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Greener on the Other Side: Assessing the Economic and Emissions Impacts of Demand-Side Technologies in Electricity Grids

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Greener on the Other Side: Assessing the Economic and Emissions Impacts of Demand-Side Technologies in Electricity Grids

by

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Abstract

The long-term goals of energy transitions are clear: to provide a secure, consistent, and cost-effective power supply that is sustainable with low Greenhouse Gas emissions. However, energy transitions around the world focus more simply on an increase in renewable energy and decrease in fossil fuel use. This focus on the generation side alone misses a key opportunity in the electricity system, demand-side technologies. Demand-side technologies are those capable of making controlled and deliberate changes to demand within the system. This thesis provides two case studies investigating demand-side technologies, firstly from the grid perspective and secondly from the perspective of a demand operator.

Grid scale impacts were explored in terms of marginal changes in the merit order, where fluctuation in supply and demand are accounted for by dispatching generators. Generators in the merit order were found to be far less organized by fuel-type than previously suggested in the literature. As a result, calculating emissions based on the marginal generator provided unreliable numbers. The economic case for demand side technologies in current grids shows potential, as a small reduction in demand across key hours had a major impact on the yearly cost of the grid.

On the operator side, demand-shifting technologies, solar PV, and a combination of solar with storage were compared based on their ability to achieve operational cost savings in different electricity grids. Grid price trends had a major impact on which technologies are most beneficial, with certain pricing patterns benefitting each technology differently. Allowing consumers access to grid wholesale prices, as well as providing pricing signals, would allow users to make informed decisions on what technology is best to invest in.

Together, the two studies show a clear case for the benefits of adopting demand-shifting technologies. Significant savings are available to the grid at large, as well as to the individual operator. During the energy transition, balancing the adoption of renewables with demand-shifting measures will be valuable in ensuring price and grid stability.

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List of Abbreviations

AEF	Average Emissions Factor
AESO	Alberta Electricity Systems Operator
CAISO	California Independent Systems Operator
CF	Capacity Factor
DS	Demand Shifting
DSM	Demand Side Management
EF	Emissions Factor
GDP	Gross Domestic Product
GHG	Greenhouse Gas
HAEF	Hourly Average Emissions Factor
HOEP	Hourly Ontario Electricity Price
IESO	(Ontario) Independent Electricity System Operator
kW	Kilowatt
MEF	Marginal Emissions Factor
MOE	Merit Order Effect
MW	Megawatt
MWh	Megawatt hour
NIR	National Inventory Report
NOX	Nitrogen Oxides
PV	Photovoltaic
SD	Standard Deviation
SOX	Sulfur Oxides

List of Variables

A	Area
C_{annual}	Annual Cost
c_{hourly}	Hourly Cost
C_{total}	Total Cost
D_{AIL}	Demand, Alberta Internal Load
D_{fluc}	Demand Fluctuation
E_e	Solar Irradiance
$E_{electrical}$	Electrical Energy
$E_{thermal}$	Thermal Energy
$G_{required}$	Generation Required
G_{wind}	Generation from Wind
M_{CO2}	Mass of Carbon Dioxide
η_{PV}	Efficiency of PV Panels
p_{margin}	Marginal Price
p_{spot}	Spot Price
P_{solar}	Power from solar PV

Chapter 1: Introduction

1.1 Motivation for Study

Global energy demand is on the rise, with primary energy consumption increasing steadily at an average of 1.5% per year over the past decade, and electricity consumption increasing faster at 2.5% per year [1]. This rise in demand comes with benefits to the global economy and quality of life; in highly developed countries, gross domestic product (GDP) is closely correlated with energy demand to the extent that “energy conservation may harm economic growth” [2]. In developing nations, a key to development is providing all citizens access to energy security, described as “uninterrupted availability of energy sources at affordable prices” [3]. However, the greenhouse gases (GHGs) emitted from the production and consumption of energy resources is the largest contributor to global climate change [4]. As a result, a shift from fossil-fuels to low-emitting electricity sources is underway across all sectors, instigating one of the largest global energy transitions in history. The goal of the transition is clear: to provide a secure, consistent, and cost-effective power supply that is sustainable with low GHG emissions. However, the path towards this goal comes with many challenges.

Solar and wind generation are the first and second highest growth rate energy technologies globally at 28.9% and 12.6% respectively for 2018 [1]. Increased adoption of these renewable technologies is a key goal of the energy transition, as both are able to provide power with no fuel consumption, no operational emissions, and at a price that is increasingly cost competitive [5]. However, both technologies provide power intermittently, predictably as in with the sunrise and sunset, and unpredictably with variations in weather. The generation efficiency of solar and wind is also geographically dependent, with generation being directly correlated with natural power resources. Concentrating renewable generators in only the highest generation areas compounds the effects of intermittency, as all renewables ramp up and down together, and can cause congestion on transmission lines [6]. To support the intermittency of solar and wind generation, technologies must be available which can balance supply and demand within the electricity grid.

In traditional electricity grids, fluctuations in demand or renewable generation are accounted for by ramping of other generators [7]. In Alberta, this ramping is most often in coal or natural gas plants. While this ramping provides a solution to intermittency, it decreases the efficiency of fossil-fueled generators, resulting in higher GHG emissions and generation costs [8]. Where available, hydro ramping can be a preferred option, where a decrease in efficiency does not come with increased fuel cost or emissions. Another common support technology is interties with neighboring grids. However, this requires robust transmission infrastructure and heavy dependence on interties can come at a high cost.

The challenges of intermittent generation compound the need for support technologies in the grid. However, many energy transitions around the world continue to focus mainly on generation alone, increasing renewables and decreasing fossil-fuel generation. This has led to a number of difficulties in transitioning countries. Examples include the 2016 blackouts in South Australia caused by a high share of wind generation [9]. As a reaction, the Hornsdale Power Reserve, the world's largest lithium ion battery, was constructed to level wind generation in the region [10]. High solar adoption in California has led to the "duck curve", where excess generation of solar during daylight hours drops to zero at sunset, requiring other generators to quickly ramp up to meet demand [11]. A report from the NREL finds that without "new market mechanisms" to incentivize grid stability services, "excessive curtailment of PV" will likely result [12]. The German Energiewende (Energy Transition) away from fossil-fueled and nuclear power and towards renewable power is one of the most ambitious early transitions. However, the rapid adoption of wind and solar energy has led to congestion not only in the North-South transmission lines in Germany, but in the transmission networks of neighboring Czech Republic, Austria, and Poland, requiring transmission development in the region to avoid "a serious problem in the grid" [13]. Furthermore, the feed-in tariffs used to promote renewables adoption have led to high economic costs which must be weighed with climate benefits [14]. In all three cases, difficulties arose due to a rapid increase in renewable generation without an equal increase or consideration towards support technologies.

On the demand side, policies towards energy transitions tend to focus on improving energy efficiency and reducing demand. However, a major opportunity exists to utilize demand to provide support and stability to current electricity grids and mitigate the challenges of adopting renewables. Demand-side technologies can provide stability to traditional grids by limiting demand, and subsequently price peaks and troughs within the system [15]. They can also assist with the adoption of renewables by actively aligning demand with renewable generation. The introduction of demand-side technologies adds a new aspect to electricity grids, as operators have the ability to alter their demand at will, depending on the current prices and/or emissions in the grid. While these changes are small, in the case of a single demand operator, they may have the potential to have a larger impact on the grid.

The term Demand Side Management (DSM) is used to refer to a wide array of technologies on the demand side. This can vary from passive technologies, such as reducing demand through increased efficiency of electrical appliances, to actively controlled demand. This thesis focuses on actively controlled DSM. Two key classes of technologies that provide the ability to actively control demand are energy storage and demand shifting (DS). Storage and DS provide economic and emissions benefits through similar means but different mechanisms. The means is the ability to shift demand such that it better aligns with the operator’s goals, whether that be using more renewable generation, balancing supply and demand, or reducing the cost of electricity. Storage achieves this by charging and discharging the storage system and is limited in operation by two key system characteristics: the power capacity of the storage system and the energy capacity, also referred to as discharge time. Storage can be used for other purposes as well, such as maintaining frequency and voltage stability in the grid or allowing consumers to become more independent from the grid. However, this thesis will focus on the use of storage for shifting demand in the grid. DS operates a different way, by scheduling demand at times that align with the operator’s goals while reducing or eliminating demand at other times. From the consumer perspective, both mechanisms ultimately provide the ability to control when electricity is purchased from the grid and when purchasing electricity is avoided. As a result of their mechanisms, storage and DSM are applicable in different situations. Where a consumer's demand can be shifted or scheduled without loss, DS is ideal. If a consistent power supply is necessary, storage allows operators to shift the timing of their grid access without a loss of productivity. However, storage systems come with a significant cost and the benefits of the system must outweigh these costs.

The potential benefits of demand-side technologies are apparent, but a lack of understanding of the scale of the benefits has resulted in limited deployment around the world. This thesis seeks to add to the knowledge on the potential impacts of demand-side technologies as they are integrated into electricity grids and adopted by individual consumers.

1.2 Objectives

Storage and DS add an aspect of controllability to the demand-side of electricity systems. This controllability is marginal, meaning demand changes act on the margin of the system and are minimal in comparison to system demand; and time-sensitive, with impacts of demand changes varying depending on when they are applied. As a result of these two qualities, the impacts of storage and DS are heavily influenced by the electricity grid they are acting in. Understanding the key drivers in grid price and emissions that lead to the largest impacts from demand shifting is critical to make informed decisions on when and how demand side technologies should be adopted. As the energy transition is expected to continue for decades [16], understanding the interactions between renewables, demand-side technologies, and current electricity grids is critical to ensure that the transition is beneficial not only in the end-goals, but during the transition period, as well. An essential aspect of assessing these impacts is understanding the underlying trends in grids that result in the largest impacts and, therefore, how positive impacts can be maximized and negative impacts mitigated. These underlying trends are often overlooked in the literature, omitting critical information that can help guide the energy transition.

This study explores the economic and GHG emissions impacts of demand-shifting technologies and solar PV in electricity grids. The impacts are explored from two perspectives: impacts to the grid at large with a case study of Alberta, and consumer-side cost savings through demand-shifting, solar PV, and a combination of the two. Two analysis methods are presented which focus on identifying the underlying trends in the grid that lead to largest cost and emissions impacts, along with quantifying those impacts. The first method focuses on the Alberta merit order, where generators submit power bids at various prices which are then dispatched to meet demand and set the price of electricity. Demand shifts are applied to determine how shifts affect the electricity price and grid emission factor when applied at different times. Through this analysis, the trends in merit order bids that most affect the price and emissions factors are identified. With the trends identified, the potential efficacy of demand-shifting technologies to contribute to the impacts is discussed. The second analysis method seeks to identify how timing patterns in grid price impact the cost savings of solar photovoltaic (PV) generation and demand-shifting technologies. The alignment of solar generation and price peaks in several grids are explored, as well as how demand-shifting technologies can improve this alignment or provide cost savings on their own. Demand-shifting is analyzed in terms of the perfect knowledge upper bound, meaning the price savings presented are the limit of what is theoretically achievable based on the pricing in each grid but not technically accessible due to the unpredictable nature of grid pricing. Through the upper bound, it is determined if and when demand-shifting can be competitive with solar PV. To visualize patterns in the grid price, a representative daily averages method is presented. This visualization is compared with the numerical results using full year hourly data to provide an explanation for the numerical results. The representative daily averages method is used to identify hourly and monthly pricing patterns in different grids and how these impact the cost savings of each technology.

The papers presented in this thesis answer two key questions relevant to demand-shifting technologies:

1. How can marginal demand-shifts impact the grid price and emissions factor?

2. How do grid pricing patterns impact the consumer cost-savings of solar PV and demand-shifting technologies?

1.3 Thesis Overview

This thesis contains two research papers, both of which will be submitted to academic journals in the near future. The papers assess how the impacts of demand-shifting are affected by electricity grid price and emissions characteristics. Each paper looks into the impacts from a different perspective, with the first focusing on grid-scale impacts and the second on consumer-scale impacts. The first is a case study of the Alberta electricity grid, with the generalization of results to other grids also discussed. The second study includes multiple grids with different pricing characteristics to determine how these characteristics impact results.

Chapter 2 assesses the impacts of demand-shifting on the grid-scale by applying marginal changes to the Alberta electricity merit order. In deregulated electricity markets, generators bid power capacity into the merit order at certain prices and these bids are dispatched to meet demand. The price of electricity and the emissions factor is then determined by the final generator dispatched, referred to as the marginal generator. By applying small or marginal shifts in demand, the final generator is shifted up or down the merit order to set a new price and emissions factor. Demand shifts were applied at different times in a variety of scenarios to determine when marginal changes have the largest impacts. The merit order was studied to determine how bids from different types of generators affect the price and emissions of the grid.

Chapter 3 assesses the potential cost savings of demand-shifting from the consumer perspective and compares these savings to those from solar PV and a combined system of PV with demand-shifting. The three technologies are explored only during the operation phase to determine how grid pricing patterns in Alberta (low solar PV grid), California (high solar PV grid), and Ontario (intermediate) affect the cost savings of each technology. A number of simplifying assumptions are made to make the three technologies comparable and determine what, if any, grid price patterns make one technology definitively superior over others. Demand-shifting is analyzed based on the higher-bound of what is theoretically achievable in different scenarios, not achievable in practical application. An analysis method referred to as the *representative daily average* method is used to most clearly identify the daily and monthly patterns in grid price. These patterns are then used to discuss when and why each technology is most effective and which should be invested in for the grids studied.

Chapter 4 combines the results of Chapters 2 and 3 to discuss the effectiveness of demand-shifting technologies and the grid situations where they would be most useful. The implications of the results on energy transitions is discussed, along with how demand-shifting technologies can play a role in the transition to renewables. The results of the thesis are put into the context of some specific demand-shifting technologies. Future work is also proposed to look into how policy mechanisms can incentivize the adoption of demand-shifting technologies.

References

[1] BP. (2019). *BP Statistical Review of World Energy*. 68th Edition. Available online: https://www.bp.com/content/dam/bp/business-sites/en/global/corporate/pdfs/energy-economics/statistical-review/bp-stats-review-2019-full-report.pdf Accessed Oct. 5th, 2019.

[2] Soytas, U., & Sari, R. (2003). Energy consumption and GDP: causality relationship in G-7 countries and emerging markets, *Energy Economics*, 25, 33–37.

[3] IEA International Energy Agency (n.d.) *What is Energy Security?* Available online: https://www.iea.org/topics/energysecurity/whatisenergysecurity/. Accessed Oct. 4th, 2019

[4] EPA United States Environmental Protection Agency (n.d.) *Global Greenhouse Gas Emissions Data.* Available online: https://www.epa.gov/ghgemissions/global-greenhouse-gas-emissions-data#Sector. Accessed Oct. 10th, 2019.

[5] USIEA United States Energy Information Administration (2019) *Levelized Cost and Levelized Avoided Cost of New Generation Resources in the Annual Energy Outlook 2019.*

[6] Hitaj, C. (2015). Location matters: The impact of renewable power on transmission congestion and emissions. *Energy Policy*, *86*, 1–16. https://doi.org/10.1016/j.enpol.2015.06.019

[7] Lew, D., Brinkman, G., Kumar, N., Besuner, P., Agan, D., & Lefton, S. (2012). Impacts of Wind and Solar on Emissions and Wear and Tear of Fossil-Fueled Generators. *IEEE Power and Energy Society General Meeting*, 1–8. https://doi.org/10.1109/PESGM.2012.6343967

[8] Kumar, N., Besuner, P., Lefton, S., Agan, D., and Hilleman, D. (2012) Power Plant Cycling Costs. *NREL National Renewable Energy Laboratory*. Available online: https://www.nrel.gov/docs/fy12osti/55433.pdf

[9] Yan, R., Saha, T. K. (2018). The Anatomy of the 2016 South Australia Blackout: A Catastrophic Event in a High Renewable Network. *IEEE Transactions on Power Systems*, *33*(5), 5374–5388. https://doi.org/10.1109/TPWRS.2018.2820150

[10] Hornsdale Power Reserve (n.d.) *Project Overview.* Available online: https://hornsdalepowerreserve.com.au/overview/

[11] California ISO (2016) *What the duck curve tells us about managing a green grid.* Available online: https://www.caiso.com/Documents/FlexibleResourcesHelpRenewables_FastFacts.pdf. Accessed September 26th, 2019.

[12] Denholm, P., O'Connell, M., Brinkman, G., and Jorgenson, J. (2015). Overgeneration from Solar Energy in California: A Field Guide to the Duck Chart. *NREL National Renewable Energy Laboratory.* Available online: https://www.nrel.gov/docs/fy16osti/65023.pdf

[13] Jan, M., Recka, L., Janda, K. (2018). Impact of German Energiewende on transmission lines in the central European region, *Energy Efficiency*, 11, 683–700.

[14] Kreuz, S., & Müsgens, F. (2017). The German Energiewende and its roll-out of renewable energies : An economic perspective, *Energy, 11*(2), 126–134. https://doi.org/10.1007/s11708-017-0467-5

[15] Strbac, G. (2008). Demand side management: Benefits and challenges, *Energy Policy*, 36, 4419–4426. https://doi.org/10.1016/j.enpol.2008.09.030

[16] Fouquet, R. (2010). The slow search for solutions: Lessons from historical energy transitions by sector and service, *Energy Policy*, *38*, 6586–6596. https://doi.org/10.1016/j.enpol.2010.06.029

Chapter 2: Spot Price and GHG Emissions Impacts of Marginal Changes in the Electricity Merit Order

Abstract

The global rise in intermittent renewable generation, along with the technologies that support renewables, present a need to understand how marginal changes in generation and demand impact the electricity grid. In order to integrate new technologies into traditional grids in an optimal manner, it is critical to quantify the economic and environmental impacts that will result. This study analyzed the Alberta electricity system to determine how marginal changes in the supply/demand balance affect the spot price and GHG emissions of the grid. The generation merit order was analyzed in high detail, along with demand, wind generation, interties, and reserves to determine the underlying trends that lead to the largest price and emissions fluctuations. Demand variations were used to determine the Merit Order Effect, where changes in the supply/demand balance shift the price up or down the generation merit order. It was found that opportunities to significantly change the price through small demand variations are rare but can have major impacts. A shift of ±100 MW, equivalent to roughly 1% of total demand, applied in 2% of hours studied, altered the yearly grid costs by ±15%, equivalent to roughly $600 Million in 2018. In terms of GHG emissions, the Marginal Emissions Factor (MEF) was quantified for a variety of demand scenarios and found to be less correlated with demand than previously suggested in the literature. The MEF is heavily dependent on the methods and assumptions used for calculations making the results highly varied. The MEF as a metric is valuable in qualitative analysis identifying sources of emissions in the grid. However, to report numerical values for grid emissions this study recommends the use of an Hourly Average Emissions Factor over the MEF.

2.1 Introduction

Electricity grids and markets are amongst the most complicated engineering and economic systems in the world. In large part, this complexity stems from the need to constantly match supply and demand in order to “keep the lights on” and maintain the physical security of transmission, generation, and distribution infrastructure [1]. The global increase in intermittent renewable energy generation [2] adds a further layer of complexity to the supply and demand balance. In response, a number of technologies are emerging intended to mitigate the impacts of intermittent generation and allow supply and demand to be matched most efficiently. Such technologies growing in popularity include large- and small-scale energy storage [3,4], demand side management (DSM) [5], optimization and smart-grids [6], and increasingly efficient ramping thermal generators [7,8]. These technologies operate on the margin of the electricity system, meaning they affect the supply/demand balance and the final generators dispatched directly, rather than having a more general impact on the system at large. These marginal technologies also present an aspect of controllability in the supply/demand balance, with the ability to vary their demand or generation at will. Along with renewable intermittency, it is important to understand how the timing of these variations impact the grid, both from an economic and environmental perspective.

Two common metrics used in marginal analysis are the Merit Order Effect (MOE), used to determine the impacts of marginal changes on the spot price [10-12,15], and the Marginal Emissions Factor (MEF), used to determine how grid Greenhouse Gas (GHG) emissions fluctuate with marginal changes [18-23]. The goal of using both metrics is to improve on analysis focusing on grid averages by quantifying how impacts change in response to time-sensitive fluctuations in demand or renewable generation. However, neither metric can represent the underlying traits of the electricity system that lead to marginal impacts, particularly traits in the generation merit order. Rather, past studies often rely upon assumptions that directly lead to conclusions, such as higher emitting generators being situated higher up in the merit order [18-20]. Understanding the underlying traits and trends that lead to the most significant impacts can allow grid operators to identify and mitigate the most harmful, and benefit from the most advantageous, marginal changes. This makes the underlying trends a critical research topic in identifying the potential impacts of marginal technologies and renewables adoption, along with quantifying the impacts through metrics.

Using published data on merit order bids from the Alberta Electricity System, this study provides an assessment of the system dynamics that lead to marginal changes in the spot price and GHG emissions of the Alberta grid. The merit order is analyzed in detail to provide a clear picture on how marginal changes lead to impacts at different times. The MOE and MEF are quantified on an hourly and yearly average basis to explore how time constraints affect the overall impacts. Results are used to assess the validity of the MOE and MEF as previously discussed in the academic literature, with results being generalized to other grids as well.

2.1.1 Spot Price Impacts of Marginal Changes in the Electricity System

In wholesale electricity markets, generators submit bids of power generation capacity at various prices and the system spot price is set by summing generators' bids until they meet current demand [9]. In traditional economic models, both supply and demand fluctuate to set the price; however, in electricity markets demand is typically inflexible and the price is simply set at the bid price of the final generator required to meet demand [5,9]. These fluctuations have a large influence on the overall cost of electricity from the grid as the price of the final generator dispatched is applied to all other generators as well. Intermittent generators add complexity to this, as fluctuations in generation must be accounted for along with fluctuations in demand. High generation from renewable sources leads to price decreases, while high demand causes price increases, and vice versa. High fluctuations in intermittent generation or demand result in high price variability, which can decrease investor confidence and increase the cost of the system at large [10]. Further background on the Alberta market can be found in section SI-2.A.

The Merit Order Effect (MOE) is a term used to describe fluctuations in price as generators are dispatched up and down the merit order. Particularly in the literature, the MOE is used to relate price changes to the adoption of renewables. Sensfuß et al. [11] use the MOE to discuss feed-in tariffs for wind power in Germany, finding that wind energy pushes the spot price down the merit order, resulting in significant savings to the overall system. Cludius et al. [12] further explores the effect in Germany, finding that system savings due to wind and PV generation are projected to reach 14-16 €/MWh in 2016.

This translates to savings of up to 45% on the average electricity spot price [13]. As of the writing of this paper, electricity price reductions are present but do not appear to consistently reach €14 [13,14]. Clò et al. [15] includes solar and wind in determining the MOE in Italy, similarly finding a decrease in average price but also noting a significant increase in price variability due to renewable penetration.

The literature on the economic effects of marginal changes is growing but incomplete. While studies on the MOE typically quantify the cost savings that result from wind and solar generation, they fail to account for the other side of intermittency, when generation falls and leads to price increases [11,12,15]. Furthermore, economic studies have not quantified impacts that could result from storage or demand-shifting, as examples. Further study is required to determine the full range of price impacts that can result from marginal changes in the supply and demand balance.

2.1.2 Metrics to Evaluate GHG Emissions from Electricity Systems

Average Emissions Factors (AEF) have been used to estimate the impacts of generating and consuming electricity in many applications. For example, National Inventory Reports (NIR) published yearly by 44 member countries quantify GHG emissions from electricity grids using an AEF based on average generation from different fuel sources in the country [16]. Within Canada, AEFs published for each province are used to calculate and publish total national GHG emissions and provide incentives towards renewable energy adoption [17]. In this way, the AEF is used to quantify GHG reductions resulting from a decrease in electricity demand in a province, or an increase in low-emitting generation. In the last two decades, it was recognized that the AEF is not always appropriate largely due to a failure to account for time-sensitive changes in grid emissions [18-22]. Seeking to amend this, the Marginal Emissions Factor (MEF) was proposed. The MEF is distinct from the AEF in that it considers only the *change* in demand and generation, and subsequently the GHG emissions, on the scale of a single action rather than for the grid system at large. As such, an operator who can cut demand may be rewarded more emissions reductions at specific times or in situations where generation is being cut from higher emitting generators.

The literature shows a variety of ways to calculate the MEF and similar variety in the resulting findings. Bettle et al. [18] develop an “implied merit order” based on data from grid generation in England and Wales. This implied merit order places higher emitting units higher up in the merit order, resulting in significantly higher emissions reductions from marginal interventions than is suggested by the AEF. Hawkes [19] compares studies using both merit order and historical data methods and calculates the MEF based on regression analysis of the AEF and system load. The average MEF is found to be significantly higher than the AEF for Great Britain. Farhat et al. [20] provides MEFs for each Canadian province based on the fuel use in the final 1 kW produced in the marginal generator. The MEFs for each province are then averaged over one year. Siler-Evans et al. [21] includes NOX and SOX emissions in MEF, with calculations based on the change in fossil-fueled generation and resulting emissions from hour to hour. The MEFs are then used to determine the emissions of regularly operated electrical appliances, with results again averaged over one year, and show that the relationship between the AEF and MEF is highly dependent on the grid generation mix. Zheng et al. [22] include ramping in the MEF calculation and find that ramping of marginal fossil-fueled generators results in higher MEF than previously predicted; however, the MEF can also be significantly lower than the AEF depending on the marginal generation type. Lastly, Oliveira [23] provides a review of previous models calculating MEF for renewable generation. Findings demonstrate large differences in MEF and associated impacts depending on the geography, grid mix, and calculation model largely due to “small differences on the hourly level compound[ing] over the lifetime of the project.” [23]

There seems to be agreement in the literature that the MEF is superior to the AEF in determining the impacts on emissions from marginal interventions. However, consistent deviation in results and calculation methods demonstrates that there is a clear need for further understanding of the mechanisms that drive change in the MEF. A significant contributor to the inconsistencies in the literature is the lack of data on the merit order, which leads to speculation on how marginal changes will actually impact the generation mix [18-23]. Furthermore, changes in demand are shown to have a consistent impact on average MEF values, which suggests some complexity within the system is overlooked. Averaged values may misrepresent the variability of real-time changes in MEF, omitting critical information on when and why interventions have the most significant effects [23].

2.2 Methods

The key objective of the study is to provide an analysis of the Alberta electricity merit order to determine how marginal changes in demand impact the costs and GHG emissions of the grid in different hours of the day and months of the year. The merit order is analyzed at the individual bid level providing a high level of detail on the breakdown of generation types throughout the merit order. This detail allows trends to be identified within the merit order to give context to cost and emissions results. Based on these trends, results are generalized to other grids.

The electricity market is simulated to shift the supply and demand balance up and down the merit order in a number of hours throughout recent years. Spot price and MEF are calculated at each studied hour for the baseline, a shift up the merit order (as in increased demand) and a shift down the merit order (as in decreased demand). Costs are determined based on the spot price of the marginal generator, the final generator dispatched to meet demand, which sets the price received by all generators. Emissions are calculated based on the heat rate and fuel type of the marginal generator. A number of scenarios are developed to explore the impacts of shifts up and down the merit order with different timing and regularity to see if any consistent patterns develop.

2.2.1 Data Sources

Data was collected from the Alberta Electricity Systems Operator (AESO) on the Alberta Internal Load (AIL) [24], system marginal price [25], generation from individual units [26], and merit order bid power quantities and prices [27]. Data on active and standby reserves and imports/exports over interties with Montana, British Columbia, and Saskatchewan was accessed through NRGStream [28]. Data on wind was collected from individual generators in the province, aggregated, and compared to plots published publicly through the AESO website for verification [29].

2.2.2 Treatment of Merit Order Data

AESO currently publishes all merit order bids with a 2-month delay. For this study, the hourly merit order bids were collected for the months of January, July, April, and October representing winter, summer, and shoulder months respectively. Data was collected for these months from 2014-2018 for 24 hours per day over 8 days per month, equivalent to 32 days per year for the study. The merit order bids were arranged in terms of bid price, bid power, and whether or not bids were dispatched at any given time. Generators were divided into seven categories as provided by AESO: Coal, Simple Cycle Natural Gas (NG), Combined Cycle NG, Cogeneration NG, Hydro, Wind, and Biomass and other. Note that while bids were assigned to these categories, each individual bid and generator was accounted for in all calculations and figures. All bids were aggregated based on price and are depicted in Figures 1 and 2 of section 2.3.

2.2.3 Treatment of Wind, Intertie, and Reserve Data

Based on merit order data, wind generators began bidding into the merit order in 2017 [35]. Wind bids must be treated differently than traditional generators due to generation depending on weather and resource availability. In the current merit order system, all wind is bid in at $0.00 totaling roughly 1,400-1,500 MW bid hourly, with small fluctuations in bid capacity due to temporary shutdowns of turbines. These bids are always dispatched in the merit order based on their bid value, but this dispatch is not reflected in actual generation. Furthermore, interties must be accounted for as imports/exports rarely appear in the merit order but often account for ±1,000 MW to the grid (with imports being positive generation and exports negative generation). Wind and interties are accounted for by removing the 1,400-1,500 MW of wind bids from the merit order and including historical data on wind generation (G_{wind}) and interties ($G_{interties}$) to adjust the generation required from the merit order ($G_{required}$) according to:

$$G_{required} = D_{AIL} - G_{Wind} - G_{interties} \qquad (1)$$

Despite these adjustments, there always exists some discrepancy in the required generation and actual generation from the merit order. This is largely due to two factors: first, some private data, most importantly on Power Purchase Agreements (PPAs) and other “behind the fence” generation, cannot be accounted for accurately. Secondly, the merit order data is on the hourly level while the supply and demand balance is adjusted each minute. These factors are further discussed in section SI-2.B.

2.2.4 Determining Marginal Generators

The marginal generator was determined by summing the merit order bids until the sum of generation bids matched with the generation required in (1). In this method, the independent variable is hourly AIL demand (D_{AIL}) (and subsequently the required generation) and the dependent variable is the marginal price (p_{margin}). These are shown in bold and italics respectively in:

$$\sum_{\mathrm{p}=\$0}^{p_{margin}} \mathrm{bids}_{\mathrm{p}} = \mathbf{G_{required}} \qquad (2)$$

As mentioned in section 2.2.3, some generation sources are not reflected in the merit order and so the total demand and merit order generation will never align perfectly. To account for this, a second calculation method was used with the merit order being summed to the spot price, rather than the required generation. It was found that while the magnitudes of the final values changed slightly, the patterns discussed in the results remained the same. As the results were similar, only the primary method is presented in the body of the report. The secondary results are further discussed in section SI-2.B.

2.2.5 Applying Marginal Shifts in the Merit Order

Demand fluctuations are applied to simulate shifts in the merit order and the resulting cost and emissions impacts for each hour of the study period. The marginal generator and price are determined at each hour as discussed in section 2.2.4, and again for demand changes of +100 MW and – 100 MW, giving three possible marginal generators at any given hour. ±100 MW is chosen as the demand change quantity so as to be higher than the average bid power (63 MW over the studied period) and therefore resulting in a change in marginal generator in most hours. While a marginal intervention of this size would likely require coordinated operation, an intervention large enough to alter the marginal generator demonstrates the impacts on cost and emissions that could be achieved in any hour. With these demand fluctuations the total required generation in the merit order is given by:

$$\sum_{\mathrm{p=\$0}}^{\mathbf{p_{margin}}} \mathrm{bids_p} = G_{required} - \mathrm{D_{fluc}};\ \text{where } \mathrm{D_{fluc}} = \begin{cases} +100\ MW \\ 0 \\ -100\ MW \end{cases} \qquad (3)$$

Interventions up to ±100 MW (i.e. 0 < $\mathrm{D_{fluc}}$ < 100 MW), as well as over 100 MW are not considered in this study as the objective is to determine the effects of minimal shifts in the merit order occurring regularly. Different scales of demand shifts will be a topic of future research.

2.2.6 Determination of Economic Impacts

For each hour in the study period, the spot price was calculated for the actual demand, demand + 100 MW, and demand – 100 MW. The variation in demand causes a shift up or down the merit order to determine the spot price in a given hour, along with the difference between the three spot prices.

The ± 100MW demand fluctuation was chosen to regularly change the marginal generator, and therefore the spot price. However, the magnitude of spot price changes vary significantly from hour to hour across the study period. Based on this, it is practical to determine the situations and hours when impacts are most significant and how often these hours occur. To accomplish this, the extent of price change in each hour was compared to a cut-off price point (c); meaning the demand change would only be applied if the resulting price change was above c. The cut-offs displayed in Table 3 are \$0.00 (i.e. any price change), a minimum price change of \$5/MWh, and a minimum change of \$50/MWh. These values were chosen to provide a baseline (\$0.00), rough optimal (\$50), and mid-optimal (\$5) cut-offs. A full range of results based on price cut-offs can be seen in section SI-2.B. The hourly spot price and total grid costs are then calculated by:

$$C_{total} = p_{spot} * G_{required};\ where\ p_{spot} = \begin{cases} p_{-100MW}, & |p_{-100MW} - p_{actual}| \geq c \\ p_{actual}, & |p_{-100MW} - p_{actual}| < c \end{cases} \qquad (4)$$

$$C_{annual} = \sum_{i=1}^{8760} p_{spot,i} * G_{required,i} \qquad (5)$$

Through (5) we can determine when marginal interventions are economically most beneficial and how frequently these beneficial events occur.

2.2.7 Determination of Marginal Emissions Factor

The MEF was calculated based on the marginal generator as identified by the merit order. GHG Emissions for renewable sources, including wind, hydro, biomass and other, were considered to be zero. Only operational emissions were accounted for with thermal generators. In the rare case that the spot price is $0.00, all generators bid in at $0.00 were considered the marginal generator and MEF was calculated based on total bids from each generator similar to the average emissions factor.

For all thermal generators, the emissions factor was calculated based on the heat rates, fuel type, and output of the individual generators according to:

$$EF\ [\frac{kg}{MWh}] = Heat\ Rate * Fuel\ Carbon\ Content;$$

$$EF\left[\frac{kg}{MWh}\right] = \frac{E_{thermal,in}}{E_{electrical,out}} * \frac{M_{CO2}}{E_{thermal,fuel\ type}} \qquad (6)$$

The MEF was then calculated based on the EF of the marginal generator resulting from actual demand, demand + 100 MW, and demand – 100 MW. The three are used to develop the scenarios introduced in section 2.2.9.

2.2.8 Effects of Ramping and Part-Loading

Ramping generators operate with a lower efficiency than similar generators operated with consistent output. This results in a higher fuel consumption and therefore higher GHG emissions per MWh generated. Estimates for increased fuel use during ramping range from 1.1 to 2 times fuel use during constant output [30,31]. For this study, a multiplier of 1.2 in fuel usage is chosen as it was shown to be representative of generators in Alberta [30]. This increase is applied when ramping would be required by the marginal generator, here defined as when the marginal demand is changed by over 100 MW over one hour or the change in marginal demand results in the dispatching of a new generator.

In general, generators operate most efficiently at their peak power capacity and suffer efficiency losses with part-loading similar to ramping. As most bids on the margin are quite small, the demand shifts applied in the analysis will only slightly change the overall loading of generators in any given hour. Therefore, the effects of part-loading are not included in the analysis as they will not have a significant effect on results.

2.2.9 Marginal Demand Change Scenario Development

Seven scenarios were developed to explore how the merit order dynamics affect consistency in the price and MEF impacts. The scenarios demonstrate the price and MEF that would result from marginal changes applied across different hours of the day and with different regularity. The purpose of the different scenarios is to determine if demand shifts applied at different times will have similar impacts on the price and MEF or if the timing of demand shifts has a marked change in these impacts. Scenario 1 is the baseline, with the price and MEF calculated based only on published demand data. Scenario 2 demonstrates 100 MW of demand subtracted at all hours and Scenario 3 100 MW of demand added at all hours. Scenarios 2 and 3 are not meant to show time sensitive impacts. Rather, they will show the impacts of consistent changes in demand, and address questions such as: will increased demand always lead to increased MEF and price? A practical example developed from the literature is peak-shaving [32,33], where demand is removed during hours of peak system demand and reintroduced in off-peak times. In theory, this would allow an operator to harness a lower price, reducing total costs, and lower MEF, reducing the emissions in meeting their electricity needs. The validity of peak-shaving in reducing costs and emissions is explored in Scenario 4. Counter to this is Scenario 5, referred to as anti-peak-shaving, where demand is increased during times of peak demand and removed during off-peak. Such an action may be undertaken by an average demand operator who does not consider grid effects and it is valuable to identify how marginal impacts in the grid change during these times. Scenario 6 demonstrates the optimal MEF, where addition or subtraction of demand is only chosen in hours where it provides the lowest MEF. Lastly, Scenario 7 provides a contrast to Scenario 6 where addition or removal is only chosen in hours where it increases the MEF to demonstrate the most harmful impact possible from marginal changes. Table 1 provides a summary of the seven scenarios.

Table 1: Summary of the seven scenarios describing the hours of the day that baseline demand, subtracted demand, and added demand are used to determine the marginal generator and price. Scenarios 6 and 7 are variable as demand is chosen based on the lowest and highest emitting generator, respectively.

Scenario	Description	Hours Actual Demand	Hours subtracted demand (-100 MW)	Hours added demand (+100 MW)
1	Baseline	1-24	0	0
2	Demand Subtraction	0	1-24	0
3	Demand Addition	0	0	1-24
4	Peak-shaving	6-14	14-22	22-6
5	Anti-Peak-shaving	6-14	22-6	14-22
6	Optimal MEF	Variable	Variable	Variable
7	Anti-Optimal MEF	Variable	Variable	Variable

The hourly MEFs are aggregated over one year and presented for 2017 and 2018, as well as over individual days to discuss findings in Section 2.3.

2.3 Results and Discussion

To analyze the impacts of marginal changes within the merit order, it is first important to understand the merit order itself. For the purposes of this study, the merit order is divided into three sections, baseload, marginal, and peaking. Baseload generators make up the majority of generation at any given time. In Alberta, a large portion of the baseload is comprised of generators bidding at $0.00. These bids are presented in Figure 1. Figure 2 depicts non-zero dollar bids which make up almost all of activity in the merit order. Patterns from marginal changes in demand are discussed. Lastly, quantitative results are presented for the seven scenarios for the MOE and MEF and how these are effected by the marginal demand changes.

2.3.1 $0.00 Bid Generation in the Merit Order

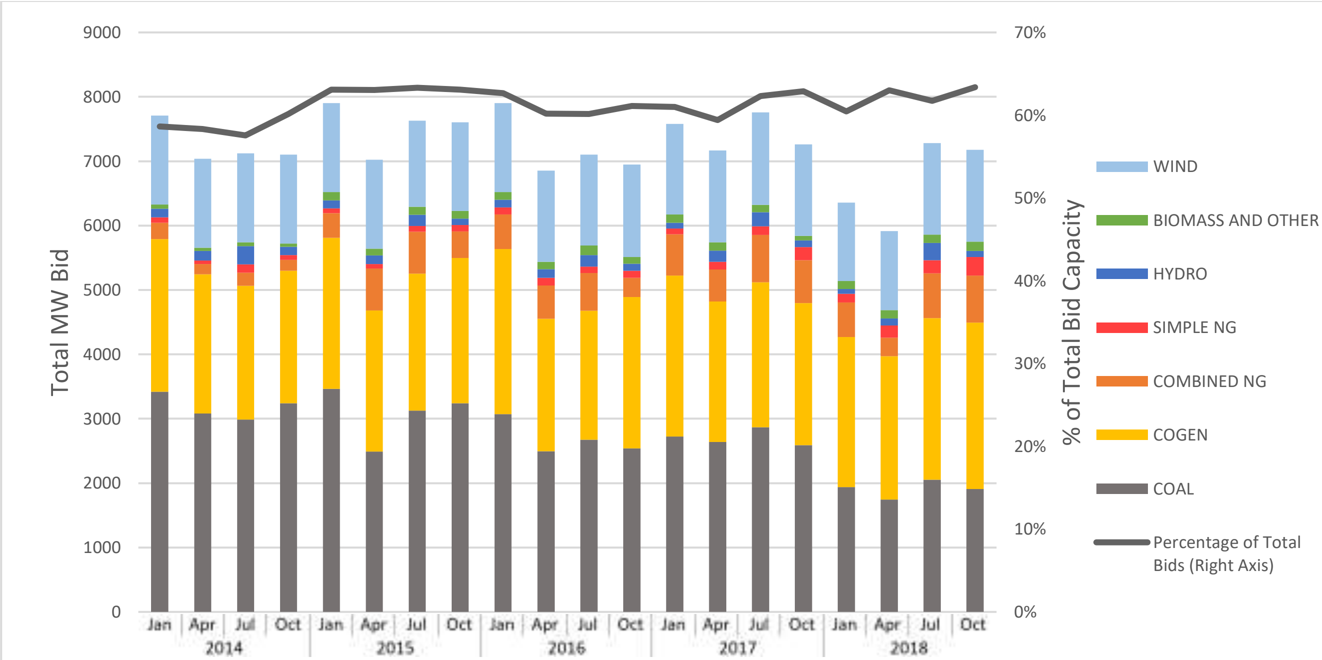

Figure 1: $0.00 bids for the period of January 2014-October 2018. The bars belong to the left-hand axis, showing the total MW bid for each generation type. The line belongs to the right-hand axis, showing percentage of total bids at $0.00. Note that wind bids prior to 2017 are estimated based on total capacity as wind bids did not appear until 2017.

As demonstrated in Figure 1, roughly 60% of Alberta's electricity generation capacity bids are bid at $0.00. In terms of energy generation, these bids cover on average 80-85% of the total generation required in any hour. These baseload generators therefore dominate the grid in terms of emissions, but have little impact in terms of price. Apart from seasonal variations, the $0.00 bids are seen to be relatively stable over the period 2014-2018, both in total generation and in generation from different fuel types. Entering 2018, a shift is seen with a decrease of 783 MW from coal bids, 158 MW from Cogen, and 105 MW from Combined Cycle NG in January 2018 compared to January 2017. The majority of this decrease is reflected in bids at higher price points in the merit order. Due to an increased share of NG over coal, the emissions factor (in terms of generation alone) for $0.00 bids drops from 650 kgCO2e/MWh to 600 kgCO2e/MWh during the same period. While this is an improvement for this portion of the merit order, shifting these bids up the merit order from the baseload to marginal zones results in an increase in prices and a higher likelihood of coal generators ramping. This subsequently leads to lower efficiencies and higher emissions from coal plants [30]. This shift from coal to natural gas as baseload is likely a result of low natural gas prices, as well as policies promoting the shift away from coal [34]. Further discussion on the breakdown of generation type within the baseload, marginal, and peaking zones can be found in section SI-2.A.

2.3.2 Analysis of Merit Order Bids

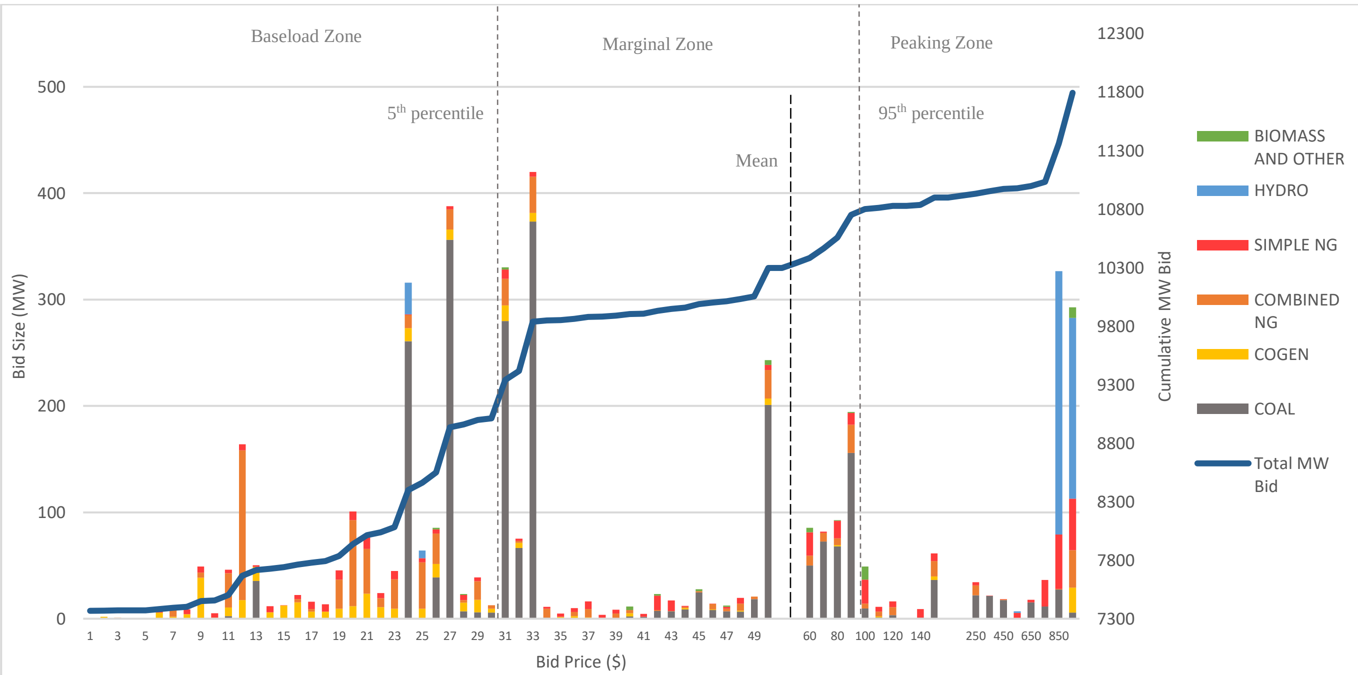

Figure 2: Power bids allocated based on bid price for the month of October 2018. Bars belong to the left-hand axis, showing the power capacity of bids in MW. The line belongs to the right-hand axis, showing the sum of the bids up to that price. The vertical lines represent, from left to right, the 5th percentile, mean, and 95th percentile of spot price in October 2018. The marginal zone is defined between the 5th and 95th percentile where price regularly fluctuates, baseload is below the 5th percentile, and peaking above the 95th. Note that the right axis beings at 7,300 MW where $0.00 bids end and the breaks in the x-axis scale at $50 and $150.

Figure 2 displays the merit order bids, excluding $0.00 bids, aggregated for the month of October 2018. The figure is split into three regions, baseload which is almost always dispatched (bids lower than the 5th percentile of spot price), peaking which are very rarely dispatched (bids above the 95th percentile of spot price), and marginal where regular changes in dispatch occur (between the 5th and 95th percentile). Contrary to the literature reviewed on the MEF [18-23], the generation mix is less organized within the merit order than previous analysis suggests. Bids from different fuel types are distributed widely across price points. This refutes previous findings that the MEF will continuously rise with demand as higher emitting fuel types take over from lower emitters as demand moves up the merit order [20]. A notable difference exists between the baseload zone, which is dominated by NG generation, and the marginal zone, which is dominated by coal. However, since the marginal generator very rarely falls into the baseload zone, this would not affect the MEF. This demonstrates a notable difference between the AEF, which is representative of all active generators, and the MEF which only represents the few generators on the margin.

The mean spot price over 2018 was $48; however, the price distribution is highly skewed with prices above $100 occurring less than 5% of the time but increasing the mean significantly. Precarious trends appear when a small generation capacity is spread over a wide price range, resulting in large fluctuations in the spot price with a relatively small fluctuations in demand. This trend can be observed in Figure 2 when the accumulated bids line (solid line) has a low-slope, as can be seen between $33 and $49 on the x-axis and again between $100 and $850. The trend is particularly influential at the higher price points, where a small increase in demand can increase the price by $100s. Further discussion on the recent trends developing in the merit order can be found in section SI-2.C.

2.3.3 Spot Price Impacts of Marginal Demand Changes

For verification, the baseline values calculated from the merit order are compared to the values stated in the AESO Market Statistics for 2017 [35] and 2018 [36]. There is a 2.7% and 4.2% discrepancy for 2017 and 2018 respectively. These small discrepancies likely result from generation not accounted for in the merit order, such as reserves and PPAs previously discussed.

In simplest terms, shifting load down the merit order will always result in a price reduction while shifting demand up results in a price increase. In fact, the correlation coefficient between demand and price, based on hourly average values, was 0.93 in 2017 and 0.82 for 2018. However, while this correlation exists over the course of the year, individual days show far less correlation with coefficients as low as 0.05. Therefore, it is important to understand when changes in demand have the largest impact on the price and overall costs of the grid.

Comparing the baseline (Scenario 1) for 2017 and 2018 in Table 2, the spot price has increased with the price in 2018 being 124% higher than in 2017. This comes despite only a 4% increase in average demand [35,36]. Scenarios 2 and 3 represent the minimum and maximum possible price impacts of 100 MW of demand change, with Scenario 2 always lowering demand and 3 always increasing it. The spot price in 2017 is more stable than that in 2018, with the minimum price only 4% lower than the baseline compared to 18% for 2018. Further discussion on the changes from 2017 to 2018 across the merit order can be found in section SI-2.C.

Table 2: Average spot price over study period with the merit order effect taken into account for each of the seven scenarios.

	Scenario	**1**	**2**	**3**	**4**	**5**	**6**	**7**
2017	Avg. Spot Price	$21.57	$20.73	$24.50	$21.40	$23.73	$22.11	$21.86
	Change from baseline	-	-4%	14%	-1%	10%	3%	1%
2018	Avg. Spot Price	$48.25	$39.74	$57.21	$42.62	$50.99	$49.92	$46.75
	Change from baseline	-	-18%	19%	-12%	6%	3%	-3%

Scenario 4 shows that the peak-shaving strategy is effective economically, with a price reduction of 1% in 2017 and 12% in 2018. Scenario 5 shows the opposite; with anti-peak-shaving increasing the price significantly, by 10% and 6% in 2017 and 2018 respectively. Prices in 2018 fluctuated more in magnitude as compared to 2017, resulting in higher savings potential for both the demand subtraction and peak-shaving scenario. Lastly, scenarios 6 and 7, which are intended to maximize impacts on MEF, show little change in regards to price, suggesting that the price and MEF have limited correlation.

Prices fluctuate most in areas where small generation capacity is bid over a wide price range, particularly at high prices. Table 3 demonstrates how much these high price fluctuations contribute to overall grid cost in 2018 and how small changes in demand can create savings. As per (5) the annual grid cost is calculated based on an average demand of 9,741 MW [36]. The baseline cost was calculated at $4.12 Billion with an average price of $48.25/MWh. Reducing demand by 100 MW in every hour of the study period translates to an average price of $39.74/MWh, reducing total cost by 18% or $725 Million. Adding a price cut-off of $5, meaning demand is only reduced in hours where the price savings are $5/MWh or higher, results in only a small reduction in total savings at 16%. Most notably, a price cut-off of $50 results in 14% savings, equivalent to $580 Million, with demand reduced in only 1.7% of hours during the study period, equivalent to 160 hours per year. It is important to note that the price cut-off results are assuming a perfect knowledge scenario, where an operator would be able to accurately predict the price in the coming hours and control their demand accordingly. In reality, this prediction is much more difficult. Subsequently, the results presented should be seen as the theoretical high bound.

Table 3: Average spot price and total grid costs with demand addition and reduction applied at price cut-offs.

Intervention	**Price Cut-off**	**Average 2018 Price ($/MWh)**	**Total Grid Cost ($Billions)**	**Change from Baseline**	**Demand Change Requirement (% of studied hours)**
Baseline (Price)	-	$48.25	$4.12	-	-
Reduced	$0	$39.74	$3.39	-18%	77%
Demand	$5	$40.34	$3.44	-16%	10%
	$50	$41.48	$3.54	-14%	1.7%
Added	$0	$57.21	$4.88	19%	79%
Demand	$5	$56.33	$4.81	17%	11%
	$50	$55.37	$4.72	15%	2.6%

The results in Table 3 show that the vast majority of potential cost savings occur in a few specific instances when small changes in demand can greatly influence the price. These instances can be the result of multiple causes, including drops in wind generation, spikes in demand, or unexpected outages in generators, transmission lines, or interties which result in demand being shifted to the top of the merit order [26,37]. Marginal demand changes at these times can significantly influence the spot price, with a total cost savings potential of $580 Million. However, the cost savings show only one side of the story. An increase in demand at these inopportune times bears the risk of price increases similar in magnitude. 100 MW of additional demand at these high risk times translates to a 15% increase in total yearly cost, equivalent to $600 Million. Outside of these opportunities to influence the price, Table 3 shows that the merit order effect is limited, with marginal demand changes applied the other 98% of the time causing only an additional 4% price change.

2.3.4 MEF Impacts of Marginal Demand Changes

Initial observations of the MEF show a decrease in the baseline MEF from 2017 to 2018. This is partially due to the marginal generator being coal less often (62% in 2017 to 57% in 2018) but more so a result of lower emitting coal generators appearing more prevalently on the margin than their higher emitting counterparts. This demonstrates that even within fuel types, small changes such as generator efficiency can have a significant impact on MEF at any given time.

Table 4: Impacts of the DSM scenarios on the yearly average MEF for 2017 and 2018 for the 7 Demand Scenarios. Negative values represent reductions in emissions factor.

	Scenario	**1**	**2**	**3**	**4**	**5**	**6**	**7**
2017	MEF (kg /MWh)	803	862	863	857	832	644	1023
	Change from baseline	-	7%	7%	7%	4%	-20%	28%
2018	MEF (kg /MWh)	748	719	773	727	751	554	928
	Change from baseline	-	-4%	3%	-3%	0%	-26%	24%

Looking deeper into the marginal demand change scenarios, there are a number of key observations which stem from a lack of consistency in the results. Scenario 2 (demand subtracted) sees the MEF increase 7% in 2017 but decrease 4% in 2018. Scenario 3 (demand added), which shows the direct opposite of Scenario 2, provides near identical results in 2017 but a change of sign in 2018 with an increase in MEF. This result follows from the observations in section 2.3.2 and Figure 2 that the merit order is not consistently organized by generation type. Changes in the MEF depend on the marginal generator and the merit order bids that surround it, which can vary at any given time. The peak-shaving Scenario 4 shows opposite signs between 2017 and 2018. Furthermore, Scenario 5 (anti-peak-shaving) shows similar results to its opposite within a few percentage points.

An explanation for the inconsistencies in the MEF results lies in comparing the average bid capacity within the marginal zone, 63 MW (for 2018) with hourly fluctuations in demand, averaging ±130

MW and reaching as high as ± 600 MW for 2018. This range encompasses a large number of generation bids with varied fuel types (and generation methods) that could all represent the MEF depending on demand in any given hour. In other words, a demand change of 130 MW versus a demand change of 230 MW can result in a drastically different MEF, with both demand changes being roughly equal in probability. Furthermore, the merit order can shift from day to day, so a change that leads to one MEF one day can lead to another the next. When looking into the average hourly MEF there are no consistent patterns that suggest demand applied at any hour will result in lower emissions than demand applied at any other hour. This is further demonstrated by the selected daily MEF results demonstrated in Table 5.

Table 5: Impacts of the DSM scenarios for specific days during the study period. Days are deliberately chosen to demonstrate and contrast high and low impacts across the different scenarios.

	Scenario	**1**	**2**	**3**	**4**	**5**	**6**	**7**
July 30th, 2017	MEF (kg /MWh)	809	822	788	898	800	496	1059
	Change from baseline	-	2%	-3%	11%	-1%	-39%	31%
July 30th, 2018	MEF (kg /MWh)	677	845	767	788	755	486	1046
	Change from baseline	-	25%	13%	16%	11%	-28%	54%
October 20th, 2018	MEF (kg /MWh)	833	702	769	748	804	617	922
	Change from baseline	-	-16%	-8%	-10%	-3%	-26%	11%

Table 5 demonstrates that, on a given day, interventions can have significantly varied effects in both the positive and negative directions. July 30th, 2017 shows that a peak-shaving strategy (Scenario 4) results in higher emissions than the baseline while adding load at peak times results in no significant change. The same date in 2018 shows that any demand change results in a higher emissions than the baseline, contrasted with October 20th, 2018 where any intervention reduces emissions from the baseline. This suggests that analysis of the MEF conducted with different data within the same grid can come to different conclusions on when marginal demand changes are effective and how effective they are, both in terms of magnitude and sign.

Scenarios 6 and 7 demonstrate the demand shifts that minimize or maximizes the MEF, respectively. Both Tables 4 and 5 show that ideal demand can significantly reduce the MEF, with a 26% reduction for the yearly MEF for 2018, while the worst case scenario for demand causes a large increase of 24% for 2018. However, these emissions results may not be representative of actual emissions savings potential. Comparing the magnitude of the Scenario 6 and 7 results with the much more muted results of Scenarios 2-5, it is inferred that while emissions savings may be available, the opportunities are not consistent or predictable on a daily basis. Reductions in MEF are achieved by both increasing and decreasing demand, depending on the time. Scenario 7 demonstrates that if these actions are done at the wrong time significant increases in the MEF are likely.

2.3.5 An Alternative Metric to the MEF – Hourly (H)AEF

There is a clear need in the literature for a metric that demonstrates the impact of marginal changes in the grid on GHG emissions. However, the marginal emissions factor (MEF) is seen to vary too significantly based on small, difficult-to-predict changes in parameters to provide meaningful *quantitative* emissions results. The marginal generator type is far less consistent than previously identified in the literature [18-22]. Furthermore, basing emissions solely on the marginal generator omits many other aspects of the grid, such as emissions reductions in baseload generation or increases in renewables.

In comparing MEF with AEF it is important to contextualize the margin within the system at large. Baseload generators are by far the largest contributor to emissions in Alberta, typically covering over 80-85% of total power generation. The baseload share in Alberta is high compared to many other grids, but in any grid generators that operate at (nearly) all times will have a major impact on emissions. In simplest terms for thermal generation, a reduction in demand will result in emissions savings due to avoided generation and an increase in demand result in an increase in emissions. This is dictated by the AEF [16,17], but does not account for changes in the generation mix that occur across hours and days. While shifting demand from one hour to another may result in reductions in MEF, the actual emissions reductions are minimal in terms of the grid at large and may be misrepresented due to uncertainty in MEF calculations, as suggested by the results of this study and previous literature [25].

Alternatively, this paper recommends the use an Hourly Average Emissions Factor (HAEF) calculated based on all generators, up to and including the marginal generator. This is defined as

$$HAEF_{Grid} = \sum_{i=0}^{margin} EF_{Generator,i} \qquad (7)$$

Using the HAEF will have two key advantages: First, the HAEF is much less volatile than the MEF allowing for more consistent quantitative conclusions. Second, the HAEF will be useful in identifying hours with low emissions to provide a basis for incentives towards renewables or DSM without the uncertainty seen in the MEF.

Table 6: Impacts of the DSM scenarios on the yearly average HAEF for 2017 and 2018 for the 7 Demand Scenarios.

	Scenario	**1**	**2**	**3**	**4**	**5**	**6**	**7**
2017	HAEF (kg /MWh)	720	723	717	713	722	690	750
	Change from baseline	-	0%	0%	-1%	0%	-4%	4%
2018	HAEF (kg /MWh)	730	724	725	742	732	703	757
	Change from baseline	-	-1%	-1%	2%	0%	-4%	4%

Table 6 shows much less fluctuation in the yearly average HAEF as compared to the MEF. Looking into the optimal and anti-optimal emissions scenarios, calculations show variability of roughly 4% in either direction. This does limit the amount of emission reductions available through small demand changes based on the HAEF metric, but is likely more reflective of actual emissions reductions achieved.

The MEF is still useful as comparing AEF with MEF identifies whether baseload or marginal generators are contributing most to grid emissions [21]. Furthermore, the MEF is valuable when analyzed in specific situations, such as preventing activation or ramping from an individual generator, capturing more generation from a renewable source, or reducing constraints on a specific transmission line (as examples). However, when aggregated to the scale of the grid, the MEF is seen to be too volatile to be used to quantify emissions.

2.3.6 Applicability of Results to Other Electricity Grids

The Alberta electricity grid has a number of unique qualities, raising the question of how the MOE and MEF results would translate to other grid systems. As discussed in section 2.2.1, the Alberta grid is deregulated with generators bidding into a merit order and is currently thermally dominated with roughly 90% of generation coming from coal and natural gas [41]. In a similar system, it can be inferred that the results in this study would apply; however, regulated and non-thermally dominated systems may defer.

A steadily increasing number of electricity markets around the world are operated similar to Alberta's deregulated model with bids dispatched in a merit order based on economics and security constraints. This includes all major markets in the US and Europe [42,43]. Any grid operating with the merit order model would be exposed to similar patterns as those seen in Alberta, with small power capacity bid over large price ranges leading to high changes in price due to small changes in demand. Furthermore, Alberta has a relatively stable demand profile due to large industrial load. Other grids with higher demand fluctuations could see the price results exaggerated. In a number of power markets, transmission constraints play a larger role resulting in different prices at various nodes of the system. In this case, the impacts of shifting demand at one node could be far greater than at others. As intermittent renewable generation increases, the price can be lowered at times of high renewable generation but price spikes are a risk if this generation falls at inopportune times. Moreover, with increased intermittent generation there is a high likelihood of increased bid prices and higher price volatility in the deregulated market [23].

Considering a regulated system, such as the vertically integrated SaskPower in Saskatchewan, the MOE is less of a consideration as units are deployed based on a dispatch model, rather than an economic merit order [39]. To meet carbon emissions goals, the operator can utilize "integrated resource planning" to dispatch lower emitting units with priority, and to replace coal-ramping with more efficient NG-ramping to backup renewable capacity [39]. This would lead to MEF results more similar to the previous literature with higher emitters appearing higher up in the order [18,19]. However, even with this system the use of the MEF would be more practical as a qualitative measure, rather than to reward shifting emissions to different hours of a day.

British Columbia is dominated by hydro power, both as baseload and peaking generation [40]. As a regulated market, the MOE again is less of a consideration. Thermal generators are mostly used to overcome geographic and transmission constraints [40]. This leads to a small-scale situation where use of the MEF would be practical, as emissions resulting from transmission constraints can be calculated more accurately in context.

Ontario operates with a nodal system where price is set at each node and collected together into the Hourly Ontario Energy Price (HOEP) [41]. With regular fluctuations in price, the MOE is likely to be present. In certain nodes, where price spikes are more common, the MOE would be more exaggerated than others. Marginal generation falls on both hydro and NG relatively regularly [41]. In this context, it could be practical to make use of the MEF to limit demand at times where NG ramping was being used and shift demand to prefer hydro ramping. However, the Alberta data suggests that these changes between marginal generators can occur unpredictably from hour to hour as demand changes, making it difficult to ensure emissions are actually being reduced with shifted demand. Likely, the MEF would still be more practical as a qualitative measure to attempt to limit NG ramping in general, rather than in specific instances. The use of the HAEF would promote long-term emissions reductions in the grid.

2.4 Conclusions and Recommendations

An analysis of the electricity generation merit order of Alberta was used to determine the impacts of marginal changes in demand. The analysis focused on spot price, with changes referred to as the Merit Order Effect (MOE), and the Marginal Emissions Factor (MEF). A key contribution of the study is analyzing the merit order in higher detail than previously seen in the literature to understand the trends that lead to the most significant changes in price and GHG emissions. With these trends identified, situations that lead to the most price volatility or highest GHG emissions may be predictable and preventable. The study quantified the impact of marginal demand changes on price and MEF.

In terms of economics, the MOE was seen to be significant in Alberta with ±100 MW of demand resulting in 37% change in total grid costs in 2018, with a potential 18% price decrease or 19% increase in total costs. The majority of the cost savings occur at times when the spot price is near the top of the merit order and susceptible to large changes from small changes in demand. There is a variety of causes for these situations, including sudden decreased wind generation, sudden increased demand, or outages in transmission lines or generators [37]. Large cost savings opportunities (defined as price changes of >$50/MWh) are seen to occur in less than 2% of the study period, but notably impact overall grid costs. A reduction of 100 MW during these times results in yearly cost savings of 14% for the system. An equal increase in demand at inopportune times results in 15% increase in the yearly grid cost. This translates to roughly $600 Million for 2018. An opportunity exists for cost savings where interventions are rarely required but have a large impact. Furthermore, these opportunities during times of high price volatility are predictable based on the merit order. The times of highest price volatility occur when small power capacity is bid over a large price range, especially when the price is near the top of the merit order. The ability to shift demand by even small amounts can significantly affect the price at these times. Outside of these opportunities, marginal changes have little impacts on price.

In terms of the MEF, the visualized merit order bids show a much more diverse breakdown in terms of generation type at different price points than previously suggested in the literature [18-22]. All types of thermal generators spread power widely across price points and in varied quantities, with bids from all types appearing in the baseload, marginal, and peaking zones. The analysis suggests that since the merit order is less organized by fuel type than previously suggested, the MEF is more challenging to predict at any given time. Furthermore, the calculated MEF is highly dependent on the time during which it was calculated. This suggests that averaging over larger time periods is inaccurate and risks the mischaracterization of GHG emissions. Moreover, the MEF represents only a small part of total generation which is regularly changing and so can be misrepresentative of actual grid-scale emissions. The MEF can still have practical uses in identifying sources of emissions in the grid and in small-scale analysis where cause and effect can be predicted in an individual operators actions. For emissions on the grid scale and where quantitative values are important, this paper recommends the use of the Hourly Average Emissions Factor (HAEF). The HAEF will more properly represent times of low emissions, when wind generation is high for example, without risking misrepresentation of emissions reductions by focusing on only the margin.

This study identifies an opportunity for cost savings within the electricity grid through marginal actions. However, the best way to achieve this cost savings through policy, private, or public action remains a large question for future work. The results of this study demonstrate that while cost savings are available, risks of price increases exist in equal magnitude. Fortunately, the causes of price volatility are predictable based on patterns in the merit order. Further study is needed to identify the best marginal actions that can be taken to reduce emissions. These reductions should be quantified based on HAEF rather than MEF. Ultimately, marginal changes in the supply/demand balance will have a significant contribution to the impacts of the transition to renewables and other new energy technologies. The results of this work help to understand the potential impacts and system characteristics that bring about these impacts and are a critical step in designing an efficient energy system for the future.

References

[1] Albadi, M. H., El-Saadany, E.F. (2008) A summary of demand response in electricity markets, *Electric Power Systems Research*, *78*, 1989–1996.

[2] BP. (2018). *BP Statistical Review of World Energy*. 67th Edition. Available online: https://www.bp.com/en/global/corporate/energy-economics/statistical-review-of-world-energy.html. Accessed May 8th, 2019.

[3] Zhao, H. et al. (2015) Review of energy storage system for wind power integration support. *Applied Energy, 137*, 545-553.

[4] Evans, A., Strezov, V., Evans, T.J. (2012) Assessment of utility energy storage options for increased renewable energy penetration. *Renewable and Sustainable Energy Reviews, 16,* 4141-4147.

[5] Palensky, P. (2011) Demand Side Management: Demand Response, Intelligent Energy Systems, and Smart Loads, *IEEE Transactions on Industrial Informatics, 7-3.*

[6] Aghaei, J., Mohammas-Iman, A. (2013) Demand response in smart electricity grids equipped with renewable energy sources: A review, *Renewable and Sustainable Energy Reviews, 18,* 64-72

[7] GE Power. (2016) *Powering the World with Gas Power Systems.* Available online: https://www.ge.com/content/dam/gepower-pgdp/global/en_US/documents/product/2016-gas-power-systems-products-catalog.pdf. Accessed April 10th, 2019.

[8] Alabdulwahab, A. et al. (2015) Coordination of Interdependent Natural Gas and Electricity Infrastructures for Firming the Variability of Wind Energy in Stochastic Day-Ahead Scheduling. *IEEE Transactions on Sustainable Energy, 6-2.*

[9] Alberta Electricity Operator (AESO) (2018) *ISO Rules.* Available Online: https://www.aeso.ca/rules-standards-and-tariff/iso-rules/ Accessed February 2nd, 2019.

[10] Hirth, L. (2013) The market value of variable renewables: The effect of solar wind power variability on their relative price. *Energy Economics, 38,* 218-236

[11] Sensfuß, F., Ragwitz, M., Genoese, M. (2008) The merit-order effect: A detailed analysis of the price effect of renewable electricity generation on spot market prices in Germany. *Energy Policy, 36,* 3086-3094.

[12] Cludius, J. et al (2014) The merit order effect of wind and photovoltaic electricity generation in Germany 2008-2016: Estimate and distributional implications. *Energy Economics, 44,* 302-313

[13] energy-charts.de (n.d.) *Electricity production and spot prices in Germany.* Available online: https://energy-charts.de/price.htm?auction=1h&year=2016. Accessed June 25th, 2019.

[14] Agora Energiewende (2014) *Comparing Electricity Price for industry: An elusive task – illustrated by the German Case, Analysis.*

[15] Clò, S., Cataldi, A., Zoppoli, P. (2015) The merit-order effect in the Italian power market: the impact of solar and wind generation on national wholesale electricity prices. *Energy Policy, 77,* 79-88.

[16] United Nations Framework Convention on Climate Change (2019) *National Inventory Submissions 2019.* Available online: https://unfccc.int/process-and-meetings/transparency-and-reporting/reporting-and-review-under-the-convention/greenhouse-gas-inventories-annex-i-parties/national-inventory-submissions-2019. Accessed May 25th, 2019.

[17] Environment and Climate Change Canada (2019) *National Inventory Report 1990-2015: Greenhouse Gas Sources and Sinks in Canada, Part 1.*

[18] Bettle, R., Pout, C.H., Hitchin, E.R. (2005) Interactions between electricity-savings measures and carbon emissions from power generation in England and Wales. *Energy Policy, 34,* 3434-3446

[19] Hawkes, A.D. (2010) Estimating marginal CO2 emissions rates for national electricity systems. *Energy Policy, 38,* 5977-5987.

[20] Farhat, A.A.M., Ugursal, V.I. (2010) Greenhouse gas emission intensity factors for marginal electricity generation in Canada. *International Journal of Energy Research, 34,* 1309-1327.

[21] Siler-Evans, K., Azevedo, I.L., Granger Morgan, M. (2012) Marginal Emissions Factors for the U.S. Electricity System. *Environmental Science & Technology, 46,* 4742-4748.

[22] Zheng, Z. et al. (2015) Assessment of Marginal Emissions Factor in Power Systems Under Ramp-Rate Constraints. *CSEE Journal of Power and Energy Systems, 1-4.*

[23] Oliveira, T., Varum, C., Botelho, A. (2019) Econometric modeling of CO2 emissions abatement: Comparing alternative approaches. *Renewable and Sustainable Energy Reviews, 105,* 310-322.

[24] AESO (n.d.) Historical – Pool Price. Available online: ets.aeso.ca. Accessed September 21st, 2018.

[25] AESO (n.d.) Historical – System Marginal Price. Available online: ets.aeso.ca. Accessed September 21st, 2018.

[26] AESO (n.d.) Current – Current Supply and Demand. Available online: ets.aeso.ca. Accessed September 2018 - May 2019.

[27] AESO (n.d.) Historical – Merit Order Snapshot - Energy. Available online: ets.aeso.ca. Accessed September 21st, 2018.

[28] NRGStream (n.d.) Data – Western Region – AB Power. Available online: https://www.nrgstream.com/. Accessed January 10th, 2019.

[29] AESO (2019) *Day Ahead Wind Power Forecast vs. Actual Wind Production.* Available online: https://www.aeso.ca/grid/forecasting/wind-power-forecasting/. Accessed April 15th, 2019.

[30] Sopinka, A. (2013). The Environmental Impact of Increasing Wind Penetrations in Thermally Dependent Electric System. *EIC Climate Change Technology Conference 2013*, (1569632137), 1–11.

[31] National Renewable Energy Laboratory (NREL) (2012) *Power Plant Cycling Costs.* Available online: https://www.nrel.gov/docs/fy12osti/55433.pdf. Accessed February 1st, 2019.

[32] Uddin, M. et al. (2018) A review on peak load shaving strategies. *Renewable and Sustainable Energy Reviews*, *82*, 3323-3332.

[33] Prasai, A. et al. (2010) Minimizing Emissions in Microgrids While Meeting Reliability and Power Quality Objectives. *The 2010 International Power Electronics Conference.*

[34] Government of Alberta (n.d.) *Phasing out coal.* Available online: https://www.alberta.ca/climate-coal-electricity.aspx. Accessed June 25th, 2019.

[35] AESO (2018) *AESO 2017 Annual Market Statistics.* Available online: https://www.aeso.ca/download/listedfiles/2017-Annual-Market-Stats.pdf. Accessed May 16th, 2019.

[36] AESO (2019) *AESO 2018 Annual Market Statistics.* Available online: https://www.aeso.ca/download/listedfiles/2018-Annual-Market-Stats-WEB-FINAL.pdf. Accessed May 16th, 2019.

[37] AESO (n.d.) Current – AIES Event Log. Available online: ets.aeso.ca. Accessed September 2018 – May 2019.

[39] SaskPower (2018) *Maintaining a Powerful Commitment – 2017-18 Annual Report.* Available online: https://www.saskpower.com/about-us/Our-Company/Current-Reports

[40] BC Hydro (2018) *2017/18 Annual Service Plan Report.* Available online: https://www.bchydro.com/toolbar/about/accountability_reports/financial_reports/annual_reports.html

[41] Independent Electricity Systems Operator (IESO) (n.d.) *Power Data.* Available online: http://www.ieso.ca/power-data

[42] Federal Energy Regulatory Commission (FERC) (n.d.) *Electric Power Markets: National Overview.* Available online: https://www.ferc.gov/market-oversight/mkt-electric/overview.asp. Accessed June 25th, 2019.

[43] European Energy Exchange (EEX) (n.d.) *Market Overview – Power Spot Market.* Available online: https://www.eex-group.com/eexg/trading/mo. Accessed June 25th, 2019.

SI-2: Supporting Information for Chapter 2

SI-2.A Further Information on the Alberta Electricity Market

This section expands on the background section with details about the Alberta electricity market. The breakdown of generation fuel type within the merit order zones for Alberta is presented to provide context to the results in the Alberta case.

The Alberta Electricity Market

Alberta has long had a deregulated wholesale generation market, meaning that all generators can freely bid their generation capacity at any price from $0.00/MWh up to the price cap of $999.99/MWh [9]. Each generation asset is allowed up to seven bids over which to distribute its total generation capacity and generators are required to bid all their generation capacity into the market. Full capacity of individual units is commonly allocated across one to three bids with all seven used very rarely [27]. Generation bids are collected and stacked into a merit order from cheapest to most expensive. Bids are then dispatched up the merit order to meet demand, with the final dispatched bid setting the spot price which is paid out to all dispatched generators [9]. In Alberta, demand is almost entirely inflexible; meaning the demand does not react to changes in price, only to changes in consumer behaviour. Figure 3 demonstrates a simplistic hypothetical merit order with inflexible demand.

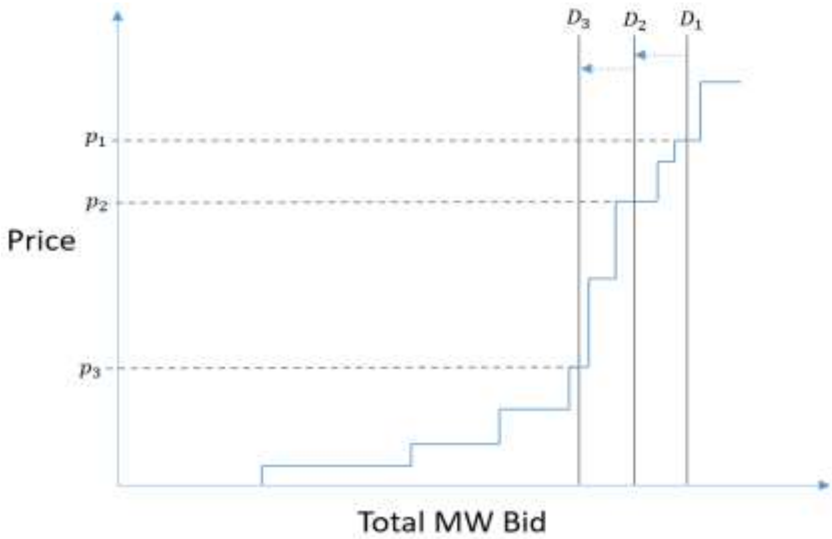

Figure 3: Hypothetical merit order bids with price plotted against power. Step-width represents the size of individual bids. Vertical lines represent demand. The price is set where the demand line intersects the stepwise merit order curve. Demand lowering the system demand can subsequently lower the price by shifting the intersection with the merit order. Equal changes in demand can result in significantly different price changes, demonstrated by the shift from D_2 to D_3 resulting in a greater price decrease than a shift from D_1 to D_2.

Deregulation allows economics and market forces to determine where generators bid their varied assets and subsequently the wholesale price of electricity. Generators can be divided into three categories: baseload, which bid at low prices and are subsequently dispatched almost all of the time; marginal, which bid close to the average spot price and regularly fluctuate between dispatched and not-dispatched; and peaking, which bid at high prices and only run on rare occasions when price is near the top of the merit order. Generators will choose where to submit their bids based on a number of factors, including the minimum power output of the unit, fuel price and ramping costs, desired return on investment, and price and demand predictions. Bids from individual units can span across the three categories, with the strategy that baseload bids will almost certainly be dispatched at some economic return and peaking bids will result in higher profits should they be dispatched.

Breakdown of Generator Type in Baseload, Marginal, and Peaking Zones

Table 7: Share of bid capacity from each generation type.

	Wind	**Biomass and Other**	**Hydro**	**Simple NG**	**Combined NG**	**Cogen**	**Coal**
Share of Total Capacity Bid	12%	2%	6%	6%	10%	24%	36%
Share of Baseload Bids	17%	2%	3%	5%	12%	34%	28%
Share of Marginal Bids	-	1%	1%	7%	11%	3%	77%
Share of Peaking Bids	-	2%	43%	23%	8%	3%	22%
Average bid size (MW)	72	13	51	17	57	75	107

Over 2018, Simple cycle NG is the most distributed of the generation types, with bids appearing at almost every price point. Biomass and other account for 3% of bids, but only 1% of capacity with an average bid size of 19 MW. On the other side of the spectrum, Cogen is the least diverse in terms of bid price with 96% of bids falling the baseload zone (up to $30). Hydro falls at either extreme with 21% of hydro bids at $0.00 and 69% over $800. Combined NG offers 72% of capacity in the baseload zone with the rest relatively evenly spread throughout the merit order. Coal bids are evenly spread over the baseload (51%) and marginal (43%) zones. Coal capacity is concentrated into fewer bids with the highest average bid capacity.

Hydro and Simple Cycle NG dominate the peaking zone, giving this zone the lowest average emissions (calculated based on bids) within the three zones of 372 kgCO2e/MWh. Coal dominates the marginal zone with 77% of total bids leading to the highest average emissions of any zone at 912 kgCO2e/MWh. This demonstrates a dangerous trend for the MEF, as regular fluctuations in the marginal zone lead to the regular ramping of coal generators and subsequently increasing overall emissions.

SI-2.B Additional Methods

As discussed in sections 2.2.4 and 2.2.5, matching demand with the merit order bids will never match exactly with the actual dispatch of generators. This is largely due to unavailable data on power purchase agreements (PPAs) and small operational constraints that are not always accounted for in the data. This can include fluctuations on the minute-scale, while data is available hourly, dispatch due to transmission constraints, or fluctuations in interties and reserves. This is accounted for as best as possible in the calculation methods discussed in 2.2.4 and 2.2.5 through the use of data on dispatch commands, intertie power, and reserves, but some error will remain.

The marginal generator was determined using two methods: The first sums the merit order bids until the total generation bid matches the generation required as defined in (2). In this method, the independent variable is hourly AIL demand and the dependent variable is the marginal price. The second sums the merit order bids until the system marginal price as reported by AESO is reached. In this method, the independent variable is the hourly price and the dependent variable is the required generation from the merit order. With the independent variable italicized and the dependent variable bolded, the method is shown by:

$$\mathbf{G_{merit\ order}} = \sum_{\mathrm{p}=\$0}^{p_{marginal}} \mathrm{bids_p} \quad (8)$$

As mentioned in section 2.2.3, some generation sources are not reflected in the merit order and so the total demand and merit order generation will never align perfectly and the spot price does not represent all generation types dispatched. By using both the price and demand methods, the study captures both extremes of reactions to marginal changes where changes are covered solely by the merit order or solely by non-merit order generation.

The second method resulted in economic results that were similar in trend but smaller in magnitude than those of the first method. For example, the maximum cost savings for 2018 shifted from 18% with method 1 to 16% with method 2. This reduction in savings is caused by a decrease in fluctuations during the average day, likely due to the use of reserve generation. However, the price spikes lasting over several hours, which contribute the most to cost savings, are still present. It follows logically that the second method would come with lower prices, as the price is set below required generation to account for generation that may not be reflected in the data. In terms of GHG emissions, the inconsistencies discussed in section 2.3.4 remain with no clear emissions savings emerging from marginal demand changes. The results presented in the paper are not substantially altered by the use of (8) rather than (2) but future work exploring the aspects of system operations that cause the differences would be valuable. However, the trends exposing cost savings potential and inconsistencies in MEF calculations are verified with both methods.

Additional Cost Savings and Demand Change Requirement with Price Cut-offs

Figure 4 demonstrates the cost savings and demand change requirement of all price cut-offs from \$1 to \$500. As price cut-off increases, the cost savings decrease but so does the requirement for intervention in lowering demand. A cut-off of \$500 results in no cost savings, meaning there is no time in the studied period where a reduction of 100 MW results in a price reduction of \$500/MWh in a single hour. A price cut-off of \$50 is seen to be a rough optimal, with high cost savings realized from low demand change requirement. \$5 is chosen as a mid-optimal with higher cost savings but also higher demand change requirement.

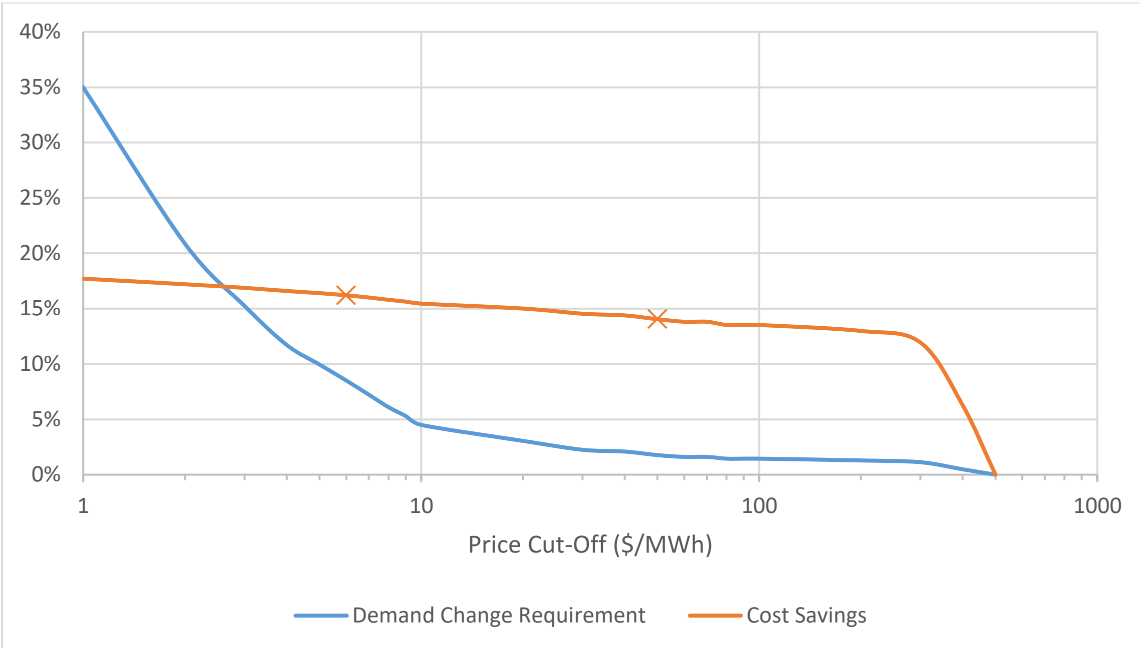

Figure 4: Cost savings (% of yearly total) and demand change requirement (% of yearly hours) plotted against various price points.

SI-2.C Developing Trends in the Alberta Merit Order

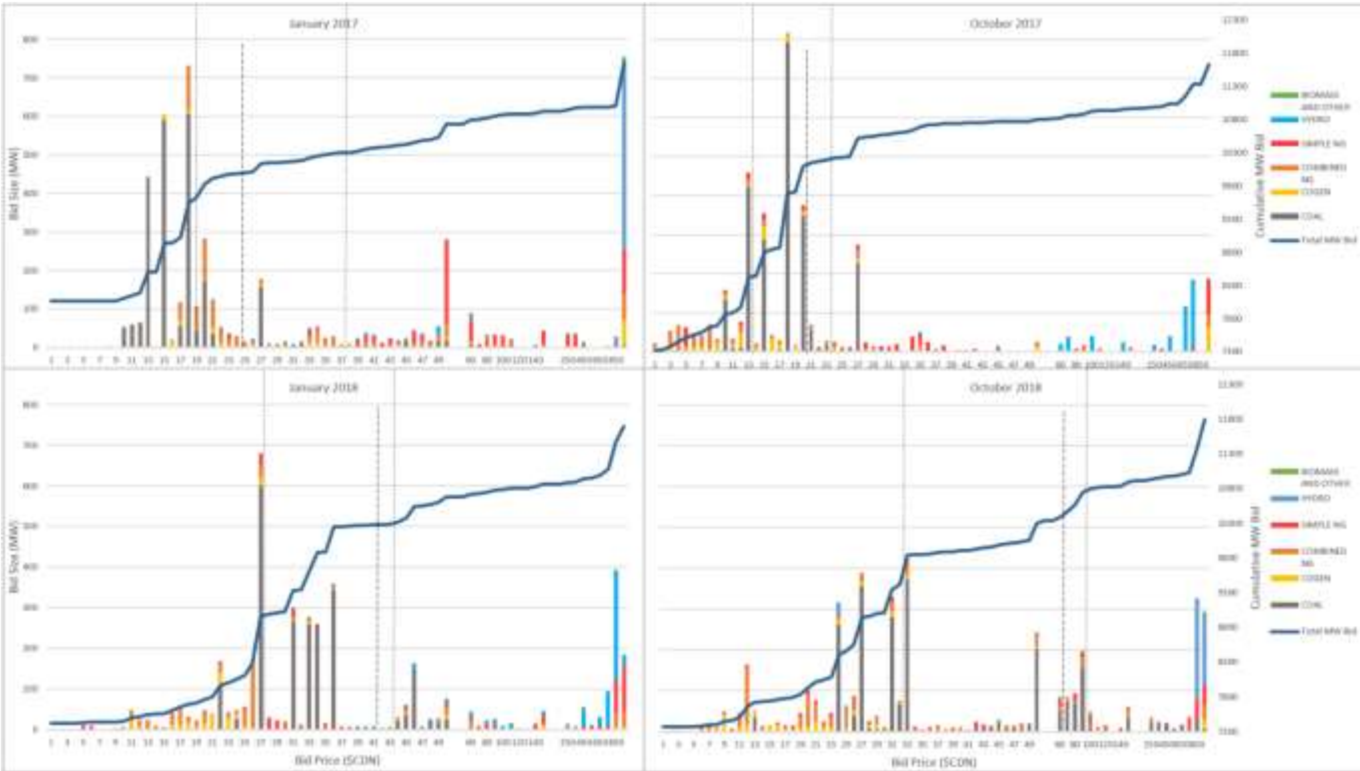

Figure 5: Merit Order Bids at each price point for January 2017 (Top left), October 2017 (top right), January 2018 (bottom left), and October 2018 (bottom right). Similar to Figure 2, bars belong to left axis. The solid line represents the accumulation of bids up to each price point. The dotted vertical lines represent, from left to right, 5th percentile of spot price over the plotted period, mean of spot price, and 95th percentile.

The results presented in 2.3.2 focus on October 2018 to identify simple trends in the merit order that lead to price and GHG emissions fluctuations. It is also practical to look at merit order trends as they develop over time to make some suggestion to as to how price and emissions will fluctuate in the near future. Figure 5 provides the merit order plot for four months within 2017 and 2018 to determine how these factors are changing over time.

A number of trends can be seen developing in the merit order bids from 2017 to 2018. Firstly, the coal bids are becoming less concentrated in the low-price points (i.e. $10-$25) and shifting further up in the $40-$80 range. The largest spike of coal bids remains near the 5th percentile of spot price and as a result coal is still frequently the marginal generator, but with a price higher than the previous year. The shift in coal also leads to more frequent ramping in almost all coal generators, contrasting the previous time periods where only a few coal units dominated the marginal generator slot. Natural gas bids make up a larger portion of the baseload zone in 2018 over 2017, resulting in an overall lower AEF for the grid.

In terms of spot price, the mean has significantly increased from 2017 to 2018 and therefore the total cost of the grid has increased as well. Also of note is the size of the marginal zone, defined between the 5^{th} and 95^{th} percentile. October 2017 (top-right in Figure 5) shows a very stable price with only \$10 separating the 5^{th} and 95^{th} percentile of spot price. Both January 2017 (\$12 gap) and January 2018 (\$15 gap) are relatively stable when compared to October 2018 which has a marginal zone spanning over \$70 (noting the break in the x-axis). This means that not only has the average spot price increased over the study period, but it has become much more volatile as well. The low-slope of the cumulative bids line in the marginal zone of October 2018 furthers this volatility, with small changes in demand being magnified in regular price changes in the marginal zone.

A final trend worth noting is the position of the mean spot price between the 5^{th} and 95^{th} percentiles, demonstrating a positively or negatively skewed distribution of spot price. A skewed distribution with the mean closer to the 5^{th} percentile, as seen in January 2017, suggests that while high price points do happen, they are contributing less to the overall grid cost (as determined by the mean spot price). Distributions with the mean closer to the 95^{th} percentile, as seen in October 2018, suggests that high price points are occurring more often and at higher prices, making demand changes at high price points even more significant.

Chapter 3: Impacts of Electricity Grid Price Patterns on Cost-Savings from Demand-Shifting, Solar PV, and Combined PV with Demand-Shifting

Abstract

The global energy transition is leading to a variety of emerging technologies consumers can utilize to lower their electricity costs. Renewable energy is at the center of this transition. As intermittent renewable generation sources are integrated with existing electricity grids, timing of generation and demand play an important role in the economics of different technologies. This study compares the cost effects of the use of three technologies: solar photovoltaics (PV), Demand-shifting (DS) technologies, such as storage and demand side management, and a combined system of PV with DS. The analysis focuses on the timing capability of each technology as it interacts with the electricity grid and wholesale price of electricity; i.e. how well PV generation aligns with high grid prices and the savings potential of deferring grid access through DS. Three electricity grids are studied with a variety of price patterns in Alberta, California, and Ontario. Findings show that grid pricing patterns have a major impact on the cost impacts of each technology, with specific patterns having varied impacts on each technology. DS strategies are applied over various time periods, from 2-hours to a full year, and found to best provide cost savings in the 12-24 hour range. DS is most effective, as compared to PV and the combined system, in grids with high price variability; particularly when variability occurs irregularly and in periods of hours as opposed to across full days. However, the DS results represents the theoretical high bound of cost savings and do not account for uncertainty in price predictions. PV on its own is most beneficial in grids with low price variability or when price peaks align with PV generation. The combined system provides highest cost savings when price peaks occur outside of PV generation hours with regularity. However, the value of the combined system over PV on its own may not justify the increase in investment costs, even in the high bound case. The cost impacts results of each technology align well with grid price patterns identified through the analysis method. This suggests that price signals which follow the grid price will guide

consumers in making technology investment decisions which benefit them economically, as well as serve to stabilize the grid system.

3.1 Introduction

Innovation in energy technologies has created a wide array of power sources available for electricity consumers. The global goal to reduce greenhouse gas (GHG) emissions from energy production has made renewable generators, particularly wind and solar, popular options for companies and individuals seeking to reduce emissions from their electricity consumption [1,2]. As generation from these renewable sources increases, intermittency adds a new level of complexity to electricity systems that must be addressed. The energy transition is also seeing a rise in distributed energy, where energy generation is physically located closer to demand sources [3]. On the consumer side, the most deployed distributed energy globally is solar photovoltaic (PV) [4,5]. However, the use of PV alone is not sufficient to provide a secure power supply and the vast majority of consumers maintain a connection to the electricity grid [6]. This connection allows power to be purchased from the grid when PV generation is insufficient to meet demand and power to be sold to the grid in the case of excess solar generation, as well as removing the need for costly power electronics to ensure PV generation meets demand instantaneously. With a connection to the grid in place, the cost of electricity to the consumer is dependent on the correlation between PV generation and electricity price, both in terms of sale and purchase.

Another emerging class of energy technologies provides a means of reducing consumer electricity costs through time-managed access to the grid. Two key technologies in this class are energy storage and demand-shifting (DS). With storage, consumers can charge batteries (or other storage mechanisms) at times of low price and discharge to meet their energy needs at times of high prices. This provides the consumer with consistent access to energy, while also reducing the cost of that energy through arbitrage-type strategies [7]. DS offers a similar strategy through a different means; consumers control their energy consumption and schedule electricity intensive tasks to align with desirable grid prices [8]. These tasks can range from running appliances, to plugging in an electric vehicle, to running industrial machinery. DS operators have limitations based on when their tasks must be completed and subsequently their ability to shift their demand [8]. While the mechanisms behind storage and DS differ, the principle is the same: taking power from the grid at times of low cost while avoiding grid power at times of high cost. For the purposes of this paper, the two will be referred to jointly as demand-shifting (DS) technologies.

The two systems, PV and DS can also be used in tandem. Wherein generation from PV can be stored and used at a later time, or consumers can run operations only at times when PV generation is available. This adds a level of controllability for the consumer, who no longer depends so highly on weather conditions but can choose when or how to deploy PV generation [9].

With these three options: PV on its own, DS on its own, or a combination of PV and DS, an important question arises of which technology can provide the highest cost savings to the consumer. This question has led to a wealth of research that quantify, analyze, and discuss the economics of these systems in a variety of grids and scenarios. Much of this research focuses on complex simulations where strategies and algorithms are developed to optimize the cost savings of technologies in specific situations or jurisdictions. Complexity arises from the large number of variables present in simulating energy technologies, such as (but not limited to) solar radiation, PV efficiency, installed storage power and energy, types of storage and efficiencies, cost of DS, possible DS mechanisms, investment costs, grid electricity prices, etc. The treatment of these variables has a significant impact on the results of simulations, leading to conclusions that are relevant only to specific situations or consumers.

In this study, a simplified method is used to compare the three energy technologies described above. The method is applied to a diverse set of electricity grids and pricing nodes: Alberta (2016, 2017, 2018), San Francisco (2016, 2017, 2018), other price nodes in California for 2018 (San Diego, Los Angeles, and Redbluff), and Ontario for 2018 in three price nodes (Hourly Ontario Electricity Price (HOEP), Atikokan, and Thunder Bay). The analysis calculates operational cost savings from a range of operating conditions for the three technologies and suggests the characteristics of electricity grids that make each technology favourable in terms of cost impacts over one another. DS is analyzed based on perfect knowledge of grid prices, meaning the results reflect a theoretical high bound of cost savings rather than cost savings that are technically achievable. The method provides a critical contribution to the literature by removing some complex variables associated with PV and DS and rather comparing the three technologies based on ideal operation, with the timing characteristics of the operation and grid price driving the results. This provides insights into what situations or grids one technology may be definitively superior in terms of cost impacts and what situations are more dependent on operating conditions and would therefore benefit from the more nuanced simulations common in the literature.

3.1.1 Solar PV Systems

On-site solar PV has become a popular power option for companies and individuals seeking to reduce their emissions and electricity costs [10,11]. For the purposes of this chapter, "on-site" refers to solar PV that is under the exclusive control of a power consumer and primarily purposed for their own consumption, not sale to the grid. This can include power purchase agreements. Economics have and continue to play a key role in the adoption of solar PV [12]. One of the first key factors studied in the literature that contributes to the economic return of PV modules is the capacity factor [12]. Capacity factor (CF) is defined as the total net actual generation over a period of time divided by the generation if the PV system always operated at its rated power [13]. The CF depends largely on the geographic location and weather patterns where it is installed [14]. Areas with higher solar radiation give a higher CF, which directly relates to a lower cost of electricity from PV as more electricity is delivered for the same investment. As demonstrated in Figure 6, the three geographic locations studied in this report have varied CFs, both in terms of the average daily CF and in the generation profile.

In the last two decades, research into the economics of PV has shifted from CF alone to the effects of variability and intermittency in the system. Variability describes predictable fluctuations that occur based on daily and seasonal solar radiation patterns [15]. Intermittency describes unpredictable (or difficult to predict) fluctuations in power generation that occur due to weather patterns, such as cloud cover [15]. Variability is a popular topic as the value of a PV system can directly relate to the time of day that the system is producing power. Borenstein [16] finds that the value of a PV system can increase by 0%-20% in typical US grids with stable capacity, but can increase to 30%-50% in grids with more demand responsive prices and daytime peaks. Black [17] discusses time-of-use (TOU) billing and net-metering in California, where summer on-peak electricity prices were $0.31/kWh compared to $0.09/kWh for off-peak (2004). TOU pricing, amongst other factors including generally high electricity rates and incentives for PV, made PV installations highly viable investments. Nearly a decade later in 2013, the California independent systems operator (CAISO) published the “duck curve” demonstrating that high production of solar during daylight hours had shifted the demand of the system [18]. The National Renewable Energy Laboratory (NREL) [19] provide an analysis of the duck-curve and find that historical measures such as TOU pricing, will be insufficient to counter the effects of “over-generation” of PV in the grid. The report suggests that acquiring grid services from new PV that shifts generation to times of high need will be essential to prevent high levels of curtailment. Baker et al. [15] add further evidence that solar variability still adds value when high generation coincides with high demand and vice versa.

Notable gaps remain in the literature on 1) identifying how PV generation aligns with wholesale electricity prices and 2) on how pricing trends impact the economic return for consumer PV. This study contributes to filling these gaps by studying the PV generation in Alberta, California, and Ontario. PV generation is compared with patterns in wholesale pricing. Figure 6 shows the differences in average PV generation across hours of the day in each region. The analysis demonstrates where PV generation most and least aligns with pricing profiles.

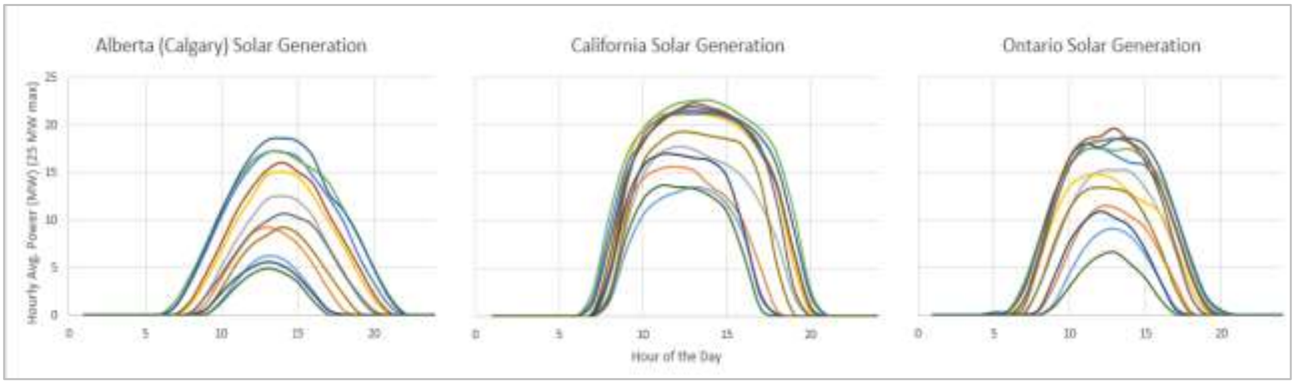

Figure 6: Average daily PV generation for each hour of the day in Alberta, California, and Ontario (from left to right). The installed capacity is 25 MW. Each line represents a month of the year, with summer months on top and winter on bottom.

3.1.2 Demand Shifting (DS) Technologies

In this chapter, Demand Shifting (DS) refers to technologies that provide the consumer the ability of time-managed access to the grid, including storage and direct demand-shifting. A large sector of DS research generally centers around two topics: the potential benefits and limitations for grid-scale applications and strategies for deployment and optimization. Walawalkar, Apt, and Mancini [20] provided an economic analysis of storage in the New York market, suggesting that storage has the highest value in less stable grids with storage realizing the highest economic benefits to the storage owner when upgrades to the grid system are deferred to later times. Strbac [21] provided similar conclusions for DS as a security mechanism, where it can be used to displace the need for investment in back-up generation which will be used infrequently. However, a number of limitations prevent the uptake of DS. Strbac [21] cites lack of metering and communication infrastructure, lack of understanding of the benefits of DS, and inappropriate market incentives as the major preventive limitations. Lindberg et al. [22] analyzed several industries to determine their potential to provide DS services to the grid, finding that a number of industries show technical potential for DS. Palensky and Dietrich [8] gave an overview and analysis of the classes and applications of DS technologies, arguing the primary challenges for DS are related to information security and system management, rather than any technical restrictions. There is clear agreement in the literature on the potential of DS technologies to stabilize the grid and lower the cost of electricity, with the key limitations being market and knowledge related, rather than technical [8,21,22].

However, the question remains of whether the economic benefits of DS to consumers would be enough to motivate adopting DS.

Much of the literature focuses on optimization strategies with varying complexity and market assumptions. These strategies are nuanced and complex enough that patents have emerged to protect the rights to optimization strategies and methods, including the co-optimization of DSM and energy storage by Tyagi [23]. Zhu et al. [24] uses an integer linear programming technique to demonstrate how peak load can be minimized in homes with smart meters. Reihani et al. [25] and Khalid et al. [26] perform programming based multi-objective optimization to find a balance between variables such as appliance waiting times, customer comfort, and cost savings for consumer side DS applications. Krishnamurthy et al. [27] used a stochastic approach to determine the arbitrage opportunity for storage systems under real-time price uncertainty to assist storage owners in estimating the economic viability of energy storage, finding that the stochastic approach better represents the variability in price than the deterministic benchmark. While these studies provide valuable insights into strategies to optimize operation of DS systems, the question remains of where and when it is best to invest in these systems over alternatives, such as simply adopting PV generation on its own. A simplified analysis, foregoing specific strategies for theoretical maximum cost savings within a time interval, can provide a perspective on where one technology may be definitively superior and where further optimization analysis is required.

3.1.3 Combined PV and DS Systems

A common goal in combining PV (or other renewable) generation with DS systems is increasing self-consumption; where electricity generated is consumed directly on-site rather than being sold to the grid. Quoilin et al. [6] provides an analysis of European households and the possibility of becoming independent from the grid through a combined system. The study shows that achieving above 80% self-consumption would require an “excessively oversize[ed]” PV/storage system, making the system uneconomic. This result suggests that in realistic cases, access to the grid will be a requirement. O’Shaughnessy et al. [9,28] studies “solar plus”, a combined approach of PV, storage, and load control where the latter two can be used to lower economic uncertainty by reducing the effects of intermittency. The analysis shows that “solar plus” increases self-consumption enough to justify the incremental cost of storage/load control especially when PV is sold to the grid at a discount and when PV generation does not coincide with price peaks. Kurland and Benson [29] provide a different perspective, finding that PV gives the highest returns in “locations with a good solar resource and a grid that can accept excess production”, with storage only beneficial when PV generation cannot be fed into the grid.

The literature shows consensus that the efficacy of combined systems depends on the ability to sell excess generation to the grid and the associated price as compared to the grid price of electricity. In systems with a PV capacity higher than peak system demand, generation must be sold or conserved through storage. However, with maintaining a connection to the grid necessary in all but excessively overbuilt systems, is it practical to install solar that will produce above demand making sale to the grid necessary? Storage would still be beneficial when peak prices don’t align with solar hours. Would the benefits of storage be significant with an “underbuilt” PV system? This study provides insights into these questions that allow the benefits of PV, DS, and a combined system to be clearly compared to one another.

3.1.4 Study Objectives

Increased renewable generation is causing higher variability in electricity grids than seen in the past. Despite advancements in solar PV and DS technologies, access to the grid remains the best economic options and therefore access to the grid should be utilized to its highest benefit. This study seeks to identify how the timing characteristics of PV, DS, and combined systems align with grid prices and what types of price fluctuations make each technology most beneficial. Analysis focuses on timing access to the grid; how well PV generation aligns with peak prices and how DS can be used to optimize grid access timing. DS is studied from the perfect knowledge perspective and therefore represents the theoretical high bound of cost savings possible in each grid and time period. The three grids studied are varied in terms of PV generation: one with very little PV generation (Alberta), one with high generation

(California), and one intermediate (Ontario). DS is studied for several time intervals during which a consumer could choose when to purchase electricity from the grid, from 2-hours to a full year. Cost impacts are compared across the three technologies and the price fluctuations that lead to the highest savings for each technology are discussed. The study identifies, based on grid price patterns, when consumers can make definitive decisions on which technology is best to invest in and when cost savings are more comparable based on operating conditions, requiring more detailed analysis.

3.2 Methods

This study focuses on quantifying the costs associated with accessing the electricity grid at different times. Economic impacts are used to compare three distributed energy systems: solar PV generation, Demand Shifting (DS) technologies, and combined PV and DS systems. A key objective is to isolate the time component and correlation of PV generation, grid pricing, and DS by making simplifying assumptions on several variables. The model centers on an electricity consumer who pays the hourly wholesale rate of electricity in the market it operates in over one year. For the purposes of this study, the consumer's electricity demand is assumed to be 25 MW continuously, with the exception of DS scenarios where the average demand over the time period is 25 MW. The cost results are generalizable to different sizes of consumers and so are normalized to per MWh consumed.

Several assumptions are made to remove decision making in operation such that the impacts of the time component and interactions between the technology and grid are isolated: The operational savings are focused on, meaning the initial investment and operation costs of the systems not included in the analysis but are included in the discussion section. Technical restrictions such as land-use restrictions and storage energy capacity and losses are not considered. Costs are calculated based on hourly data over one year (i.e. 8,760 hours). To help visualize the pricing patterns in each grid, representative daily averages are taken and used to develop heat plots of a representative day for each month of the year. The representative daily average (RDA) method is also used to calculate cost savings results with a comparison to the full year hourly data calculations in Section SI-3.A.. The key simplifying assumptions are summarized in Table 8.

Table 8: Key simplifying assumptions for analysis.

Assumption	Motivation/Justification
DS operators have perfect knowledge of grid pricing	- Gives maximum theoretical cost savings for comparison
Only operational costs associated with purchasing grid electricity are considered	- Simplification to isolate time component - Investment costs are discussed in section 3.4.5 and will be a key part of future work
Electricity is purchased at wholesale electricity price	- Direct access to price variability - Reasonable for large-scale consumers
Time-of-use billing structure is in place	- Goes along with access to wholesale price
Consumer has an even demand profile of 25 MW for baseline	- Reasonable for industry application - Isolates generation component (i.e. PV and DS) by removing uncontrolled demand variability
Solar PV capacity does not exceed demand	- Isolates time component - Eliminates pricing uncertainty with sale to grid
Transmission/Distribution charges ignored	- Isolates time component - This is discussed in section 3.4.5 as it effects the technologies differently
Systems have equal power capability (25 MW)	- Simplification to isolate time component

3.2.1 Grid Data

Data on the electricity demand and price was collected for Alberta [30,31], California [32,33], and Ontario [34,35,36] from their respective independent system operators (AESO, CAISO, IESO). Alberta data was collected for the years 2016, 2017, and 2018. California data was collected for the years 2016, 2017, and 2018 for a single node in San Francisco (BAYSHOR2_1_N001). Three other California nodes were also analyzed for the year 2018: San Diego (SAMPSON_6_N010), Los Angeles (CTRPKGEN_7_B1), and Redbluff (REDBLFF_6_N005). However, the results for these nodes were very similar to San Francisco 2018 and so are not included in the main sections of this chapter but can be found in section SI-3.B. Results for California discussed in the paper are thusly from the San Francisco node (California (SF)). Ontario data was collected for 2018 for the Hourly Ontario Electricity Price (HOEP) as well as the nodal price for Atikokan and Thunder Bay. The latter two were chosen as they represent a high and low standard deviation of price, respectively, in comparison to the other Ontario pricing nodes.

Apart from the average price, there are three characteristics of grid price that determine the efficacy of DS technologies: 1) variability, meaning the average change in price from hour to hour; 2) peaks, as in how far apart the maximum and minimum daily prices are to the average; and 3) spikes, as in how often the price goes well above or below a typical peak for a short period of time. The Alberta market has been in a state of transition over the study period and so the three years studied provide a good balance of these three drivers. The price in 2016 had low variability, low peaks, and low spikes; 2017 medium variability, low peaks, and medium spikes; and 2018 with high variability, medium peaks, and high spikes. These three years therefore serve as a good contrast to one another, providing a wider range for comparison of the results. California presents a more stable pricing profile across the three years, while Ontario shows a high concentration of price spikes.

3.2.2 Solar Generation

Solar irradiance data for the City of Calgary was collected for the years 2016, 2017, and 2018 [37]. This data is used as an estimate for solar irradiance in the province. An assumed efficiency of PV panels is 18% taken from a high efficiency module from *Canadian Solar* [38]. For analysis purposes, a capacity of PV is installed to match the demand of the consumer of 25 MW. This translates to 140,000 m^2 of PV modules installed (note that this value is panel area, not accounting for spacing of panels). These values are used for calculation and discussion, but results presented are normalized to per MWh. This installed area is multiplied by the solar irradiance and efficiency of the modules to arrive at a total average power across each hour of the year, as demonstrated by:

$$P\ [MW] = \eta_{PV} * E_e\ \left[\frac{W}{m^2}\right] * A[m^2] * 10^{-6} \qquad (9)$$

For California, data on total solar generation in the state was collected from the CAISO on 5-minute intervals for the study period [39]. The 5-minute data was aggregated into hourly averages for the year and these hourly averages were used to create the RDA discussed in section 3.2.5. The generation was normalized to a capacity of 25 MW. As this data represents solar generators from across the state, the generation profile is smoother compared to Calgary and Ontario.

For Ontario, solar data was collected from the IESO for all solar facilities available on hourly energy generated (MWh) for the studied period [40]. Due to some inconsistencies (such as generation being reported during nighttime hours and omitted days), the two facilities with the most consistent data were chosen and aggregated across the entire study period to create one average. These sites were the Kingston Solar Farm (100 MW) and Grand Solar Farm, located in Haldimand County, Ontario (100 MW). Both of these sights are located in Southern Ontario but are assumed as representative of the province as a whole due to a lack of data from other locations. As with California, the generation is normalized to a capacity of 25 MW.

Solar generation at each hour is subtracted from the baseline demand of 25 MW to derive a net demand purchased from the grid. This net demand is multiplied by the wholesale electricity price at that hour to get a total cost of electricity for each hour. This is shown by (10).

$$c_{hourly}\ [\$] = (D_{25MW}[MW] - P_{solar}[MW]) * p_{wholesale}\ \left[\frac{\$}{MWh}\right] \tag{10}$$

The hourly costs are then summed over the year and divided by the baseline demand of 25 MW to arrive at an average cost per MWh for the year:

$$p_{avg}\left[\frac{\$}{MWh}\right] = \sum_{i=1}^{8760} c_{hourly,i}\ /25\ MW \tag{11}$$

Solar generation reduces the amount of power that must be purchased from the grid to meet demand in any hour. Therefore, the savings mechanism is a direct reduction in the electricity purchased. The total cost savings depends on the price in the hours during which reductions occur.

3.2.3 DS Technologies

The savings mechanism for DS differs from that of PV in that the amount of electricity purchased from the grid is not reduced but shifted in time. Savings are achieved by accessing the grid at the times of lowest prices and avoiding the highest prices within a time period. For this study, the consumer is assumed to have double their demand capacity available for DS operation. In other words, a DS operator would have the capability to run at 0 MW or 50 MW in any given hour to achieve an average of 25 MW over the time interval. This means that power will be purchased from the grid in half of the hours of the time interval. Time intervals studied are 2-, 6-, 12-, 24-, 72-hour, and full-year intervals. As an example, the 6-hour time period means that the operator will purchase electricity from the grid for 3-hours at 50 MW and not purchase from the grid for 3-hours within each interval. For a storage operator, this would be equivalent to a storage system with a power capacity equivalent to the facility demand and an energy capacity of 3 hours of facility demand. Thus, the operator would access the grid at double demand in low price hours (regular demand plus charging the storage) and discharge the storage to meet demand in the remaining hours. For a direct DS operator, demand itself would simply be shifted. This approach, while highly simplified, provides a maximum savings that could theoretically be achieved through a DS strategy for each time interval studied. This entails a DS operator with perfect knowledge and prediction of grid pricing. As such, the results represent the theoretical upper bound of cost savings. However, in reality lack of certainty in predictions would make these results unachievable. Intermediate strategies (i.e.$0\ MW \leq D \leq 50\ MW$) are not explored as they will achieve lower cost savings. A quadruple capacity (i.e. 0 MW or 100 MW) was explored but results did not significantly improve on the double strategy.

Optimizing cost within each time interval is achieved by sorting the hourly prices from lowest to highest. The lower half of prices are then multiplied by double demand, with no electricity being purchased in the higher half of price hours. This occurs for the total number of time intervals in one year (i.e. 1,460 time intervals for the 6-hour shift strategy). The results are then averaged on a per MWh basis and compared to see how the time interval affects the total possible savings. The full year strategy involves sorting prices over every hour of the year. This strategy is unrealistic as it involved shifting demand across months or longer, but it is indicative of the maximum fluctuations in price that occur across the year to be used for comparison.

3.2.4 Combined PV with DS

PV and DS have different savings mechanisms. PV reduces the amount of electricity purchased from the grid and DS shifts the time that electricity is purchased to low cost hours. The combined system utilizes both mechanisms, using DS to shift the electricity produced from PV to reduce the electricity purchased in high cost hours. In this study, PV generation can be freely shifted within a 24-hour period. This means that the electricity produced from PV within a 24-hour period can effectively be stored and used only in highest price hours of that 24-hour period. The approach is simplified and does not consider restrictions in storage capacity (energy) to demonstrate the alignment of PV generation and peak price hours and the maximum gain from time shifting PV.

3.2.5 Representative Daily Averages (RDA) and Heat Plots

Complete yearly data provides the most thorough results on the cost savings of each technology as the full range of daily peaks and all price spikes are included, whereas averages dilute the spikes. However, the full year of data is more difficult to visualize and, subsequently, the use of all data points makes it more difficult to identify patterns in prices. To identify these patterns, a representative daily average (RDA) method was used for each month of the year. These RDAs capture the general patterns that occurred across the average 24-hour cycle and how these patterns changed from month to month. RDAs were calculated by summing the price for each hour of the day across a full month (e.g.. every price at 1 am) and dividing by the total number of days in the month. This provided 24 representative hours per month, for a total of 288 data points.

All cost savings calculations were done using both the 288 data points of the RDA method and 8,760 data points from the full year. The results between the two methods were found to have general agreement with error below 10% for most calculations. The full year hourly data results are therefore the only ones presented in the paper. RDA results along with a discussion of the error between the two methods can be found in Section SI-3.A. The key difference between the two is that the RDA method dilutes price spikes. As a result the RDA method always reports lower cost savings potential than the full year method.

Heat plots were created to visually represent the daily and monthly fluctuations in the electricity price, as well as the PV generation in each grid studied. The heat plots are then used to determine how the grid price impacts the cost savings results. Three heat plots were developed for each grid studied: one for the RDA prices, one for PV generation, and one for the hourly price the consumer would pay with PV generation accounted for, as shown in (10). The third plot was developed to demonstrate how well solar aligns with price in each grid, with good alignment reducing price peaks.

3.3 Results

The DS results are presented first in Figure 7 which compares the cost savings of the different time intervals studied. The PV results are presented in Table 9, comparing the total cost savings with the CF in each grid. The total cost savings for each technology are combined to make Figure 8. Tables with full results for cost savings of each technology can be found in section SI-3.C.

3.3.1 DS Time Intervals

The full-year time interval is the maximum possible cost savings that could be achieved through a DS strategy. In this case, the consumer has the ability to forego days or months to access only the lowest prices of the year. Figure 7 compares the cost savings achieved in each time interval to this maximum value.

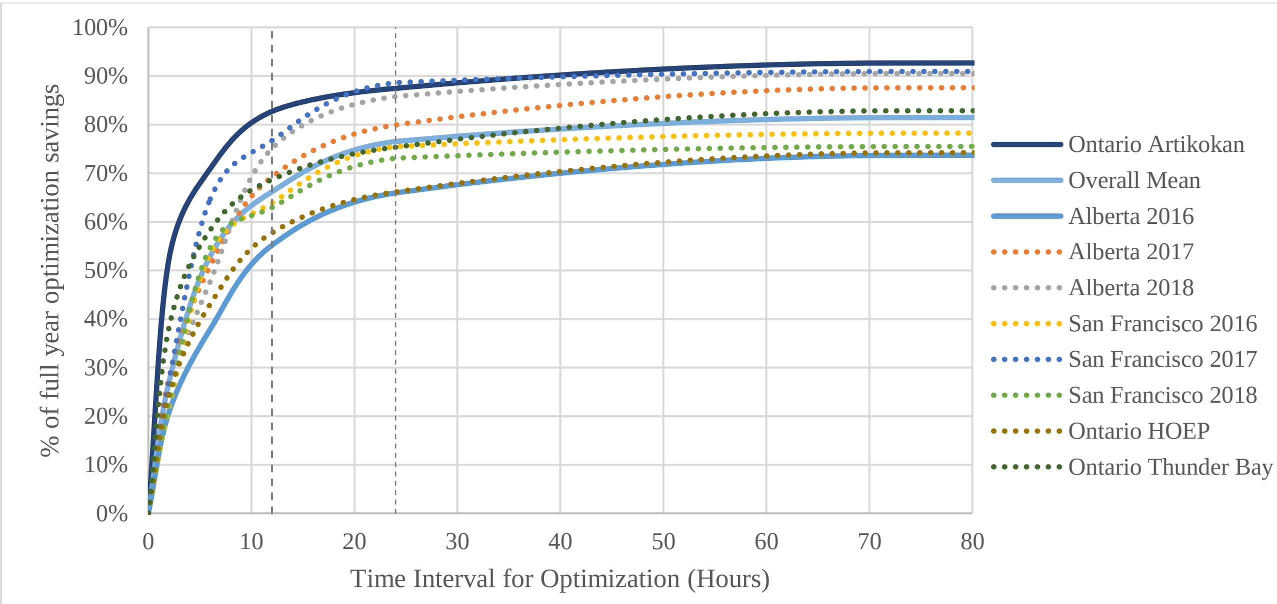

Figure 7: Cost savings from each time interval as a percent of maximum cost savings from the full year time interval for each grid studied. Top solid-line is Ontario: Atikokan, Bottom Line Alberta: 2016, Middle line is the average of all grids. Dotted lines represent all other grids.

Figure 7 shows a clear logarithmic-type curve for all studied grids, with cost savings increasing rapidly in the low time intervals and reducing in slope as the time interval goes above 12-24 hours. At 24-hours, total cost savings vary between 89% (San Francisco: 2017) and 66% (Alberta: 2016) of the total cost savings that could be achieved. Savings potential is reduced after this point, with large increases in time interval required to increase savings further. This suggests that each grid follows 24-hour patterns consistently and therefore optimizing within this time interval would provide the most benefit.

3.3.2 Solar PV Capacity Factor

Operation of solar PV systems achieves cost savings by reducing the amount of power that must be purchased from the grid, However, the extent of these cost savings are dependent on the time that PV is generating electricity. In a grid with constant pricing, the cost savings from PV would be the same regardless of when the power was produced. If the installed capacity of the PV system is equivalent to demand, the cost savings in a constant priced grid would be exactly equal to the CF of the PV system. If the cost savings exceed the CF, PV is generating more often in hours with prices higher than the daily average and vice versa. Table 9 presents the cost savings and CF for each of the grids studied.

Both Alberta and Ontario consistently provide cost savings higher than the CF, meaning that, on average, high price hours occur during PV generation hours. The cost savings in Alberta progressively increase from 2016-2018 suggesting more high price hours are occurring during PV generation. California cost savings are close to, but consistently below the CF. This means that on average prices during PV generation hours are below the average. The reasons behind this observed in the heat plots are further discussed in section 3.4.2.

Table 9: Comparison of PV Cost Savings with Capacity Factor. Savings performing above CF are highlighted green.

		Baseline	With Solar PV		
		$/MWh	$/MWh	Savings	CF
Alberta	2016	$18.28	$15.43	16%	*15%*
	2017	$22.19	$18.25	18%	
	2018	$50.35	$38.03	24%	
California (SF)	2016	$30.66	$22.41	27%	*28%*
	2017	$35.98	$27.39	24%	
	2018	$40.72	$31.06	24%	
Ontario (2018)	HOEP	$46.07	$34.32	25%	*18%*
	Atikokan	$38.07	$29.52	22%	
	Thunder Bay	$46.47	$33.89	27%	

3.3.3. Comparison of PV, DS, and Combined Systems

Figure 8 shows the side-by-side comparison of DS for each studied time period, PV on its own, and PV optimized within 24-hour periods with DS. Since the combined PV and DS optimizes PV generation within a 24-hour period, it will always have higher cost savings than the PV on its own. To show the increase in cost savings, and compare the increase in savings with that of DS, the PV with DS is shown stacked on top of PV alone. Alberta 2016 and 2017 are seen to have the lowest savings potential for any of the technologies. This is largely due to low and relatively stable prices in the grid during these years. Comparing Alberta 2018, the savings potential nearly doubles for the DS strategies and PV increases as well, despite an identical CF. San Francisco, with the highest CF, shows high savings potential for PV and also the highest potential for the combined system, with savings increasing from 24% to 43%

respectively in 2017. Notably for Alberta and San Francisco, PV on its own has equivalent savings to a DS of 24-hours or more, with an exception in Alberta 2018 where PV is equivalent to a 12-hour DS strategy. Ontario shows DS strategies consistently outperforming PV with a 12-hour strategy or less. Combined PV and DS show promising results in Ontario, with savings doubled in the Atikiokan node. However, these savings are only equivalent to a 6-hour DS strategy. Section 3.3.4 goes into more detail discussing the results in the context of each grid.

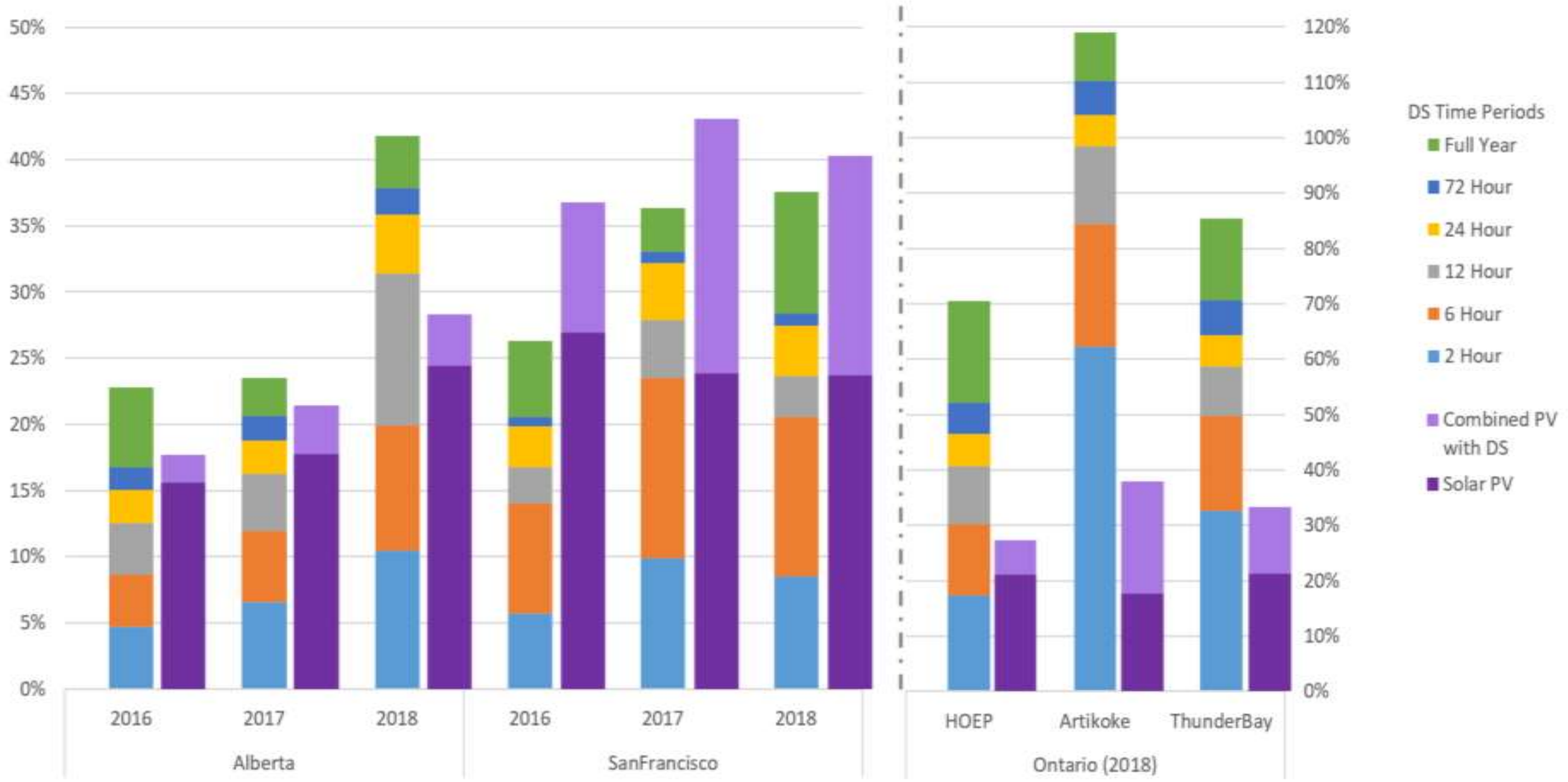

Figure 8: Comparison of cost savings over one year for DS, PV, and Combined PV and DS. Cost savings are taken as % reduction from the baseline cost. The left bar represents the cost savings from DS for each time interval. Right hand bar represents solar PV and PV optimized with DS. Note the change in the y-axis for the Ontario nodes.

3.4 Discussion

Results from Figure 8 are discussed along with heat plots (Figures 9-11) to determine the pricing patterns that lead to the most favourable results for each technology. Each grid is discussed independently initially and results that are relevant to all grids are discussed in section 3.4.4.

3.4.1 Alberta Heat Plots

Figure 9 depicts the pricing heat plots for Alberta 2016, 2017, and 2018. The left hand plots are the average price for each hour of the RDA, the middle plot is PV generation, and the right hand plot is the average price adjusted for PV generation as per (10) from section 3.2.3. Note that the heat plots are normalized on a per year basis, not across years. In other words the 2016 rows were compared to the average price in 2016 of $18.26, whereas the 2018 rows are compared to the average price in 2018 which was $50.20. A red block in 2018 thusly has a higher price than a red in 2016.

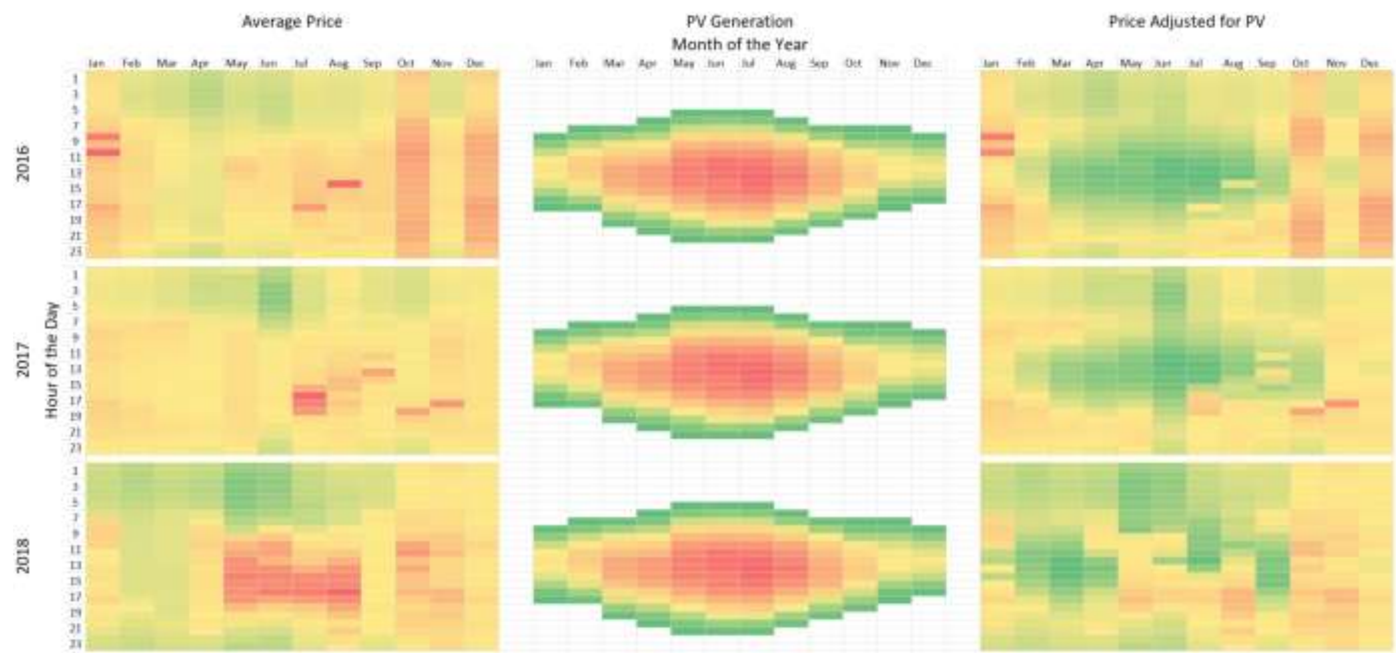

Figure 9: Alberta Grid Electricity Price and PV generation heat plots. Red represents highest values and green lowest values. The "Price Adjusted for PV" plot is calculated based on (10).

Both 2016 and 2017 had the most consistent pricing of any of the grids studied, with Standard Deviations (SD) of only $2.77 and $5.24 respectively across each 24-hour period. Savings from PV match the 72-hour DS strategy and the combined system results in almost no additional savings. The consistency in prices lead to little benefit from accessing the grid at different times and so the savings associated with self-generation from PV provides the best economic benefits, even with the analysis method giving DS cost savings that are above what is realistic.

Alberta 2018 shows much more fluctuation in price with a SD of $20.02 and more price spikes in the midday of the summer months. The highest and lowest prices of the year fall on the same days, on average, making the 12- and 24-hour DS strategies effective in achieving cost savings. Most of the high price hours occur during times of high solar PV generation, as seen by the reduction in red prices in the price adjusted for PV plot. This gives PV a 24% cost reduction with only a 15% CF. Little additional savings are achieved by optimizing PV with DS, which only increased total savings from 24% to 28%.

For Alberta, PV has a clear advantage with cost savings consistently above CF and increasing as price spikes become more frequent in high PV generation hours. The stability of the price in 2016 and 2017 makes cost savings from DS difficult to achieve. For 2018, while cost savings from DS are available, a 12-hour strategy is required to bring cost savings level with that of PV on its own. A 12-hour DS strategy could likely be realistic for a DS operation which could shift load throughout the day [22]. However, achieving a 12-hour strategy with storage would be more difficult as it would require large energy storage capacity. The pricing patterns in Alberta are consistent, with peaks occurring during daytime hours and troughs in nighttime hours, meaning a DS operator could come close to a perfect knowledge scenario. Nevertheless, PV shows clear advantages over DS based on the pricing patterns in the Alberta grid.

3.4.2 California (SF) Heat Plots

The pricing heat plots for California are clearly affected by the high adoption rates of solar. The “duck curve”, where price spikes occur as PV generation ramps up in the morning and again when PV ramps down in the range of 5-7 PM, is clearly visible in Figure 10 for 2016, 2017, and 2018. As a result, PV savings are below the CF for all three years. However, due to the high CF in California savings from PV are high in comparison to the DS strategies. PV was equivalent to the 24-hour DS strategy in 2017 and 2018 and outperformed even the full year DS strategy in 2016. This is a surprising result given the duck-curve trend in prices. The result is explainable by two patterns in the price: 1) high price hours still occur during peak PV generation, providing savings to the consumer; and 2) while prices spike as all PV aggregated across the grid declines, the individual consumer is still achieving some savings in these hours despite falling generation. There is an opportunity for optimizing the use of PV to only high price hours with the combined system. Cost savings can be increased from 27%, 26%, and 25% to 37%, 43%, and 40% for 2016, 2017, and 2018 respectively. In all three years, the savings from the combined system exceed the savings from the DS system. The savings from the DS strategies are higher for the 2- and 6-hour time intervals as compared to Alberta, suggesting that storage could be beneficial. However, these savings fall below PV on its own and well below the combined case.

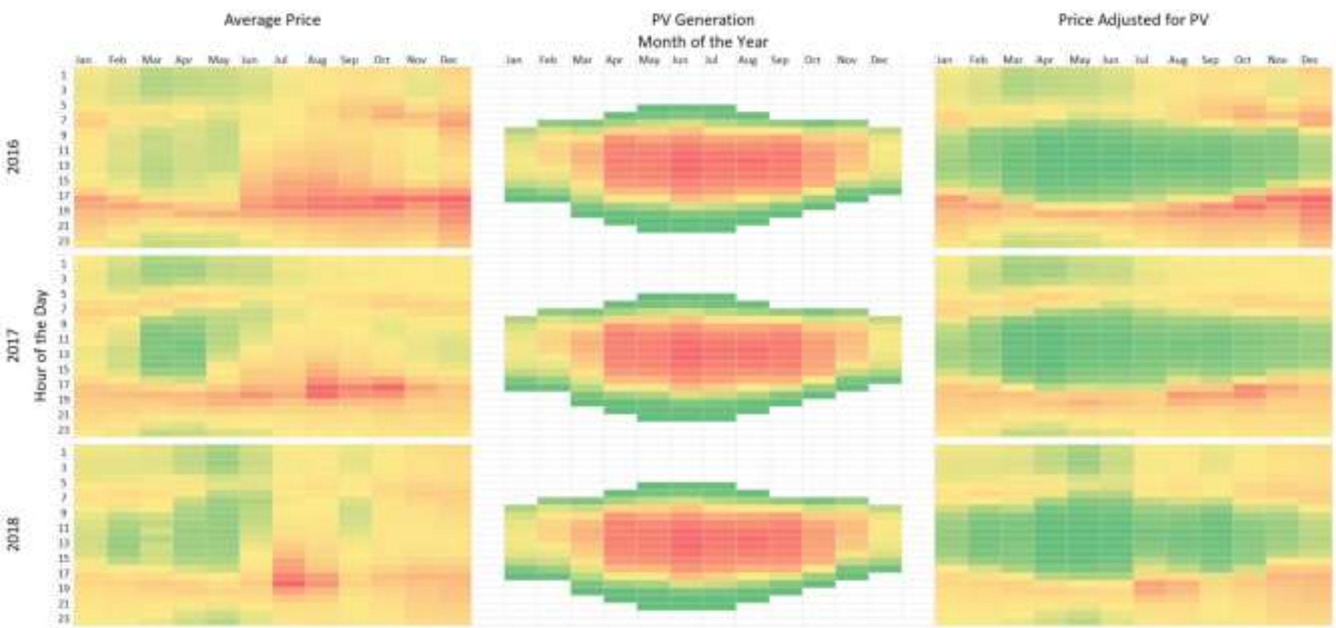

Figure 10: California (SF) Grid Electricity Price and PV generation heat plot. Red represents highest values and green lowest values. The "Price Adjusted for PV" plot is calculated based on (10).

Despite having the most installed solar of the grids studied, the California case shows a high cost savings benefit for consumers who install PV. These benefits can be increased through the use of a combined system. The benefits of DS on its own are lower, suggesting that opportunities for cost savings from arbitrage are lesser than for power generation.

3.4.3 Ontario Heat Plots

All Ontario results shown in Figure 11 are for the year 2018 across three nodes: the top is the HOEP, middle is the Atikokan node chosen for having the highest Standard Deviation of price, and right is the Thunder Bay node chosen for having the lowest Standard Deviation of price. While the HOEP shows high variation between months, there is a daily trend of low prices in the nighttime/morning hours and high prices in the midday peak hours, similar to Alberta 2018. The other Ontario nodes have the least consistency of the three grids studied, with the heat plots appearing more random than following specific patterns. Three large contributors to this variability are 1) the price regularly being negative 2) a higher allowable range in prices from $2,000 to (-) $2,000 per MWh and 3) a higher frequency of price spikes in both the positive and negative directions. Moreover, price spikes in the studied nodes of Ontario tend to occur more rapidly and last for a shorter period of time than in Alberta or California, with prices jumping in the range of $100s per MWh across a single hour. The most likely system cause of these spikes is transmission congestion at and between the different nodes, an increase in installed capacity of renewables that, coupled with nuclear and decreased demand, result in regular exports to other jurisdictions [41].

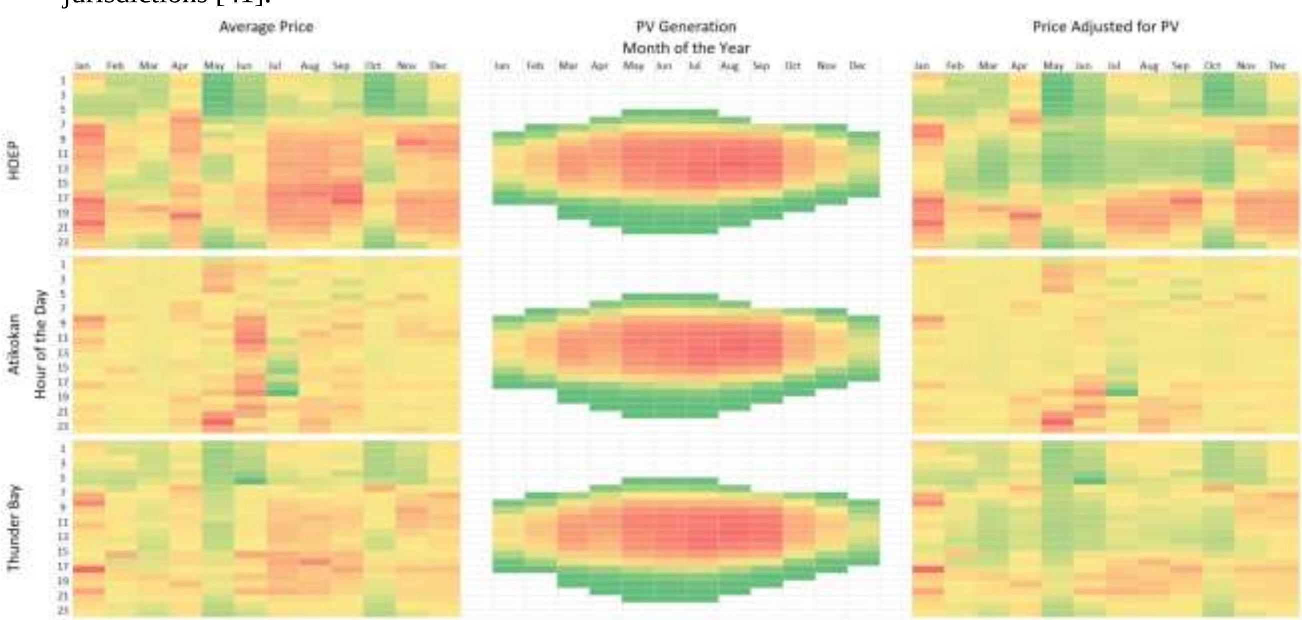

Figure 11: Ontario Grid Electricity and PV generation heat plot. Red represents highest values and green lowest values. The "Price Adjusted for PV" plot is calculated based on (10).

Translating these price patterns to the results of Figure 8, it is clear that Ontario has the best case for consumer level DS. This is most clear in the Atikokan node (highest standard deviation), where a 2-hour strategy surpasses the savings from PV on its own and a 6-hour strategy surpasses the combined system. The Atikokan node has the highest savings potential of any system in any of the grids studied with the full year DS strategy providing 119% cost savings. The Atikokan node also shows much improvement for the combined system over PV alone. This is largely due to a few specific hours of the year, where PV is generating during times of high negative prices (July) and not producing in hours of high positive prices (Jan, May, Jun, Aug). However, the same randomness that gives DS the highest cost savings of any grid studied also makes those cost savings the hardest to achieve in practice. Most often, price swings in the Ontario nodes occur rapidly (over one to two hours) and are very large in magnitude. The methods of this study assumed perfect prediction of the grid price, meaning that all of these large swings could be accounted for in the DS strategy. In practice, these swings would be much harder to predict. Therefore, while Ontario shows the most promise for consumer cost savings through DS, the results of this study also represent the largest disparity between what is theoretically possible and what is technically achievable. The sudden price spikes in the Ontario grid are, in large part, due to transmission constraints. DS ability in the grid can serve to reduce the strain on transmission lines, easing congestion. However, DS is not likely to provide a full solution to this problem.

The HOEP has a smaller standard deviation in price than any of the individual nodes in the Ontario system. The findings for the HOEP are very similar to Alberta 2018, where PV generally lines up well with high price hours and the DS strategies benefit from fluctuations that occur during 12- to 24-hour periods.

The Ontario results are less dependent on the alignment between PV generation and grid pricing and more dependent on fluctuations in price that have do not occur in regular hours. With DS applied in specific nodes (such as the Atikokan), transmission congestion could be avoided bringing a benefit to the system at large. However, the cost savings are more dependent on accurate prediction which is a major challenge in practice.

3.4.4 General Comparisons of PV, DS, and Combined Systems

The three grids studied provide a range of grid characteristics which lead to different results for the PV, DS, and combined cases. Alberta 2016 and 2017 suggest that PV alone is the best option in a grid with high consistency in the price of electricity. Alberta 2018 shows benefits for both PV and DS on their own due to price fluctuations occurring consistently within 24-hour periods and high price hours occurring during PV generation hours. California shows high cost savings from PV due to a high CF, with the combined PV and DS system showing the highest benefits of all. This is due to a number of high cost hours occurring just outside PV generation hours as a result of the “duck curve”. As such, a consumer does receive high cost savings from investing in PV but these savings can be improved with a combined system. Consistent pricing patterns in both Alberta and California make operation of DS relatively uncomplicated as consistent demand shifting can be applied each day. The DS system provided the most cost savings in Ontario nodes due to high price variability and sudden price spikes. However, the sudden nature of these price spikes also makes building a DS strategy around these price spikes. The 2- and 6-hour strategies were more effective in these nodes as compared to any of the other grids studied. In Atikokan and Thunder Bay, the combined system is also seen to have a large increase in cost savings over PV on its own. However, this is not necessarily due to a lack of alignment between high cost hours and PV generation hours as both nodes provide cost savings above the CF, meaning PV is generating more in hours above the average price.

The results allow for some definitive statements in comparing the three systems. On the spectrum of price variability, low variability makes PV the most beneficial technology while high variability, particularly with sudden spikes, favour DS systems with perfect price knowledge. The combined system provides the most benefit when the highest price hours and PV generation do not align. This effect is clear in the California case, where peak prices occur as PV generation falls in the evening and subsequently small amounts of storage would allow a consumer to avoid these high price hours. In the Atikokan and Thunder Bay nodes in Ontario, the savings from the combined system simply result from the high variability in the grid, rather than a lack alignment with PV generation. DS could be the most favourable technology in this case but only if price prediction were sufficient to predict and shift demand within hours with price spikes. Furthermore, in a grid with unstable pricing it is important to identify the root causes of the instability to properly stabilize the system. DS could serve as an assist to stabilization but further investigation into transmission infrastructure is also necessary.

3.4.5 Implications of Assumptions

The assumptions stated in Table 8 have differing effects on the three technologies studied. The assumptions were chosen to focus on the time component by assuming a best case scenario for a number of variables, such as DS capacity. This section provides some context to the results based on those assumptions.

Transmission and distribution charges are ignored as these are highly variable across consumer types (i.e. residential vs. industrial) and jurisdictions. Distribution charges increase the more the consumer accesses the grid [42]. For the PV system studied in this paper, PV generation would result in less grid access and therefore lower distribution charges. For DS, since grid access is only shifted, these charges would be the same.

Systems Power Capability and Investment

The installed capacity of PV was assumed to match the power demand of 25 MW. To go along with this, it was assumed that DS would allow demand to be shifted by a factor of 0 or 2. In other words, a 25 MW average demand can be achieved through a 0 MW and 50 MW demand in an even number of hours. For the higher time intervals, this would require an increasing freedom to shift load in a DSM case or an increased energy capacity in a storage case. As such, the higher time intervals for DS will require an increasingly high investment to make the DS strategy possible.

The NREL [43] provides a baseline for investment costs for a 100 MW PV system, a 60 MW battery storage system with various energy capacities, and a combined system of 100 MW PV with 60 MW battery storage with various energy capacities. Roughly scaling the results of the NREL study to match those presented here, the investment cost of a 2-hour storage strategy (equivalent to 1-hour of storage capacity) is roughly half the price of the PV system on its own; the investment cost of a 6-hour storage strategy (3-hours of storage capacity) is roughly equal to the price of the PV system; and a combined system has an investment cost of roughly 60-80% higher than the PV system alone. Based on these values, the Atikokan and Thunder Bay nodes of Ontario would be attractive for investments in storage alone as DS comes with cost savings well above those of PV within the 2- and 6-hour time frames. The combined system is a contentious case with maximum benefits of in California at 35%, 65%, and 58% higher than PV alone. This suggests that the economic benefits of investing in the combined system may not be as high as investing in PV alone.

The assumptions made for combined system are generous as all hours of the day are assumed accessible, meaning that storage capacity is ignored and the system is capable of "discharging before charging". This suggest that while the combined system does improve on the savings of the PV system, the overall return on investment will be lowered.

The analysis of Lindberg [22] suggests that a number of industries could practically apply DSM at the scale of 12- or 24-hours. With these time intervals, DSM could be more attractive than storage coming with cost savings competitive with PV in all Ontario nodes, California in all years, and Alberta in 2018. Alberta 2016 and 2017 are the only cases where DSM capable of a 12- or 24-hour strategy would not offer higher cost savings than PV, due to the price consistency seen in these two years.

Access to Wholesale Price

The results of this study are contingent on the consumer having access to the wholesale price of electricity; In Alberta, consumers can apply as a "self-retailer" to gain access to the wholesale price so long as financial restrictions are met and they are technically capable of accessing transmission lines [44].

In Ontario, consumers with a peak demand of 50 kW or more pay the wholesale price unless they are in a fixed-rate contract with a utility [45]. Large California consumers can similarly choose to enter a time of use contract through a utility or access the wholesale market directly [46]. Residential consumers will typically go through a utility scale retailer who provides a fixed rate, monthly floating rate (Alberta) [47], or time-of-use rate (California and Ontario) [48]. Net metering is also available in all three grids providing incentives for solar producers who sell excess generation back to the grid [49,50,51].

A fixed rate contract, along with net-metering, would provide the highest incentives for PV, similar to the results seen for Alberta 2016 and 2017 which had very stable pricing. With consistent hourly pricing, there would be no incentive for the DS strategies. Similarly, a floating monthly contract only changes rate from month to month so does not provide incentive to shift within a daily period.

A time-of-use rate would incentivize consumers to avoid certain hours as determined by the rate setter, being the system operator or the retailer. However, these rates may not be indicative of the wholesale price at any given time, particularly in a nodal system or as the grid evolves from year to year. Ontario is a good example of this, where the timing and frequency of price spikes, both positive and negative, occur with little hourly consistency throughout the year. Furthermore, with increasing PV penetration leading to a fall in generation at sunset times, time-of-use must be adjusted regularly to avoid duck-curve effects. These adjustments, however, may be ineffective if previous rates have already made a long-term change on customer behaviour.

The results of this study suggest that access to and knowledge of the wholesale price is the clearest way to send price signals that can change consumer habits. All three grids have mechanisms that allow large commercial and industrial scale consumers to access the wholesale price but not smaller and residential consumers. With access to the wholesale price, large consumers should react to price signals and adopt technologies that provide them the most cost savings and subsequently bring stability to the grid. However, there are many barriers to this and other variables that must be considered, such as incentives, business, and social goals. In the grids studied, Ontario consumers would benefit most from

DS technologies which should level the frequent price spikes, while in California adopting combined systems brings the highest cost savings and should mitigate the effects of the "duck-curve" prices.

3.5 Conclusions

Three technologies for consumer side electricity, solar PV, Demand Shifting (DS) technologies, and combined PV with DS, were analyzed to determine how price savings to the consumer compare. The technologies were compared across three different electricity grids, Alberta (2016, 2017, 2018), California (BAYSHOR2_1_N001 node, 2016, 2017, 2018), and Ontario (HOEP, Atikokan, and Thunder Bay nodes, 2018). The analysis was simplified to isolate the time component and determine how 1) timing of PV generation and 2) shifting demand between hours impacted the cost savings of each technology.

Demand shifting was analyzed in 6 time intervals, during which a consumer would purchase electricity from the grid for half the hours with the lowest price across the time interval. I.e. for a 6-hour time interval, electricity is purchased from the grid during the 3-hours with the lowest price and the 3-hours with higher prices are ignored. Time intervals studied were 2-, 6-, 12-, 24-, 72-hours, and a full year. Data for PV generation in each grid was subtracted from consumer load in each hour as per (10). The combined PV with DS allowed PV generation to be spread out in the highest price hours of any given day.

DS in all three grids was found to rapidly increase in cost savings by increasing time interval up to 12- to 24-hours, with the benefits of DS levelling out after a 24-hour time interval. This was verified both through the use of full year data and representative daily averages. This finding follows with grids generally operating under 24-hour cycles, with maximum and minimum prices occurring each day. While full days or months of higher prices can occur, a DS strategy of 24-hours allows a consumer to realize the most consistent benefits.

The analysis methods gave the most favour to DS through the assumptions of perfect price knowledge and limited physical limitations of the DS system. However, DS was shown to be at best comparable with PV in Alberta and California. In Ontario, the DS results are most favourable but achieving these DS results in practice would also be the most challenging of the three grids studied. The pricing patterns and fluctuations of each grid had a large impact on the cost savings from each technology. Alberta 2016 and 2017 had the most stable pricing and resulted in highest savings from PV, with a combined system and DS providing lesser benefits. Alberta 2018 saw the closest alignment between high price hours and PV generation, giving PV a high cost savings over the capacity factor (CF). DS had comparable savings due to consistent price fluctuations over 24-hour periods. California saw the most benefit from the combined system due to pricing peaks occurring just outside of times of PV generation. However, both PV and DS on their own had comparable cost savings. From the results, California would be the grid most requiring more thorough analysis than the simplified method presented here for decision making as each technology shows comparable savings. Ontario, with the highest price fluctuations of any of the grids studied, saw the highest cost savings from DS, and highest cost savings potential of all, with up to 119% savings in the Atikokan node. However, as these savings are dependent on rapid price fluctuations, achieving the cost savings shown in the results would be the most challenging in the Ontario nodes. DS can provide some assistance in stabilizing the price within the grid, though larger interventions that serve to prevent nodal price spikes would also be necessary to bring stability to the price.

The cost savings results align well with the price patterns observed in the heat plots and subsequently the technologies that provide the highest potential cost savings in each grid. This suggests that this type of analysis identifying representative daily averages of price can be useful in identifying the best technologies for consumers to choose depending on grid price patterns. Access to the wholesale price, along with analysis showing patterns in the price, should allow consumers to make investment decisions that not only benefit them in the form of cost savings but also serve to increase the adoption of renewable energy and level fluctuations in the grid price. Despite the alignment between pricing patterns and cost savings, the best method to encourage consumers to adopt the most beneficial technologies is unclear and should be a focus of future research.

References

[1] Hontao Yi (2014) Green businesses in a clean energy economy: Analyzing drivers of green business growth in U.S. States. *Energy*, 68, 922-929, http://dx.doi.org/10.1016/j.energy.2014.02.044

[2] BP. (2019) *BP Energy Outlook 2019 Edition.* Available online: https://www.bp.com/content/dam/bp/business-sites/en/global/corporate/pdfs/energy-economics/energy-outlook/bp-energy-outlook-2019.pdf Accessed September 25th, 2019

[3] Poudineh, R., Jamasb, T. (2014) Distributed generation, storage, demand response and energy efficiency as alternatives to grid capacity enhancement. *Energy Policy*, 67, 222-231. http://dx.doi.org/10.1016/j.enpol.2013.11.073

[4] Cai, D. W. H., Adlakha, S., Low, S. H., Martini, P. De, & Chandy, K. M. (2013). Impact of residential PV adoption on Retail Electricity Rates. Energy Policy, 62, 830–843. https://doi.org/10.1016/j.enpol.2013.07.009

[5] Comello, S., Reichelstein, S., & Sahoo, A. (2018). The road ahead for solar PV power. *Renewable and Sustainable Energy Reviews*, 92(May), 744–756. https://doi.org/10.1016/j.rser.2018.04.098

[6] Quoilin, S., Kavvadias, K., Mercier, A., Pappone, I., & Zucker, A. (2016). Quantifying self-consumption linked to solar home battery systems: Statistical analysis and economic assessment. *Applied Energy*, 182, 58–67. https://doi.org/10.1016/j.apenergy.2016.08.077

[7] Akhil, A. A., Huff, G., Currier, A. B., Kaun, B. C., Rastler, D. M., Bingqing Chen, S., Cotter, A.L., Bradshaw, D.T., and Gauntlett, W. D. (2015). SANDIA REPORT: DOE / EPRI Electricity Storage Handbook in Collaboration with NRECA, *Sandia National Laboratories*. SAND2015-1002

[8] Palensky, P., Dietrich, D. (2011). Demand Side Management: Demand Response, Intelligent Energy Systems, and Smart Loads. *IEEE Transactions on Industrial Informatics*, 7(3), 381–388. https://doi.org/10.1109/TII.2011.2158841

[9] O'Shaughnessy, E., Cutler, D., Ardani, K., & Margolis, R. (2018). Solar plus: A review of the end-user economics of solar PV integration with storage and load control in residential buildings. *Applied Energy*, 228(July), 2165–2175. https://doi.org/10.1016/j.apenergy.2018.07.048

[10] Solar Energy Industry Association (n.d.) *Solar Means Business: Top Commercial Solar Customers in the U.S.* Available online: https://www.seia.org/research-resources/solar-means-business-top-commercial-solar-customers-us Accessed: September 26th, 2019

[11] Apple (n.d.) *Apple now globally powered by 100 percent renewable generation.* Available online: https://www.apple.com/ca/newsroom/2018/04/apple-now-globally-powered-by-100-percent-renewable-energy/. Accessed September 26th, 2019.

[12] Schaefer, J. C. (1990) Review of Photovoltaic Power Plant Performance and Economics. *IEEE Transactions on Energy Conversion*, 5(2), 232-238.

[13] United States Nuclear Regulatory Commission (n.d.) Home -> NRC Library -> Basic Reference -> Glossary -> Capacity Factor (net). Available online: https://www.nrc.gov/reading-rm/basic-ref/glossary/capacity-factor-net.html Accessed September 26th, 219.

[14] Salameh, Z. M., Borowy, B. S., & Amin, A. R. A. (1995). Photovoltaic Module-Site Matching Based on the Capacity Factors, *IEEE Transactions on Energy Conversion*, 10(2), 326–332.

[15] Baker, E., Fowlie, M., Lemoine, D., & Reynolds, S. S. (2013). The Economics of Solar Electricity. *Annual Review of Resource Economics.* https://doi.org/10.1146/annurev-resource-091912-151843

[16] Borenstein, S. (2008) The Market Value and Cost of Solar Photovoltaic Electricity Production. *Center for the Study of Energy Markets.* https://escholarship.org/uc/item/3ws6r3j4

[17] Black, A. J. (2004). Financial payback on California residential solar electric systems, *Solar Energy*, 77, 381–388. https://doi.org/10.1016/j.solener.2004.02.003

[18] California ISO (2016) *What the duck curve tells us about managing a green grid.* Available online: https://www.caiso.com/Documents/FlexibleResourcesHelpRenewables_FastFacts.pdf. Accessed September 26th, 2019.

[19] Denholm, P., O'Connell, M., Brinkman, G., and Jorgenson, J. (2015). Overgeneration from Solar Energy in California: A Field Guide to the Duck Chart. *NREL National Renewable Energy Laboratory.* Available online: https://www.nrel.gov/docs/fy16osti/65023.pdf

[20] Walawalkar, R., Apt, J., & Mancini, R. (2007). Economics of electric energy storage for energy arbitrage and regulation in New York, *Energy Policy*,35, 2558–2568. https://doi.org/10.1016/j.enpol.2006.09.005

[21] Strbac, G. (2008). Demand side management: Benefits and challenges, *Energy Policy*, 36, 4419–4426. https://doi.org/10.1016/j.enpol.2008.09.030

[22] Lindberg, C., Zahedian, K., Solgi, M., and Lindkvist, R. (2014). Potential and limitations for industrial demand side management. *Energy Procedia*, 61, 415–418. https://doi.org/10.1016/j.egypro.2014.11.1138

[23] Tyagi, R., Fisher, R.A., Black, J.W. (2015) *Method and System to Co-Optimize Utilization of Demand Response and Energy Storage Resources.* United States Patent, US 9,209,625 B2, Dec. 8, 2015

[24] Zhu, Z., Tang, J., Lambotharan, S., Chin, W. H., Fan, Z.(2011). An Integer Linear Programming Based Optimization for Home Demand-side Management in Smart Grid. 2012 IEEE PES Innovative Smart Grid Technologies (ISGT), 1–5. https://doi.org/10.1109/ISGT.2012.6175785

[25] Reihani, E., Motalleb, M., Thornton, M., & Ghorbani, R. (2016). A novel approach using flexible scheduling and aggregation to optimize demand response in the developing interactive grid market architecture. *Applied Energy*, 183, 445–455. https://doi.org/10.1016/j.apenergy.2016.08.170

[26] Khalid, A., Javaid, N., Guizani, M., Alhussein, M., Aurangzeb, K., Ilahi, M. (2018). Towards Dynamic Coordination Among Home Appliances Using Multi-Objective Energy Optimization for Demand Side Management in Smart Buildings. *IEEE Access*, 6, 19509–19529. https://doi.org/10.1109/ACCESS.2018.2791546

[27] Krishnamurthy, D. Uckun, C. Zhou, Z., Thimmapuram, P.R., Botterud, A. (2018) Energy Storage Arbitrage Under Day-Ahead and Real-Time Price Uncertainty. *IEEE Transactions on Power Systems.* 33(1), 84-93, 10.1109/TPWRS.2017.2685347

[28] O'Shaughnessy, E., Cutler, D., Ardani, K., & Margolis, R. (2018). Solar plus: Optimization of distributed solar PV through battery storage and dispatchable load in residential buildings. *Applied Energy*, 213(October 2017), 11–21. https://doi.org/10.1016/j.apenergy.2017.12.118

[29] Kurland, S. D., & Benson, S. M. (2019). The energetic implications of introducing lithium-ion batteries into distributed photovoltaic systems, *Sustainable Energy & Fuels*, 3, 1182–1190. https://doi.org/10.1039/c9se00127a

[30] AESO Alberta Electricity Systems Operator (n.d.) Historical –> Pool Price. Available online: ets.aeso.ca. Accessed July 2019.

[31] AESO Alberta Electricity Systems Operator (n.d.) Historical –> System Marginal Price. Available online: ets.aeso.ca. Accessed July 2019.

[32] CAISO California Independent Systems Operator (n.d.) Price Map. Available Online: http://www.caiso.com/PriceMap/Pages/default.aspx. Accessed July 2019.

[33] CAISO California Independent Systems Operator (n.d.) Oasis -> Price -> Location Marginal Prices; System Demand -> Actual. Available online: http://oasis.caiso.com/mrioasis/logon.do. Accessed July 2019.

[34] IESO Ontario Independent Systems Operator (n.d.) Reports -> public -> PriceNodal;. Available online: http://reports.ieso.ca/public/PriceNodal. Accessed July 2019.

[35] IESO Ontario Independent Systems Operator (n.d.) Reports -> public -> PriceHOEPPPredispOR; Available online: http://reports.ieso.ca/public/PriceHOEPPredispOR . Accessed July 2019.

[36] IESO Ontario Independent Systems Operator (n.d.) Reports -> public -> Demand; Available online: http://reports.ieso.ca/public/Demand. Accessed July 2019.

[37] Environment and Climate Change Canada (n.d.) Charts -> Solar Radiation -> Hourly Data. Available online: https://calgary.weatherstats.ca/charts/solar_radiation-hourly.html. Accessed July 2019.

[38] Canadian Solar Inc. (2019) *HiKu Super High Power Poly Perc Module, 395W ~ 415 W*. Available online: https://www.canadiansolar.com/upload/55bb2d3819da47c6/0ac3c8f850d7224a.pdf. Accessed August 15th, 2019.

[39] CAISO California Independent Systems Operator (n.d.) TodaysOutlook -> Supply -> Renewables Trend -> Data. Available online: http://www.caiso.com/TodaysOutlook/Pages/Supply.aspx. Accessed August 15th, 2019.

[40] IESO Ontario Independent Systems Operator (n.d.) Reports -> public -> GenOutputCapability; Available online: http://reports.ieso.ca/public/GenOutputCapability/PUB_GenOutputCapability.xml Accessed August 16th 2019.

[41] Aliakbari, E., Stedman, A., Green, K. P. (2017) Ontario's power-price crisis – how did it happen and who got hurt. *Fraser Institute.* Available online: https://www.fraserinstitute.org/article/ontarios-power-price-crisis-how-did-it-happen-and-who-got-hurt. Accessed August 16th, 2019.

[42] AUC Alberta Utilities Commission (n.d.) *Items on your bill.* Available online: http://www.auc.ab.ca/Pages/items-on-your-bill.aspx#targetText=Distribution%20charge%20–%20The%20distribution%20charge,and%20maintaining%20their%20distribution%20systems. Accessed August 17th, 2019.

[43] Fu, R., Remo, T., Margolis, R. (2018) 2018 U.S. Utility-Scale Photovoltaics—Plus-Energy Storage System Costs Benchmark. *NREL National Renewable Energy Laboratory.* Available online: https://www.nrel.gov/docs/fy19osti/71714.pdf

[44] AESO Alberta Electricity Systems Operator (n.d.) *Joining the Energy Market.* Available online: https://www.aeso.ca/market/joining-the-energy-market/. Accessed September 15th, 2019.

[45] IESO Ontario Independent Systems Operator (n.d.) Electricity Pricing for Mid-sized and Large-Businesses. Available online: http://www.ieso.ca/en/Learn/Electricity-Pricing/For-Mid-sized-and-Large-Businesses. Accessed September 15th, 2019.

[46] CPUC California Public Utilities Commission (n.d.) *What Are TOU rates?* Available online: https://www.cpuc.ca.gov/General.aspx?id=12194. Accessed September 15th, 2019.

[47] ENMAX Corp. (n.d.) *Electricity Rates.* Available online: https://www.enmax.com/ForYourHomeSite/Pages/Rates-Easymax-Electricity-After.aspx#targetText=EasyMax®%20Floating%20Rate**,and%20service%20area%20and%20taxes. Accessed September 15th, 2019.

[48] Alectra Utilities (n.d.) *Time-of-Use (TOU) Pricing and Schedules.* Available online: https://www.powerstream.ca/customers/rates-support-programs/time-of-use-pricing.html. Accessed September 16th, 2019.

[49] AUC Alberta Utilities Commission (n.d.) *Micro-Generation.* Available online: http://www.auc.ab.ca/Pages/micro-generation.aspx. Accessed September 16th, 2019.

[50] Go Solar California (n.d.) *Net Energy Metering in California.* Available online: https://www.gosolarcalifornia.ca.gov/solar_basics/net_metering.php#targetText=You%20are%20eligible%20for%20net,is%201%2C000%20kW%20or%20less. Accessed September 16th, 2019.

[51] Hydro One (n.d.) *Net Metering.* Available online: https://www.hydroone.com/business-services/generators/net-metering. Accessed September 16th, 2019.

SI-3: Supporting Information for Chapter 3

SI-3.A Comparison of Full-Year and Representative Daily Average Results

Tables 10 and 11 of section SI-3.C provide a direct comparison between the demand-shifting (DS) results from analysis of full-year data, where results were calculated across all 8,760 hours of the year, and the Representative Daily Averages (RDA), where time intervals were calculated on a representative 24-hour day for each month. The full-year method is more accurate and so the difference between the two is referred to as the error in the RDA method. Figure 12 shows the error of the RDA method for the different load shifting intervals, for all grids other than Ontario. Error for Ontario is shown in Figure 13.

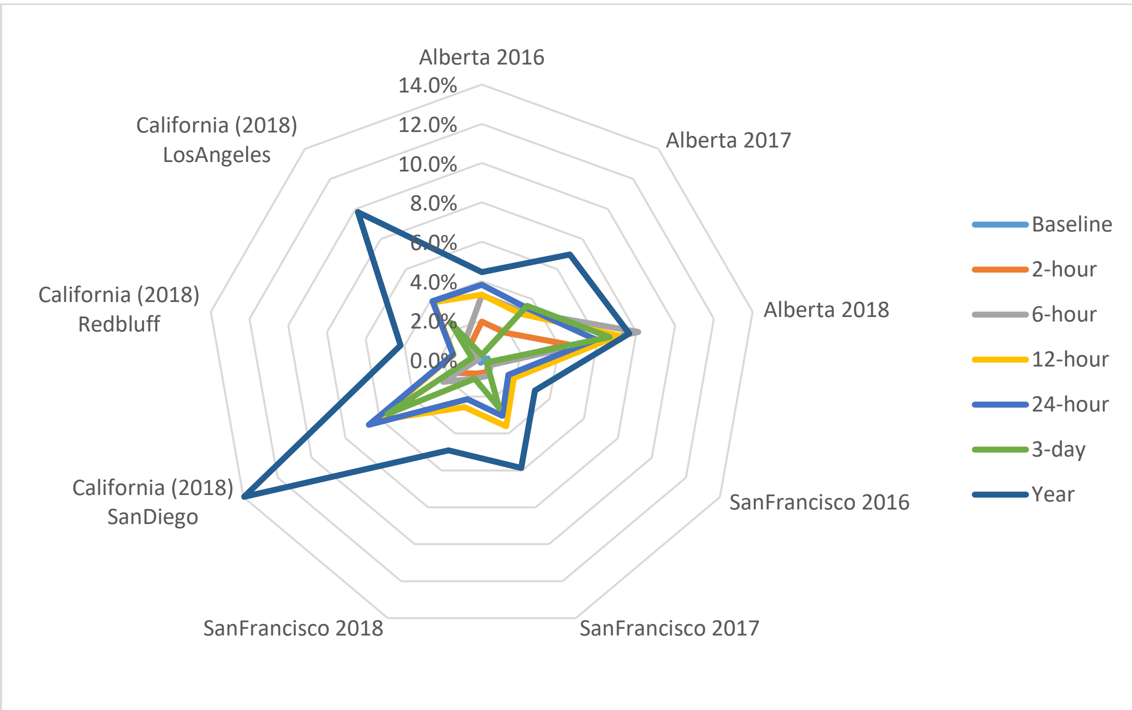

Figure 12: Percent Error for the representative daily average analysis method versus the full year data analysis method for load-shifting time intervals.

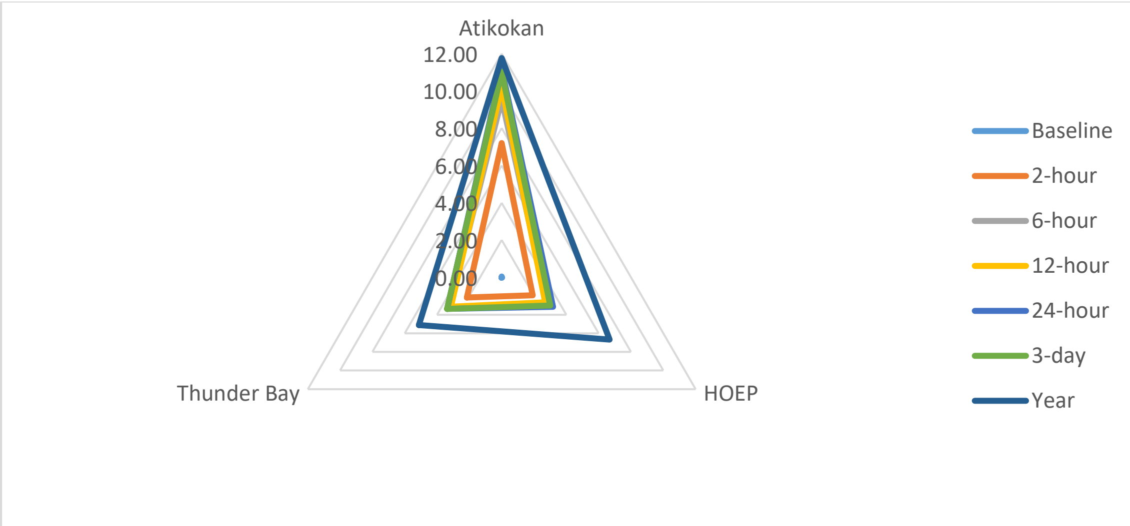

Figure 13: Error for the representative daily average analysis method versus the full year data analysis method for Ontario nodes. Values shown are in \$/MWh discrepancy between the two methods.

As seen in Figure 12, the error in the RDA method as compared to the full-year method increases as the time interval increases, with the highest error coming from the full-year time interval. This error is caused by price spikes which are diluted in the RDA method. The full-year time interval captures every price spike, both when prices go well above and below average. The price spikes in the San Diego and Los Angeles nodes are more frequent than in the other grids studied, leading to a higher error from the RDA method. Furthermore, the price spikes in these nodes are smaller in magnitude, meaning they become more diluted when averaged over the year. Price spikes in Alberta 2018 are slightly less frequent but higher in magnitude, making the error more prevalent in small time intervals. Error in Alberta 2018 does not exceed 8% and, exempting the full-year time interval for San Diego and Los Angeles, no other error exceeds 5% between the two methods.

Figure 13 shows the error to be much higher for the Ontario nodes. The price between the two methods is shown rather than the % error as the % error is exaggerated by negative price values, particularly in the Atikokan node. The Ontario nodes see price spikes in both positive and negative prices and so these spikes are captured less with the RDA method than the Alberta and California grids which only have positive pricing. The largest price differences occur in the Atikokan node where the RDA method calculates a final price of $7.70 compared to -$4.06 for the full-year method. This discrepancy of $11.77, equivalent to 55% of the baseline price, results in a % error of 153%. The HOEP has a maximum discrepancy of $6.67, equivalent to 30% of the baseline price. Figure 14 shows the comparison between the three technologies for Ontario with the full year data.

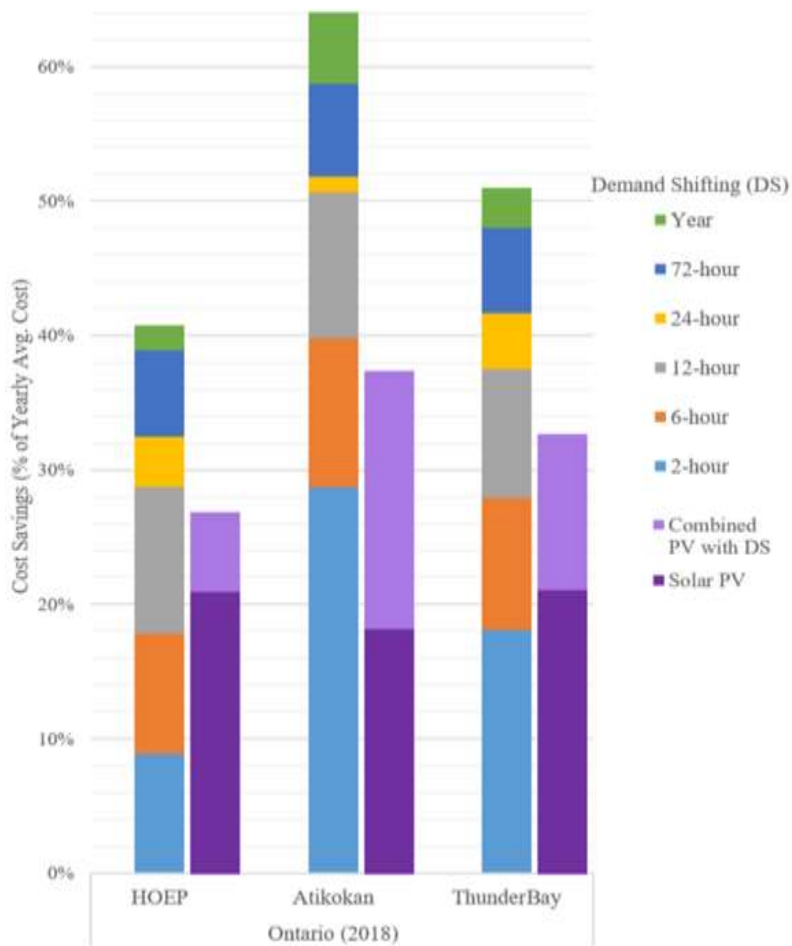

Figure 14: Comparison of cost savings for Ontario using the full year data analysis method.

From Figure 14, the solar PV and combined system results are far lower when compared to the DS results for the full-year method. This reinforces the conclusion that load-shifting strategies are the best technology to employ in the Ontario grid.

Figure 15 shows the error between the RDA and full-year methods for the solar PV calculations. The maximum error between the methods was only 2.8%. This suggests that many of the price spikes in Ontario, which lead to high error in the load-shifting scenarios, do not occur in solar generation hours and therefore do not create error in the PV calculations.

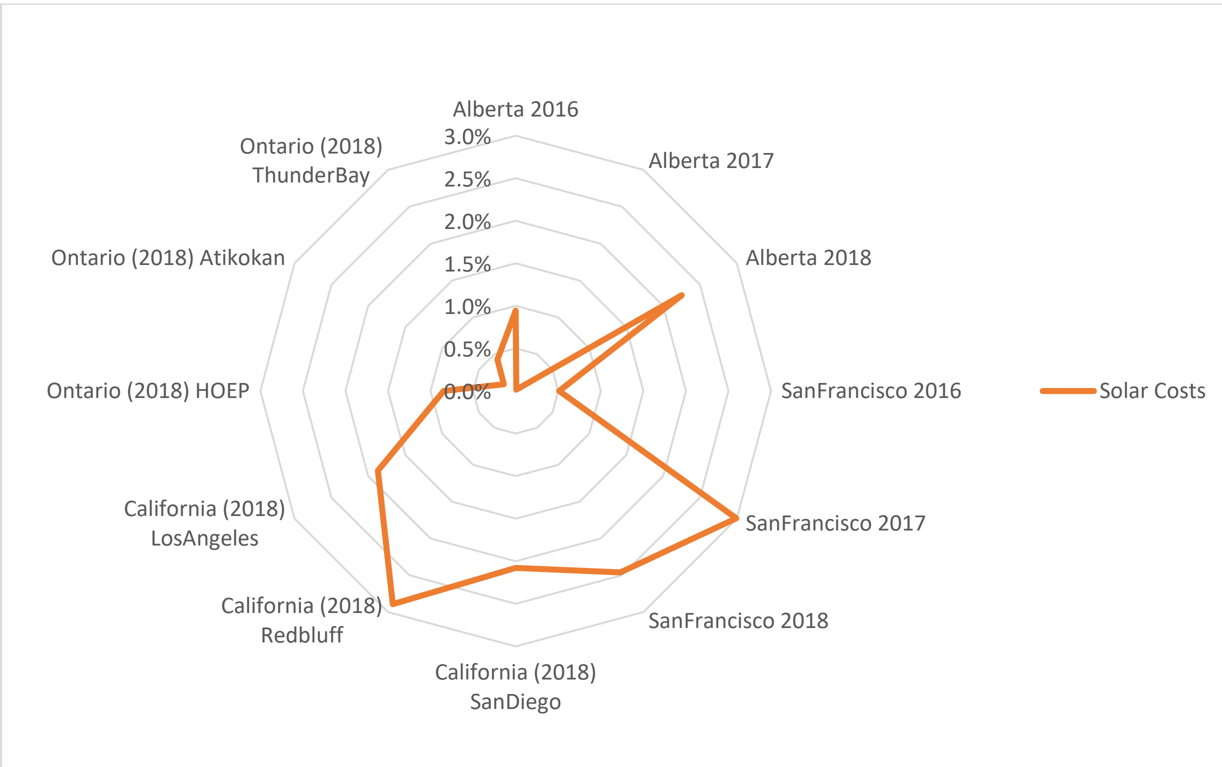

Figure 15: Percent Error for the representative daily average analysis method versus the full year data analysis method for PV.

SI-3.B California Nodes Outside San Francisco

The results for the California nodes outside of San Francisco (San Diego, Red Bluff, and Los Angeles) were not shown in the chapter. This is because the results were very similar to those for San Francisco 2018 and did not show any patterns the effected on the comparison of the three technologies differently than San Francisco. Figure 16 shows the final cost savings results for these three nodes compared to the results of San Francisco 2018. Figure 17 provides the heat plots for these three nodes.

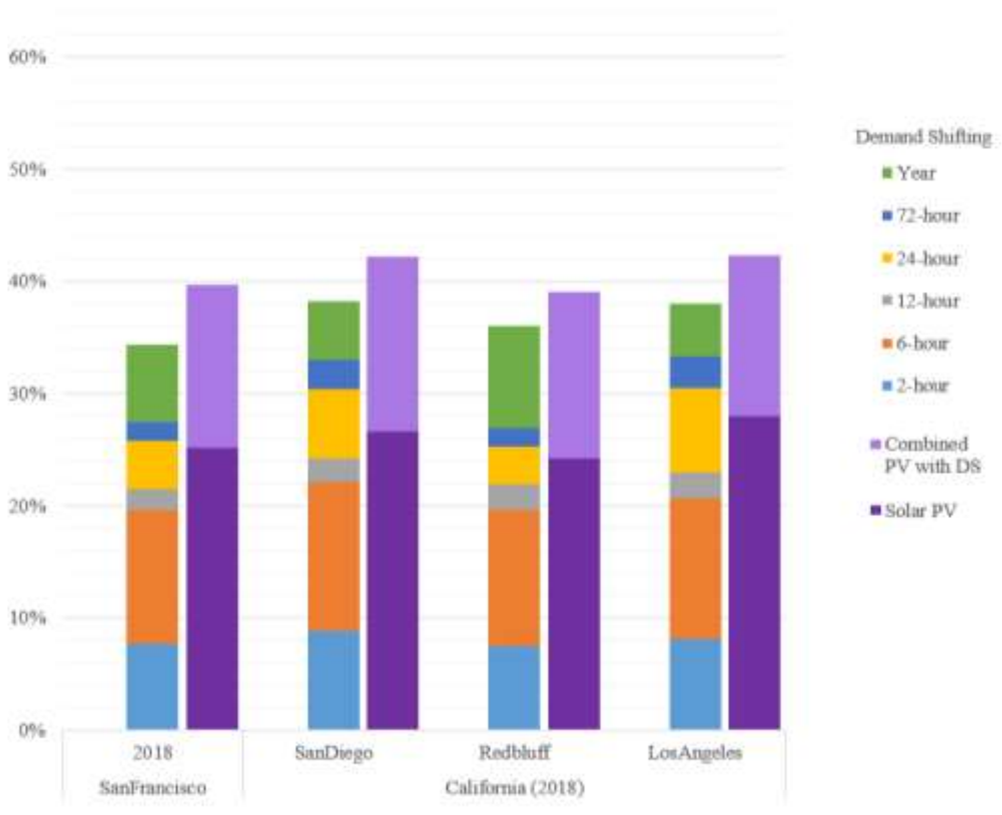

Figure 16: Comparison of cost savings for California nodes. These nodes were not discussed in the paper due to similarity with the San Francisco 2018 case.

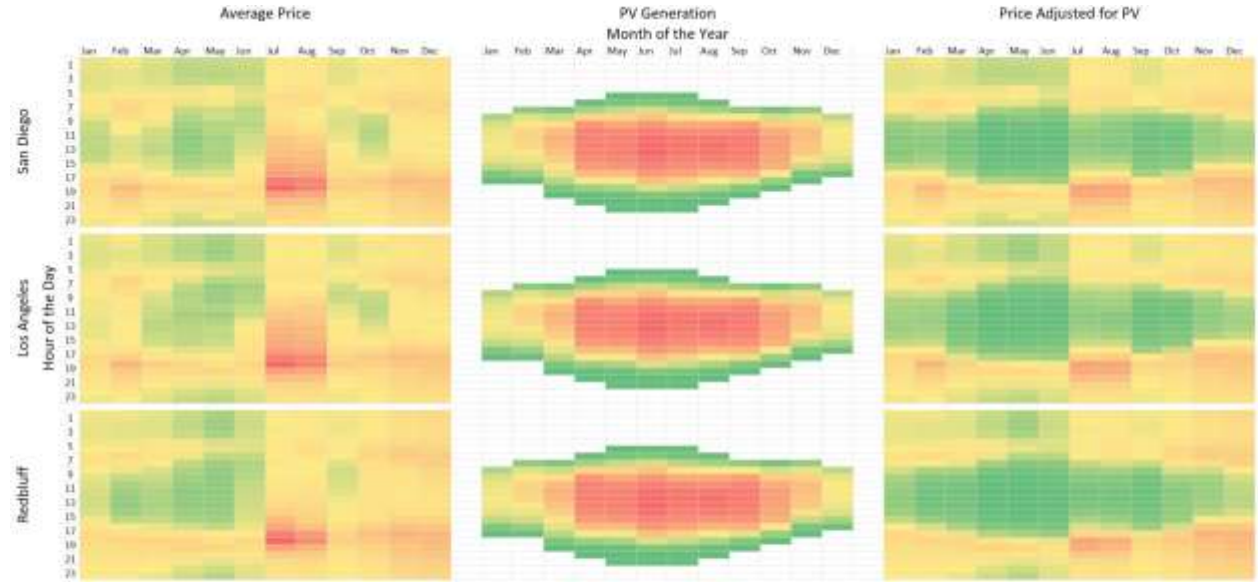

Figure 17: California Nodal Grid Electricity Price and PV generation heat plot. Red represents highest values and green lowest values. The "Price Adjusted for PV" plot is calculated based on (10).

SI-3.C Tabulated Results

Table 10: Results for representative daily average analysis method for all load-shifting time intervals.

		Baseline	2-hour		6-hour		12-hour	
		$/MWh	$/MWh	Savings	$/MWh	Savings	$/MWh	Savings
Alberta	2016	$18.26	$17.75	3%	$17.25	6%	$16.51	10%
	2017	$22.17	$21.10	5%	$20.15	9%	$19.14	14%
	2018	$50.19	$47.10	6%	$43.57	13%	$36.99	26%
San Francisco	2016	$30.62	$29.03	5%	$26.50	13%	$26.00	15%
	2017	$35.94	$32.65	9%	$27.77	23%	$26.89	25%
	2018	$40.65	$37.52	8%	$32.69	20%	$31.90	22%
California (2018)	San Diego	$46.01	$41.93	9%	$35.85	22%	$34.87	24%
	Redbluff	$37.96	$35.13	7%	$30.53	20%	$29.65	22%
	Los Angeles	$46.40	$42.65	8%	$36.80	21%	$35.73	23%
Ontario (2018)	HOEP	$22.47	$20.47	9%	$18.46	18%	$16.01	29%
	Atikokan	$21.41	$15.25	29%	$12.89	40%	$10.57	51%
	Thunder Bay	$14.91	$12.22	18%	$10.75	28%	$9.32	37%
		Baseline	24-hour		3-day		Full Year	
		$/MWh	$/MWh	Savings	$/MWh	Savings	$/MWh	Savings
Alberta	2016	$18.26	$16.13	12%	$15.25	16%	$14.74	19%
	2017	$22.17	$18.64	16%	$18.25	18%	$18.15	18%
	2018	$50.19	$34.21	32%	$33.38	33%	$31.54	37%
San Francisco	2016	$30.62	$24.96	18%	$24.43	20%	$23.31	24%
	2017	$35.94	$25.14	30%	$24.72	31%	$24.25	33%
	2018	$40.65	$30.18	26%	$29.48	27%	$26.67	34%
California (2018)	San Diego	$46.01	$32.03	30%	$30.81	33%	$28.41	38%
	Redbluff	$37.96	$28.37	25%	$27.72	27%	$24.30	36%
	Los Angeles	$46.40	$32.28	30%	$30.95	33%	$28.77	38%
Ontario (2018)	HOEP	$22.47	$15.17	32%	$13.72	39%	$13.31	41%
	Atikokan	$21.41	$10.31	52%	$8.83	59%	$7.70	64%
	Thunder Bay	$14.91	$8.70	42%	$7.75	48%	$7.31	51%

Table 11: Results for full year data analysis method for all load-shifting time intervals.

		Baseline	2-hour		6-hour		12-hour	
		$/MWh	$/MWh	Savings	$/MWh	Savings	$/MWh	Savings
Alberta	2016	$18.28	$17.41	5%	$16.70	9%	$15.98	13%
	2017	$22.19	$20.73	7%	$19.53	12%	$18.57	16%
	2018	$50.35	$45.09	10%	$40.31	20%	$34.55	31%
San Francisco	2016	$30.66	$28.91	6%	$26.36	14%	$25.51	17%
	2017	$35.98	$32.43	10%	$27.53	23%	$25.96	28%

	2018	$40.72	$37.24	9%	$32.36	21%	$31.10	24%
California (2018)	San Diego	$46.07	$41.37	10%	$35.05	24%	$32.83	29%
	Redbluff	$38.07	$35.03	8%	$30.48	20%	$29.23	23%
	Los Angeles	$46.47	$42.27	9%	$36.34	22%	$34.42	26%
Ontario (2018)	HOEP	$22.44	$18.56	17%	$15.64	30%	$13.32	41%
	Atikokan	$21.37	$8.05	62%	$3.33	84%	$0.34	98%
	Thunder Bay	$14.93	$10.06	33%	$7.50	50%	$6.18	59%

		Baseline	24-hour		3-day		Full Year	
		$/MWh	$/MWh	Savings	$/MWh	Savings	$/MWh	Savings
Alberta	2016	$18.26	$15.54	15%	$15.21	17%	$14.12	23%
	2017	$22.17	$18.02	19%	$17.62	21%	$16.97	24%
	2018	$50.19	$32.30	36%	$31.31	38%	$29.31	42%
San Francisco	2016	$30.62	$24.58	20%	$24.36	21%	$22.60	26%
	2017	$35.94	$24.40	32%	$24.10	33%	$22.91	36%
	2018	$40.65	$29.55	27%	$29.17	28%	$25.42	38%
California (2018)	San Diego	$46.01	$30.04	35%	$29.19	37%	$24.93	46%
	Redbluff	$37.96	$27.95	27%	$27.58	28%	$23.32	39%
	Los Angeles	$46.40	$31.07	33%	$30.22	35%	$26.20	44%
Ontario (2018)	HOEP	$22.47	$11.99	47%	$10.72	52%	$6.64	70%
	Atikokan	$21.41	-$0.87	104%	-$2.20	110%	-$4.06	119%
	Thunder Bay	$14.91	$5.33	64%	$4.37	71%	$2.18	85%

Table 12: Results for full year and representative daily average analysis method for PV and combined system cost savings.

		Baseline	Full Year Solar		RDA Solar		Combined	
			$/MWh	Savings	$/MWh	Savings	$/MWh	Savings
Alberta	2016	$18.28	$15.43	*16%*	$15.28	16%	$15.04	*18%*
	2017	$22.19	$18.25	*18%*	$18.26	18%	$17.43	*21%*
	2018	$50.35	$38.03	*24%*	$38.88	23%	$36.11	*28%*
San Francisco	2016	$30.66	$22.41	*27%*	$22.29	27%	$19.39	*37%*
	2017	$35.98	$27.39	*24%*	$26.57	26%	$20.49	*43%*
	2018	$40.72	$31.06	*24%*	$30.30	25%	$24.32	*40%*
California (2018)	San Diego	$46.07	$34.32	*25%*	$33.61	27%	$26.34	*43%*
	Redbluff	$38.07	$29.52	*22%*	$28.67	24%	$22.95	*40%*
	Los Angeles	$46.47	$33.89	*27%*	$33.26	28%	$26.52	*43%*
Ontario (2018)	HOEP	$22.44	$17.70	*21%*	$17.67	21%	$16.31	*27%*
	Atikokan	$21.37	$17.59	*18%*	$17.44	19%	$13.26	*38%*
	Thunder Bay	$14.93	$11.76	*21%*	$11.71	21%	$9.95	*33%*

Chapter 4: Overall Conclusions

This thesis explores the impacts of demand-shifting in electricity systems from two perspectives identifying whether it would be beneficial for a grid operator to acquire demand-shifting ability in the grid and whether it would be beneficial for a consumer to provide it. The results show that there is potential for a decrease in the cost of electricity from both the grid and the consumer perspective and that emissions are largely unaffected by demand-shifting alone.

From the grid perspective, small or marginal changes in demand applied in rare hours throughout the year have the ability to significantly lower the price for those hours, which add up to provide a large savings to the yearly cost of electricity. Chapter 2 identified these cost saving by applying demand shifts to the merit order of the Alberta grid. The study is the first in the literature, to my knowledge, that utilizes each bid from each individual generator in the merit order, along with data on wind generation, interties, and reserves, to determine how the spot price and emissions factor would change from hour to hour with shifts in demand. The Merit Order Effect, where the price is shifted due to changes in demand, was found to be important, as a regular reduction in demand of roughly 1% of total system demand resulted in a reduction of yearly grid electricity costs of 18%. The opportunities for large cost savings were rare but had a large impact, as applying demand reductions in less than 2% of hours in the study period still resulted in a 14% reduction in costs. These hours occur when the price is near the top of the merit order and small changes in demand result in changes in the spot price on the order of $100s. This demonstrates a major opportunity for price savings through small, occasional actions on the demand side and provides a clear motivation for grid operators to acquire or promote demand-shifting technologies in the grid.

In terms of emissions, the merit order was far less organized than previously suggested in the literature and, as a result, the marginal emissions factor (MEF) was very inconsistent. The MEF is not ideal to *quantify* the emissions for a grid, as grids with low emissions from baseload, but high emissions from the marginal generators, are unfairly punished by the MEF, and grids with high baseload emissions but low marginal emissions unfairly rewarded. It is recommended to use the Hourly Average Emissions

Factor (HAEF) to quantify grid-scale emissions. Based on the HAEF, demand-shifting of the scale studied has little impact on grid scale emissions, with the maximum possible change in HAEF of ±4%. Based on this, demand-shifting alone should not be seen as a mechanism to reduce grid emissions. However, demand-shifting can contribute to a reduction in emissions by assisting with the adoption of renewables and preventing ramping in fossil-fueled generators.

Based on the study of the merit order, specific trends were identified that result in the price fluctuations and spikes within the grid. Where a low amount of power is bid across a wide price range in the merit order, small fluctuations in demand can have large impacts on the grid price. This is of particular importance when these low power bid zones occur at high prices in the merit order, where a small change in demand can change the spot price by hundreds of dollars per MWh. By assessing the merit order bids, these danger zones are easily identifiable and the use of intelligent demand-shifting at these times could greatly reduce fluctuations in price and the overall yearly grid costs. This result suggests that a small amount of demand-shifting ability within the grid, while rarely needed, can have a large benefit to grid costs.

On the consumer side, it was determined whether a consumer would obtain more cost savings from the use of demand-shifting technologies, solar PV, or a combination of the two. The results show that the answer is highly dependent on the pricing patterns within the grid the consumer is purchasing from, particularly in terms of the timing of pricing peaks. In grids with low price fluctuations or peaks that align with solar generation, simply installing solar PV is the best option to achieve cost savings. In grids with large fluctuations in daily price, particularly when those fluctuations are irregular, demand-shifting can provide much higher cost savings than solar PV but only in situations where demand operators are capable of predicting changes in price. This provides a counterintuitive result for the potential of demand-shifting on the consumer side, as the greatest opportunity for cost savings overlaps with the greatest difficulty in predicting and subsequently achieving savings. While the cost savings presented in the results are not achievable in practice, the high potential for cost savings is an indicator that such grids would benefit from DS ability. With price spikes regularly occurring outside of PV generating hours, PV combined with storage can be a better option. However, the latter presents the most complicated case where the three systems have relatively similar savings benefits and therefore more thorough analysis would be required.

The *representative daily average* method used in the study was effective in identifying the pricing patterns that made each technology the most beneficial and the cost savings from each technology were seen to align well with the pricing patterns. This is a key finding of the study, as the pricing patterns also tend to align with the technical issues or difficulties in each grid studied. Alberta in 2018 saw high prices in the daytime summer months due to plant shut-downs in hot days with low wind production. The resulting pricing patterns shows that consumers would benefit most from installing solar PV panels, which would act to counter the price spikes seen in the summer daytime hours. In Ontario, transmission congestion and nuclear power lead to sudden price spikes in certain nodes and in the HOEP, both in the positive and negative prices. The consumer benefits most from avoiding these price spikes (or accessing the grid during negative spikes) with demand-shifting, which in turn would provide stability to the grid. In California, overproduction from solar in the grid results in price peaks just outside of solar generating hours. This trend suggests that consumers with demand-shifting capacity can avoid these hours, while still benefitting from solar throughout the day.

Implications on Energy Transitions

In deregulated electricity markets where the price is set through a merit order or similar type of system, technical issues in the grid will directly result in patterns in the price. These patterns were observed in this thesis for all grids studied. Consumers with access to the wholesale price will therefore be directly incentivized to provide some benefit to the grid by pursuing savings in their electricity costs. This is clear in grids with unstable prices, where consumers are incentivized to shift demand to times of low prices and avoid high prices. However, a challenge arises in the irregularity of changes with unstable prices. While the opportunity for cost savings is large, the ability to predict and act on this opportunity is difficult. In stable grids, limited cost savings can be achieved by shifting demand. In these cases, installing distributed generation, such as solar PV, replaces some access to the grid to provide cost savings. As solar PV takes a larger share of total generation, as seen in California, it becomes practical for consumers to shift their demand outside of typical PV ramping hours.

For residential consumers, studies have found that self-generation and access to dynamic pricing has resulted in a shift in demand habits. Kobus et al. [1] found that Dutch homeowners showed a consistent "structural shift in demand" when given a smart washing machine and a dynamic electricity tariff. Gottwalt et al. [2] found that demand shifting in the residential sector was so effective under time-of-use pricing that new peaks would develop outside of high price hours. This behaviour in residential consumers has been observed far before the emergence of "smart" technologies, with Sexton et al. [3] finding that giving consumers the ability to simply monitor prices led to demand shifts. Allowing consumers access to the wholesale price of electricity will provide the grid with a way of self-correcting on the demand-side. This will provide a stability mechanism with no additional grid infrastructure. However, residential electricity use may not compare to the opportunity available from large-scale and industrial consumers.

Sources of Demand-Shifting

Storage has uses outside of the demand context discussed in this thesis, such as being paired with a grid-scale renewable generator to level their power output. The economics of adding storage in this way are still contentious [4]. On the consumer side, storage offers the ability to shift demand without the need to lower a consumer's actual electricity consumption. However, this does come with drawbacks, most notably the limitations of energy storage capacity. The cost of a storage system increases with the energy capacity, also described as the discharge time of the storage system. This cost can only be recouped by using the storage system to reduce electricity costs. Storage is the most valuable when it must only be operated for a short-time (and therefore require a lower energy capacity) and cycles regularly, so as to maximize savings. The results of Chapter 2 suggest that, in Alberta, this does not make storage an ideal demand-shifting technology, as shifts are required very rarely. Chapter 3 suggests that storage would be valuable in Ontario, where sudden price spikes make energy capacity less important. This is less true in California, where price fluctuations happen over sustained periods, requiring a larger energy capacity.

Direct demand-shifting is ideal as no external mechanism is required other than the ability to control one's consumption. However, this does require an operator who can remain productive while shifting demand throughout the day. So the question remains of what industries and consumers have this ability. Lindberg et al. [5] provide a quick summary of several industries and their opportunities and limitations to make use of DS. In general terms, industries which regularly operate below 100% capacity, have low start-up and shut-down times/energy, have no working day restrictions (particularly in the case of high automation), where high electricity consumption processes feed into slow, low energy consumption process, or where electrical energy is a major contributor to costs are suitable to provide DS. Lindberg et al. identify thermo-mechanical pulp and paper, wire & wire rod production, cement production, and meat production as potential DS industries from a limited study set. Charging of electric vehicles, as well as other battery devices, has also been suggested as a source of DS.

Another industry that meets almost all of the criteria to be suitable for DS, but is not often discussed in the literature, is data centers and other large computer operations. Data centers have a large electricity load, consuming 1.1-1.5% of global electricity in 2010 [6]. Data centers rarely operate at full capacity at all times and are often capable of deferring computer operations within a time window. Once at minimum capacity, computer operations can rapidly ramp up and down and operations directly correlate with electricity consumption.

Access to industries capable of DS can provide benefit both to grid operators and to the industry operators themselves. As renewables increase, the demand side can benefit the energy transition not by a decrease in demand but rather an increase in demand control. Attracting industries that are capable of demand-control, such as data centers, could provide the grid with stability even as renewables take a larger role in the grid. By balancing the grid from both sides, less stress would be put on the need for ramping generators and auxiliary capacity, which is only needed on rare occasions, by rather only rarely requiring demand to shift down. Unlike a ramping generator, which can sit idle for most of the year in the hopes of achieving high prices when they do run, demand shifting sources will benefit from operation throughout the year, only being required to withhold operations on rare instances when ramping generation would otherwise be required. From the results of Chapter 2, it can be seen that emissions reductions from demand shifting are unlikely in the direct sense. However, by making the demand side more flexible, renewables can be utilized to a higher extent to reduce grid emissions. Furthermore, operation of inefficient and high emissions ramping generators can be avoided by demand-shifting instead.

Future Work

The analysis methods applied in this thesis seek to provide a better understanding of underlying trends in electricity grid structure and pricing. Through these trends, pricing and emissions impacts of changes in the grid can be predicted and allow for actions that mitigate harmful impacts. The analysis provided in Chapter 2 is a case study of a single grid and Chapter 3 of three grids with varied generation mixes. Applying the analysis methods to further grids and systems would be valuable to assess if the trends identified in this thesis are consistent in other grids and what other trends can be targeted for improvements through energy transitions.

The potential benefits of demand-shifting technologies, from both the grid and consumer perspective, are clear. A key contributor to these benefits is access to the wholesale price of electricity. As discussed in section 3.4.5, many grids do have the potential for large consumers to directly access the wholesale price; however, this alone has not been sufficient to see any significant adoption of demand-shifting in these systems. In part, this is due to a lack of understanding of the benefits and difficulty in designing business practices around DSM and industry [7,8]. A key direction of future research should be into policy that allows for demand-shifting to be incorporated within the grid structure, whether through compensation from the grid operator, access to information on pricing trends and predictions, and/or access to the wholesale price. This could include incentives for providers of DSM to assist in the adoption of renewables, benefiting industries that directly promote the adoption of renewables into the grid as opposed to purchasing renewable credits from distant sources.

Identifying and evaluating the potential for key industries, such as data centers, to provide DSM services should also be a focus of future research. With these industries identified, and proper policy and business mechanisms in place, the opportunity to utilize the benefits of demand-side actions as a part of the energy transition can be realized.

References

[1] Kobus, C. B. A., Klaassen, E. A. M., Mugge, R., & Schoormans, J. P. L. (2015). A real-life assessment on the effect of smart appliances for shifting households' electricity demand. *Applied Energy*, *147*, 335–343. https://doi.org/10.1016/j.apenergy.2015.01.073

[2] Gottwalt, S., Ketter, W., Block, C., Collins, J., & Weinhardt, C. (2011). Demand side management — A simulation of household behavior under variable prices. *Energy Policy*, *39*(12), 8163–8174. https://doi.org/10.1016/j.enpol.2011.10.016

[3] Sexton, R. J., Johnson, N. B., Konakayama, A. (1987) Consumer Response to Continuous-Display Electricity-Use Monitors in a Time-of-Use Pricing Experiment. *Journal of Consumer Research. 14(1), 55-62.* https://doi.org/10.1086/209092

[4] Lazard (2018) *Lazard's Levelized Cost of Storage Analysis – Version 4.0.* Available online: https://www.lazard.com/media/450774/lazards-levelized-cost-of-storage-version-40-vfinal.pdf

[5] Lindberg, C., Zahedian, K., Solgi, M., and Lindkvist, R. (2014). Potential and limitations for industrial demand side management. *Energy Procedia*, 61, 415–418. https://doi.org/10.1016/j.egypro.2014.11.1138

[6] Koomey, J. G., (2011). Growth in Data Center Electricity Use 2005 to 2010. *A report by Analytics Press, completed at the request of the New York Times.*

[7] Strbac, G. (2008). Demand side management: Benefits and challenges, *Energy Policy*, 36, 4419–4426. https://doi.org/10.1016/j.enpol.2008.09.030

[8] Behrangrad, M. (2015). A review of demand side management business models in the electricity market. *Renewable and Sustainable Energy Reviews*, *47*, 270–283. https://doi.org/10.1016/j.rser.2015.03.033