Optimization of the Western Canada Power Grid:
Incorporation of Renewable Energy

by

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ABSTRACT

The goal of the current research is to understand the economic consequences of integrating renewable energy into existing power systems, design policies to achieve an optimal mix of generating assets in an electricity grid, and determine the costs and benefits of using renewable energy sources to reduce carbon dioxide and other greenhouse gas (hereafter just CO_2) emissions.

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Chapter 1

Research Context

The goal of the current research is to understand the economic consequences of integrating renewable energy into existing power systems, design policies to achieve an optimal mix of generating assets in an electricity grid, and determine the costs and benefits of using renewable energy sources to reduce carbon dioxide and other greenhouse gas (hereafter just CO_2) emissions.

In most countries, electricity and heat constitute the most important sector accounting for CO_2 emissions, although this sector ranks lower in Canada, because 59% of its electricity comes from hydro sources. Yet, 35 coal power units across Canada, mainly in Alberta, Saskatchewan, Manitoba, New Brunswick and Nova Scotia, represent over 70% of emissions in Canada's electricity sector, while providing only 11% of the country's electricity (David Suzuki Foundation. 2016). The importance of coal-fired power globally cannot be overemphasized – about 80% of China's and more than two-thirds of Australia's and India's power is generated by coal, while more than 40% of electricity produced in the United States and Germany comes from coal.[1]

To mitigate the impact of coal on climate change, many developed countries are planning to phase out coal-fired power plants. To our best knowledge, Austria, Britain, Denmark, Finland, France, the Netherlands and Canada have committed to close coal-fired plants by 2025 or 2030 (McCarthy 2016). However, to meet the growing demand for electricity, more than 570 GW of coal-fired power capacity was under construction globally as of January 2017.[2] Although well below last year, this

[1] http://wdi.worldbank.org/table/3.7, [accessed April 4, 2017]

[2] Construction of new coal-fired power plants fell worldwide in 2016, EnergyMarketPrice, http://www.energymarketprice.com/energy-news/construction-of-new-coal-fired-power-plants-fell-worldwide-in-2016, [accessed April 4, 2017]

represents 570 new 1,000 MW capacity new plants, and does not include those recently approved or planned (Guo 2017). China, India and other developing countries, and even rich countries like Japan, are building or planning to build new coal power stations.

It is not easy for us to get rid of coal. In 2012, with regulations on emissions from the coal-fired electricity sector, Canada became the first major coal user to ban construction of traditional coal-fired power stations.[3] However, without coal power to meet the growing demand of electricity, Alberta and Saskatchewan had invested on natural gas power stations, which did little to reduce their total greenhouse gas emission (Environment Canada 2011).

To stop climate change, we need to move away from fossil fuels, which requires investment in alternative energy sources. On the pathway to decarbonization, many people put a lot faith on renewables. 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 government plans to phase out all coal-fired electricity generation facilities by 2030, and replace two-thirds of the lost electricity production by renewables (Alberta Government 2012).

Decarbonization comes with a cost. First at all, even if costs are falling over time, most renewables, such as wind and solar, are still more expensive than the fossil fuels (Lazard 2016). Replacing fossil fuels by renewables means rising electricity bills. Moreover, a stumbling block in the development of modern renewable energy globally is the intermittent nature of renewable energy, and of solar and wind power specifically. 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 et al. 2016), and thus the integration of renewable energy into the grid has proven problematic for many countries (Timilsina et al. 2013). From 2015, Hawaii local utility company has slowed down connection of new rooftop solar system to the grid due to the safety and reliability issue of the grid. Intermittency in wind (and solar) power output is unavoidable, and the gaps result in large costs of ramping existing generating assets or investing in new assets to compensate for this intermittency (van Kooten 2016a). Therefore, the opportunity cost of introducing renewables is much higher than the explicit accounting cost.

[3] 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 end of life.

To balance the trade-off between clean and cheap electricity, certain public policies are needed to provide incentives for firms to develop and operate renewable generating assets.[4] 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. Meanwhile, Ontario adopted a cap-and-trade system for facilities producing over 25,000 tCO_2 annually (Ontario Power Authority 2016), while providing a feed-in tariff (FIT) for medium- and small-scale renewable energy providers, known as microFIT, and renewable procurement processes for large renewable energy providers (IESO 2016). Furthermore, the Alberta government implemented an economy-wide carbon tax of \$20/tCO_2 beginning in 2017 and increases it to \$30/tCO_2 in 2018; provide subsidies to encourage renewable energy; and cap emissions from oil sands developments at 100 megatons of CO_2 (Government of Alberta 2016).

The current research will study the cost and benefit to society from replacing fossil fuels by renewables in a power system. To determine what is the optimal generation mix in a carbon constrained jurisdiction such as Alberta, we adopt a grid optimization model to solve this problem (van Kooten et al. 2013). With the assumptions of rational expectation of the grid operator/asset owner and interties between adjacent jurisdictions, the grid operator/asset owner optimize load across assets in each hour. Using this optimization grid model, we can calculate the optimal tax or subsidy required to introduce renewables into grid and to achieve a climate change target. Therefore, we also can get the estimated social cost or shadow price of the decarbonization from a fossil-fuel based electricity sector.

Moreover, to examine the performance of a grid, we need accurate economic cost evaluation for generation technologies. This economic cost evaluation needs to take explicit and implicit costs into account. Different technologies are developed to evaluate the social benefits and costs of electricity. I will look at the impact of the cost of electricity on the generating mix by using the load-duration-screening-curve framework, and I will use positive mathematical programming to calibrate the economic cost of generation technologies.

[4] In 2016, after the Nevada Public Utilities Commission lowered the price that utility companies pay homeowners for their electricity from rooftop solar panels, the solar installations in Nevada decreased dramatically. http://www.pbs.org/newshour/bb/debate-over-solar-rates-simmers-in-the-nevada-desert/, [accessed April 4, 2017]

1.1 It is time to change the power system

It is not easy to incorporate renewables into the power system. The problem is that the original power system is not designed for variable and distributed power resources like wind and solar energy. To build an electricity power system that integrates the renewable sources of energy, we need to redesign the power system by reforming the pricing mechanism, improving regulations, and changing the business model. 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.[5]

There are at least two challenges we face when we incorporate renewables into the power system. One is the intermittency of renewables. 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. In the beginning of 2017, the South Australian blackout was blamed on wind generation failures (Murphy et al. 2017). We still rely on other controllable power sources as backup to provide reliable energy supply.

The second challenge is that wind and solar power disrupt electricity 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 the wind and solar are available. The return of the other conventional generation assets will decline and, in the long run, the investment of those conventional assets will decline.[6] Without those assets as a backup reserve, when wind or solar was not available, disruptions and blackouts can occur. Apparently, the current power systems are not ready to balance the contributions from conventional energy and renewables.

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[5]For the same reason, Nevada Energy decided to charge rooftop solar panel owners more than non-solar users. https://www.bloomberg.com/features/2016-solar-power-buffett-vs-musk/ [accessed April 4, 2017]

[6]Wind and solar power are disrupting electricity systems, Economist, http://www.economist.com/news/leaders/21717371-thats-no-reason-governments-stop-supporting-them-wind-and-solar-power-are-disrupting [accessed April 4, 2017]

1.2 The approaches we can take

To overcome the intermittency problem of renewables, three approaches are possible. 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 and solar. In one place, the wind may stop blowing, but it might start to blow 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. In a much more restricted region, such as western Canada, the wind power from Alberta and hydro energy from British Columbia can work together to provide reliable, clean and sustainable electricity. The current research will study the feasibility and effect of this small-scale electricity connectivity approach.

One aspect of the BC-Alberta connection relates to the second method for overcoming intermittency – storage. Electricity can be stored in the reservoir behind a hydroelectric dam, in a battery, as compressed air, or using a chemical storage such as hydrogen. Energy storage is likely going to play an important role any future power system. The current research will look at the impact of the hypothetical energy storage in a carbon constrained province.

The third approach to intermittency occurs on the demand side. With new technologies, the demand for electricity (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 2011, p.9). 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" (Ibid). 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.

All those developments will converge in a future power system. In the conventional system, generation is centralized, transmission is unidirectional, and distribution is passive. Electricity is generated in one place and is transmitted from upstream to downstream. All power generated must be distributed instantaneously to users (Bakke 2016). In the future, with the incorporation of intermittent (variable) renewables, distributed generators such as the rooftop photovoltaic will grow, and power flows can be bidirectional between different microgrids. The distributed generation sources are getting more active based on smart grid control system. More microgrid systems are needed to manage various energy sources and coordinate controllable demand loads with power supply sources.[7] It is time to reconstruct power systems to accommodate clean but variable renewables. It creates the opportunities to expand economy just like a hundred of years ago when the coal and gas replaced wood to become main energy sources.

1.3 Research Questions

The current research focuses on three types of questions. The first relates to the economic impacts of incorporating renewables into an existing power grid and, thereby, to the costs of reducing greenhouse emissions. High penetration rates of intermittent power sources have an impact on system CO_2 emissions; however, reduced emissions from wind power do not replace emissions from thermal power plants one-for-one. For example, if a coal-fired power plant needs to lower output to accommodate wind, this leads to inefficiencies in fuel use resulting from operating below optimal capacity. The first part of the current research will look at the optimal generation mix, in which a carbon tax or a feed-in-tariff is used to incentivize removals of fossil fuel generation and investment in solar panels and wind turbines.

The second part of the current research examines the effect of flexible storage of electricity on a power system with wind and solar sources. Storage can alleviate the volatility and uncertainty of renewables, and also enable coal plants to operate more efficiently, thereby saving fuel and potentially reducing CO_2 emissions. The connectivity between different jurisdictions can achieve the same kind of functionalities. For example, Alberta sells coal-fired power to BC at night, buying back hydroelectric-

[7] The smart gird revolution, Energia16, http://www.energia16.com/the-smart-grid-revolution/?lang=en [accessed April 4, 2017]

ity at peak times during the day – de facto storage. Researchers have investigated the problems associated with non-dispatchable wind and combined heat and power (CHP) (Liik et al. 2003; White 2004; Lund 2005). They found that grids are difficult to manage when the output from large-scale wind farms reaches a maximum (often at night when CHP output also peaks) and the load is minimal, while the output from base-load facilities remains high. Unless electricity can be 'dumped' into another jurisdiction during these times, the adjustment costs imposed on extant generators might be large (AESO 2008). Successful integration of wind energy depends on the generating mix of the extant system (Maddaloni et al. 2008b; Prescott & van Kooten 2009). The second part of the current research is devoted to studying a system with massive electricity storage when relatively high levels of wind and solar generated electricity enter the grid.

The last part of the current research will be devoted to calibration of electricity cost. Due to the complexity added by integration of renewables, the costs for generation technologies, especially for wind and solar, are not so obvious. In the electricity cost literature, many measures of the levelized costs of electricity (LCOE) are available, although they often differ because LCOEs are based on estimates of the overnight construction cost, operating and maintenance costs, fuel costs, expected capacity factors, and so on. However, the value of electricity supplies varies over time. In peak time the electricity is more valuable than in off peak time, which in reflected by the wholesale market price. Dispatchable generating technologies can be utilized any time, but intermittent renewables are not so. Relatively, solar power is more valuable than wind power because solar provides power during the day time but wind usually provides power during the night. The LCOE calculations do take into account capacity factors but fail to take into account the timing of available power from intermittent sources and how this impacts other assets providing power to the grid at the time (Joskow 2011).[8] To understand the true economic value of electricity, a comprehensive evaluation should consider the life time cost and expected profitability of the generating technologies. Therefore, I will use positive mathematical programming and maximum entropy methods to calibrate the economic costs for generation technologies.

[8]A generating assets capacity capacity factor (CF), whether a wind or gas turbine or coal plant, is given by the actual megawatt hours (MWh) of electricity generated in one year divided by the capacity rating of the asset (MW) multiplied by 8,760 hours in the year. For example, if a wind turbine has a capacity of 2.5 MW and generated 3,942 MWh of electricity in a year, it has a CF = 3942 MWh / (2.5 MW8760 h) = 0.18, or 18%.

By solving a well-calibrated model numerically with real world data, we can be confident that the model can be used for policy analysis (Paris 2011). We will be able to track changes in the utilization of renewable power sources and CO_2 emissions as electricity demand changes over time. We will be able to examine how the optimal structure of an electricity grid in a particular jurisdiction would change under various policies to mitigate climate change, highlighting opportunities for improving the performance of the current electricity system. Further, we can estimate potential costs of such policies. Finally, we can determine whether and under what circumstances the grids we examine can reduce CO_2 emissions by 30% below 2005 levels by 2030, as has been agreed to in international negotiations (Government of Canada 2016).

Chapter 2

Research Methods

The principal method of analysis will be to develop energy system models to examine the allocation of power across renewable and non-renewable generating sources, and between jurisdictions along interties. Furthermore, the models are used to study the controllable load, demand response, and distributed generation in the future power system.

My research focus is on western Canada's electricity system and I will construct a decision support model for two separate electricity grids, each representing a different mix of generating facilities. The grids are connected by a transmission intertie that allows the two regions to trade electricity and meet the constraints imposed by different forms of generation. (Decision variables include the allocation of generation to the various generators in the system, plus the capacity of the transmission line.) One grid relies primarily on hydroelectricity, with remaining load met by natural gas and other power sources (including biomass and imported power). The other system meets the base-load power needs with coal, combined-cycle gas turbine (CCGT) and/or biomass assets, while marginal power is produced by a mix of hydro and open-cycle natural gas for peak power production. Renewable sources such as wind and solar are introduced at various levels. The two grids are representative of British Columbia and Alberta, respectively; in both situations, one grid is fossil fuel driven while the 'partner' grid consists almost exclusively of hydro assets. An objective of the research is to examine how wind investment in Alberta might be able to employ hydroelectric storage in British Columbia.

The energy system models employ mathematical programming and simulation methods. The description of the type of models that will be used in the study is found in van Kooten (2012). The models to be developed in the proposed research will expand extensively on the prototype modeling to include the integration of two grids in a more explicit fashion, a sub-model detailing the operation of hydroelectric facilities, the interaction between disparate grid operators, the calibration procedures, and welfare analysis of demand response policies.

2.1 Mathematical programming

Optimization is subject to technical constraints that are specific to each electricity grid. Accurate specification of the constraints is important for measuring the true impact of renewable energy on the generation assets, the overall grid and CO_2 emissions. Thus, data collection will be a major component of the research. In addition to data collection, the research will consist of two principal activities – (i) developing mathematical programming models that can be solved numerically; and (ii) determining how a mathematical programming model of this type can be calibrated so that it can be used for policy purposes. I will employ an optimization approach (Ravindran et al. 2006) that builds upon methods used previously (Prescott et al. 2007; Benitez et al. 2008; Maddaloni et al. 2008a, 2008b; Prescott and van Kooten 2009; Timilsina et al 2013; Sopinka et al. 2013).

2.2 Calibration of Mathematical Programming Models in PMP

Modeling energy systems such as electricity grids is fraught with complexities related to the engineering of physical assets, the economics of regulated (command-and-control) versus unregulated (privatized) decision making (e.g., BC vs. Alberta), calibration and solution techniques in mathematical programming, et cetera. The complexity of the programming problem poses many challenges. The main one relates 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, economic models generally aggregate several or even all generators of a particular fuel type. In that case, engineering costs are no longer relevant for modeling purposes as costs need to consider how the 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 analyst to discover the economic cost functions. This has not been done previously in this context. Thus, 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 modeling.

Positive mathematical programming has been used to calibrate a dynamic model in agriculture and resource economics. PMP has yet to be applied to the estimation of cost functions in the operation of electricity grids. With a calibrated model, we can recover the observed output and agents' behavior. Thus, the calibrated model provides a baseline model for us to do policy analysis. The levelized costs of electricity (LCOE) has been used broadly in many researches for comparison of the costs of intermittent and dispatchable generating technologies. However, many factors that influence the cost of electricity are likely omitted due to measurement error, selection bias or technological difficulties. Therefore, a systematic approach to recover a cost function or production function of electricity is useful for policy analysis.

One early approach to calibration is referred to as the historic mixes approach (McCarl 1982; nal and McCarl 1989, 1991). This method does not find the explicit economic cost function, but, rather, constrains future allocation of load across generators so it resembles the historic mix. It assumes that observed choices – allocations of load across generators – are optimal; that is, past choices are optimal or else they would not have been chosen. Further, because solutions occur at extreme points or corners (viz., a simplex algorithm for solving linear and quadratic programming problems), a linear combination of observed mixes is also optimal.

A mathematical programming (MP) model would take historical choices into account by constraining the current decision to be a weighted average of past decisions, with the weights determined endogenously within the MP model and the sum of the weights constrained to equal 1. Chen and nal (2012) suggest an extension of this approach that might be used to include new sources of energy, which have not previously been observed to generate power. This method adds synthetic (or simulated) mixes of the decision variables to the historical mixes, allowing the optimization procedure to choose the weights, and constraining the sum of the historic and synthetic weights to equal 1. Notice that the 'cost' problem is not really solved, although the optimal allocation of load to generators is found.

The most promising alternative approach that directly enables one to find the economic cost functions is based on positive mathematical programming (PMP), which was originally proposed by Howitt (1995) and is increasingly applied to resource management problems (Paris 2011; Heckelei et al. 2012). PMP is especially suited for estimating cost functions for groups of generators, with the level of aggregation chosen dependent on the problem to be addressed and the overall complexity of the programming model. PMP 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. PMP has yet to be applied to the estimation of cost functions in the operation of electricity grids.

The PMP approach usually requires specification of a strictly diagonal quadratic cost matrix, implying that there are no substitutionary or complementary effects among generating sources. Yet, the almost universal existence of multi-sourced electrical generating grids (viz., coal, natural gas, hydro, wind) implies that the regional power authorities are well aware of the interdependencies among generators, and use them together to maximize profits. Clearly, the assumption of a diagonal cost matrix may not be realistic. Fortunately, the PMP method has been extended by employing information theory and the principle of maximum entropy (ME) to obtain parameter estimates for the entire cost matrix (Howitt 1995, 2005; Paris & Howitt 1998; Buysee et al. 2007).

2.3 Generalized Maximum Entropy Approach

Heckelei and Wolff (2003) argue that in some cases PMP is inconsistent because the derived marginal costs will not converge to the true MCs. They introduce a generalized maximum entropy approach in which the shadow prices associated with the calibration constraints of PMP and the parameters of the cost function are estimated simultaneously using mathematical programming, something they refer to as econometric programming. The method employs a standard Lagrangian with econometric criteria applied directly to the Karush-Kuhn-Tucker conditions. This permits prior information to influence the estimation results even in situations with limited data while ensuring computational stability.

The ME approach can be used in conjunction with PMP methods to reconstruct electricity production functions; the contribution of ME is to reconstruct the parameters of the production function to duplicate the multiple-output generating mixes historically observed. By specifying a set of observed costs associated with power production (i.e., operating and maintenance costs, the cost of planned and unplanned shutdowns and retrofits, etc.), the ME technique estimates a unique distribution from the prior cost information. It has been shown that the distribution with the maximum entropy is the best estimator. Again, maximum entropy has yet to be applied to electrical grid management settings, but it appears to be well suited for solving problems associated with interdependent decisions. The proposed research will thus investigate how an electricity grid management model can be calibrated using historical mixes, PMP and maximum entropy methods.

Chapter 3

Data and work completed to date

According to the United Nations Environment Programme (UNEP et al. 2016), the investment in renewables excluding large hydro represented about 24% of the all new capacity electrical generating capacity installed globally in 2015, which is the first-time renewables represented a majority. On the other hand, investment in coal and gas-fired electricity generation was less than half the recorded investment made in solar, wind and other renewables capacity.

The volatility and uncertainty of renewables are key characteristics of the future power system. To study an optimal generation mix, we are going to calculate the output of intermittent wind and solar energy by simulation. I have already collected the wind and solar data for Alberta over a period of ten years and used this data to calculated the simulated output for typical wind and solar facilities located across the province.

3.1 Load Data

We collected Alberta's load data up to 2015 from AESO. The load duration curve can then be constructed by arranging load during each hour through the year from highest to lowest as indicated in Figure 1. The maximum load in Alberta 2015 was 11,229 MW, and the minimum was 7,203 MW. Further, this dataset includes observed output from various energy sources. This information can be used as a benchmark to calibrate cost functions. Figure 1 provides some indication of how the demand or load pattern might change if must run solar energy that occurs during the day is subtracted from load (see Figure 1).

[CHART]

Figure 1 Alberta Load Duration Curve MW 2015

Source: Author calculation, data from AESO

3.2 Wind Data

Wind speed data was collected from 17 locations in Alberta, and a weighted average was taken across regions (weighted in favor of Pincher Creek, which exhibited above-average wind speeds) for a period of ten years, from 2006-2015 inclusive.

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.

The Alberta electricity grid is characterized by industrial consumers and three main types of generation – coal, natural gas, and co-generation. We collect the load data for 2015 and draw a load duration curve for Alberta. The actual capacity and generation in Alberta Electric System for 2014 are also used in the analysis.

Alberta has an enormous wind potential, but still relies mostly on fossil fuels.[1] Alberta is Canada's third largest wind energy market with 1500 MW capacity. Wind power generates 9% of the electricity in Alberta, while Alberta heavily relies on fossil fuel like coal and gas for electricity generation.

The supply structure of the power system in Alberta is going to change in the foreseeable future. Alberta has invested wind farms in recent years, and is expected to increase wind capacity by thousands of MW over next 15 years (Canadian Wind Energy Association 2016). Alberta already planned to build more wind farms.[2] The land-based wind power has relatively lower LCOE and, recently, the LCOE of solar photovoltaic has fallen dramatically (Figure 3).

[CHART]

Figure 2 Annual Installed Wind Power Capacity (Megawatts)

Source: Author calculation and data from Canadian Wind Energy Association (Can-

[1] Source: http://canwea.ca/wind-facts/wind-facts-alberta/ . And new data is possible to get from NREL which also provides the energy output estimation. [accessed April 4, 2017]

[2] New wind projects data is available from https://www.aeso.ca/market/market-and-system-reporting/long-term-adequacy-metrics/ [accessed April 4, 2017]

WEA).

3.3 Solar Data

With increasing capacity in renewable energy, in some countries renewable energy has already begun to play an important role. In May, 2016, solar generated more electricity than coal in the UK, a new record for May. The increase in solar-powered electricity comes as the amount of coal power in the national grid fell to zero several times during that month, which is thought to be the first time this had happened in more than 100 years. Solar made up 6 percent of the UK's electricity in May, while coal made up only 4 percent (Sheffield 2016). Furthermore, in terms of the levelized cost of electricity (LCOE), renewables are competitive with conventional energy at the utility level. Figure 3 shows that wind and solar energy have near grid parity, which means that wind and solar power are cost competitive with fossil fuels at the utility level. The dashed line is the upper and lower bound of 75% confidence interval of costs for coal and gas.

Chapter 4

DISSERTATION OUTLINE

4.1 Chapter 1 Background

Chapter 1 provides a historical overview and research context of the optimization of the power grid in Canada.

4.2 Chapter 2 General method of MP, PMP, Simulation

Chapter 2 consists of a literature review for the integration of renewables into electricity grids. To better understand the cost of integrating renewables, a meta regression will be employed to study the impact of renewables on the cost of electricity. Furthermore, I will discuss the general method of mathematic programming, simulation method and cost calibration in the context of electricity grids.

4.3 Chapter 3 Load Duration Curve and Screening Curves: A Framework for Analysis

Load duration and screen curves constitute a basic framework for determining the optimal mix of generating assets in a grid (Stoft 2002). I extend this approach to consider the potential to invest in wind and solar technologies. A load duration curve can be plotted and used to determine the number of hour' power demand is above certain levels. The load duration curve captures the structure of the load: the peak load, intermediate load and the based load. The screening curves are the cost curves for generation assets. A linearized screening curve will typically include an intercept representing fix cost and a tilted strait line, whose slope represents the variable cost of a certain generation technology.

The load duration and screening curves are used to guide grid operators, investors and policy makers in making optimal investments in generating capacity. When the load/demand is low, the wholesale market price is also low, and grid operator will dispatch the low marginal cost base load generating units. When the load is increasing, grid operator then turns to dispatch high marginal cost generating units. By allocating the dispatchable generating unit, grid operator can achieve the least cost generating mix. In this chapter, I will extend this framework to include intermittent renewables. Besides the accounting cost of the certain generating technology, the social benefit and costs of the technology are taken into account as well. With broader consideration of the benefits and costs, the load-duration, screening-curve framework is used to study the optimal mix of the gereration assets regarding the impact of carbon taxes and feed-in tariffs.

4.4 Chapter 4 Wind and Emission Reduction Targets

In Chapter 3, I study the general power system optimization problem. A region with a high proportion of fossil fuel generation asset is considered to decrease its emission by introducing wind energy. The electrical load that the system operator must satisfy varies a great deal throughout the day – from low demand at night to peak demand during the late afternoon or evening – and throughout the year. Power demand at night is some 50% to 80% below daytime peak demand (based on data for the Texas, Ontario and Alberta grids). In most jurisdictions, base-load demands are met by combined-cycle gas turbines (CCGT), coal or nuclear power. Because it is difficult and costly to adjust the output from base-load plants, it is necessary at peak demand times to have generation sources (e.g., open-cycle gas plants, hydroelectricity) that can adjust output very quickly.

In the chapter, I explore the viability of relying on wind power to replace upwards of 60% of electricity generation in Alberta that would be lost if coal-fired generation is phased out. Using hourly wind data from 17 locations across Alberta, I can simulate the potential wind power output available to the Alberta grid over a 10-year period is simulated. Using wind regimes for the years 2006 through 2015, it turns out that available wind power is less than 60% of installed capacity 98% of the time, and below 30% of capacity 74% of the time. In addition, there is a correlation between wind speeds at different locations, so it will be necessary to rely on fossil fuel generation as backup source. The results from the grid allocation model indicate that CO_2 emissions can be reduced by about 30%, but only through a combination of investment in wind energy and reliance on purchases of hydropower from British Columbia. Only if nuclear energy is permitted into the generation mix would Alberta be able to meet its CO_2-emissions reduction target in the electricity sector. With nuclear power, emissions can be reduced by upwards of 85%.

4.5 Chapter 5 Hybrid Renewable Energy Systems with Battery Storage

In Chapter 4, I will expand the Chapter 3 model to include solar energy resources and an option to store electricity via a general battery. The supply structure has implications for the integration of renewable power from intermittent sources such as the wind (Hirst & Hild 2004; Lund 2005; Kennedy 2005; van Kooten 2010). The wind often blows at night when the demand is met entirely by the base-load plants. At that point in the demand cycle, the price is often below the marginal cost of production and the system operator must take some generating facilities off-line. Due to ramping considerations and the high costs of operating at less than optimal capacity, the output of base-load power plants is generally reduced very little and plants are rarely taken offline (Nordel's Grid Group 2000; Lund 2005; Scorah et al. 2012). Rather, hydro and/or wind output is reduced because it is simple and cheap to do so. This problem can be mitigated, for example, if intermittent electricity can be stored in a reservoir (Benitez et al. 2008; Scorah et al. 2012).

One proposed solution for overcoming intermittency has been to store intermittent power behind hydroelectric dams or, if such storage is unavailable, in grid-scale batteries. Grid-scale batteries can be used to store surplus power during off-peak times for use during periods of peak demand. This could be especially useful for electricity grids that rely significantly on intermittent renewable energy, which would otherwise need to be sold at very low or even negative prices, or otherwise wasted.

Table 4.1: TIMELINE

Time	Chapter
2017 Summer	Chapters one are currently in draft form as part of the development of this research proposal.
2017 Winter	Chapter two and three: General methods of MP, PMP, and simulation
2017 Winter	Chapter four is based on an existing paper entitled Is there a Future for Nuclear Power? Wind and Emission Reduction Targets in Fossil-Fuel Alberta. It is published in PLoS one.
2018 Spring	Chapter five is under the second stage of research. It will be completed at the end of summer 2017. It will be submitted in the near future to a journal for publication.
2018 Summer	Chapter six is at its early stage. A draft of the chapter containing the revised model and a comparison with actual observations will be completed by the end of 2017.
2018 Winter	Chapter seven will summarize the findings for the developed models and provide conclusions about the influence of integration of renewable energy.

4.6 Chapter 6 Calibration of Electricity Cost for Power System Optimization

In chapter 6, I will discuss the cost of electricity in a mathematic programming approach. Specifically, this chapter study how to calibrate electricity cost using historical mixes, PMP, and maximum entropy methods.

4.7 Chapter 7 Conclusion

In this chapter, I provide a brief summary of the findings and discuss the implications of the research on policy.

4.8 TIMELINE

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