]Conversion of the available mechanical energy (wind speed) to electricity is based on the technical specifications (van Kooten et al., 2016)
[5] CWEEDS provides annual data on a range of meteorological elements, recorded hourly at about 10 km grid spacing (Government of Canada, 2021a). The solar energy outputs were calculated by using the PVLIB package in Python, developed by Sandia National Laboratories (Holmgren et al., 2015).

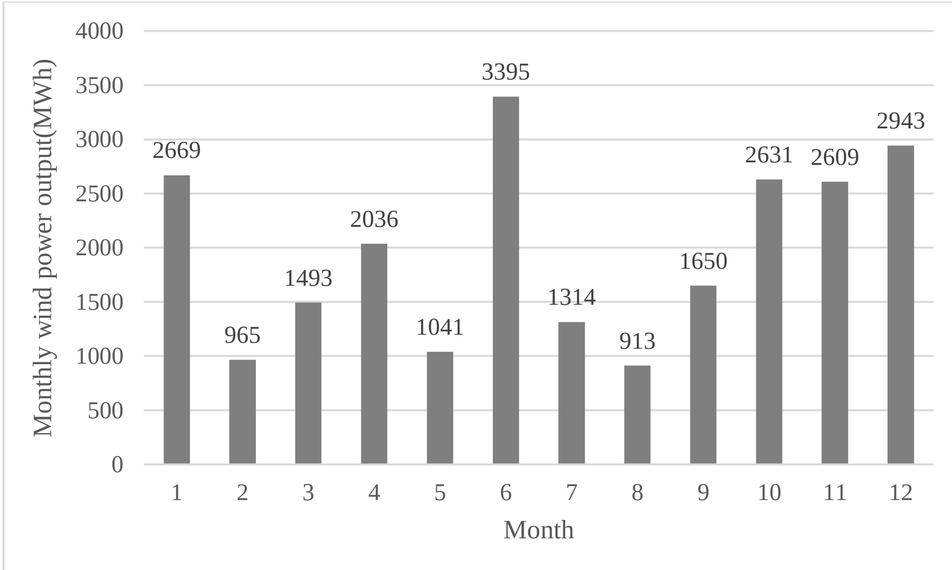


Figure 5.2: Monthly Wind Power Output from an ENERCON E-126 7.58 MW wind Turbine in Pincher Creek, 2019

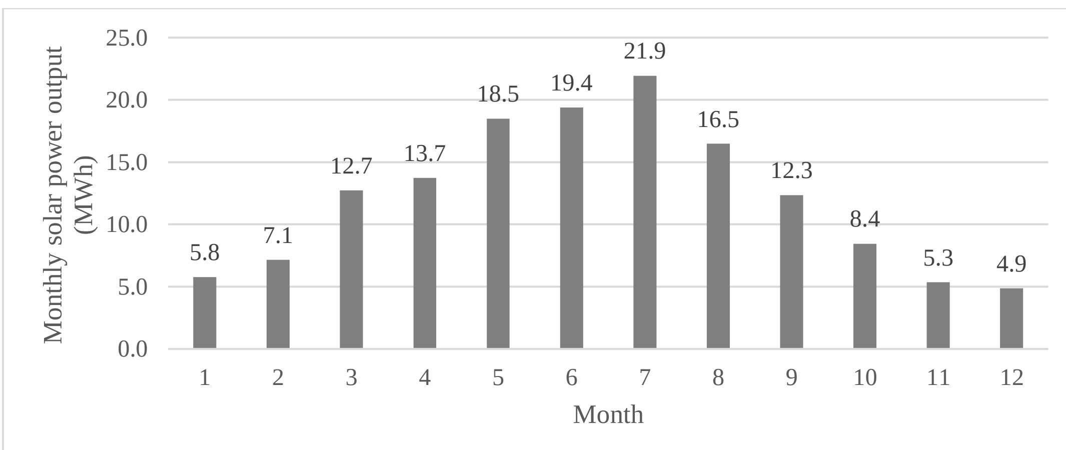


Figure 5.3: Monthly Solar Energy Output from a 75600W Canadian Solar CS6X_300P Solar Panel Array in Pincher Creek 2017(CWEEDS)

5.4.2 Calibrating Cost Functions for Alberta Electricity Generation

Using the quadratic cost functions in equation (5.21), we can recover observed generation for the Alberta grid in 2019 by asset types. The differences between model solutions and observed generation are summarized in Table 5.3 using the second identification strategy [S2] in equation (5.25). The calibrated cost functions not only capture the explicit accounting costs but also the implicit economic costs as they replicate observed generation. The implicit economic costs could come from capacity constraints or ramping up/down constraints, et cetera.

Table 5.3: Differences between Calibrated and Observed Outputs for Four Generator Types, Based on the Second Calibration Method

	Coal	Open-cycle gas turbine (OCGT)	Combined-cycle gas turbine (CCGT)	Brazeau & Bighorn Reservoir
RMSE [a]	4.018	0.121	0.189	0.103
MAE [b]	0.496	0.116	0.130	0.103
MAPE [c]	0.000	0.000	0.000	0.002

[a] Root mean squared error
[b] Mean absolute error
[c] Mean absolute percent error

5.4.3 Power Generation Mix Optimization with Calibrated Cost Function

Once the grid optimization model is calibrated, we simulate the impacts of various climate policies on the electricity generation mix. In doing so, we allow the system operator to remove fossil-fuel power plants and add renewable power assets along with battery storage. However, since electricity prices are not known at this stage (they are used only in calibrating the parameters of the cost functions), a cost minimization problem now needs to be specified—the system operator must satisfy the electricity demand and all technical constraints at minimum cost. The system operator specifically minimizes the following total cost function:

$$Z_{AB} = \Sigma_{t=1}^{T} \left[\Sigma_f \left(d_{f,t} + \frac{1}{2} q_{f,t} G_{f,t} \right) G_{f,t} \right] + \Sigma_{t=1}^{T} \left[\Sigma_r c_r G_{r,t} \right] + \Sigma_i^I \left[\left(c_i^{on} + c_i^{fom} \right) K_i^+ + c_i^{fom} (K_i - K_i^-) \right] +$$
$$\Sigma_{t=1}^{T} \left[\Sigma_i \left(E_{i,t}\, G_{i,t} \right) \right] \tau, \qquad (5.27)$$

where *f* refers to coal, open-cycle gas (OCGT), combined-cycle gas (CCGT), and the Brazeau-Bighorn hydroelectric facility that has storage reservoirs; *r* refers to wind, solar, battery storage and other non-dispatchable assets; *i* refers to all generating assets; c_i^{on} represents the annualized overnight cost of electricity (C$/MWh); c_i^{fom} is the fixed operation and maintenance cost ($/MWh); K_i refers to existing generating capacity (MW); K_i^{+} is added capacity (MW); and K_i^{-} is capacity that is removed (MW). Finally, E refers to CO_2 emissions (t/MWh) and τ is the carbon tax ($/t$CO_2$).

Equation (5.27) is minimized subject to demand (equation 5.16) and other technical constraints (e.g., ramping constraints). To study the effects of policies on generation and asset capacities, the model allows the system operator to change the fossil fuel and renewable capacities so that the system could achieve proactively the CO_2 emission reduction goals. Therefore, the capacity constraints (5.15) change accordingly.

For the base case, we employ no carbon tax or no emission targets and use the 2019 hourly demands to solve for the optimal generation mix. The model does not add any renewable power capacity to the system. Instead, as a means of minimizing cost, it removes around 15% of the existing capacity of CCGT, 26% of OCGT, and 24% of coal in the base case. Since we assume that the existing asset investments in the grid are optimal, we consider these removed capacities as reserves necessary for avoiding outages. Hence, in the subsequent policy analysis sections, any fossil fuel capacities removed (or added) beyond the base case are treated as actual.

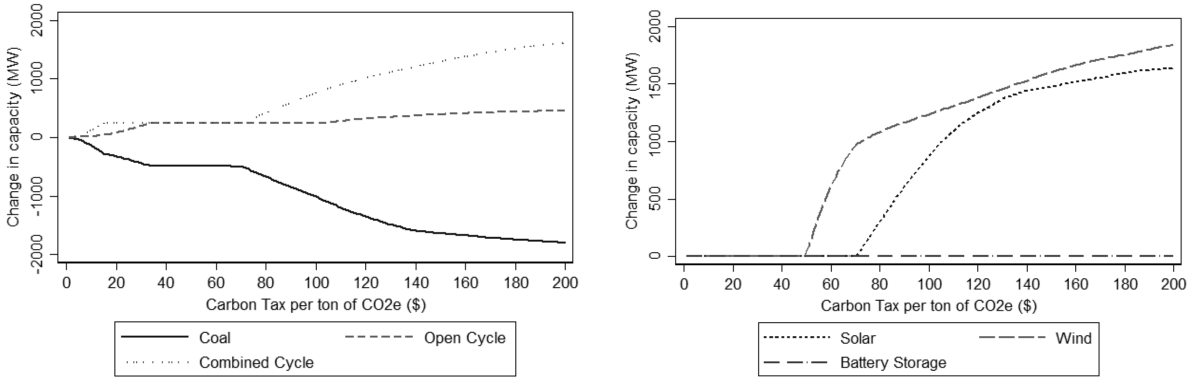
The main policy instruments in our analysis are a carbon tax and an emissions standard. Under the carbon tax, we first solve the model imposing increasing carbon taxes up to $200/t$CO_2$ using the current cost level (section 5.4.4); we then halve the costs of renewables, considering the fact that the costs of renewables keep declining (section 5.4.5); and, finally, examine the impacts of emission standards (section 5.4.6).

5.4.4 Carbon Tax Scenarios

It is evident that, with a rising carbon tax, the optimal solution reduces fossil-fuel capacities and increase renewable energy sources in the generation mix. One aspect worth considering, however, is how these assets displace one another in the process.

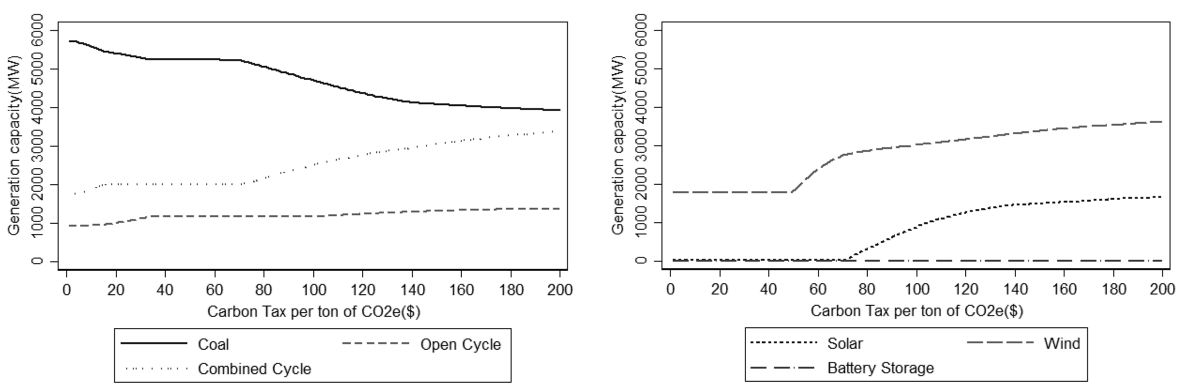
Figure 5.4 presents the changes in asset capacities that occur as the carbon tax increases, while Figure 5.5 provides total capacities. There is high correlation between changes in coal capacity and changes in CCGT capacity; when coal capacity falls, CCGT capacity increases, and when coal capacity is unchanged so is CCGT capacity. Surprisingly, there is no correlation between changes in coal capacity and changes in the capacities of renewable energy sources—when the capacity of renewables increases, coal capacity does not decrease correspondingly. However, there is competition between renewables—when solar capacity increases, the investment in wind assets slows down. When the carbon tax increases to around \$35/tCO_2, coal capacity declines rapidly, while OCGT and CCGT capacities increase slightly. Tax rates between \$35/tCO_2 and \$70/tCO_2 have little impact on optimal capacities of fossil-fuel generators, but, when the tax rate exceeds \$70/ tCO_2, coal capacity declines further while there is an increase in CCGT capacity—baseload gas capacity replaces baseload coal capacity. At the same time, there is hardly any change in OCGT capacity. Although peak-load OCGT is used to meet rapid changes in load due to intermittent wind, say, reliance on OCGT is more expensive than CCGT. Yet it is surprising that the model does not add more peak OCGT capacity, although CCGT assets ramp up and down somewhat faster than coal assets.

Finally, wind power capacity increases sharply when tax rates are between \$50/tCO_2 and \$70/tCO_2. When the carbon tax reaches \$70/tCO_2, new solar capacity is added to the system, while reliance on wind energy slows down. However, additional wind and solar capacities are not able to replace baseload or peak load gas capacity. In terms of capacity substitution, additional wind and solar capacities do not have much impact. When the carbon tax reaches \$200/tCO_2, wind capacity reaches 3617 MW and solar capacity 1652 MW. The amount of renewable capacity added to the system is much greater than the reduction in coal capacity.



(a) (b)

Figure 5.4: The changes in capacities (MW) with increasing carbon tax



(a) (b)

Figure 5.5: The Capacities of Generators with the Increasing Carbon Tax

If we consider the impact of renewables on total generation, we find that renewables play a vital role in substituting for fossil-fuel generation (Figure 5.6). Starting from 9% in the base case, the total generation share of renewables reaches around 23% (18% from wind, 5% from solar) when the carbon tax is \$200/tCO_2. Some 1600 MW of solar capacity is added to the base solar capacity of 15 MW, which is about half of the total wind capacity; nonetheless, the generation share of solar power is only one-third that of wind, which implies that the capacity factor of solar is lower than that of wind power. Further, the share of the generation coming from coal declines from 42% (base case) to 6% (\$200/tCO_2 tax), but importantly the generation share of CCGT increases from 16% to 35%. Overall, less than half of the lost generation share from coal is replaced by renewables, with more than half replaced by CCGT.

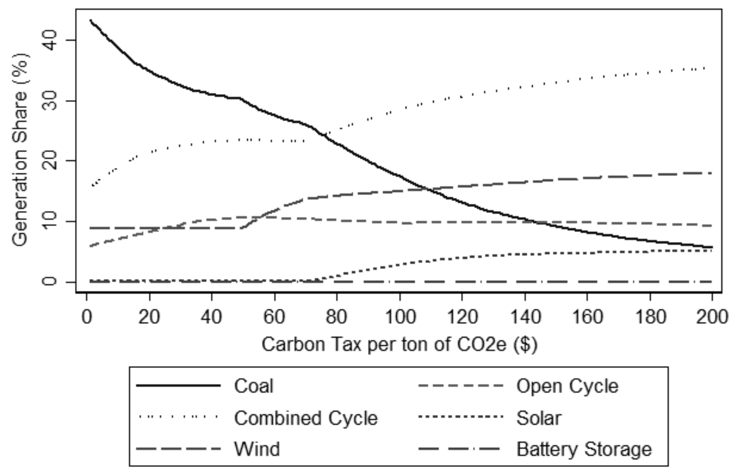


Figure 5.6: Power Generation Shares with an Increasing Carbon Tax

The capacity factor (CF) is determined as actual generation over a period divided by potential generation. For example, a 100-MW capacity generator has the potential to produce 876,000 MWh of energy over a year (=8760h×100MW); if it produced 450,000 MWh over some year, its CF is 51.4% (=450/876). The CF helps us understand the interaction between fossil fuels and renewables (Figures 5.4 and 5.5). In Alberta, the CF for coal generation fell from 80% to 60% in the years before 2020, while the CF of CCGT has continued at about 70% (AESO, 2021).

Results in Figure 5.7 are similar. First, the CF for coal continues to decline from 54% to 11% as coal generation decreases faster than the reduction in coal-fired capacity. When we have abundant renewables, coal-fired power is not needed, but a large amount of coal capacity is still required as backup capacity. Newly added renewable capacity replaces some coal generation, but it has less impact on reducing coal capacity. Second, the CFs of OCGT and CCGT initially increase, but when new wind and solar power are added, the CFs slowly decline. More renewable capacity and generation lead to less efficient OCGT and CCGT power use.

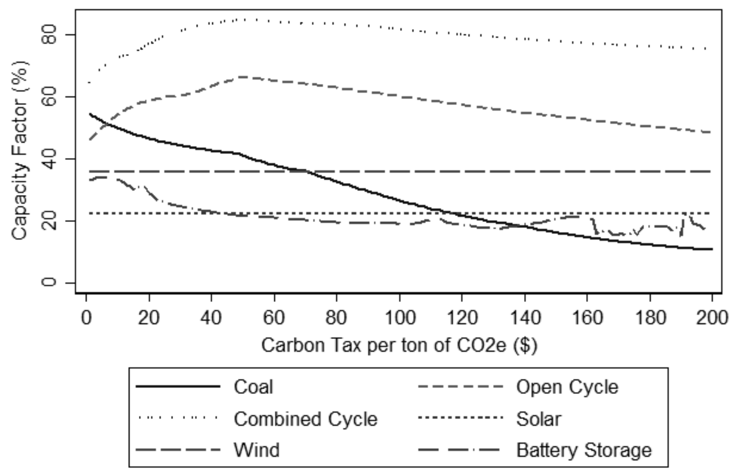


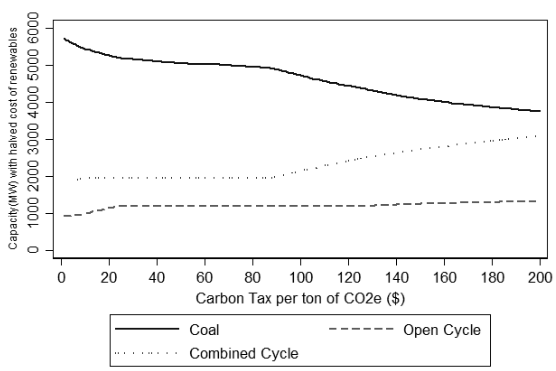
Figure 5.7: The Capacity Factors Generators with Increasing Carbon Tax

The CFs for wind and solar power in our model are decided by the natural wind and solar resources, which do not change when the carbon tax increases. However, the CF of a storage device does fall from 33% to 16%, but there is too little storage to decide whether this result is applicable under different conditions.

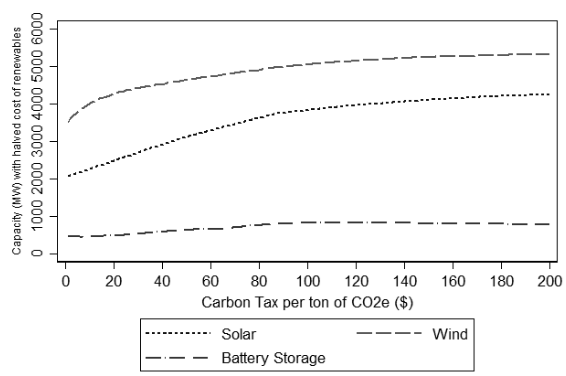
5.4.5 Reduction in the Costs of Renewable Assets

As the costs of renewable energy sources are expected to decline relative to traditional thermal power, we simulate the case where fixed and variable costs of wind, solar and battery storage decline to half those of the base case while the cost structure of fossil fuel generation remains unchanged. However, the costs imposed on the operation of fossil-fuel generating assets need to be taken into account. The impacts on generation capacity and capacity factors are provided in Figures 5.8 and 5.9, respectively.

Similar to previous scenarios, the reductions in coal capacity are highly correlated to increases in CCGT capacity but not in sync with changes in renewables capacity. A large amount of coal capacity remains in the mix, but the generation share of coal power declines to 4%. Unlike the earlier scenarios, capacities of wind, solar and battery storage continue trending upwards. Renewables feature heavily in the generation mix even when the carbon tax is less than \$50/tCO_2.



(a)

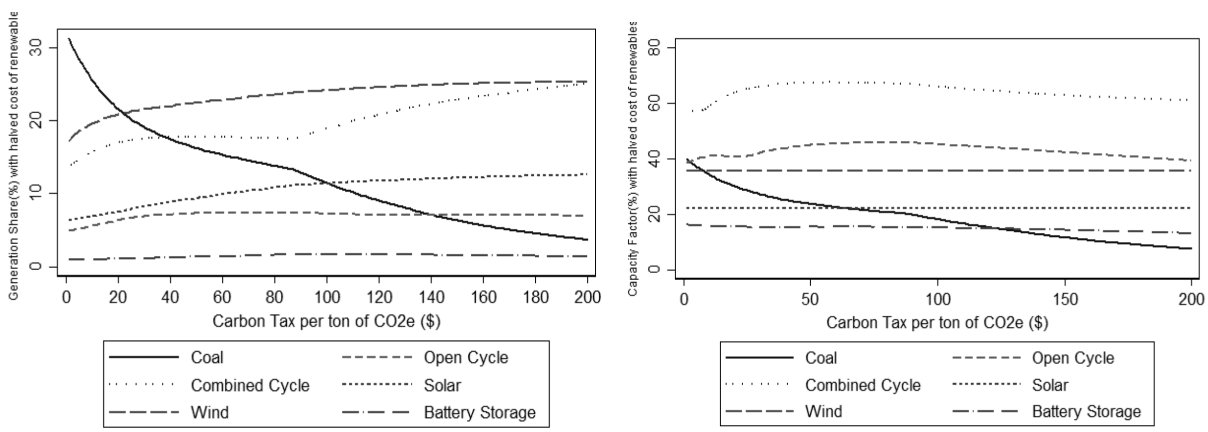


(b)

Figure 5.8: The Capacities of Generators When Renewable Costs Are Halved

With the costs of renewables are halved, the marginal effect of a carbon tax falls significantly when the tax rate gets to about \$90/tCO_2. The increase in renewable capacities does not substitute for coal capacity as much as expected as coal capacity is replaced by CCGT capacity. This trend is more apparent when the carbon tax exceeds \$90/tCO_2—CCGT capacity increases rapidly as expansion in renewables slows down (see Figures 5.8a and 5.9a). In a market saturated with wind and solar power capacities, baseload CCGT capacity replaces much of the coal capacity. Meantime, peaking assets such as OCGT and battery storage backstop intermittent renewables—the increase in intermittent resources results in a greater need for peaking capacity.

The low cost of renewables further lowers the capacity factors of fossil-fuel generating assets. With a higher proportion of capacity and generation coming from renewables, the CF for CCGT assets falls to about 60%, lower than the 75% in the previous scenario. With lower costs of renewables, the CF for OCGT assets declines to nearly 40%, compared to 55% in the previous scenario. The CF of coal also declines to 7% compared to 11% previously. Overall, gas assets are required to maintain the stability and reliability of the grid. Even when a private investor may have no incentive to invest in gas assets (due to the so-called ‘missing money’), the system operator must still ensure that sufficient gas capacity exists in the system.



(a) (b)

Figure 5.9: Generation Share (a) and Capacity Factor (b) When Renewable Costs Are Halved

5.4.6 Clean Electricity Emission Standards

An alternative policy instrument is to implement emission standards. To investigate the impacts of clean electricity standards on the generation mix, we introduce emission reduction requirements as an additional constraint in the model, while imposing no carbon tax and keeping renewable costs at the base level. With an increased carbon emission reduction target, we expect to see a reduction in fossil-fuel generation capacities and an increase in renewable capacities. When the emission reduction target reaches 85% compared to the base case, optimal solar power capacity falls while wind and CCGT capacities rise sharply (Figure 5.10). When the target increases to 90%, solar power is even driven out of the generation mix, and the share of coal power in the generation mix steadily declines toward zero. The reason is that the lifetime emissions from solar power are higher than from wind due to the construction of solar panels. Hence, the simulation results show that, in the extreme situation, we choose wind over solar to reduce carbon emissions.

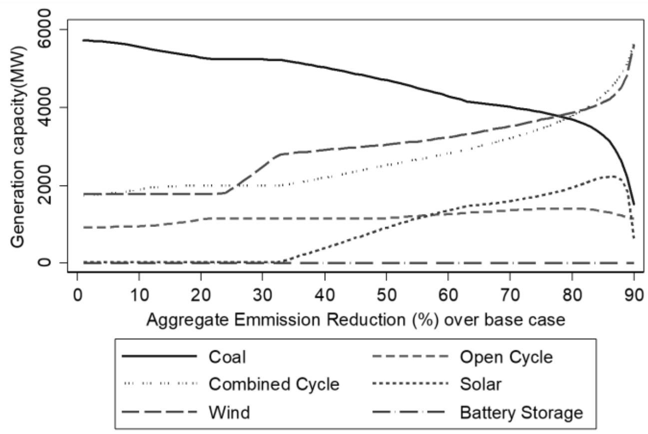


Figure 5.10: The Capacities of Fossil Fuel Power and Renewables with Increasing Carbon Emission Reduction

With an 85% emissions-reduction target, the total capacity of wind and CCGT is 11256 MW, which is much higher than peak demand (8854 MW). At the same time, OCGT capacity remains quite high. The results show that, to backstop intermittent renewables when the emission reduction standard is high, overinvestment in CCGT, OCGT and renewable capacities is unavoidable, which might lead to economic inefficiency and further reinforce the missing money problem. With a 90% emission-reduction target, total capacity rises to 14570 MW, and the total capacity for wind and CCGT assets remains at 11256 MW.

The changes in generation shares (Figure 5.11) and capacity factors (Figure 5.12) reflect a similar situation. CCGT and wind power production dominate electricity supply. Despite a high capacity, the generation share of OCGT declines rapidly when the reduction target reaches 70%; the CF begins to decline as early as an emissions-reduction target of 25%. The CFs for coal and battery storage steadily decrease with an increasingly strident carbon emissions reduction target.

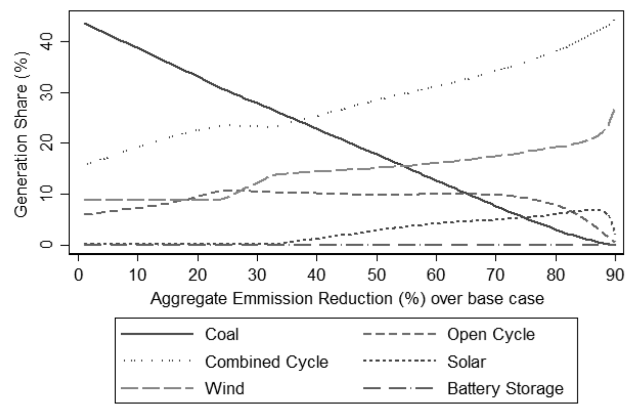


Figure 5.11: Generation Shares with Increasing Carbon Emission Reduction Target

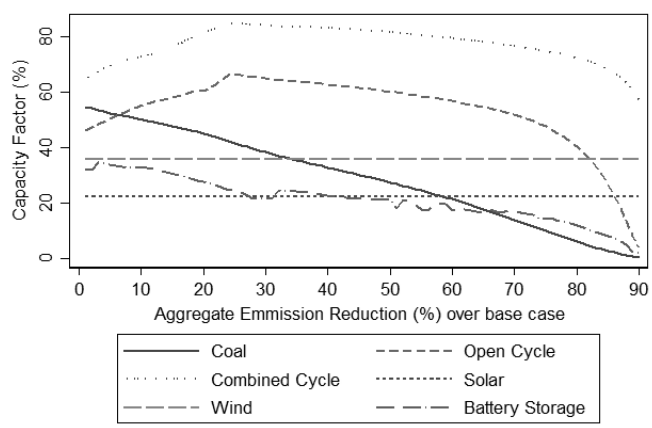


Figure 5.12: Capacity Factors with Increasing Carbon Emission Reduction Target

Overall, the simulation results here indicate that renewables generation could replace coal generation, but wind and solar power cannot be used as reliable baseload assets, requiring instead a large degree of CC gas capacity and generation. Further, the capacity factors of thermal generators fall because they are relied upon to generate power less often resulting in inefficient resource allocation. To improve the efficacy while meeting the carbon emission reduction goal, the electricity industry needs some reliable and less carbon-intensive alternatives to provide necessary baseload capacity. For example, many developing countries such as China and India have turned to nuclear power, with some developed countries, such as France and the Netherlands, also planning to build more nuclear power plants (World Nuclear News, 2021).

5.5 Concluding Discussion

We examined several climate policies options to determine how renewable wind and solar generating assets would optimally enter an electricity grid that was originally dominated by fossil-fuel assets. For policy purposes, a grid optimization model was first calibrated using several methods. The standard fixed marginal cost (horizontal supply) functions for thermal generating assets were thereby replaced by upward sloping supply functions, which provided a more realistic and continuous allocation of load across assets. For example, rather than coal power suddenly disappearing from the generation mix when there is a small change in the carbon tax, a smooth phasing out process becomes optimal, thereby avoiding disruptive and costly shutdowns and start-ups (Henton & Varcoe, 2015). Accordingly, we are able to make better and more reasonable predictions of the interplay between fossil-fuel generating assets and intermittent assets such as wind and solar, and even between different fossil-fuel or renewable assets. This is very useful for policy impact studies.

Our application was to the Alberta electricity grid. We analyzed the impact of two policy scenarios—a carbon tax and an emissions reduction target. Not surprisingly, the capacities and generation shares of renewables increase, and those of coal-fired power decrease, under both an increasing carbon tax and an emission reduction target; however, the share of capacity and generation of natural gas assets increases. The capacity factors of both CCGT and OCGT plants rise with increases in the carbon tax or the emission reduction target, although the CFs of both begin to fall as more is invested in renewable energy sources. OCGT and CCGT replace coal to ensure there exists reliable baseload and peaking generation, so optimal capacities of these generation types remain high, but their use declines as more electricity is produced by renewables. This results in the loss of quasi-rents ('missing money') required to cover fixed costs.

Overall, wind and solar power are not reliable and not suitable for constantly meeting baseload requirements. A large amount of fossil fuel power capacity is required to backstop intermittent sources of generation. However, the contradiction between large capacities and small generation shares leads to low-capacity factors for fossil fuel power. This results in higher costs and greater CO_2 emissions as fossil-fuel plants operate at less-than-optimal efficiency. Further, often side payments in the form of capacity payments are required to ensure adequate generation exists to maintain grid reliability, which also adds to the costs of operating the electricity system.

Chapter 6 SUMMARY AND CONCLUSION

Renewables must become an essential and important part of the current electrical system in order to cut CO_2 emissions from electricity production and combat climate change. However, in order to integrate renewable energy supplies into the electrical grid, the grid must overcome three significant hurdles.

To begin with, renewable energy generation is more costly. Renewable energy is not attractive if we solely evaluate the financial accounting feasibility of removing coal from the power mix. But renewable energy has a long-term environmental benefit. As a result, we must assess the economic viability of replacing coal with renewable energy in the generation mix, taking into account both the social and financial benefits as discussed in Chapter 2.

Second, the intermittent nature of renewable energy, particularly wind and solar, renders it unsuitable for use as either baseload or peaking power sources, and adds to the higher cost, instability and uncertainty of power output in everyday operations. Chapter 3 provides detailed discussion.

Third, the current power grid is not well suited to incorporating renewable energy. When wind and solar generators are available, for example, as we demonstrate in Chapter 4, they disrupt the bid and distribution mechanism by forcing other generation units to shut down or operate at less-than-optimal output since the marginal costs of wind and solar power are near zero. As a result, the return on conventional generating assets decreases, and the incentive to invest in conventional assets to maintain required generation capacity decreases. If renewable resources are not accessible when demand exceeds the capacity of the remaining generation assets, power outages and blackouts will result.

These supply adequacy and grid reliability problem become crucial for modernization and decarbonization of electricity grids. As the events of August 2020 in California and February 2021 in Texas indicate, supply shortages could have had significant economic and public health effects. These problems must be solved by new technologies, proper regulations, and wise economics policies. Only if we can fix the “missing money” by providing enough quasi rent and scarcity rent for conventional dispatchable generation assets as discussed in Chapter 2, the chaos brought by wind and solar power would be alleviated.

In this dissertation, we investigate the issues raised by the aforementioned obstacles using a grid optimization model based on Alberta’s electricity system. A grid optimization model is utilized because it is ideal for establishing the optimal generation mix with various generation assets, including renewable energy, as stated in Chapter 3.

The Alberta energy market was selected for four reasons: First, it is carbon intensive, and the Alberta government is working to phase out coal. However, decarbonizing the Alberta grid is difficult since oilsands development uses a lot of electricity and is a vital part of the Canadian economy that cannot be shut down. Second, Alberta's natural environment is conducive to the utilization of renewable energy due to the abundance of wind and solar energy. Third, the electricity market in Alberta is deregulated. Electricity producers make their own investment decisions on generation assets. As a result, policy incentives such as carbon taxes have a strong impact on the market. The final consideration is data accessibility. Hourly data on energy prices, load, and generation per asset are provided by the Alberta Electric System Operator (AESO).

The first research topic in this dissertation is to determine whether it is economically feasible for Alberta to replace two-thirds of its coal-fired power generation assets with wind. In Chapter 3, we demonstrate that a carbon tax with two tax levels is established to reflect the social costs of GHG emissions. Even without incentives, we find that in southwestern Alberta, particularly near Pincher Creek where most of Alberta's present wind farms are located, the return on investment in wind power is reasonable. In other wind regions within the province the unpredictability of wind speeds over hours and years has a negative influence on wind energy investments. Furthermore, Alberta will not be able to meet its emission reduction targets just by replacing coal with wind. Alternatively, Alberta might buy carbon offsets from outside the province or invest in other renewable energy sources. Nuclear power is one viable alternative as shown in Chapter 3, given the rising costs of carbon offsets, the production costs of other renewables, and Alberta's natural characteristics.

The intermittency problem, as outlined in Chapter 1, is the most significant barrier to integrating renewable energy into the electricity grid. First and foremost, it causes system instability because we cannot regulate the timing and amount of electricity generated by renewables. Further, when significant renewables are included in the power mix, greater backup thermal generation capacity is necessary due to the intermittent renewables as shown in Chapter 3. The near-zero marginal cost of renewable energy, on the other hand, reduces the return on thermal generating facilities and discourages investment in these assets, particularly fast-responding peak producers.

As a result, the second goal of this dissertation was to explore the impact of flexible electricity storage on a power system with wind and solar sources, and whether storage helps to ease the missing money problem in today's technological and economic environment. These questions are addressed in Chapter 4. Coal is not considered because Alberta plans to phase out coal; only GT gas, CC gas, wind, solar, and battery storage are examined. In Chapter 4, the consequences of integrating wind and solar renewable energy, as well as a storage battery, into an ideal generating mix are then simulated using ten years of data from Alberta. We found that CO_2 emissions decrease when more renewable energy is integrated into a fossil-fuel electrical system, yet the required peak-load generation capacity grows, while peak-load generator usage and earnings decline. Furthermore, at current prices, battery storage will not be included in the ideal mix until the carbon tax reaches $200 per MWh. In Chapter 4, we found that, if the capital cost of the battery falls by 40% or more, the battery enters the generation mix with a substantially lower carbon tax, and the battery capacity scales up dramatically in the mix. We conclude in Chapter 4 that there are two advantages to including lower-cost battery storage into the generation mix: (1) A portion of peak generators can be shifted, which not only helps to reduce CO_2 emissions but also helps to offset the missing money problem. (2) With storage, the social cost of reducing emissions falls dramatically.

When solving for the optimal mix of generating assets in the first and second studies, we directly use available cost data for each type of generating asset and assume that these costs do not change with capacity levels. We collected different costs information throughout the years of our study from different sources. For example, 2012-2015 cost data in Chapter 3, and 2018 and 2019 cost data in Chapters 4 and 5, are from AESO, IEA and/or EIA. The results show that, in our economic optimization problems, the relative cost matter more than absolute values. The order of the costs does not change over years, and the model results are rather robust across years using historical data. To further investigate the impacts of relative costs on the electricity generation system, we also implemented economic shock analyses in Chapters 4 and 5. In Chapter 4, we decreased the cost of battery storage to 30% of its current level in decrements. And then, in Chapter

5, we assumed the costs of renewables were halved. The shocks are introduced to change the relative costs of renewables and fossil fuel power to investigate how the system responds to the cost uncertainties. The resulting values are presented to show the trend and the future potential impacts of the policies and economic shocks in Chapters 4 and 5.

Given the importance of power generation costs in our study, the next question we investigated concerned how we can obtain better economic costs; instead of accounting costs, we looked for costs of power generation that better represented observed decisions by asset holders. To do that, we proposed a positive mathematical programming method to calibrate the cost functions. The parameters of economic cost functions for generation assets must be identified in order to better simulate how generating assets operate in the actual world while staying flexible enough to foresee changes in the optimal mix with future regulations. Because calibrating MP models is uncommon in the world of electrical grids, the dissertation's third objective was to investigate how we might calibrate cost parameters and then use the calibrated models for policy analysis. To calibrate the cost functions in the operation of power grids, we used a positive mathematical programming approach. In Chapter 5, the system operator is assumed to act as a social planner, maximizing the grid's overall net revenue while adhering to a set of technical and economic limitations. The system operator can only control the production from fossil fuel generators because wind, solar, and run-of-river hydro are non-dispatchable assets. The calibrated grid optimization model is then used to investigate the effects of carbon taxes and emission requirements on the optimal electrical generating mix's generation shares and capacity factors. In Chapter 5, we also demonstrate that as carbon taxes and emission reduction targets rise, renewable energy capacity and generation share rise, while coal-fired power capacity and generation share fall. At the same time, as a peaking generating asset, GT capacity has increased while with a lower capacity factor.

Overall, the dissertation demonstrates that wind and solar power are inadequate for addressing baseload and peaking generating needs. To supplement intermittent power sources, a large quantity of thermal generation capacity is necessary. Climate policies, such as carbon taxes or reduction targets, help to monetize and express the societal costs of CO_2 emissions, promoting the incorporation of renewable energy into the power system. However, the higher cost of managing the power grid and the severity of the missing money problem are two negative consequences. Battery storage can be utilized to partially replace baseload generation capacity if the cost of battery storage falls, which helps to ameliorate the missing money problem and lower operation costs.

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