Power Intermittency and Technoeconomic Performance of Solar Photovoltaic Systems With Energy Storage

by

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Abstract

In support of continued photovoltaic (PV) electricity development this thesis uses measured PV generation and residential load data to evaluate the impacts of PV intermittency on grid stability, and the importance of electricity tariffs on PV value. The potential of pairing PV with energy storage for intermittency mitigation or to increase PV electricity consumption and system value was also assessed using an energy storage model.

PV intermittency was evaluated using two metrics: power ramp rates and output variability. The intermittency of PV generation was compared to previous work done using pyranometers, and to the intermittency of residential loads. Measured generation data closely matched data obtained using pyranometers, supporting their application for future intermittency studies. Pairing residential PV and load profiles showed that PV has a negligible impact on net load intermittency. This impact was even less significant when considering the aggregation of net loads rather than a single dwelling. Energy storage requirements for intermittency reduction are an order of magnitude larger when addressing a single home compared to using an aggregate of all homes, suggesting the application of energy storage at a community level rather than for individual systems.

Changing from the current flat-rate tariff in Nova Scotia to a Time-of-day (TOD) tariff reduces PV generation value by 11.1% due to the treatment of weekends as off-peak, which is not supported by grid load profiles. A more critical policy is the ability to net-meter. Enforcing a self-consumption only condition on residential PV decreased its economic value by an average of 62% but did cause pairing PV with energy storage to become economically viable. Energy storage capacities of 10 to 18 kWh_{DC} paired with converter sizes of 2 to 3 kW_{AC} were found to provide the most value in all scenarios observed and had greater economic value than using PV without storage.

List of Abbreviations and Symbols Used

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A	Annual revenue
CC	Capital Cost
D	Dispersion Factor
E	Energy
FIT	Feed-in-tariff
FSA	Forward sortation area
G	Storage capacity (kWh_{DC})
HRM	Halifax Regional Municipality
I	Converter size (kW_{AC})
L	Length of PV fleet
OV	Output Variability
P	Power
PV	Photovoltaic
PVS	PV + Storage
ROV	Relative Output Variability
RR	Ramp Rate
RTE	Round-trip efficiency
S	Spacing
SOE	State-of-energy
STG	Energy Storage
t	Time
TOD	Time-of-day
V	Cloud Transit Speed

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Chapter 1: Introduction

Energy is one of the most critical resources for humanity's development and well-being. This is demonstrated by the strong correlation between energy consumption and gross domestic product, as well as between energy consumption and the Human Development Index [1]. As noted in [1], prediction of future energy consumption is extremely difficult given the vast range of technological and political possibilities. It can be said with a high degree of confidence however that global energy consumption will continue to increase based on historical trends due to a combination of increased human population and the development of poorer nations. From 2005 to 2019, energy consumption rose by 27.7%, primarily due to growth in developing countries [2]. Historically, as energy consumption grows so does the amount of carbon dioxide emissions generated by the energy industry. Over the last 15 years annual CO_2 emissions have risen by 21.2% [2]. This is largely due to the use of traditional fossil fuels (coal, oil, and natural gas) which were responsible for 84.3% of global primary energy consumption in 2019 [2]. The contribution of CO_2 emissions on global climate change has long been established, the impacts of which were recently highlighted in a UN report on the impacts of global warming of 1.5 °C above pre-industrial levels [3].

The year 2020 is expected to show a major short-term reversal in terms of both energy consumption and energy related emissions due to the onset of the COVID-19 pandemic [4]. As noted in [4], this represents a major event in the energy industry which stands to impact fossil fuel sources much more heavily than renewable ones and presents the opportunity for a major shift in energy generation. Where all other major energy sources of electricity generation experienced declines in 2020, renewable energy generation continued to grow [4].

The desire to reduce global CO_2 emissions has led to increased market penetration of low-carbon electricity generation. The most common low-carbon emitting electricity generation methodologies are nuclear, hydroelectric, biomass, wind, and solar photovoltaic (PV). Of these, nuclear, hydro, and biomass have essentially the same generation characteristics as conventional generation. That is, they either have the same operating principles (steam cycle) and/or have large system inertias due to rotating turbines. They are also regarded as dispatchable generation, where their output can be carefully controlled when needed. Wind and PV on the other hand, have very little (wind) or no (PV) system inertia, and can have rapid power fluctuations, potentially leading to large discrepancies between electricity generation and consumption [5]. In 2017 a total of 7300 GWh (6.2% of generation based on [2]) of PV was curtailed in China due to concerns about grid stability caused by PV output fluctuations [6]. As residential PV electricity generation increases electricity grids become more susceptible to the negative implications of rapid power generation fluctuations, such as increased system maintenance costs [7].

To support technically justified discussion on PV policy, this research evaluates PV generation and model's energy storage systems to provide objective insights into future development. Background information is given in Chapter 2, with a detailed literature review for material presented in this work provided in Chapter 3. Data sources and quality control methods are presented in Chapter 4, and methodologies used to generate study results are described in Chapter 5. The study topics covered in this work are:

- PV generation intermittency: A common concern for having large amounts of PV generation is that the intermittent nature will be detrimental to grid stability. This thesis investigates the severity of PV intermittency at different geographic scales (Chapter 6), the interaction of PV generation and residential home loads on system intermittency (Chapter 7) and the application of energy storage to mitigate intermittency (Chapter 8).
- Residential PV value: Current electricity utility policies and tariffs are very favorable to residential PV installations, but it is worth exploring potential changes and the technoeconomic impact on residential PV systems. This is done by manipulating the electricity pricing scheme, and the ability for residential systems to sell excess generation to the grid. The impact of these policy decisions is explored in Chapter 9, and the potential value of adding battery energy storage to these systems is evaluated in Chapter 10.

Major conclusions and future study recommendations are provided in Chapter 11.

Portions of this thesis were originally published in [8] and are included under the terms of a licence agreement with Elsevier (shown in Appendix A). The following is a list of all copyrighted material included:

- Chapter 4: Figure 9, Figure 12, Figure 13, Figure 14, and Figure 16
- Section 2.1.2
- Chapter 6

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Chapter 2: Background

2.1. Electricity System

For most North American consumers, the supply of electricity is expected to be delivered with minimal disruptions. Electricity systems require careful balancing of generation and load to ensure grid stability, where grid operators seek to match consumer loads by tightly controlling generation. Electricity load patterns are dependant on changes in consumer behaviour seasonally (e.g., winter vs summer) as well as hourly (e.g., overnight vs early evening). Because of this, grid operators need to predict, monitor, and react to changes in the electrical load by dispatching or curtailing generation assets. Different generation assets come with varying capital and operating costs, ramp rate limits, and minimum operating levels motivated by their intended purpose. Base load assets are designed to run at or near a design setpoint continuously and so tend to have lower operating costs and slower ramp rate capabilities. Intermediate and peak load assets have more operational flexibility, but this comes at the cost of efficiency and operating costs.

2.1.1 Grid Services

In addition to actual electricity generation and consumption, there exists several services the grid requires to ensure power availability and quality. First, to adequately follow electricity demand, grid operators require access to capacity reserves. These are often categorized as either spinning or non-spinning determined by how quickly the reserve can be brought online. Spinning reserves are typically thought of as extra generation capacity available from an already generating asset; but may also include bulk battery storage systems because of their rapid response time [9]. Non-spinning reserves have a longer delay before generation associated with system start-up; a common example would be a turned off diesel generator used for back-up power (in the context of a residential electricity system).

Maintaining a consistent system frequency is critically important to avoid instability. When system loads and generation are not equal system frequency can deviate from its nominal (50 or 60 Hz depending on the market) frequency due to generating equipment being over or underloaded. Corrections are often required at small time scales (2-5 seconds) requiring rapid responses [9].

2.1.2 Power Ramp Rates

Both grid services discussed are required to due to changing load or generation, which can be expressed in terms of the change in power over a given time interval (e.g. MW per minute). This change is commonly referred to as power ramp rate and is calculated using Equation 1, where *RR* is the power ramp rate at time *t*, *P* is power, and Δt is the time interval of the power measurement.

$$RR_t = \frac{P_t - P_{t-1}}{\Delta t} \tag{1}$$

The power ramp rates of PV systems, residential home loads, and net loads are presented in this work. PV ramp rates are defined as positive when PV generation exceeds that of the previous timestep (increasing PV generation), and negative when the opposite occurs (decreasing PV generation). Net load ramp rates are considered positive when the net load of a home increases (decreasing grid load), and negative when the net load increases. This is consistent with the position that increased PV generation causes positive ramp rates since increased generation from a residential PV system decreases the net load of the home assuming the home load stays constant.

Ramp rates are critically important to electricity grid operators, who need to ensure instantaneous changes in demand and generation are balanced. Traditional generation can be tightly controlled to accommodate grid ramp rates but may struggle if a high level of renewable energy is introduced because it is expected that these generation sources are very intermittent. The intermittency and ramp rates of renewable generation may not be easily accommodated by thermal generation plants, and so greater understanding of ramp rate severity from different generation sources is important. Failure to properly accommodate ramp rates may result in voltage and frequency fluctuations which impact the quality of electricity provided, and extreme deviations from standards may result in a blackout.

While absolute ramp rates are of importance to the utility, it is useful to observe relative ramp rates (which are normalized by the system size) for comparison of systems with different sizes. This was done using Equation 2, where RR_{rel} is the relative ramp rate.

$$RR_{\mathrm{rel,t}} = \frac{RR_t}{P_{max}} \tag{2}$$

Fluctuations in PV output can cause issues to grid operators with high levels of PV penetration since they can occur very rapidly and so are difficult to compensate using conventional generation. This has led some jurisdictions to impose ramp rate restrictions on PV systems, an example being the Puerto Rico Electric Power Authority imposing a +10% per minute restriction [10]–[12]. Generally speaking, meeting positive ramp rate requirements is easier to accomplish through curtailment by purposefully shifting the voltage below the PV's maximum power point. Buffering negative ramp rates requires more advanced solutions, such as the inclusion of adequate energy storage or accurate solar irradiance forecasting available throughout the day. Both ramp rate and relative ramp rate are presented in this work, but a greater emphasis is placed on relative ramp rate to control for system size.

2.1.3 Electricity Pricing

Structures for electricity pricing vary across the world but there are some common items based on customer supply requirements. Different rate structures are typically offered based on consumer type (residential, commercial, industrial), and the amount of electricity consumed. Using Nova Scotia Power as an example, common charges for electricity consist of: service, energy, and demand [13]. A service charge is applied to all customers for the ability to access the electricity on the grid. Energy charges represent the sensible cost of electricity, where the amount of energy used by the consumer has a price determined by the cost of generating and delivering the electricity. Energy charges can either be flat-rate or a function of the time-of-day. Time-of-day (TOD) rates offer customers flexibility by decreasing costs during low load periods and raising them during high periods. This encourages customers to shift discretionary loads to low load times, alleviating grid stress during high load times.

Demand charges typically apply to non-residential customers who have larger electrical power requirements. The demand charge is based on a customer's peak electricity consumption. In Nova Scotia is determined by the largest 15-minute power consumption for the billing period and billed as $ per kW demand.

There are two approved electricity tariff structures: domestic service, and domestic service TOD. The domestic service rate has a fixed rate which applies regardless of the season, day of week, or time of day. Domestic service TOD rates are currently only available to customers with an electrothermal storage system and have rates which vary throughout the year, day of week, and time of day. The objective of this tariff structure is to influence customer consumption patterns to shift load away from grid load peaks (on-peak, highest price of electricity) and into load valleys (off-peak, lowest price of electricity). A third price exists for periods where grid load is in between highs and lows, referred to here as mid-peak.

Table 1. Summary of electricity pricing in Nova Scotia

Tariff category	Conditions	Price (¢/kWh)
Flat rate	Applies throughout the entire year	16.008
TOD Off-peak	Between 23:00 and 07:00. year-round All weekends and holidays	9.081
TOD Mid-peak	07:00 to 23:00 on workdays from March – November 12:00 to 16:00 on workdays. from December – February	16.008
TOD On-peak	07:00 to 12:00 and 16:00 to 23:00. on workdays from December – February	20.366

Table 1 provides a summary of electricity prices in Nova Scotia for 2021 [13] for both flat rate and TOD (currently available only to customers with electric-thermal storage units) tariffs. For this work the holiday off-peak condition was ignored since simulation dates vary and holidays represent only 3% (11/365) of days each year. Analysis of provincial grid loads and the impact of TOD rates on PV values (discussed in Chapter 9) warranted the creation of an alternative TOD tariff which applies workday TOD pricing to weekends (Wknd. TOD). This is justified since provincial grid load profiles show almost identical electricity demand profiles for both workdays and weekends (discussed further in Section 9.3).

2.2. PV Electricity Generation

Reduced PV prices have led to enormous growth in the PV electricity generation capacity around the world in the past decade. As shown in Figure 1, the year over year growth in PV generation has been exponential and stands to continue as it displaces carbon intensive fossil fuel generation. It is important to note the order of magnitude difference in scale between fossil fuel consumption and PV production, showing how much room for growth there is for renewable energy.

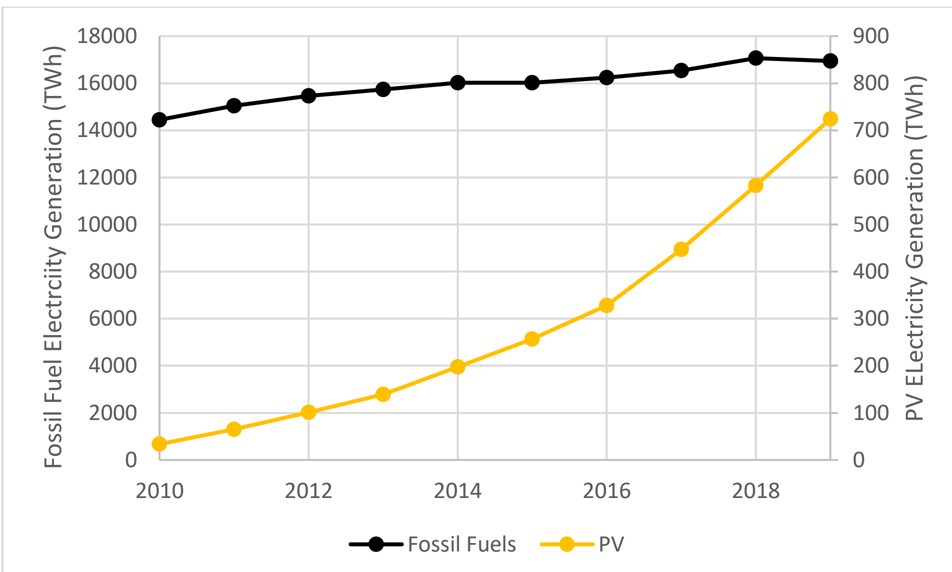

Figure 1. Fossil fuel and PV electricity generation from 2010 to 2019 (data source: [2]**)**

The nature of these systems also allows for both residential and commercial entities to invest in their own energy supply. PV generation is scalable, allows for significant design flexibility to accommodate physical layouts, and requires little maintenance from customers once installed (not needing to refuel a generator for instance). These factors make it an ideal entry point for electricity consumers to assume a more proactive role in the transition to a carbon neutral electricity system.

An important characteristic of many real-world systems is the deliberate under sizing of inverters for a given DC generation capacity. This is an economic trade-off which sacrifices some generation potential for lowered inverter capital costs. Often described in terms of the DC (PV capacity):AC (inverter size) ratio this normally leads to a phenomenon known as clipping. An example of this is shown in Figure 2 which compares an unclipped system (blue) to a clipped one (orange).

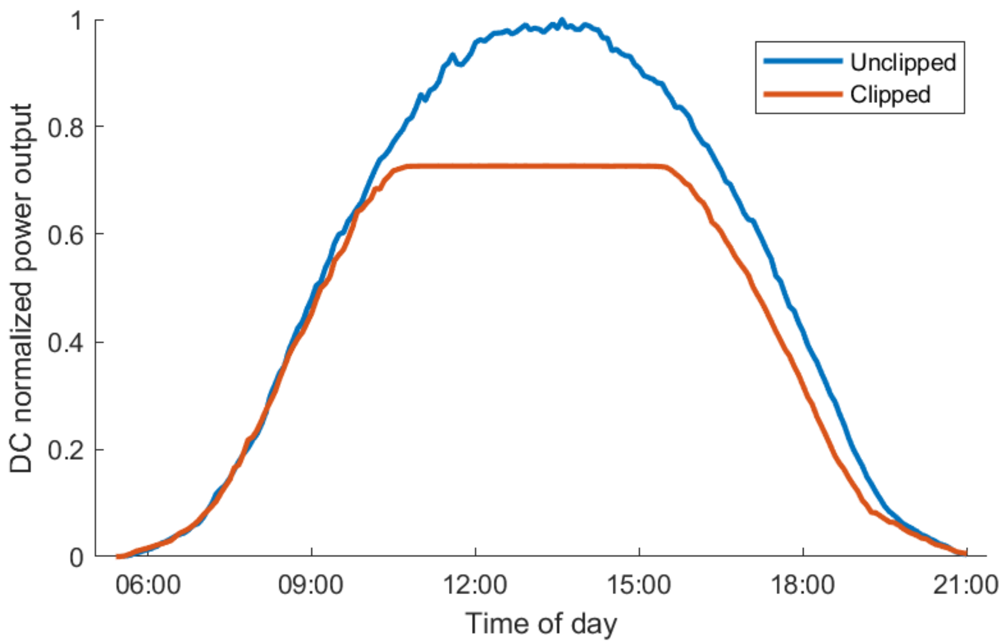

Figure 2. Comparison of two residential PV systems showing a traditional PV generation profile (blue) and a system with undersized inverters, referred to as "clipping" (orange).

The addition of PV to a home changes its interaction with the electricity grid. Net load refers to the combination of the original home load profile and the home's PV generation profile, as shown in Equation 3. Positive net loads indicate net electricity generation (and potentially export to the grid), while negative values indicate a net consumption of electricity.

$$Net\ Load = PV - Load \tag{3}$$

The addition of PV generation to a home can result in a change of paradigm, where homes are no longer strictly electricity consumers.

2.2.1 Incentive Mechanisms

To promote the adoption of PV among residential consumers, jurisdictions around the world have implemented a wide array of incentive mechanisms. These can be separated into 2 major streams: offsetting of capital cost and increasing PV generation value.

Offsetting capital cost can be done using either up-front cash incentives (an example being the SolarHomes program offered by Efficiency Nova Scotia[1] which provides a rebate of up to 6000 CAD), or by providing attractive financing options to consumers (Halifax's Solar City 2 program[2]).

PV generation value can vary greatly based upon what combinations of electricity rates and grid connection conditions are applied [14], [15]. Grid-tied PV generation is by far the most common type of residential installation and are accompanied by varying feed-in tariffs (FIT). Traditionally, FITs have been used extensively to incentivize residential PV uptake. FITs operate by enabling PV producers to export excess generation to the grid at a given price. In the absence of an export agreement, PV generation value is limited to what can be used immediately by the home which diminishes the system's value. This scheme is referred to as self-consumption, where PV generation that is not immediately consumed by the building (or stored) has no value. Regardless of the value of PV generation exported via a FIT agreement (excluding negative prices which may occur due to grid oversupply) the ability to obtain some value for excess PV generation naturally increases the systems economic value. FIT policies can range in complexity, and even further incentivize self-consumption as proposed by [16]. A special FIT case known as net-metering is commonly applied as a means of incentivizing PV uptake. Under a net-metering scheme, excess PV generation is valued at the same price as purchased electricity. Net-metering is applied to most residential PV systems in Nova Scotia, with exceptions based on PV system size relative to annual electricity consumption.

The effectiveness of policy incentives in the United States was explored by Matisoff and Johnson [17] who found that the presence of a FIT is likely critical for consumer uptake since it provides a near-immediate and visible benefit to consumers. This was closely

[1] https://www.efficiencyns.ca/residential/programs-services/solar-homes/
[2] https://www.halifax.ca/home-property/solar-projects/about-solar-city-halifax

followed by capital incentives provided to offset installation costs. The preference for FIT may be explained by the loss aversion phenomenon, where consumers overvalue the lost revenue potential of exporting electricity to the grid. Lost revenue would occur over the lifetime of the system and consumers are less likely to properly evaluate the present value of longer-term incentives (or in this case losses).

Work by Ramirez et al. [18] investigated the idea that FIT strategies can be flexibly applied by using different combinations of PV generation which was either valued at a fixed FIT or net-metered. Their work provided an economic evaluation of 5 different scales of PV plant in different EU countries. This work highlighted the importance of local electricity pricing, where a higher cost of electricity greatly enhances PV net-metering/self-consumption value and so plays a crucial role in increasing residential installations.

2.3. Residential Battery Energy Storage

As the price of both PV systems and battery storage fall the application of combined systems is becoming more common. Battery energy storage can enhance PV generation by mitigating the rapid fluctuations of power outputs (intermittency control) and by shifting generation to match electricity consumption (load shifting).

PV and energy storage can be coupled either directly with both battery and PV system on the DC side, or indirectly where both the PV and battery have their own DC to AC (and vice versa in the case of batteries) conversion units which are connected by an AC circuit. PV systems are paired with an inverter which is restricted to one-way flows, while batteries are paired with a converter, which is capable of bi-directional flows.

Key specifications used in this thesis to describe battery energy storage systems include:

- Energy conversion efficiency. This can be broken down into two parts, the electrical efficiency of the converter, and the electrochemical efficiency of the battery which is dependent on its chemistry. This is often presented as the round-trip efficiency (RTE). RTE is measured as the percentage of stored electricity which can be returned (excluding leakage losses from longer storage periods).
- Rated capacity. This represents the total amount of energy which can be stored in the battery. Note that this is reported before taking the discharge efficiency of the

system into consideration, at which point it is typically referred to as the usable capacity.

- Remaining capacity. This represents the total amount of energy which is currently stored in the battery. In this thesis the remaining capacity does not take the discharge efficiency into consideration, so it does not represent the usable amount of energy remaining in the battery.
- State-of-energy (SOE). Used to represent remaining capacity as a percentage of rated capacity, as shown in Equation 4.

$$SOE = \frac{Remaining\ Capacity}{Rated\ Capacity} \times 100\% \tag{4}$$

- Converter power. The maximum input/output power of the system, typically based on the AC side. This terminology is used to distinguish the bidirectional AC/DC converter paired with the battery from the DC to AC inverter paired with the PV system.

PV systems can be coupled with battery energy storage in two ways: DC coupled systems, and AC coupled systems. DC coupled systems have a single DC bus which connects the PV system to the battery via DC:DC voltage regulators. This in turn is fed into a single converter which supplies the home with AC electricity for use. Alternatively, AC coupled systems have both an inverter for the PV system, and a converter for the battery and are coupled with the AC circuitry of the home. Ranaweera and Midgård [19] found that the impacts of using either one of these methods was negligible when evaluating energy storage and so results from this thesis are applicable regardless of coupling architecture.

Chapter 3: Literature Review

This thesis assesses the intermittency and technoeconomic impacts of policy on PV systems, and the impacts of adding energy storage to enhance PV systems by reducing PV intermittency or increasing system technoeconomic factors. The purpose of this chapter is to provide an overview of the relevant literature to this work in each of these fields. The results of these studies are useful for both developing methodologies and providing results for comparison with the outcomes of this work.

Two methods of mitigating PV intermittency which frequently appear in the literature, and which are explored in this thesis are geographic smoothing and the application of energy storage. These subjects are treated separately, and so are given their own subsections.

3.1. PV Power Intermittency

3.1.1 Geographic Smoothing

Many researchers use models to assess the behaviour and grid impacts of PV system fleets. The advantage to PV models is that they are significantly less expensive than measurement networks and allow for comparison of measured data to a baseline model. Research by Hoff and Perez [20] modeled PV smoothing and introduced a metric called dispersion factor which is a function of cloud speed, PV fleet configuration, and the time interval of interest. A limitation of the dispersion factor metric is that it assumes consistent PV system orientation, size, and spacing for the entire fleet. Obviously, this is not the case in a diverse real-world residential PV system fleet. In addition, modeled data often relies on interpolation methods to take historic insolation data and apply it to a wide geographic area. Another methodology was presented by Lave, Kleissl, and Stein [21] who proposed a Wavelet Variability Model to use a single irradiance sensor, known PV system density, and a scaling coefficient. The scaling coefficient was first determined using a set of global horizontal irradiance measurements but future work was later able to identify a linear relationship between the scaling coefficient and cloud speeds [22].

Measured insolation values at real sites provide a better representation of real-world installations due to the inclusion of physical system parameters like non-ideal slope/azimuth and DC:AC ratio, localized weather conditions, soiling and snow cover, shading, and inverter control strategy. Early work by Otani, Minowa, and Kurokawa [23] used 9 pyranometers to collect data over a 4 x 4 km region to investigate smoothing over a region and found that distributing sensors reduced output fluctuations by an average of 40% compared to single sensor readings. Similar results were obtained by Lave, Kleissl, and Arias-Castro [24] using 6 pyranometers collecting 1-second global horizontal irradiance data with spacings ranging from 0.69 to 2.47 km. They found that site irradiance data variations were uncorrelated for timescales shorter than 10 minutes, showing the importance of shorter timestep data. A fleet of 14 large plants totalling 20 MW with distances between any two plants ranging from 10 to 1065 km was modeled by Riaz, Repo, and Lindfors [25] using a year of 1-second pyranometer data. They found diminishing returns when increasing the number of plants, and that smoothing had a greater impact at shorter time scales.

These above works represent radically different spatial scales and do not capture the impacts of PV spread across a municipality since they use small areas or use a small number of sites with large distances between sites. Municipal scale (approximately 50 x 50 km) is important because of land use planning and electrical distribution circuit design. A municipal level investigation was accomplished by Adye, Pearre, and Swan [26], who used pyranometer data from 215 homes in Nova Scotia, Canada to contrast modeled PV output of distributed and centralized systems. Using 1-minute data they found that distributed systems had much smaller ramp rates than a centralized group of pyranometers. This difference was especially pronounced over shorter time scales, again showing the importance of obtaining high resolution measurements. A drawback of using pyranometer data is that it represents a singular point, rather than the larger area of an actual PV array. This may be insignificant when considering cloud cover over an extensive network of PV arrays but could miss important real-world effects such as localised shading of a portion of the roof throughout the day. For these reasons, the use of measured PV data is useful for detailed analyses.

To better understand real-system dynamics, researchers use real power production data from installed PV sites when available. Production data from seven PV plants totalling 20

MW was collected by Marcos et al. [27] in 2009 to investigate the effect of system spacing using real world data. Data with a timestep of one second from plants separated by 6 to 360 km was analyzed. The authors found that 6 km of distance was enough to de-correlate plant outputs, and that the number of plants had a greater effect than geographical spacing on resource smoothing at timescales below 10 minutes. Research by Klima and Apt [28] collected data from 50 PV systems in the Gujarat area of India spaced up to 470 km. They found that most smoothing in the frequency domain occurs in the first 4-5 plants added, with diminishing returns for plants added after this point. An important point addressed by the authors was that results of these studies are specific to a geographic region. This highlights the importance of both geographic conditions and weather patterns on the results of irradiance studies. At a smaller scale, Lave et al. [29] analyzed power output of 553 homes in a neighbourhood of Ota City, Japan and found that the impacts of geographic smoothing become more pronounced as the timescale is decreased (timesteps of 10 minutes, 1 minute, 30 second, 10 seconds, and 1 second were evaluated). They also found that above a certain number of homes, additional systems did not reduce system output variability. The study provides insight into the effect of mass residential adoption because 80% of homes in the studied neighbourhood had PV installations. Residential installations were also studied by Elsinga and van Sark [30], who found that longer time intervals require greater geographic spacing for smoothing and that spacing can be dependant on the time of year. It was found that shorter geographical spacings were required to achieve decorrelation during the winter months compared to summer months. This difference was attributed to the increased number of completely overcast days in the winter, during which output variability was minimal, and the low number of perfect clear sky days during the summer resulting in higher variability.

3.1.2 Use of Energy Storage

While geographic distribution can reduce the intensity of PV generation intermittency, its impacts are limited by the available geographic area, and so the application of distributed energy storage is be of interest to the electricity utility.

A critical characteristic of energy storage for ramp rate smoothing is that systems have large converter power to storage capacity ratios, as shown by Marcos et al. [31] who determined empirical equations for sizing the storage capacity required for PV ramp rate mitigation. These equations take in the PV system peak output, the smallest PV system layout length, and the maximum allowed ramp rate and were developed based on 2 utility scale plants. While these results are unlikely to translate to residential systems in Nova Scotia, they reinforce the need for a high-power but relatively small energy. To satisfy a ramp rate limit of 10% per minute, the ratio was roughly 6 kW of converter power per kWh of storage capacity. Jahromi et al. [32] obtained similar results using a full-year of 1 second resolution solar irradiance data from the State of New York to calculate the energy storage parameters required to offset PV intermittency. The data was average to 1 minute and normalized so that a value of 1 would represent a PV systems peak output. Four ramp rate limits were considered (2/5/10/20 % of peak output per minute) and energy and power requirements were calculated for each scenario. The results of this found that to satisfy ramp rates of 10% per minute a battery capacity of 0.0793 kWh of battery capacity was required per kW PV capacity and a converter power of 0.5868 kW per kW of PV capacity were required, a 7:1 storage converter size to storage capacity ratio. This highlights the importance of high-power energy storage systems for ramp rate smoothing. The impact of different ramp rate limits on battery sizing parameters for ramp rate mitigation was shown by Schnabel and Valkealahti [10]. They noted a linear relationship between the ramp rate limit and converter power requirements and an exponentially increasing relationship between ramp rate limit and battery capacity.

These studies of battery sizing for PV smoothing all utilized a simple ramp-rate control strategy which included a tendency to return the systems SOE to 50%, which is ideal if a positive ramp rate is just as likely as a negative one in the next timestep. This assumption is not ideal, as ramp rates are not random events. For instance, a -1 kW_{AC} per 5-minutes ramp rate is infinitely more likely than a +1 kW_{AC} per 5-minutes ramp rate for a 10 kW_{AC} PV system generating 9.6 kW_{AC}, since its output is near an upper limit, but far from a lower limit. The issue with continuously trying to actively bring SOE to 50% is that it increases battery usage, introducing unneeded conversion losses and battery degradation [33]. Other methodologies for ramp rate mitigation include using moving averages and low-pass filter techniques, and numerous studies on optimizing control strategies exist and help alleviate the issue of increased battery usage, but these strategies are optimized for particular case studies [33]. A general ramp rate limit methodology is applied in this thesis, but rather than trying to maintain a SOE of 50%, the desired SOE is banded between 40 and 60% to reduce the frequency of charge/discharge operations while ensuring the system can still adequately react to either positive or negative ramp rates.

3.2. Energy Storage for Residential PV

To properly evaluate the potential for pairing residential PV systems with energy storage, both generation and electricity consumption profiles are required. Like PV generation, obtaining measured electricity loads is not always feasible for a given area, and so representative datasets or modeling software are used.

Akter, Mahmud, and Oo [34] developed a framework for evaluating residential PV and battery energy storage systems using a TOD tariff and applied it to a single modeled load profile, with 5 different sizes of PV (3, 4, 5, 8, 10 kW) and energy storage (4, 5, 6, 10, 12 kWh). Each size of PV was paired with one size of energy storage based on their size. The study found that all PV paired with storage had positive economic results for systems which were not grid-tied. This would be the equivalent of a self-consumption scenario for grid-tied residential systems. The study did not evaluate a range of storage sizes for each PV capacity, nor did it consider the impact of the storage converter size. Additionally, the timestep resolution was not disclosed, and so potential error due to mismatching cannot be determined.

Ranaweera and Midgård [19] used a single, modeled load profile to represent European homes, and PV generation data based on a single PV module which was scaled to 4.2 kW_{DC}. The objective of the study was to optimize an energy storage control algorithm which would minimize the operational cost of the system. The study used a flat sell price for electricity exports, and a TOD rate structure for imports. This allows for the system to prioritize self-consumption during on-peak times, and energy exports during off-peaks. To avoid immediate reselling of energy during off-peaks, only the PV system has the capability to export to the grid. A major benefit to using a fixed export electricity price is it reduces the uncertainty of PV generation value, and economic assessments of systems become more reliable.

Parra and Patel [35] used load data from a single home in the UK with modeled PV generation based on pyranometer measurements from a weather station at the University of Geneva. The authors justify the use of a home load profile from another region since the load consumption of the home is equal to that of the mean residential load in Switzerland. This is still problematic, as energy usage patterns are not examined and could cause significant matching errors when paired with PV. The dataset had a timestep resolution of 1 minute. The authors evaluated the economic performance of both lead-acid and lithium-ion chemistries using a capital cost calculation which considered both the storage capacity and converter size. The cycle life and maintenance costs of system were also incorporated to provide a more complete life-cycle assessment. It was found that despite the increased up-front cost of lithium-ion batteries, they had a lower levelized cost of electricity making them a more suitable chemistry for residential battery systems. The impact of tariffs was also discussed, and as expected the economic performance of energy storage is critically dependent on the prices of importing and exporting electricity.

Vieira, Moura, and de Almeida [36] paired 15-minute residential load data from a single home in Portugal with hourly irradiance data interpolated to 15 minutes to evaluate an energy storage model. Interpolation of hourly irradiance data is not ideal, and PV and load mismatching is significant even at 15-minute timescales with measured data, let alone interpolated results [37]. The objective of the energy storage control strategy was to maximize PV self-consumption and used forecasts of the total PV generation and load consumption for each day. Different behaviours were applied based on the forecasted net electricity consumption of the home to accommodate a two-tier TOD electricity pricing scheme. A 2.4 kW PV system was simulated based on irradiance data, and a 10.2 kWh battery was considered, only 70% of which was made available to reduce degradation due to discharging to low SOE. This resulted in a 78% reduction in grid energy consumption. Results from this work are not easily applied to a broader market since they come from a single household and use a very small PV array compared to typical residential systems in North America.

Luthander et al. [38] paired 10-minute residential electricity consumption data from 21 homes in Sweden with modeled PV systems based on the homes' roof characteristics and local irradiance data. Battery energy storage capacities ranging from 0 – 2 kWh per kW of installed PV capacity were examined. The authors chose to model lead-acid batteries, which as previously discussed have less attractive economics than lithium-ion batteries. The authors also considered different aggregations of home net loads and found that without any storage PV self-consumption could be increased by 15% through aggregation. The benefits of system aggregation were shown for all battery rated capacities, making the argument for one large storage site in a community vs installing smaller systems in each residence.

de Oliveira e Silva and Hendrick [39] evaluated the impact of different combinations of installed PV and energy storage capacity on residential PV self-consumption in Belgium. Annual load profiles with a timestep of 15-minutes from 25 homes were normalized to 3500 kWh, which is the annual mean Belgian household load. Only one PV profile was used and was scaled to a range of installed capacities. This resulted in the generation of optimal battery and PV size combinations for different percentages of PV self-consumption. Under the given electricity rate structure and capital costs for storage and PV, they found that increasing self-consumption levels increased the cost of electricity for consumers. The use of a singular PV profile obtained from meteorological data is unlikely to capture the impacts of a wide variety of residential installations but does offer a good starting point. The normalization of load profiles is also confusing, since a wide array of representative homes is believed to provide a better evaluation of real-world applications.

3.3. Evaluation of the Literature

The literature for both geographic smoothing and energy storage techniques to address intermittency fails to account for electricity grid load, which is just as important since load and generation must be roughly equal for the grid to function properly. This gap in the literature may be due to a lack of available load data which overlaps with PV generation data. Another possible cause is that the literature is more focused on the novelty of utility-scale (>1 MW) intermittent energy sources. Traditionally generation has been tightly controlled to match a variable load, but the introduction of intermittent renewable energy generation adds uncertainty to the generation side, and so is of greater interest. A major advantage of intermittency work done in this thesis is the availability of both real measured

PV generation and residential load data can better represent the interaction of PV with the electricity grid.

While there are a wide array of methodologies and optimization techniques presented for various regions of the world, there are clear gaps in the literature with respect to the techno economics of residential PV generation paired with energy storage:

- Most studies do not use real measured data. Use of measured data rather than models or representative measurements is that it captures practical phenomena. This thesis makes use of measured generation and production data to capture these phenomena and provide results based on real systems.
- Studies often pair a single load profile and a single PV profile. Using a single representative load and PV profile does not capture the wide variety of load and PV profiles which may occur in practice. For instance, PV profiles may drastically vary from one home to the next based on roof angles.
- Converter sizes are often not considered. Converter sizing plays an important role in both the energetic and economic performance of energy storage, since it can directly limit the capability of storage to charge and discharge. The size of the converter also factors heavily into the cost of the energy storage system [40].

This thesis contributes to the literature by using multiple real-world load and generation profiles from the same municipality, and considers the cost and limitations applied by sizing of converters.

Chapter 4: Data Sources

PV generation data and residential load data from the Halifax Regional Municipality (HRM) in Nova Scotia, Canada were used to evaluate the impact of geographically distributing PV generation, PV generation value under different electricity policies, the potential for energy storage under the policies, and the impact of energy storage on grid intermittency. Residential loads from 50 homes were made available from across Nova Scotia, of which 28 were used in this work. PV generation data was obtained from 97 residential locations, and from 2 commercial locations within the HRM. Of the 97 homes, between 21 and 60 were used in this work based on the age of the system and the implementation of quality control checks. The two commercial PV systems were categorized by size, with one being considered a medium sized installation (medium commercial, ~12) and the other a large installation (large commercial, ~760 kW_{AC})

4.1. Residential Load Data

Residential load data from 50 homes with a timestep resolution of 10 seconds was provided by Efficiency One[3] to represent a residential load in Nova Scotia. Data spans from Jun-2017 to Mar-2019 as shown in Figure 3, where the horizontal lines represent points at which load data was available for a particular home. Of these, 30 were identified as both having at least one year of data (important to avoid seasonal effects) and are located in the HRM (for pairing with PV generation data from the HRM).

[3] http://www.efficiencyone.ca/

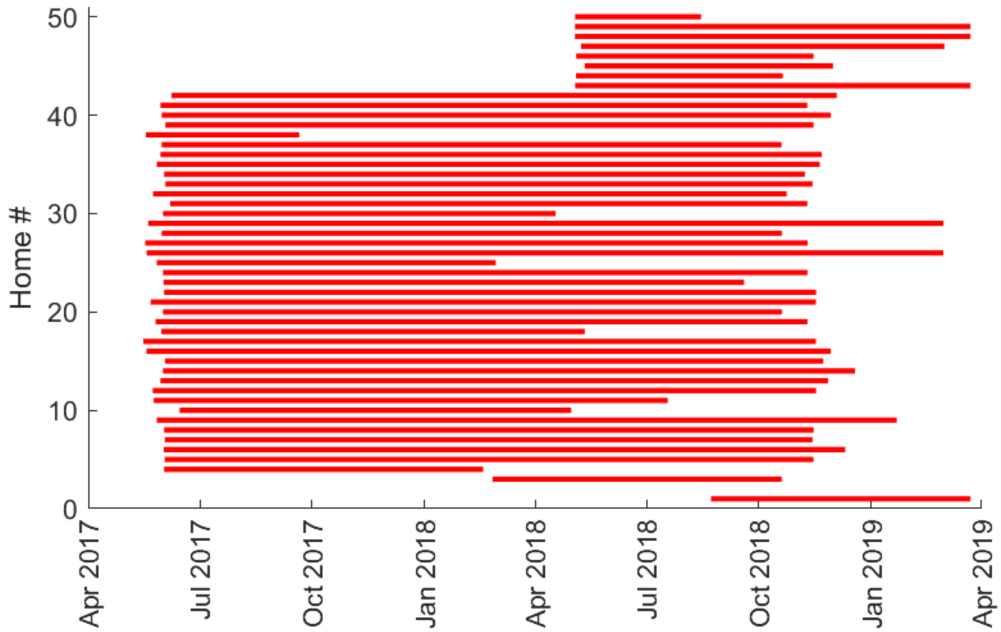

Figure 3. Load data availability for each home in the original dataset (n = 50)

Since the timestep resolution of the data is much shorter than what is available for PV generation data the datasets were down sampled to 5-minute intervals. This interval is also suggested by Beck et al. [41] to be the minimum resolution to properly size battery converters. This was completed by averaging data points prior to the nearest interval (e.g. the average of the 30 data points from 04:55:01 to 05:00:00 is used to represent 05:00:00). The entirety of each profile was plotted to check for any major data quality issues, with a typical load profile shown in Figure 4.

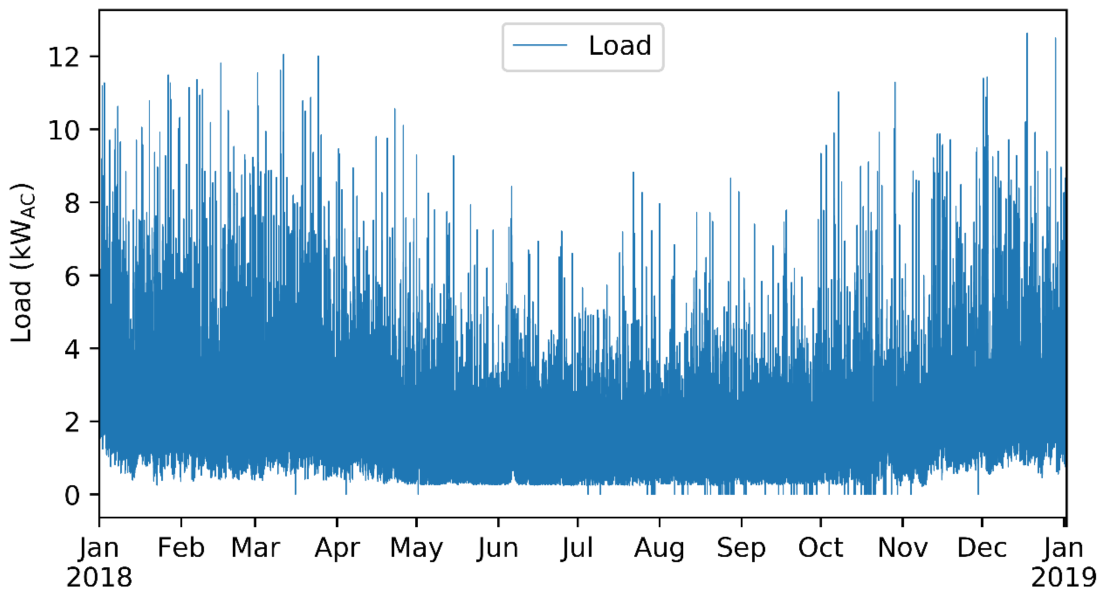

Figure 4. Representative residential load profile

Manual inspection of load profiles identified one system (profile shown in Figure 5) which was subsequently removed due to a noticeable lack of electricity usage from Jul-Oct in both 2017 and 2018. This resulted in 29 homes which could be used in this study.

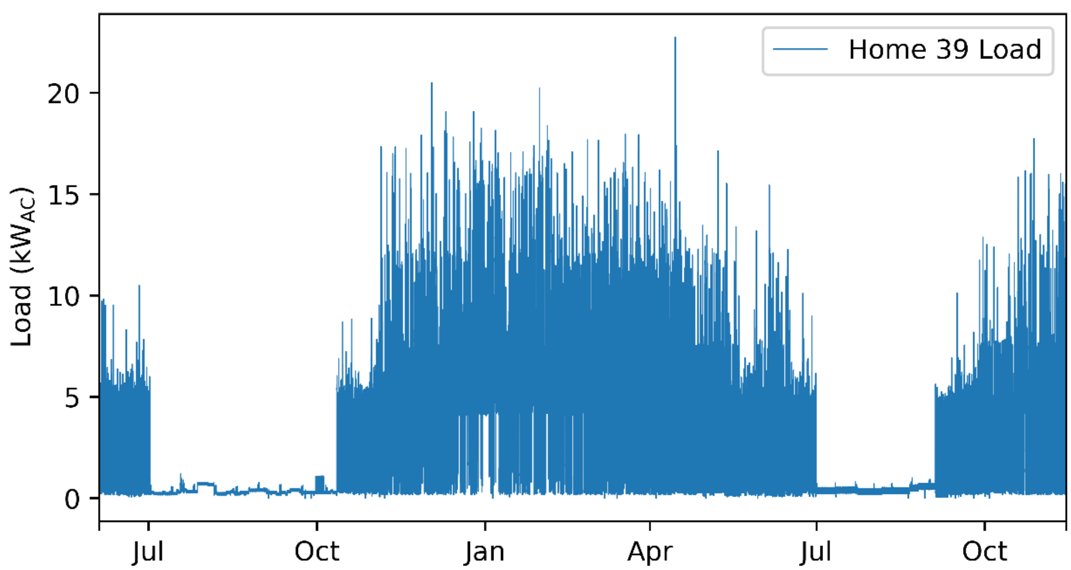

Figure 5. Residential load profile which was excluded due to lack of consumption during summer months.

The lack of electricity consumption is uncharacteristic for residential load profiles. This is highlighted by Figure 6 which shows that electricity consumption increases during colder months, which can be attributed to increased heating requirements due to colder temperatures and increased use of lighting due to fewer hours of sunlight. Note that one profile has a noticeable jump in electricity consumption during August, likely due to an air conditioning system.

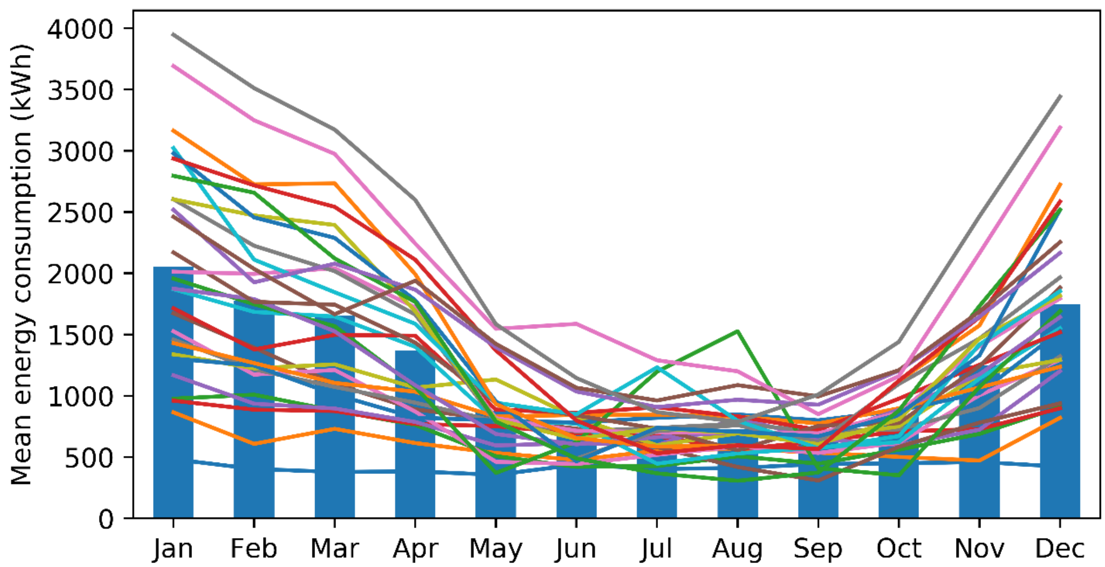

Figure 6. Average monthly electricity consumption of all residential load profiles (columns) and individual home monthly electricity consumption (coloured lines, n = 28)

Since all 28 homes report data for the period of 18-Sep-2017 to18-Sep-2018, this timespan was used to calculate metrics of interest presented below.

Figure 7 shows the distribution of 5-minute average power consumption for each residential system used in this study. The maximum values observed from each home are substantially larger than the average load. This is likely caused by both a combination of seasonal fluctuations of electricity consumption, and by consumer appliance usage patterns. For example, evening heating loads on a day could coincide with cooking (or laundry), both of which are energy intense activities.

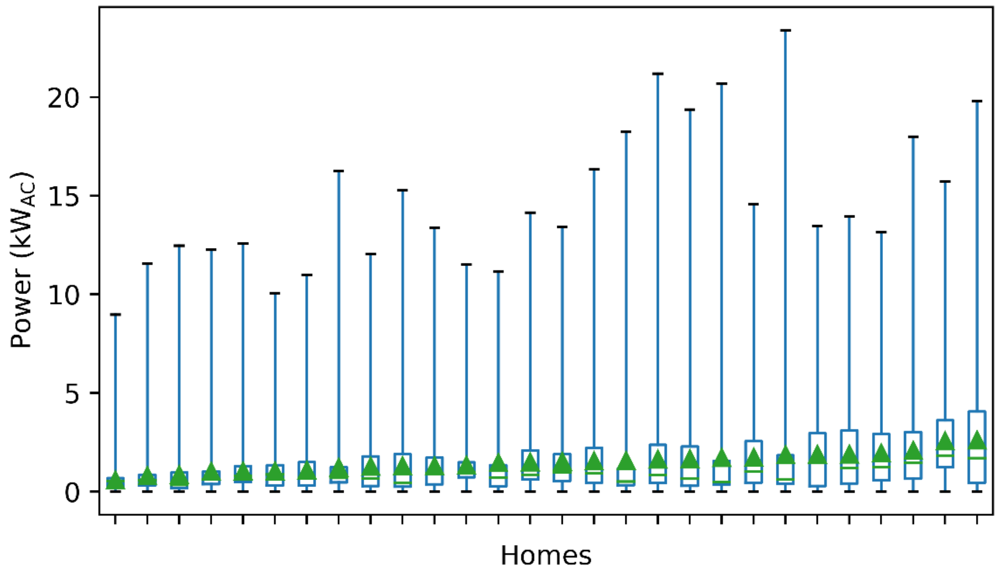

Figure 7. Boxplot showing the minimum, 25th percentile, median, 75th percentile, and max values of power consumption for residential systems used, sorted by average power consumption which is marked with green triangles

4.2. PV Generation Data

PV generation data was obtained from 97 residential systems spread across the HRM, and from 2 commercial systems located within the HRM. Residential PV data was made available through the HRM Solar City 2 program[4] and was accessed using a data portal operated by the Applied Energy Research Lab at Nova Scotia Community College[5] which collects PV data from participating installations in Nova Scotia, Canada.

4.2.1 Residential PV

This dataset provides AC generation (in W) data at a 5-minute interval from 97 microinverter systems distributed across the HRM. Data spans from 18-Jul-2017 to 25-Jul-2020, with an increasing system count over time up until May 2019 as new systems were added to the dataset. Timespans for raw data are presented in Figure 8.

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[4] https://www.halifax.ca/home-property/solar-projects/about-solar-city-halifax
[5] https://data.solardatans.ca/communitysolar/signIn.php

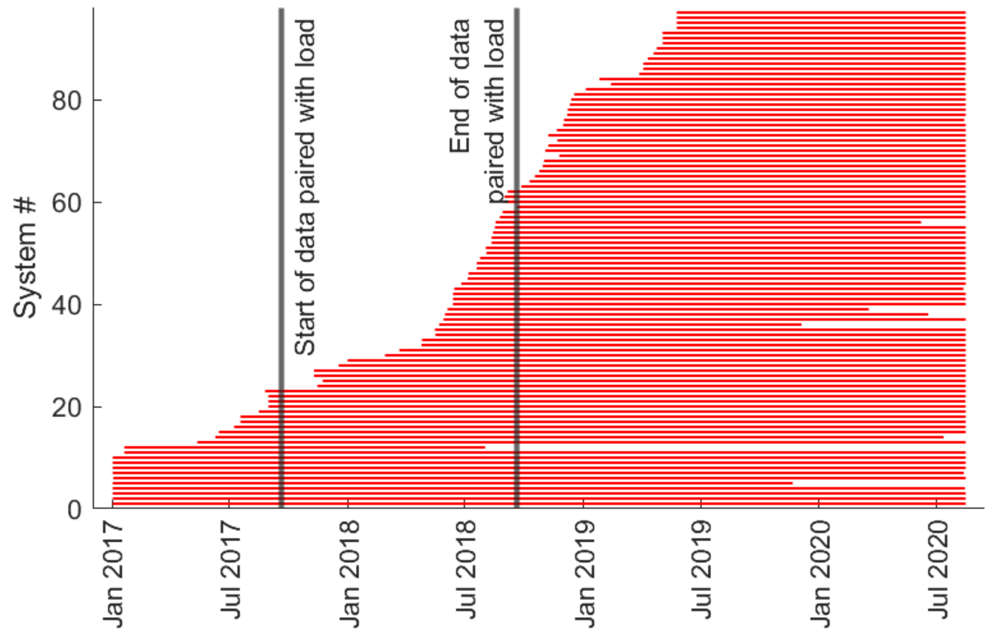

Figure 8. Timespan of data availability for each system in the residential PV dataset

Microinverter system architecture means that each PV module in the PV system has its own inverter which feeds into a main AC bus. While each inverter has its own MPPT system, the data reported is that of the total system, which is the sum of all modules. The number of PV panels reporting at anytime is recorded however, which can be useful for detecting anomalies. Data from HRM's SolarCity 2 program also contained the postal code forward sortation area (FSA) which provides an estimate of the systems location in the municipality, and the AC and DC ratings of each of the systems allowing for the calculation of DC:AC ratios.

Measured real-world data has quality issues such as false generation or a failure to report. In order to address data quality the following were implemented:

1- Only systems which had been reporting for at least one year were considered to account for seasonal variance. This removed 16 systems.
2- Systems which had more than 25 days total missing data within a 1 year period, or more than 7 days in a row of missing data within a 1 year period were removed. This removed 21 systems.

After applying these quality control schemes, 60 PV systems remained.

Residential PV systems have output profile which can vary drastically depending on design considerations; whether they be physical limitations to match roof orientation or economical choices such as under sizing inverters to reduce capital costs. A visualization of the variety of PV output profiles is shown in Figure 9, which plots a sample of PV output profiles for cloudless days near the summer solstice.

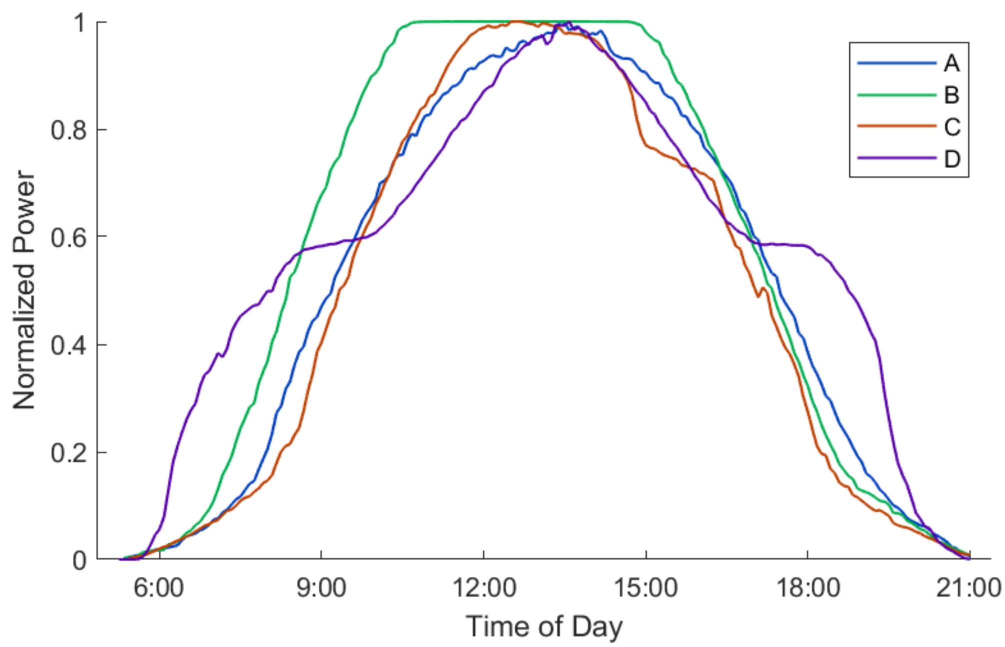

Figure 9. Sample output from four residential PV systems on a clear day near summer solstice. (A) normal production curve; (B) high ratio of DC capacity to AC capacity with clipping; (C) afternoon shading; (D) multi-string with East, South, and West facing slope

A summary of metrics of interest is provided in Table 2, and a distribution of the installed capacity (measured in kW_{DC}) is shown in Figure 10.

Table 2. Metrics of interest for complete residential PV dataset (n=60)

Metric	Min	Mean	Median	Max
Installed capacity (kW_{DC})	3.8	8.4	8.5	12.7
DC:AC ratio	1	1.26	1.3	1.55
Annual generation (MWh_{AC})	3.46	8.17	8.31	12.40
Capacity factor based on installed DC capacity (%)	7.8	11.1	11.3	13.4

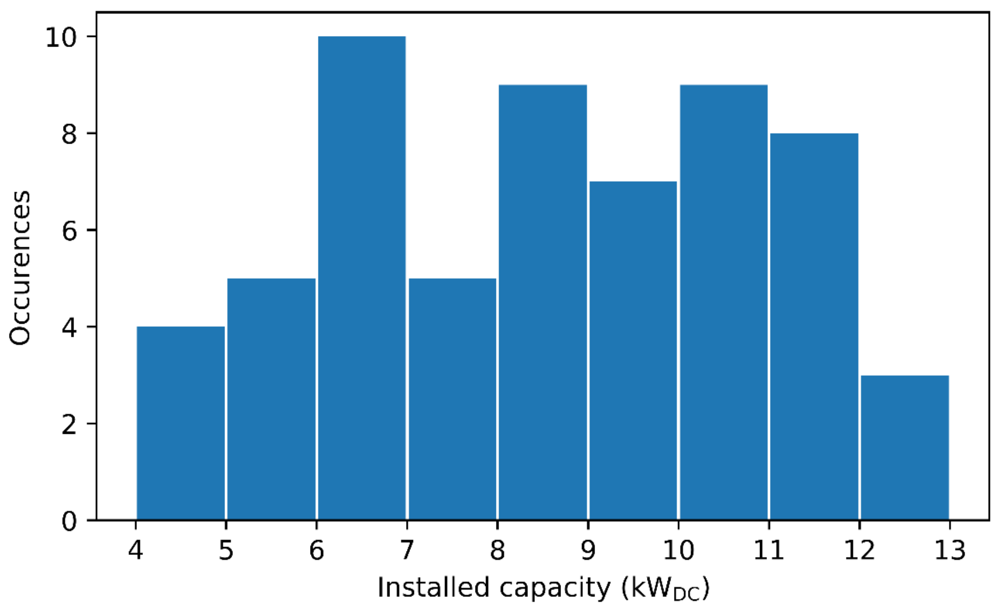

Figure 10. Distribution of total PV dataset installed capacity

As with the residential load, PV generation varies seasonally as shown in Figure 11. Peak residential solar generation occurs from May to Sep due to longer daylight hours. This is the opposite to what is observed for residential load, where loads are smaller throughout the summer and peak during the winter.

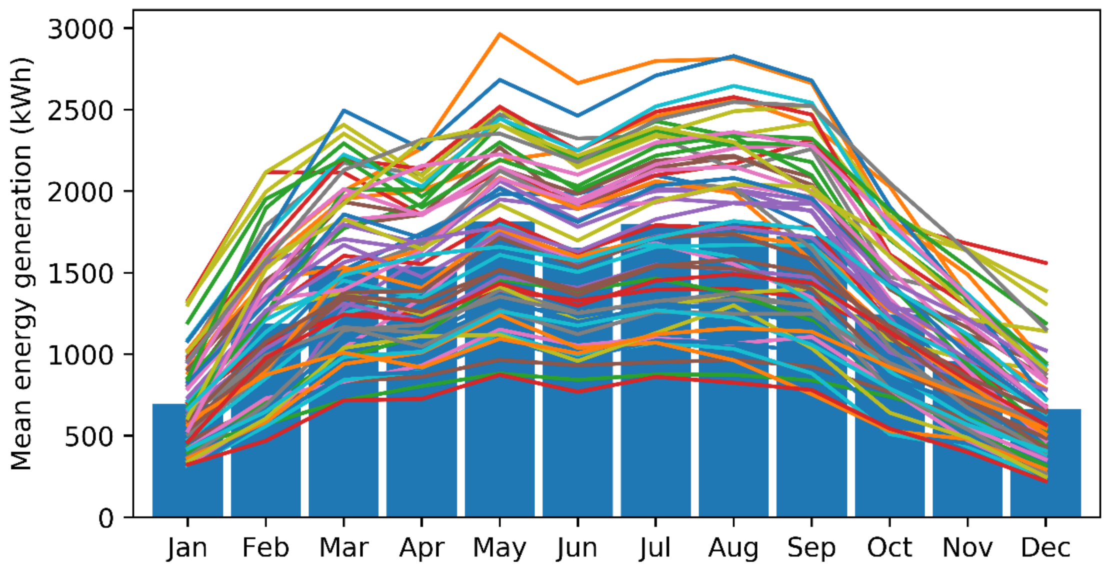

Figure 11. Average monthly PV generation of all systems (columns, n=60) and individual systems (coloured lines)

For intermittency studies, the aggregation of residential systems was required. To compute the aggregate output of the distributed residential systems, the AC production for each system was normalized by its maximum value occurring in the timeseries rather than the native power values (W). This was done so that the size of installed systems was not a factor; geographic location and system count effects are of interest, not evaluating where the largest systems are installed (e.g. in a wealthy neighborhood with large rooftops). Consequently, the aggregated distributed residential system never reaches a normalized output value of 1. This indicates that systems in the distributed profile never all reach their maximum value simultaneously, even though most systems in the dataset display some degree of clipping. The resulting aggregate distributed power output profile, along with resultant percentiles, is shown in Figure 12.

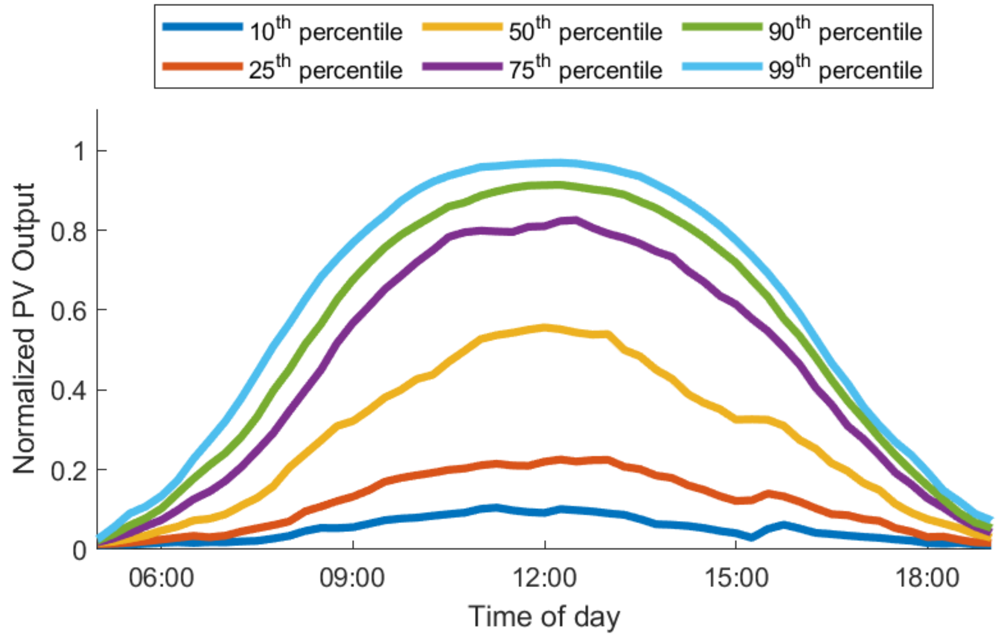

Figure 12. Normalized distributed residential PV power percentiles from an aggregate of 60 systems for an entire year

Since residential load data was only available for 2017 and 2018, a subset of 28 PV system profiles which had recorded data as early as 18-Sep-2017 was paired with residential load data to evaluate the implication of several electricity policy scenarios on the economic value of PV (Chapter 9), and the impact pairing energy storage with PV systems (Chapter 8 and Chapter 10).The requirement for inclusion of PV systems in this subset was that they had at least one year of overlap with residential load data. This is a critical requirement since both PV generation and residential load are impacted by weather, and so it is important that combined data used to generate results are time-synced. The importance of using an entire year is that PV generation and load peak during different times of year. PV generation is greatest during May to Sep, while load is greatest from Dec-Mar. Not using an entire year's worth of data would bias results because of these differences.

Since residential data is available from 2017 and 2018, this means that the subset of PV systems can be compared with the full set to get a sense of how PV systems in the region have developed over time. Table 3 summarizes some metrics from the subset of PV data which was paired with residential load data. Over time the average installed capacity of PV systems has grown, likely due to a mix of reduced PV system prices and development of the industry in the region. The DC:AC ratios of systems have also increased over time which may indicate an increasing importance of PV system economics, since clipping to a certain extent is generally accepted to increase economic viability of PV [42], [43].

Table 3. Summary of selected metrics PV generation data which was paired with load data (n=28)

Metric	Min	Mean	Median	Max
Installed capacity (kW_{DC})	4.2	6.6	5.8	11.5
DC:AC ratio	1	1.12	1.14	1.26
Annual generation (MWh_{AC})	4.18	6.07	6.26	11.42
Capacity factor based on installed DC capacity (%)	4.1	9.9	10.3	13.5

4.2.2 Commercial PV

Commercial PV data was obtained to compare ramp rates from commercial and residential PV installations in Chapter 6. Residential PV systems are typically constrained by roof orientation, while commercial PV systems are mounted on flat roofs, allowing for more optimal orientation.

Two sets of commercial-scale PV data were used to study the intermittency of centralized and distributed PV generation. A 130 kW_{AC} array located on the Sexton Campus of Dalhousie University in Halifax, NS, Canada was used to represent a medium commercial system, and a 650 kW AC array located on the roof of an IKEA store in Dartmouth, NS, Canada was used to represent a large commercial system. Both datasets spanned from 25-Jul-2019 to 25-Jul-2020.

Medium commercial data was provided with a 1-minute timestep and was averaged to a 5-minute interval to match residential generation data. A profile of normalized system output vs time of day is presented in Figure 13 which shows a significant amount of AC side clipping based on the flattened production values mid day. Further evaluation of this dataset did not identify any data quality issues.

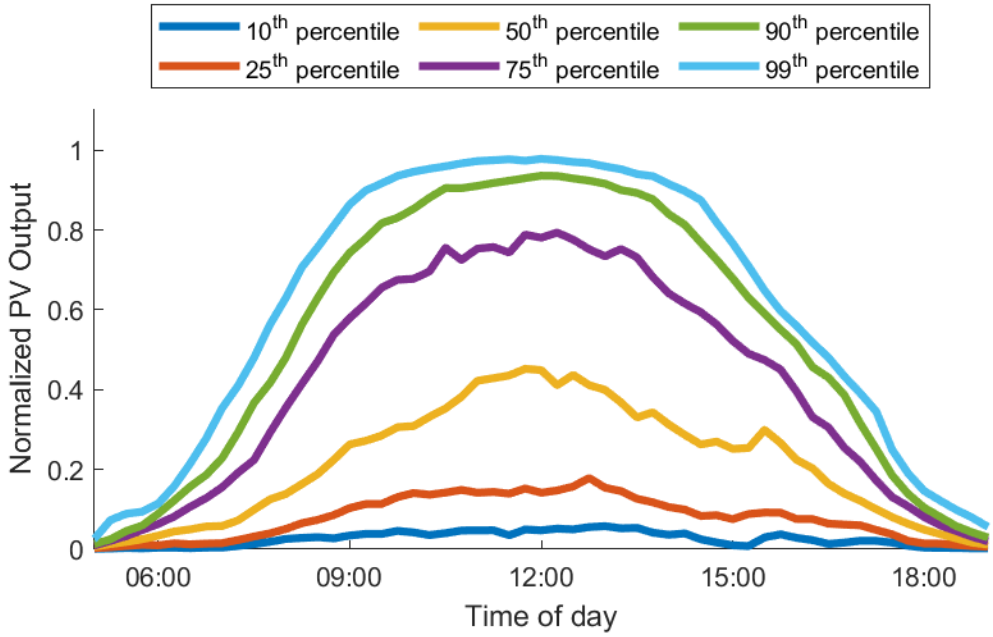

Figure 13. Normalized medium commercial PV system power percentiles for an entire year.

Large commercial data consisting of a 650 kW_{AC} PV array providing data from 28 separate string inverters, whose output was summed and normalized. Data recording for this site began in Nov 2017 and is ongoing. The highest observed power output from the dataset (674.9 kW_{AC}) was used to normalize data rather than the nominal AC capacity. Normalized power values are shown in Figure 14 with percentiles. Like the medium commercial system there is a noticeable (though smaller) amount of clipping in the profile, resulting in the lack of a distinct production peak.

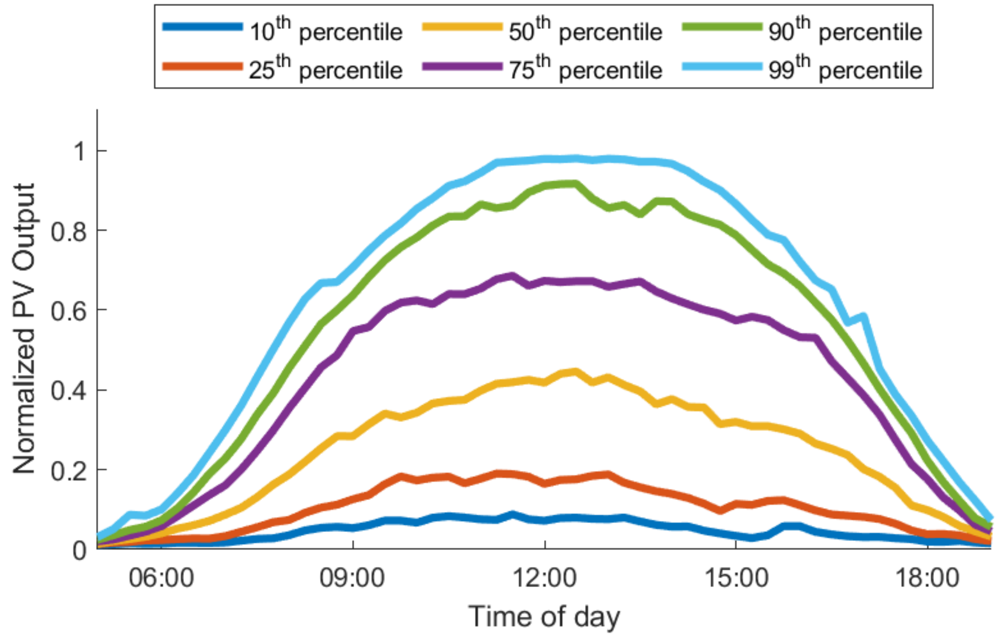

Figure 14. Normalized large commercial PV system power percentiles for an entire year.

Several data quality control steps were implemented:

1. Due to a interconnection agreement, the PV production of the large commercial system must never exceed building load and export to grid. This means that when the building load minus PV generation reaches approximately 50 kW, PV output is curtailed. To avoid including curtailed data, any time the net building load (included in the supplied data set) fell below 60 kW, corresponding PV data was excluded from the analysis. This occurred in 3674 data points (3.5% of the time).
2. A filter flagged any stretch of three consecutive identical datapoints (to within 10 W). This identified 133 points (0.1% of data) which were then removed.

A summary of metrics of interest for both installations is presented in Table 4. Interestingly, the calculated DC:AC ratio of both systems was the same and is close to results obtained by Wang et al. [44]. Both systems have identical DC:AC ratio which is indicative of system optimization which is also highlighted by the physical orientation of the arrays. Unlike residential PV, the physical orientation of commercial PV is less restricted by the attributes of the buildings roof. A portion of the large commercial system is shown in Figure 15 and represents a typical layout for commercial PV arrays, with a smaller tilt angle and facing near due-south.

Table 4. Commercial PV metrics of interest

Metric	Medium Commercial	Large Commercial
Installed Capacity (kW_{DC})	150	836
Max observed power (kW_{AC})	121	675
Calculated DC:AC ratio	1.23	1.23
Annual Generation (MWh)	139	883
Capacity factor based on installed capacity (%)	10.6	12.1

Figure 15. Photo of the large commercial PV system used in this study

4.2.3 Geographic Distribution of PV Within the Municipality

The FSA provided for each residential site used in this work indicates the approximate location within the municipality. Figure 16 presents a map with the number of residential systems located in each FSA (green numbers), as well as the medium (red dot) and large (blue dot) commercial locations. There is a notable concentration of systems around the city center.

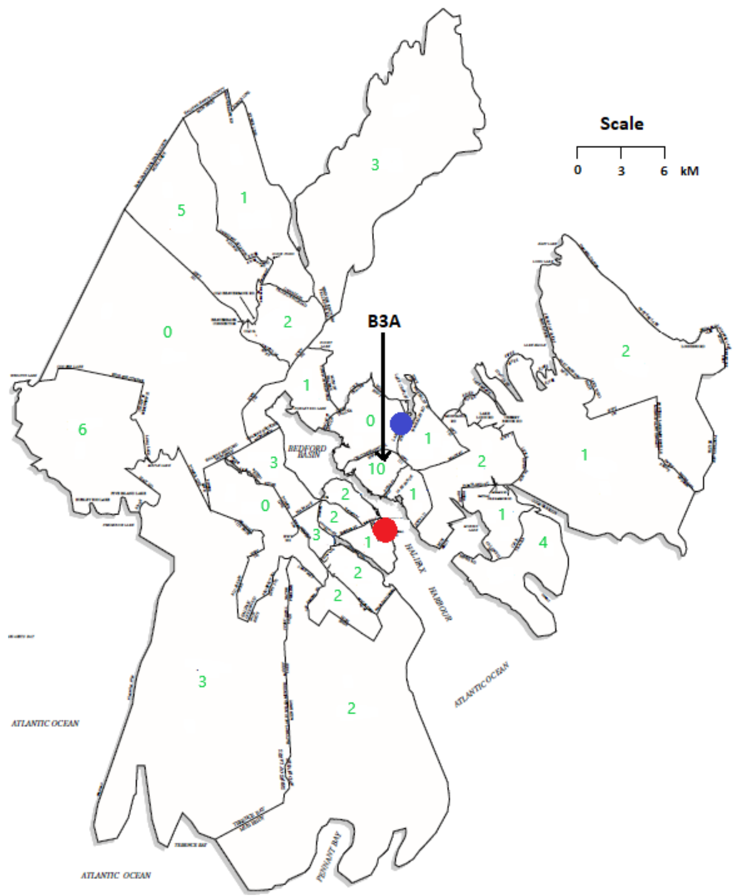

Figure 16. FSA map of Halifax Municipality. Green numbers give the number of residential systems within each FSA. The locations of commercial systems are marked in red (medium) and blue (large). The specific FSA example of B3A is identified [map based upon Canada Post 2001]

Assuming all residential PV systems are located at the center of the FSA, the mean distance between residential sites was calculated using Equation 5, where *S* is the spacing between sites (in km), and *n* is the number of systems, in this case 60, and $\binom{n}{2}$ is the number of possible combinations of 2 systems selected from *n* systems. This resulted a mean distance between sites of 16.1 km.

$$S_{mean} = \frac{\sum_{i=1}^{n} \sum_{j=i+1}^{n} S_{i,j}}{\binom{n}{2}} \tag{5}$$

Chapter 5: Methods

This chapter presents methods used to evaluate PV intermittency (Section 5.1, with results presented in Chapters 6 to 8) and the technoeconomic impacts of tariffs on PV and PV + storage (PVS) systems (Sections 5.2 to 5.6.1, with results presented in Chapters 9 and 10).

Intermittency was evaluated using two metrics: power ramp rates (discussed in Section 2.1.2), and output variability (Section 5.1). Ramp rates provide a practical evaluation of intermittency for grid operators while output variability is a useful quantitative method for comparing different aggregations of systems.

The impact of residential PV generation on net load intermittency, and the implications of net-metering policy, require consideration of PV generation profiles and their alignment with residential loads. This required pairing of PV and load profiles which were likely not from the same home because the data came from different collection programs. To simplify analysis and increase the simulation solution space to capture the variability that would be expected in practice, PV generation data was scaled to installed capacities of 5 and 10 kW_{DC}. These sizes are meant to represent a small (5 kW_{DC}) and large (10 kW_{DC}) PV systems for the region based on the distribution of installed residential PV sizes (shown in Figure 10, Section 4.2.1). Geographic variability between homes was assumed to not be significant, but temporal alignment of profiles was required. This meant that any PV systems and load profiles with at least one year of overlapping data could be paired to generate a representative net load. This is shown in Section 5.2.

To evaluate the potential for energy storage using net loads created using PV and load data, an energy storage model was developed using the Python 3 programming language. An object-oriented programming approach was used, which led to the creation of 4 custom classes used to represent different components and control. A battery class was used to control the system specifications of energy storage systems, and a controller class was used to enact specific operational strategies to exploit opportunities in different electricity policy scenarios. A solar + storage class was used to handle simulation inputs and outputs, and a PV class was used to facilitate PV data scaling. The model is described in Section 5.3, and a discussion of control strategies is presented in Section 5.4.

Determination of the economic value for all PV and storage systems is presented in Section 5.6, and was done using the annual revenue and estimated capital cost of the PV or PV with storage system. Revenue was calculated based on either measured PV data (for determinations of PV only value) or simulation net loads and the prevailing tariff for each timestep. The estimated cost of a PV array was determined for a 5 kW_{DC} array and a 10 kW_{DC} array, and storage cost was determined using a 3-factor model based on storage capacity, storage converter rating, and a flat installation cost.

5.1. Quantification of Ramp Rate

Two quantitative measures of PV power variability presented by Hoff and Perez [20] were used in this study: output variability and relative output variability. Output variability (OV) is the normalized standard deviation of power ramp rates as shown in Equation 6, where $P_{\text{agg,max}}$ is the peak output of the aggregate system, N is the total number of systems, and RR_n is the ramp rate timeseries for the n^{th} system.

$$\text{OV} = \left(\frac{1}{P_{\text{agg,max}}}\right) \times \sqrt{Var\left[\sum_{n=1}^{N} RR_n\right]} \tag{6}$$

Relative output variability (ROV) quantifies the reduction in PV power variability caused by "dispersing" the PV fleet. The ROV is the system output variability divided by the output variability of a single location. This allows for the impact of geographic smoothing to be quantified. Hoff and Perez [20] predicted relative variabilities based on a system dispersion factor, shown in Equation 7, where D is the dispersion factor, L is the length of the PV fleet in the direction of cloud motion in meters, V is the cloud transit speed in m/s.

$$\text{D} = \frac{L}{V \times \Delta t} \tag{7}$$

While (relative) output variability is useful for quantifying the impact of different system configurations, both it and the output variability metric on which it is based rely on the standard deviation as the principal descriptor of statistical variability. While the standard deviation is a universally recognized and broadly applied metric of variability, there is concern that it is non ideal in this application for two reasons. First, the standard deviation assumes a symmetrical distribution of values, which while a reasonable first assumption, is not necessarily the case due to system orientations and natural phenomenon (e.g. foggy mornings). Second, in the context of a zero-biased distribution, the standard distribution only describes the approximately 33rd percentile of ramp events. This latter point suggests that OV may be poorly suited to indicate the real-world impacts seen by electricity grid operators, which must be prepared to accommodate the worst power ramp rates observed.

To compare results from this study to those presented in [20], a cloud transit speed for the region is required to calculate a dispersion factor. [22] presented a scaling coefficient, A, and coefficient maps for their Wavelet Decomposition Model, which they found to be half the cloud transit speed. While there are notable seasonal fluctuations, for the purposes of this study an annual average of A = 6 (cloud speed of 12 m/s) will be applied. Based on the map of HRM presented in Figure 16, the system length for the aggregate residential system is taken to be 48 km. Using a timestep of 5 minutes, this results in a dispersion factor, D, equal to 13.3 which was used to evaluate the Hoff & Perez [45] intermittency model using data from the HRM in Section 6.2.

5.2. Pairing Residential PV Generation and Load

When examining the impact of electricity pricing schemes which do not include net-metering on the economic value of PV systems, temporal alignment between PV generation and load is critical. In these cases, PV generation which can not be used by the home is either lost or exported at a reduced rate, lowering the economic value of the system. An example of pairing home load and PV generation is shown in Figure 17 with the resultant net load seen by the grid also shown. The x axis is shown in red to differentiate periods of electricity exports (positive net load) and imports (negative net load).

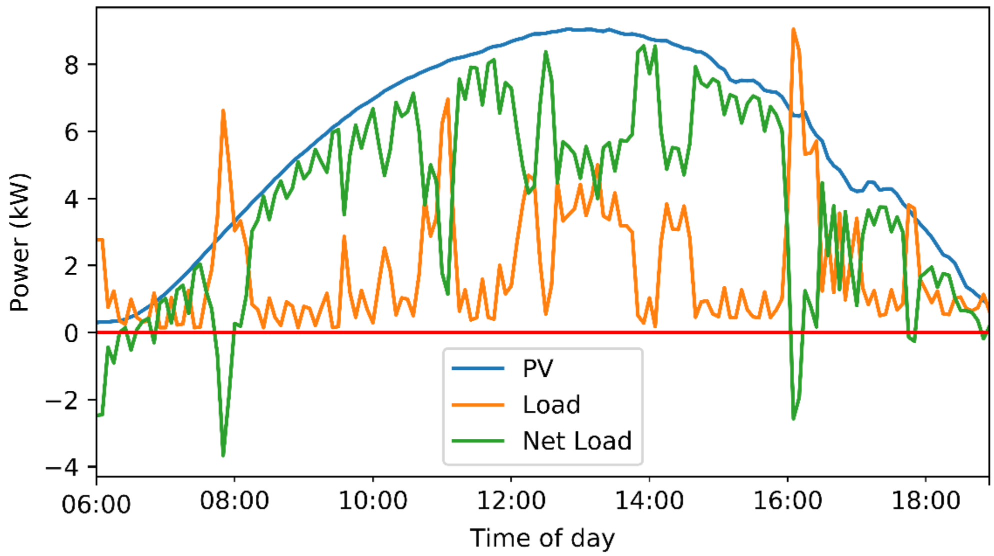

Figure 17. PV generation, home load, and paired net load of a sample system for a sunny day. Positive net loads indicate electricity is exported to the grid, while negative indicates electricity is imported.

Net load profiles used for this work were generated using combinations of load and PV profiles. This was done by matching load and PV data with at least one year of overlap. Since the location of the load data within the HRM is unknown the assumption must be made that the geographic variability of residential building loads is not significant at the municipal scale.

Since residential load data has varying timespans, the number of PV systems each home can be paired with is different. This leads to some loads and PV profiles having a greater weight when evaluating the average of all systems. For example, if a set of PV systems can only be paired with 2 homes, then those homes will be used more than others and have a greater impact on the combined average. Figure 18 shows a matrix of load profile and PV system pairings, with each square representing a potential pairing of load and PV. Green squares show viable pairings based on the criteria of at least one year of overlapping data, while red squares are non-viable pairings. A yellow line is inserted to visualize the impact of enforcing equal representation (which would remove 77 combinations, greater than 10% of all potential pairings).

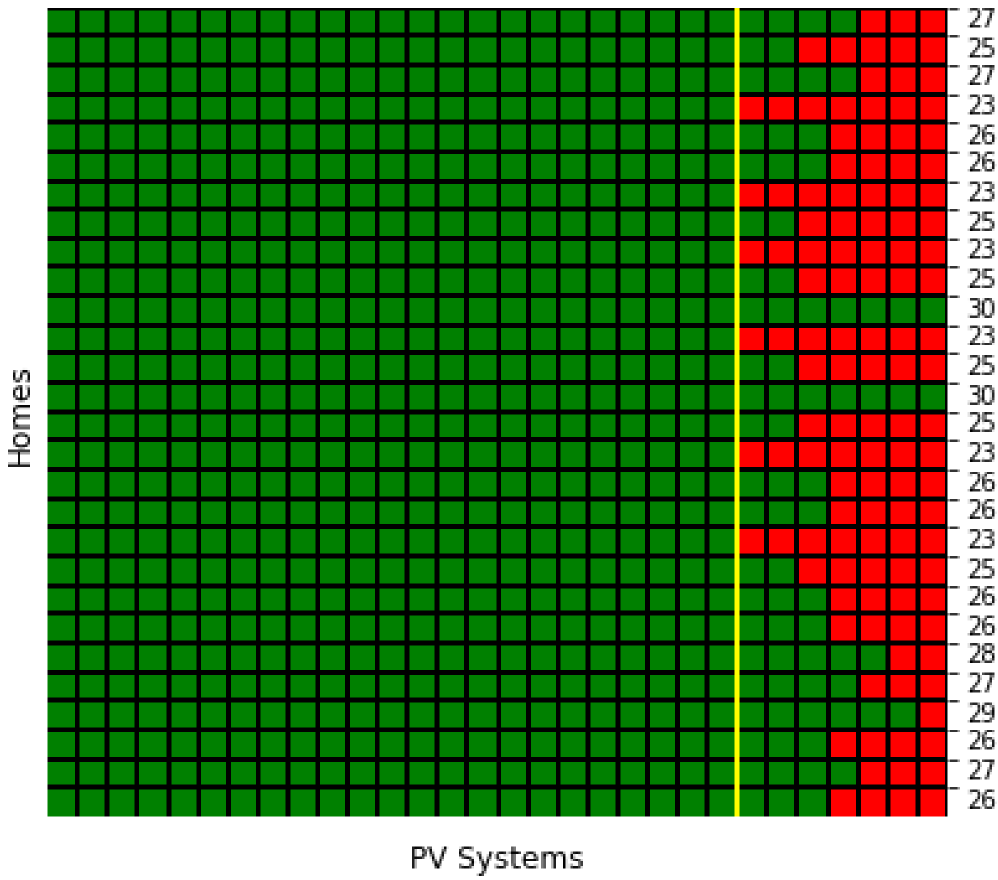

Figure 18. Visualization of available pairings for residential load (Homes) and PV generation (PV Systems) profiles. Green indicates a possible pairing based on overlap of at least 1 year's worth of data with a count of pairings for each home shown on the right. The yellow line shows the maximum number of pairings if equal representation of all homes and PV was applied

For studies interested in the net energy consumption (and subsequent value of said energy) it was decided that the inclusion of more homes was preferable to capture the impacts of pairing a larger variety of unique PV and load profiles, and so all PV and home pairings were included. A total of 28 homes were paired with 23 to 30 PV systems, resulting in a combined system count of 721. Note that this methodology did not take into consideration the likelihood that small homes (which tend to have smaller loads) may not have the space to install larger PV systems. Conversely, large homes are less likely to have small PV systems. This assumption is mitigated by the scaling of PV generation which is discussed in the following section.

An alternative method would be to select a static period of 1 year and only incorporate load and PV data which fell within this timespan. This would lead to equal representation of all homes and PV systems, but sacrifices potential combinations. This methodology was adopted for studies focusing on intermittency, since the aggregation of systems is time sensitive (01-Apr-2017 cannot be combined with 01-Apr-2018). The year-long period of interest spans from 19-Sep-2017 to 19-Sep-2018 and combines 28 homes with 21 PV systems for a total of 588 paired profiles.

5.2.1 Residential PV Scaling

As previously mentioned, scaling PV systems could over or underestimate the benefits of adding PV to a given home. Sizing of residential PV systems is limited by a home's physical characteristics such as roof size and orientation. Additionally, residential PV policy in Nova Scotia restricts the size of a PV installation based on the electricity consumption of the home, where the estimated amount annual PV generation cannot exceed consumption. This can lead to both over and underestimation of the potential value of net-metered PV, where the benefit is overestimated for smaller homes, and underestimated for larger ones.

The impact of scaling assumptions also presents itself when evaluating the impacts of imposing a self-consumption electricity policy on the value of both PV and energy storage. If the scaled PV underestimates the feasible size of a PV system for a given home, then the impacts of self-consumption on PV value will be mitigated since larger loads will likely lead reduce export opportunities. The opposite is true for scaled PV which is oversized, where smaller loads will increase the amount of export opportunities. The value of adding energy storage to a PV system is dependent on the amount of energy recovered from otherwise wasted generation. As such, oversized PV scaling will benefit energy storage, while undersized scaling reduces its value.

To mitigate these factors, home load profiles were distinguished as either large or small homes based on their annual load consumption. Annual consumption of less than 13 MWh was considered to be a small home (13 of 28 homes in the dataset), while greater than 13 MWh was considered a large home (15 of 28 homes in the dataset).13 MWh was chosen as a cut-off point since it is both near the median annual consumption (13.22 MWh) and the average electricity consumption of single detached homes in Nova Scotia (12.81 MWh based on 2018 data) [46].

The installed capacity of the available PV profiles was scaled to two representative sizes: 5 kW_{DC} (for small homes) and 10 kW_{DC} (for large homes). This was done using Equation 8, where φ is the DC:AC ratio of the system, and DC is the desired DC capacity (either 5 or 10 kW_{DC}).

$$P_{\mathrm{PV,scaled}} = P_{PV,norm} \times \frac{DC}{\varphi} \tag{8}$$

This methodology assumes the peak power observed in the PV dataset is the actual peak for the system design. This could be untrue if the systems fail to reach their designed peak output due to shading.

In the case of system shading, the microinverter architecture of the available data is advantageous. System level generation data from large string inverters may not detect partial shading of arrays if the inverter is undersized. This would occur if partial shading of a PV system reduced the DC output, but not by enough to fall below the maximum AC output of the inverter. System level microinverter data does not have this issue, since the generation from each module is summed, and shading of one module would produce a dip in overall production. Microinverters have the same limitations if we consider shading at the module level, where partial shading of the module is undetected if it does not fall below the microinverter rating. Since generation data is scaled at the system level, and the scaled system has the same AC:DC ratio, the shape of the generation profile would remain intact.

Of the 721 paired profiles used for residential energy storage modeling, 421 are classified as large (10 kW_{DC} PV) and 320 as small (5 kW_{DC} PV) with an aggregate PV capacity of 5.81 MW_{DC}. For homes used for intermittency studies, 315 are classified as large, and 273 as small with a total aggregate PV capacity of all 588 paired profiles equal to 4.515 MW_{DC}.

5.3. Energy Storage Modelling

A PV + storage (PVS) model was developed to investigate the impacts of pairing PV generation with energy storage in a variety of electricity rate scenarios. The model is technology agnostic and as such, it is only concerned with energy flows, and does not simulate elements such as temperature or voltage.

An object-oriented programming approach was used, and the model makes use of four custom-built objects described in Table 5. Figure 19 provides a high-level overview of object interaction and general model workflow. The advantage of this approach is flexibility to add new parameters and functions easily, and to facilitate code readability. For example, the addition of a new control strategy can be applied by adding a sub-function to the Controller class source code (see Appendix E), independent of other objects.

Table 5. Custom objects used to simulate energy storage and their functionality

Object	Description and functionality
PV System	Contains PV generation data and a function to normalize the PV profile
Battery (energy storage)	High-level representation of a battery system, including the converter. Tracks storage capacity and restricts charge/discharge requests based on input parameters. Also handles conversion between AC and DC energies.
Controller	Generates an energy request which is sent to the battery for each timestep based on rate structure and net load.
SolarStorageSystem	High level object made up of a PV profile, a load profile, a Controller, and a Battery. Runs timestep simulations and generates results.

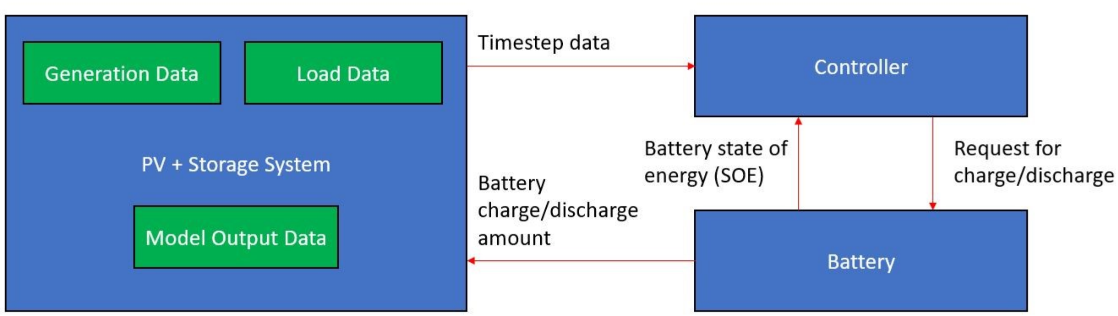

Figure 19. Simple outline of the energy storage model design showing object interaction and workflow

A PV System class (code presented in Appendix C) was created to handle generation data and has one function of practical importance: scaling PV data.

The purpose of the SolarStorageSystem class (code presented in Appendix B) is to run the timestep simulation, manage the interactions between the controller and battery, and handle input and output data. A sample of the simulation output is shown in Figure 20. All values presented are in units of Wh; and are on the AC side of the system except for capacity. In this example, the controller attempts to maintain a net energy of 0 and does so by charging the battery with excess PV generation and discharging when load exceeds generation, evidenced by the changing capacity value.

DateTime	Load (Wh)	PV (Wh)	Net Load (Wh)	Capacity (Wh)	Net Load + Battery (Wh)
2017-11-05 09:15:00	14	279	265	303	0
2017-11-05 09:20:00	11	250	239	531	0
2017-11-05 09:25:00	216	251	35	564	0
2017-11-05 09:30:00	527	251	-276	273	0
2017-11-05 09:35:00	122	216	94	362	0
2017-11-05 09:40:00	11	142	131	487	0
2017-11-05 09:45:00	61	142	81	564	0
2017-11-05 09:50:00	294	134	-160	396	0
2017-11-05 09:55:00	54	220	166	553	0
2017-11-05 10:00:00	11	220	209	752	0
2017-11-05 10:05:00	11	192	181	924	0
2017-11-05 10:10:00	254	144	-110	809	0
2017-11-05 10:15:00	149	144	-5	804	0

Figure 20. Sample of PVS model output for a single system

5.3.1 Battery Object

The battery object holds all information about the energy storage system and executes charge and discharge commands, imposing limitations based on its parameters (cannot charge past the battery's max capacity for example). Table 6 presents the key input parameters applied to battery objects and provides a description of their functionality.

Table 6. Important battery parameters and their function

Parameter	Description
Remaining Capacity	The amount of energy remaining (prior to conversion to AC) in the battery which varies throughout the simulation.
Rated capacity	The batteries nominal capacity when fully charged, prior to conversion to AC.
Charge efficiency	Efficiency of converting AC energy from the system to DC energy stored in the battery.
Discharge efficiency	Efficiency of converting DC energy from the battery to AC energy used by the system
Maximum charge rate	Maximum power (AC) which can be used to charge the battery
Maximum discharge rate	Maximum power (AC) which the battery can supply

Conversion efficiencies between AC and DC are handled using the battery object. A round trip energy efficiency (RTE) of 87% was assumed for this work and is in line with commercially available products [47]–[49]. Charge and discharge efficiencies were derived from the RTE using Equations 9 and 10.

$$Charge\ Eff. = RTE^{\frac{2}{3}} \tag{9}$$

$$Discharge\ Eff. = RTE^{\frac{1}{3}} \tag{10}$$

Different efficiencies were applied to the storage system to account for both conversion and electrochemical inefficiencies present in battery storage systems. In this case all the electrochemical inefficiency is applied to the charge along with conversion efficiency, while the discharge only experiences converter efficiency. This assumes that converter efficiency is equal to electrochemical but produces results which are consistent with the Tesla Powerwall 2 specification [48]. A Powerwall 2 has a specified RTE of 90%, and 13.5 kWh (96.4%) usable of a 14 kWh pack; 0.964^3 is roughly 90%.

Although the capability exists to use different maximum charge and discharge rates, they were equivalent for all simulations used in this work. This value is referred to as converter size and is discussed in terms of its AC side input/output (units of kW_{AC}).

Code for the battery class object is provided in Appendix D.

5.3.2 Controller Object

The purpose of the controller object is to read-in the system's net load and the battery's capacity for each timestep and make a judgement as to what the storage system should do. The controller object takes in the desired control strategy and the rate structure for the simulation and selects the appropriate sub-function. Details of the control strategies used in this work are discussed in Chapter 5.4.

Code for the controller class object is provided in Appendix E.

5.4. Strategies and Policy Scenarios

While Nova Scotia currently has a policy of net-metering for residential PV systems, jurisdictions with higher PV installation rates have seen an evolution in their approach. This could be done through changes to rate structure or the removal of net-metering; where energy exports have reduced value or are restricted altogether (e.g. PV self-consumption).

The application of different residential PV policy may provide opportunities for energy storage, whether it be mitigating PV intermittency, shifting energy under a TOD scheme or conserving excess PV generation if self-consumption policies are applied.

To simplify control strategy design, charge/discharge limitations due to battery parameters are not explicitly included in strategy descriptions. Instead, control strategies operate with the assumption that the storage capacity and converter size can accommodate control requests. In practice, this results in each charge/discharge request from the controller to the energy storage system being limited by the system's specifications, where the actual charge/discharge energy can be less than desired by the control strategy (e.g. requesting a discharge when the battery has with no remaining capacity, or requesting a 5 kW_{AC} charge when the converter size is only 3 kW_{AC}).

5.4.1 Intermittency Reduction

Since the objective of energy storage systems in this application is to offset ramp rates associated with residential load and PV the control strategy is simply to evaluate the change in net load as seen by the grid and ensure it does not exceed a predefined limit. A ramp rate limit (RR_{limit}) of 10% of the installed DC PV capacity per 5 minutes as the was used based on grid requirements for interconnected PV generation from other jurisdictions [10]–[12]. The ramp rate limit can be applied statically or dynamically. A static limit enforces a ramp rate limit on the PV profile without considering what the ramp rate of the home would have been without PV. An example of this is shown in Figure 21.

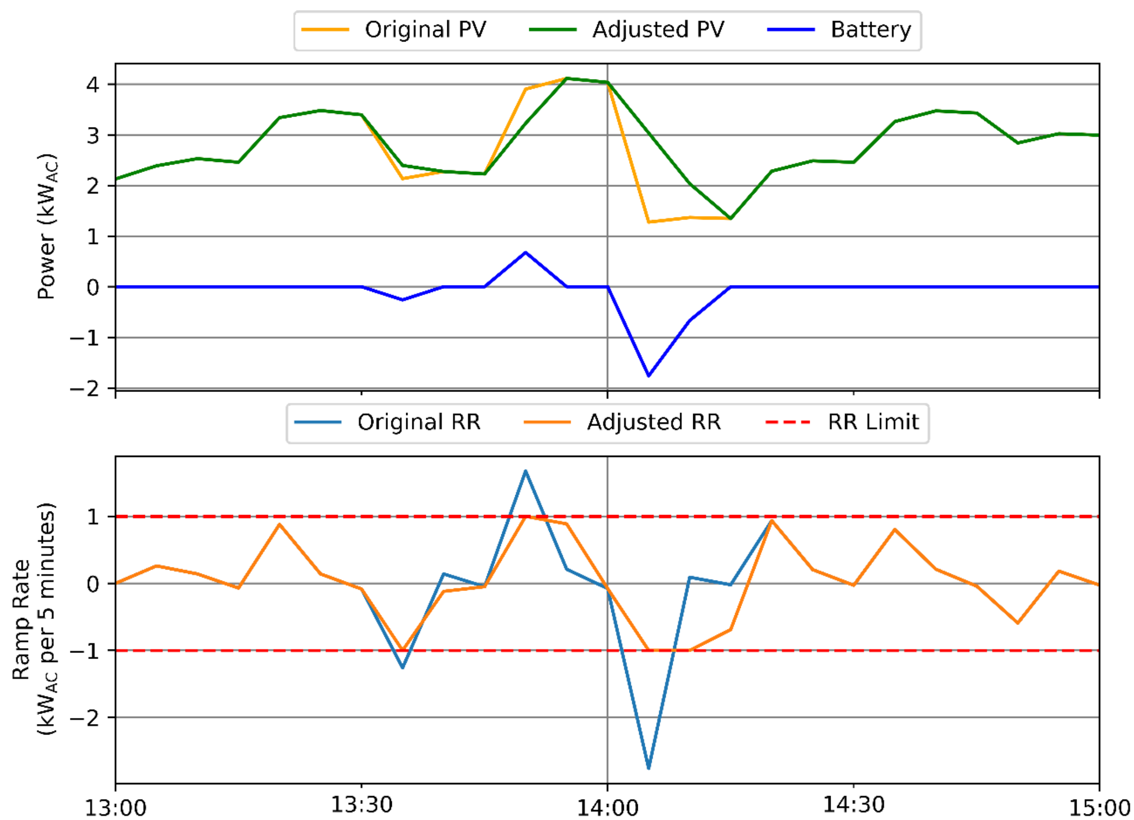

Figure 21. Example of a static net load ramp rate limitation showing PV power flows (top) and ramp rates (bottom)

An alternative interpretation of the ramp rate limit is that it should apply only to ramp rates which are made more severe due to the addition of PV to a home. The ramp rate limits are thus dynamic since the requirement is to now maintain ramp rates to within ± 10% of PV capacity per 5 minutes of the original load ramp rates. This is shown in Figure 22.

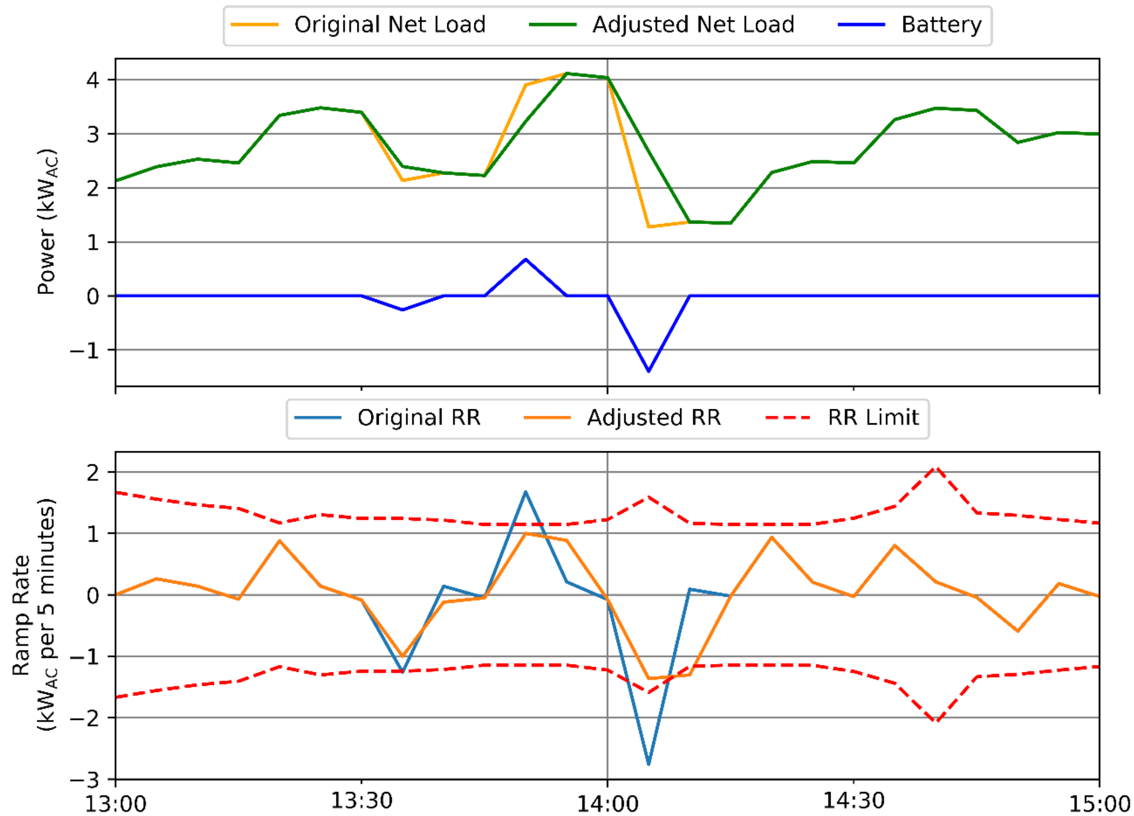

Figure 22. Example of a dynamic net load ramp rate limitation showing power flows (top) and ramp rates (bottom)

Initial testing of ramp rate control strategies identified failures which were caused by ramp rates occurring while the energy storage system was either too depleted or too fully charged. These situations occur when ramp rates in a given direction outweigh those in the opposite direction over period of time. To remedy these occurrences, the control strategy was adjusted to allow the battery to charge/discharge itself to try and maintain a SOE of between 40 and 60%. This was done by implementing a condition that if the battery was below 40% SOE, and the present ramp rate does not exceed the limit, and the net load ramp rate was positive the battery would charge. The desired magnitude of this charge was set to be the amount of energy required to fully offset the ramp rate experienced, or the amount of energy required to return the battery to 50% SOE (at least 10% of the rated capacity), whichever was smaller. There are three outcomes of this decision: the battery will charge to between 40 and 50% SOE and fully offset the ramp rate, the battery will charge to 50% SOE and reduce the magnitude of the ramp rate, or the battery will be unable to meet the request due to its converter size. In the event it is unable fulfill the request, the battery will still have mitigated some of the ramp rate and increased its SOE above 40%. The same strategy was applied if the battery SOE was above 60%, except the system would be discharged in the event the grid experienced a negative ramp rate. A summary of the control strategy is shown in Figure 23.

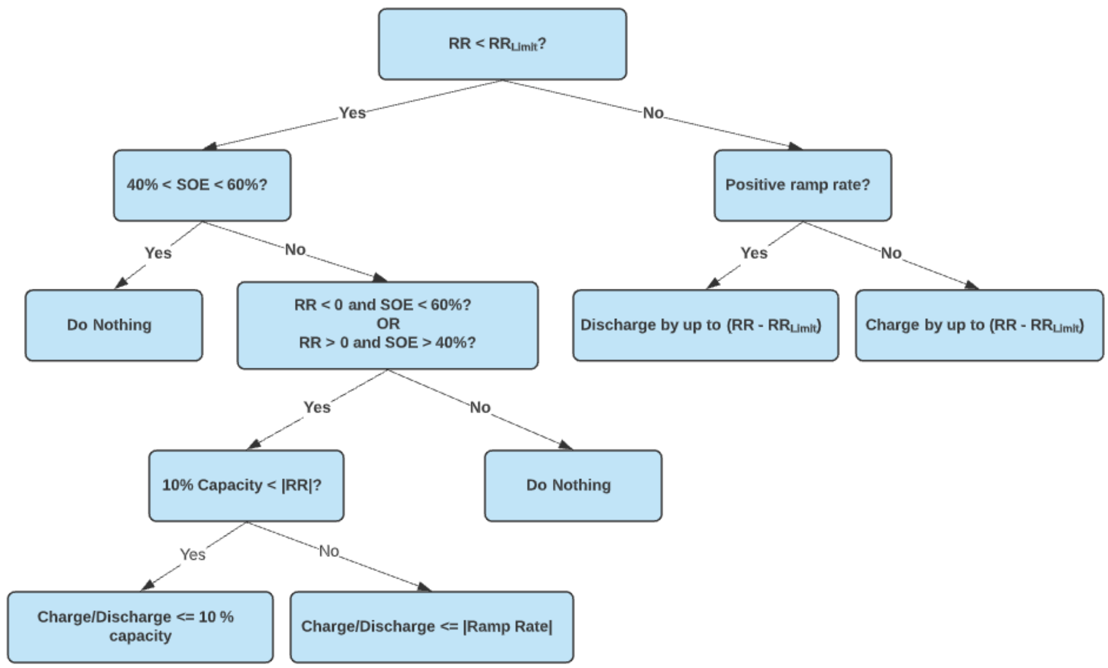

Figure 23. Decision tree representation of the Intermittency Control strategy

Banding the SOE between 40 and 60% may be restrictive and lead to more frequent cycling of the battery, but since degradation was not considered, and the only objective was to mitigate large ramp rates, maintaining a SOE near 50% as often as possible is preferable. Reducing the frequency of small ramp rates (<10% PV capacity per 5 minutes) is not as important as ensuring there is sufficient capacity to offset large ones.

The storage capacity and converter size needed to mitigate residential PV ramp rates for homes with PVS systems was determined separately. First, the storage capacity was determined iteratively by removing any converter restrictions. An original storage size equal to 1 kWh_{DC} per 10 kW_{DC} of installed PV capacity (1 kWh_{DC} for a 10 kW_{DC} PV system) was set and a simulation started. If at any time the system failed to mitigate ramp rates, the simulation was stopped, and the observed storage capacity deficiency was added to the original capacity. This could be done since converter size was not considered, and so could not be the limiting factor.

Once the required storage capacity was determined the converter size was taken as the largest power required by the simulation.

5.4.2 Net Load Following

The objective of this strategy is to maximize the amount of PV generation which can be used to meet home loads by attempting to maintain the net load of the home at 0. This means that whenever the home has an energy deficit (load greater than PV generation), the storage system will attempt to discharge to match it. Conversely, whenever the home has an energy surplus (PV generation greater than home load), the storage system will charge using as much of the excess energy as possible. A representation of this is shown in Figure 24.

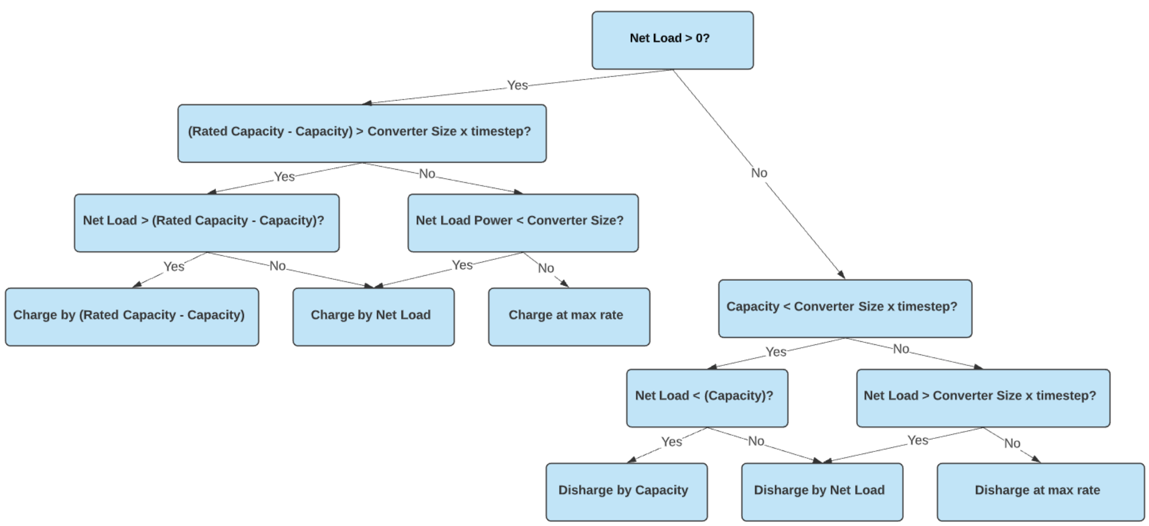

Figure 24. Representation of the Net Load Following control strategy

5.4.3 Energy Arbitrage

Under the TOD scheme used in this study there are two periods to consider for an energy storage strategy: during the non-winter months (Mar – Nov), and during the winter months (Dec – Feb). During off-peak months, there exists only 2 rates (off-peak and mid-peak) which alternate once per day, and so the strategy is to charge during off-peak pricing, and discharge during mid-peak pricing. During months with on-peak pricing the battery has two cycling opportunities, charging during the overnight off-peak and the afternoon mid-peak and discharging during the morning and evening on-peak time periods. During non-winter months the system can only cycle once per day, charging overnight off-peak and discharging during the daytime mid-peak. The summary of this strategy is pictured in Figure 25.

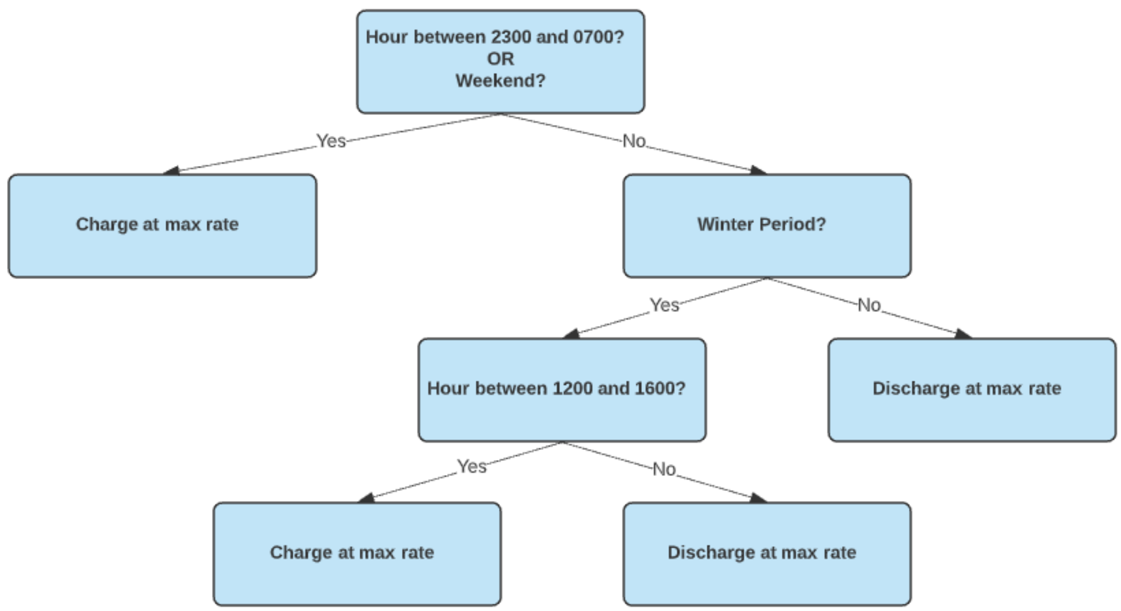

Figure 25. Decision tree representation of the Energy Arbitrage control strategy

Since the entirety of weekends are priced as off-peak, the controller does not discharge during these days, and instead waits for the Monday morning change to on-peak or mid-peak, depending on the time of year. This does not require any specific controls to be implemented, since the system will remain fully charged until Monday. The only change required to apply this strategy to a TOD tariff which treats workdays and weekends equally (Wknd. TOD) with net-metering tariff is that weekends are no longer observed as off-peak for the entire day, and so the control strategy will cycle the battery on weekends as well as workdays.

5.4.4 Restricted Energy Arbitrage

Under a TOD scenario where net-metering is not available excess PV generation needs to be captured by the energy storage system. This means that charging from the grid during the day (mid-peak) could be counterproductive if there is not enough remaining capacity to store excess PV. To accommodate this, the strategy discussed in Section 5.4.3 was altered. First, any time the net load is positive (PV generation is greater than home load), the energy storage system will charge. During the on-peak months, the battery will discharge only when the net load is negative during on-peak times (morning and evening). During off-peak months, it will discharge during the mid-peak. A summary of the control strategy is shown in Figure 26.

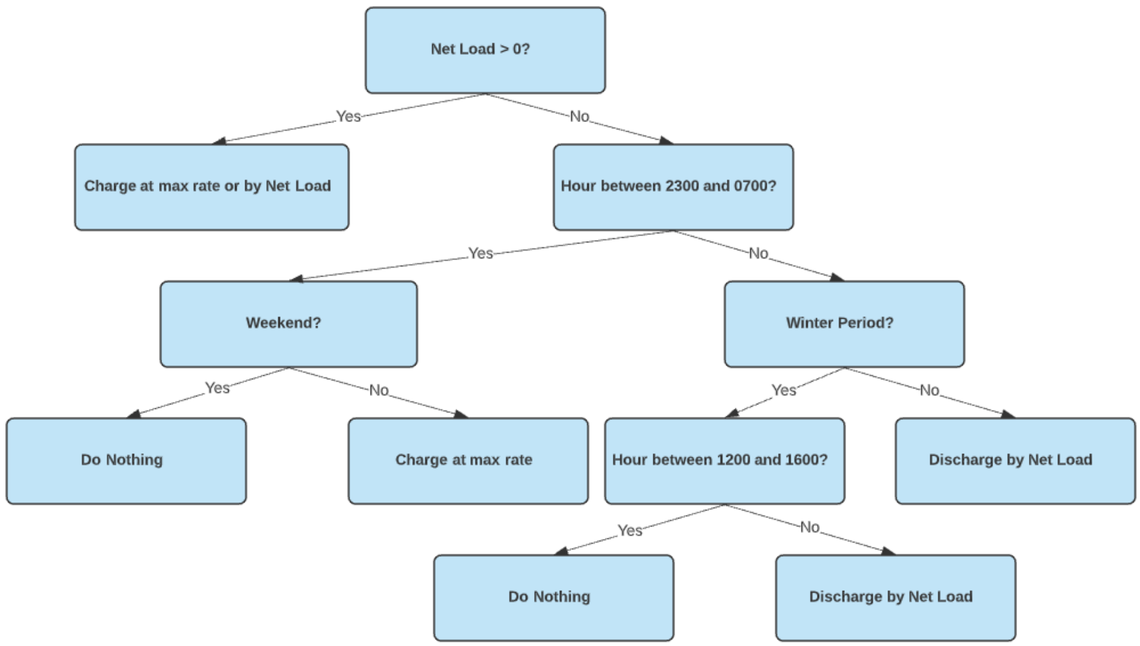

Figure 26. Decision tree representation of the Restricted Energy Arbitrage control strategy

Since the entirety of weekends is priced as off-peak, the storage system avoids charging overnight on Friday and Saturday so that capacity is available for excess PV generation which occurs on the weekend.

Of note is that the battery does not attempt to charge from the grid or discharge during the mid-peak time from Dec-Feb since on-peak pricing is available later in the day. It is likely that the battery will experience use cases where it has excess energy which could be discharged during the mid-peak and replenished using excess PV generation prior to the arrival of the on-peak pricing. Conversely, the system may not fully charge prior to the onset of on-peak pricing. A more sophisticated strategy could be developed which makes use of solar forecasting to determine whether charging from the grid or discharging during the mid-peak is appropriate. This could be modeled with the available data but is outside the scope of this thesis.

The Wknd. TOD tariff has the same implications for the self-consumption control strategy. Now, instead of avoiding charging overnight on Friday to accommodate weekend off-peak PV generation, the system cycles throughout the entire week.

5.5. Application of PV + Storage Model

Post-processing of model results generated sums of PV generation, load, original net load, and net load including the battery for each tariff category. The tariff categories are coded using integers from 0-2, with 0 being off-peak, 1 being mid-peak/flat rate, and 2 being on-peak. Figure 27 provides an example of the run summary data for a single system.

Rate Code	Load (MWh)	PV (MWh)	Net Load (MWh)	Net Load with Battery (MWh)
0	10.64	2.35	-8.29	-9.66
1	4.65	5.60	0.95	1.88
2	2.15	0.24	-1.90	-1.60

Figure 27. Sample of run summary output data for a single system

Post processing of this data allows for the evaluation of results such as the impact of net-metering and the added value of energy storage to the system under different tariffs.

- The PV data column provides the raw potential generation of the PV system, regardless of net-metering policy. This means that the difference between the *Load* and *Net Load* columns is the amount of PV generation consumed as shown in Equation 11, where E is electrical energy.

$$E_{\text{PV,consumed}} = E_{\text{Load}} + E_{\text{Net Load}} \tag{11}$$

- The net impact of battery charging/discharging can be measured by comparing *Net Load* and *Net Load with Battery* columns. *Net Load* is the original net load of the home prior to the addition of storage. Any difference between *Net Load* and *Net Load with Battery* must be due to operation of the energy storage system (if *Net*

Load with Battery is larger than *Net Load* than $E_{\text{STG,Net}}$ will be positive, and the battery must have supplied more electricity than it consumed). This is shown in Equation 12. Note that a negative value indicates a net consumption of electricity, while a positive value indicates a net supply.

$$E_{\text{STG,Net}} = E_{\text{Net Load w.STG}} - E_{\text{Net Load}} \tag{12}$$

The only case where the sum of net battery calculations can be positive (more discharge than charge) is under self-consumption scenarios. This occurs since the model sets any timestep values of net load which are positive to 0 since energy cannot be exported to the grid (or if it is, it has no value).

5.6. Economic Valuation

The economic value of PV and PV paired with storage was calculated using the estimated annual value of the energy generated by PV or shifted using the battery, and the system estimated capital cost. This was done using the annual revenue per capital cost, shown in Equation 13, where V is the economic value of the system, *A* is the estimated annual value, and *CC* is the capital cost.

$$V = \frac{A}{CC} \tag{13}$$

The annual value is calculated using Equation 14, where *i* is used to represent each rate code.

$$A = \sum_{i=0}^{2} \left[\left(E_{PV\ consumed,i} + E_{STG\ Net,i} \right) \times Price_i \right] \tag{14}$$

The capital cost is made up of two components, the cost of the PV system, and the cost of the battery.

5.6.1 PV and Energy Storage Costs

The installation cost of PV systems was estimated to be 2.85 $\$/W_{DC}$ for a 5 kW_{DC} system (14,250 \$ total) and 2.5 $\$/W_{DC}$ for a 10 kW_{DC} system (25,000 \$ total) based on [50].

Energy storage costs were calculated using installation values taken from [40], and comprise of three parts: a base installation cost, a cost per kWh_{DC} of storage capacity, and a cost per kW_{AC} of storage converter size. This model is useful for this work since storage capacity and converter size can be valued independently to evaluate diminishing returns for each. A summary of the energy storage capital cost is provided in Equation 15, where I is the storage converter size in kW_{AC} and G is the storage capacity in kWh_{DC}, and capital cost is in dollars.

$$CC_{\mathrm{STG}} = 1300 \times I + 230 \times G + 5200 \tag{15}$$

For comparison, this model estimates the cost of a Tesla Powerwall at 17405 \$, which is representative of commercially available units[6].

[6] http://mpowersolutions.ca/faq Accessed on 8-Mar-2021

Chapter 6: PV Intermittency and Geographic Smoothing

PV generation data from 60 residential systems and 2 commercial systems was used to evaluate the output variability and system ramp rates from 25-Jul-2019 to 25-Jul-2020.

The intermittency of residential and commercial systems was compared to evaluate difference in intermittency which could be caused by different system design considerations. Residential systems are typically constrained by roof orientations, while commercial systems are normally installed on flat roofs which allows for greater optimization. Comparing residential and commercial systems is also of interest since they represent different approaches to increasing PV generation capacity in a municipality: a large number of small distributed systems (residential) or a small number of large centralized systems (commercial).

The availability of residential data from across the HRM also allowed for the evaluation of different aggregations of PV systems. This allowed for an evaluation of intermittency at the individual system level, at a distribution feeder level (single FSA), and for the entire municipality. Of particular interest to the utility are the distribution feeder and municipal scales, which are susceptible to increased maintenance costs due to excessive intermittency [7].

6.1. Individual System Intermittency

To compare the individual and collective output variability characteristics of PV systems, relative ramp rates for each system and for the aggregated residential systems were sorted into bins with a width of 2% per 5 minutes. For the individual residential systems, the number of occurrences in each bin was divided by 60 houses and used to represent an average residential system. For output variability, the mean output variability of all 60 residential systems was taken.

The frequency distribution of 5-minute ramp rates for the average residential system (green), medium commercial (red) and large commercial (blue) systems are shown in Figure 28. Note that a logarithmic y-axis scale is used to make visible both very large and very small frequencies of occurrences. As expected, small ramp rates (values near 0%)

dominate the frequency distribution. The distributions are nearly symmetrical, indicating sunrise, sunset, and cloud cover/relief effects occur at the same rate and frequency. Ramp rates greater than ±50% are not shown; these high ramp rates occurred 7 times (0.007% of total occurrences) for the mean residential system, 17 times (0.016% of total occurrences) for the medium commercial system and 25 times for the large commercial system. Also shown in the figure legend is the average residential system output variability, and the output variability of the medium and large commercial systems.

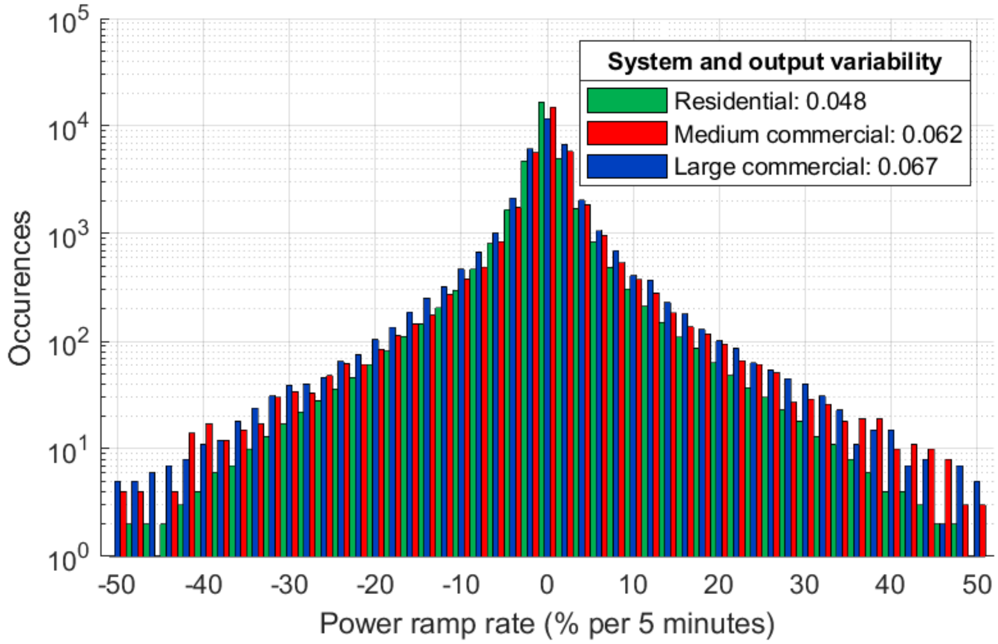

Figure 28. Individual system power ramp rate occurrences

Medium and large commercial systems had a larger output variability score (0.062 and 0.067) respectively) compared to the mean residential system score. Output variabilities for individual residential systems ranged from 0.029 to 0.061, so even the most severe residential system had lower output variability than either of the commercial systems. This result was unexpected, as smaller systems were thought to be more susceptible to partial shading and passing cloud cover.

Since most of the residential systems used in this analysis had noticeable clipping, it is possible this would result in a reduced output variability. Any time an inverter is clipping, a slight decrease in solar irradiance intensity would have no impact on power output, and consequently no power ramp rate. To test this, the variability of all residential systems was re-calculated while excluding power values which were within 2% of maximum. This resulted in a negligible change, indicating clipping does not significantly reduce ramp rates.

Comparison of ramp rates for residential and commercial systems may be impacted by the system architecture. Residential systems exclusively used micro-inverters while commercial systems use string inverters. This means residential systems are more susceptible to partial shading, since small decreases in generation from a module would be measured in the sum. In contrast, if partial shading of the commercial system does not cause its net output to fall below the inverter rating, it appears as though no change in production has occurred.

6.2. Impact of System Aggregation

Increasing the number of systems within a municipality should reduce the variability of the aggregate output as systems are not perfectly correlated. Both geographic distribution and differences in the physical layout of systems reduce output correlation. Take for example two 10 kW_{AC} PV systems generating at full capacity. A cloud obscures one of the systems over a period of 5 minutes, reducing its output to 50% of full capacity. If we only consider the obscured system, a ramp rate of 50% capacity per 5 minutes is observed. If instead we consider both systems as an aggregate, a ramp rate of 25% per 5 minutes is observed.

To estimate the impact of scaling up residential PV generation the output variability and the impact of incrementally adding systems was assessed. This was done by taking 60 random selections of residential system groups of 1 – 60 systems. The impact of system aggregation on relative output variability is shown in Figure 29. Range bars are included to show the range of relative output variability (ROV) results obtained from all sample variants for each number of systems. Also shown is the ROV of systems from a single FSA (B3A), sized 2.0 x 2.5 km, which contains 10 residential systems and could represent a community or commercial business park. Note that the values of the output variability plot at system count of 1 is the mean and range of variability of all systems, whereas the value at the highest system count includes the aggregation effects of all systems.

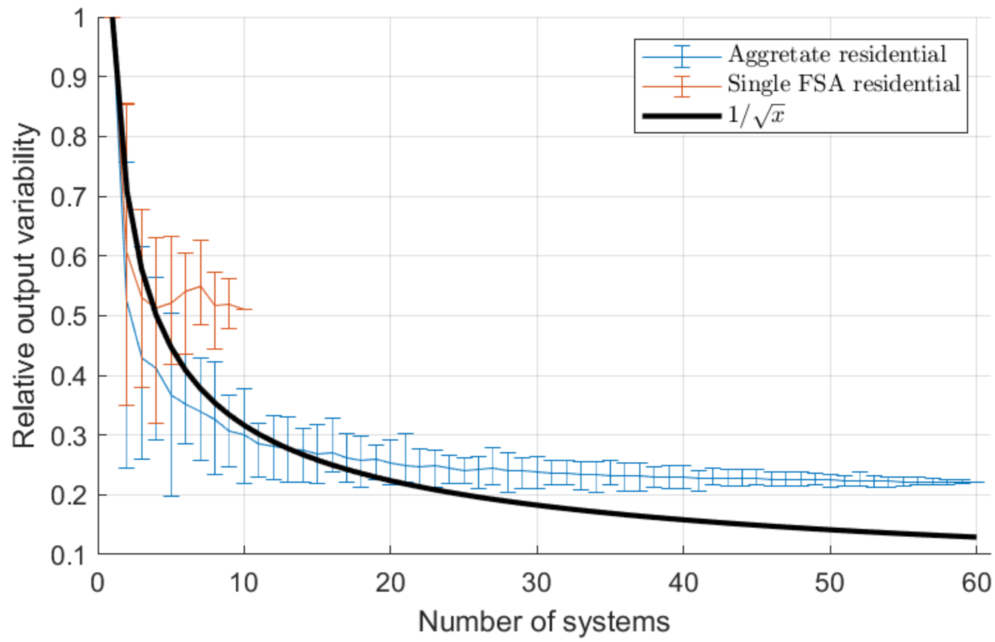

Figure 29. Impact of adding additional PV systems on output variability

Hoff and Perez [20] observed that the aggregation of distant, identical, uncorrelated systems should result in a ROV which followed a $1/\sqrt{x}$ relationship, where x is the number uncorrelated systems. Using a dispersion factor of 13.3, it would be expected that while the number of systems is well below this number the ROV would follow the $1/\sqrt{x}$ relationship. Up to the dispersion factor the average ROV of aggregations is below the expected trendline, likely due to the range of physical orientations present in the residential dataset, which could further reduce output variability from seasonal and daily fluctuation in solar irradiance. When the number of systems is greater than the dispersion factor the aggregate ROV is expected to trend to 1 divided by the dispersion factor, which in this case is 0.075. This is much smaller than the observed value of 0.22 and should cause electricity grid planners concern. While the variability of physical orientations present in residential systems violates the assumption made by Hoff and Perez [20] of identical systems, it illustrates the importance of using real production data for analysis. In practice systems are not identical, and so the values presented in this thesis are more representative of what to expect at these geographical scales.

Data from within a single FSA shows markedly higher ROV and does not appear to completely flatten by the time 10 systems are reached. However, it approaches 0.5, which is more than twice what is observed at the municipal scale.

The practical application of these output variability reductions is shown in Figure 30 using aggregate system ramp rates. As the geographic area increases, ramp rate severity is drastically reduced. The output variability of a municipality is 2 times smaller than that of any individual community or commercial business park. This is a conservative estimate for commercial systems in a business park because they are not expected to benefit from the heterogeneity of physical orientations common in residential systems.

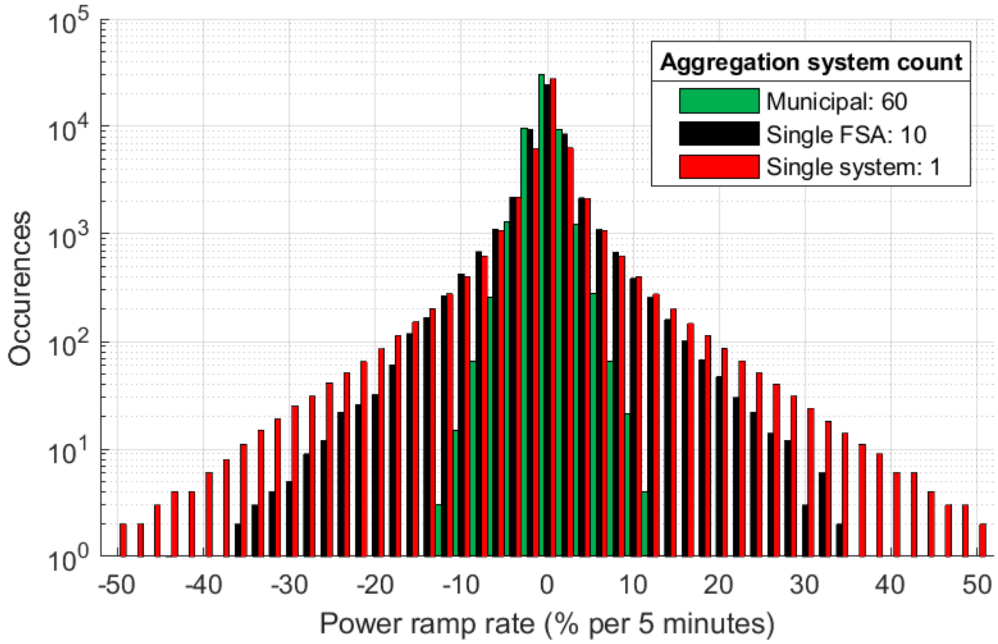

Figure 30. Power ramp rate occurrences for residential systems with different scales of aggregation

These ramp rate distributions may change as more systems are added to each aggregation. Further reductions for the municipal aggregation would be expected if each FSA had an equal number of PV systems, since it would provide better geographic diversity throughout the entire municipality. Currently there is bias towards the interior region of the municipality, and the addition of systems near the geographic perimeter would increase the average system spacing, and so be expected to decrease the aggregate ROV and produce less severe ramp rates.

Adding more PV systems to the single FSA aggregation is not expected to have a substantial impact, since the ROV curve appears to level off. If additional PV systems added to the FSA were located far apart from the current systems there is the potential for further reduction, but this would likely be small since the average system spacing would not be significantly impacted due to the limited area.

The impact of system spacing could be visualized by the of combining two distant FSA's. If for example another 10 systems were added to the single FSA ROV curve (applied for aggregations of 11 to 20 homes) from a distant FSA (located at the perimeter of the HRM) a step change decrease in ROV would be expected because of the sudden increase in the average system spacing, followed by a similar exponential decay approaching a new asymptote.

6.3. Comparison of Pyranometer and PV System Ramp Rates

Adye, Pearre, and Swan [26] modeled distributed and centralized PV generation based on pyranometer data. It is useful to compare the power ramp rate distributions of real PV power output with these predictions. Data in [26] came from 215 pyranometers across the same municipality with a similar, though not identical, distribution. Each pyranometer was mounted on the roof to represent likely PV orientation. While the study data were collected in separate years, this is unlikely to impact the ramp rate results because a full year of data is available for both datasets.

6.3.1 Distributed Systems

Figure 31 shows the ramp rate frequency distribution of aggregate pyranometers and aggregate PV systems, both distributed over the municipality. Pyranometer data has higher maximum ramp rates, and a higher output variability than the PV data. This is surprising, since the pyranometers sample size was much larger than that of the distributed PV systems and covered the same geographical area. However, at a single home a pyranometer would be expected to have greater ramp rates since it measures at a single point and would experience a cloud or other shadow as a substantial step change. In contrast, the ramp rate of a PV system on the same roof is to some extent mitigated by averaging effects over the larger array collection area. The conclusion of this is that modeling aggregate distributed PV based on pyranometer measurements overstates both positive and negative ramp rates at the municipal level. The impacts of clipping were again tested for by removing data points near peak values, and it was found to have a negligible impact on the ramp rates (and output variability) of the aggregate system.

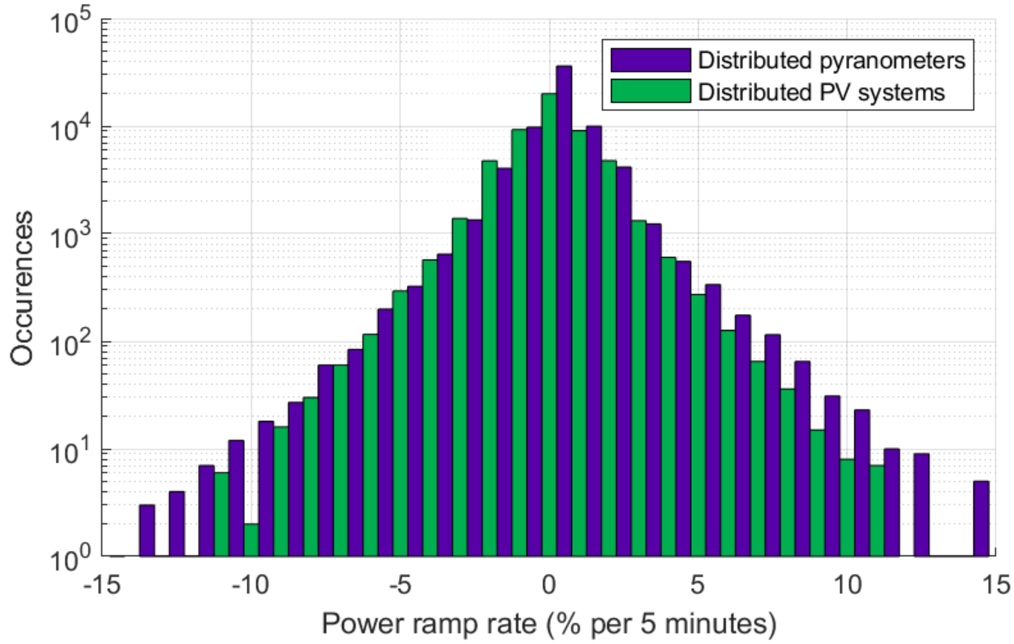

Figure 31. Comparison of distributed residential ramp rates using pyranometers and PV systems

6.3.2 Centralized Systems

A centralized comparison was completed to mirror the centralized generation representation from [26], which used 7 pyranometers over an area of 1.5 x 1.5 km. A centralized set of 7 PV systems was randomly selected from an FSA (B3A) which has an area of 2.0 x 2.5 km, was chosen to closely mimic the centralized pyranometer dataset presented by Adye, Pearre, and Swan [26].

The ramp rate distribution of the centralized pyranometers and PV datasets is shown in Figure 32 and is remarkably similar, although pyranometers capture more ramp rates equal to zero, and more frequent large ramp rates. This is likely caused by partial shading of roof spaces, where PV arrays are more often impacted, but the impact is more severe for pyranometers because they measure a single point. The overall similarity of the two profiles suggests that the use of pyranometer data in PV models can accurately assess ramp rates over areas the size of a community or commercial business park.

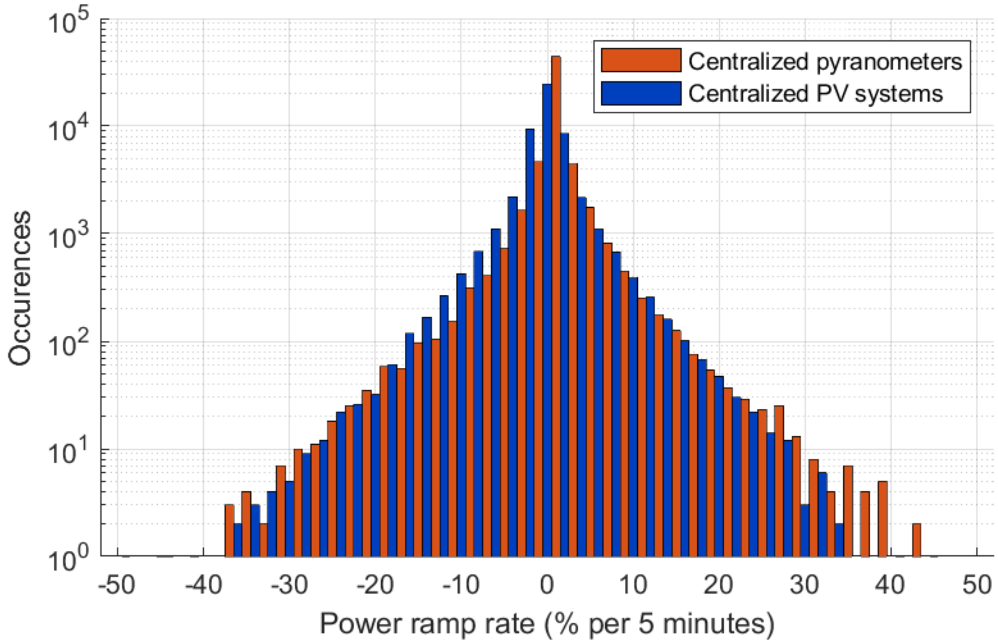

Figure 32. Comparison of "centralized" ramp rates using pyranometers and PV systems

6.4. Conclusions

The intermittency of PV generation from 60 residential and 2 commercial systems was evaluated using power ramp rates and output variability. The impacts of system type (residential vs commercial) and geographic dispersion were evaluated, and a comparison to pyranometer data was completed. Three different geographic scales of PV aggregation were considered:

- The output variability of a single system was observed using the average output variability and ramp rates from all 60 PV systems.
- The aggregate output of 10 PV systems which were from the same FSA were used to represent a neighbourhood or small community.
- The aggregate output of all 60 systems was used to represent the intermittency of PV generation at a municipal scale.

The individual output variability of any of the 60 residential systems was smaller than that of either commercial system. This may be due to the timeseries data being normalized by the maximum observed output value for each system. Since commercial systems are not as constrained by roof angles, they are better able to maximize production, spending a greater amount of time near peak output. Spending more time at higher outputs increases the likelihood of a large power ramp rate when a cloud passes overhead.

Geographical distribution of PV generation reduces the overall system intermittency. Consistent with previous literature, as geographic scale increases the intermittency of the aggregate system decreases. This was observed using ramp rate distributions as well as relative output variability.

Using a model developed by Hoff & Perez [20], the estimated relative output variability of the municipal scale aggregate generation was expected to be 0.075 which is much lower than the observed outcome of 0.22. For the Hoff and Perez model to align with observed data, a dispersion factor of 4.5 would be required, which is three times smaller than the estimate made by this thesis and so unlikely to explain observed differences. This means that real world data is more correlated than predicted by the model and emphasizes the benefit of measured data. The assumption of identical PV systems will always be violated by aggregations of residential PV systems, and so the addition of a factor based on system heterogeneity should be explored.

Measured data at both a municipal and single FSA scale produced smaller ramp rates than data obtained using pyranometers. This is likely due to the increased area covered by PV systems in comparison to pyranometers. In the event of partial shading PV systems are only partially obscured, while pyranometers represent point measurements which can quickly fluctuate due to partial roof shading. This thesis supports the use of pyranometers for evaluating PV intermittency since they offer a conservative estimate of the impacts of real-world systems. This validates previous work using pyranometers to measure intermittency in the HRM by [26] and supports the use of pyranometers to measure the impacts of adding PV to the roofs of businesses in the HRM. This would enhance discussion of whether PV incentives should target commercial or residential markets, since the intermittency of PV spread across business parks in the HRM has not previously been evaluated.

Chapter 7: Impact of Building Load on Intermittency

While Chapter 6 evaluates the intermittency of different forms of PV generation, additional insight can be gained from pairing distributed generation with the load profile of homes. The net load of a home with PV is what is experienced (and so important) for utilities. It is possible that misalignment between power ramp rates of PV generation and residential load could exacerbate or mitigate existing intermittency in residences. For example, residential loads typically increase during the early evening. This coincides with a decline in PV generation as the sun sets, and so would be expected to create a larger net ramp rate than consideration of either power ramp rate source individually. For these reasons intermittency is revisited with the additional context of residential load to evaluate the net load intermittency of homes with and without PV systems. This also serves as an evaluation into whether energy storage should be used to mitigate the intermittency of residential PV systems, since if the addition of PV decreases net load intermittency, there is no need for mitigation.

A subset of available load and PV data was used to evaluate residential net load intermittency. This subset was limited to a 1-year window (19-Sep-2017 – 19-Sep-2018) due to household load data availability constraints. Seasonal variance is still accounted for due to the availability of data for an entire year. This led to the inclusion of 28 residential load profiles, and 21 PV profiles, for a total of 588 paired systems.

7.1. Residential Load and PV Intermittency

Based on the observation that the average and median loads for homes used in this study were significantly lower than peak consumption, it was expected that residential loads would have more severe ramp rates than residential PV. This is demonstrated in Figure 33, which shows the average relative ramp rate distribution of the 21 individual PV profiles and 28 individual load profiles were used for this Chapter. It should be noted that the data used for this figure was restricted to daytime hours (0600 to 2000) since PV has no ramp rates overnight. In addition to having more severe normalized ramp rates, the max power consumption of residential loads is much higher than peak PV generation since peak loads are typically larger than peak PV production.

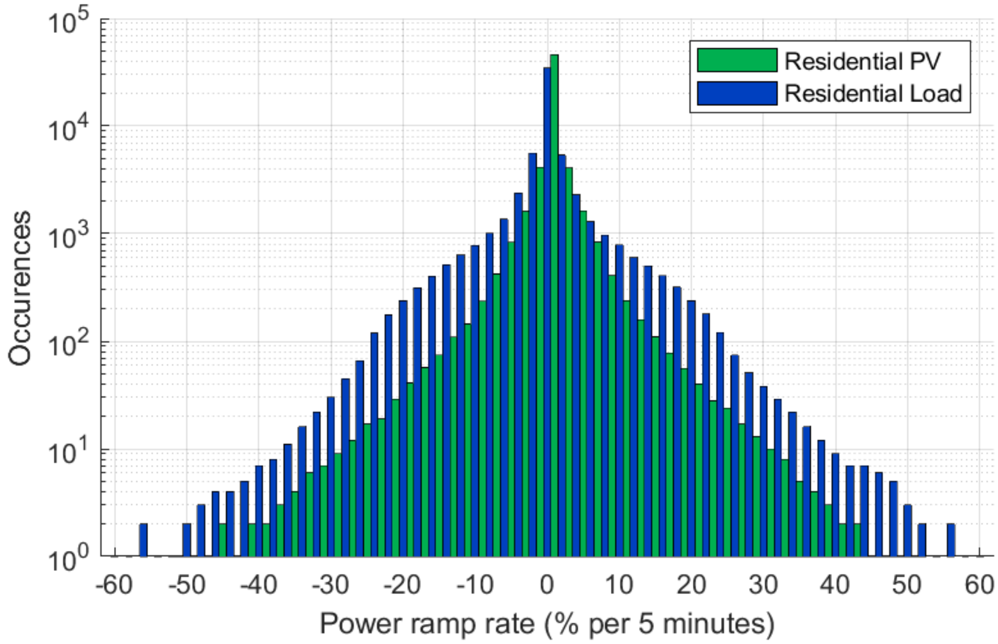

Figure 33. Residential PV generation and load normalized ramp rates and average output variability

Like PV generation, it was expected that the aggregation of multiple homes would reduce the overall output variability. To examine the impacts of aggregation on PV and load intermittency, the average output variability of each was calculated for collections of 1 to *m* systems, where *m* is the total number of either PV or load profiles. The average value of 21 samples for each number of aggregates was used to create Figure 34. Also included is a $1/\sqrt{x}$ line which is the expected result of aggregating uncorrelated systems. Interestingly, residential load profiles follow this relationship almost perfectly indicating a lack of correlation for residential loads. While geographic variability was assumed to be insignificant this would suggest that there is no temporal correlation of power ramp rates between homes at the 5-minute scale.

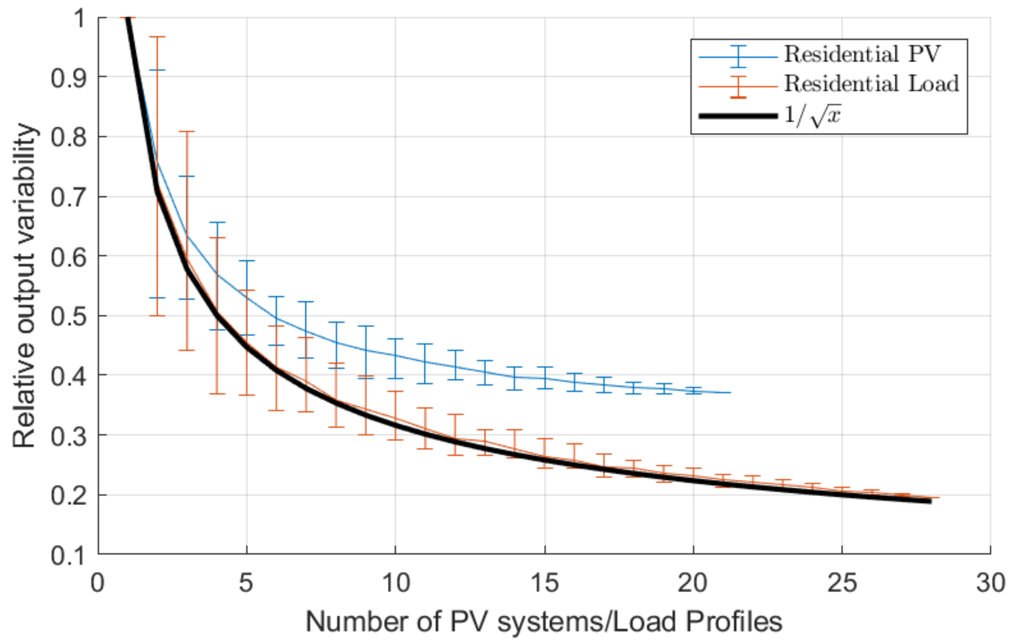

Figure 34. Residential PV and Load relative output variability

The relative output variability plot of aggregate PV systems shows larger values than those observed in Chapter 6, indicating a stronger correlation between PV systems in this subset.

When considering the impact of aggregation, the large intermittency of residential loads may be offset by the reduction each additional home provides. While this is subject to diminishing returns and is unlikely to follow the $1/\sqrt{x}$ relationship as the number of homes increases, the impacts could be significant at a distribution scale. This would be due to PV's strong geographical correlation with other systems, while building load likely has no geographical correlation at this scale. For example, the relative output variability of PV within a single FSA was estimated to asymptotically approach 0.5 in Chapter 6, two and a half times the relative output variability seen for an aggregation of 28 residential loads.

7.2. Net Load Intermittency

Since PV generation and residential load are independent of one another the addition of PV to a home is likely to impact the output variability observed by the grid. This was evaluated by generating a net load profile for every combination of 21 PV systems with 28 load profiles (588 total). In this case, overnight values were included since otherwise the impact of PV on the system is likely overstated. The addition of PV generation may also reduce the maximum net load seen by the grid which would impact output variability since it is normalized by the largest observed value. For example, if the largest observed load value occurs at the same time as PV generation, the magnitude of the net load will be smaller than the original load. Since the power value with the largest magnitude is used to normalize output variability, a smaller value would increase the output variability. To account for this, the net load profiles were normalized using the maximum load, rather than the maximum net load. The results of combining home loads with PV systems are summarized in Table 7.

Table 7. Summary of output variability measures when PV systems were normalized to 10 kW_{DC}

Data Source	PV Generation	Load Consumption	Net Load with net-metering	Net Load with Self Consumption
Average OV	0.024	.061	0.062	0.057
Minimum OV	0.020	0.038	0.039	0.036
Maximum OV	0.034	0.090	0.092	0.085

This clearly shows that load profiles dominate the output variability measure of residential net loads. There were no combinations of PV generation and residential load which produced net load output variability which was less than the output variability of the load profiles alone. This means that the addition of PV always increased grid intermittency. Enforcing a self-consumption scenario which prevents exports reduced the output variability of net loads. This occurs since the range of net load values is restricted, and so ramp rates which occur when net loads change from positive to negative (or vice versa) are mitigated. In either scenario, it is important to note that the impact of adding PV generation to a home on grid intermittency is significantly less impactful if electricity load is considered rather than observing stand alone PV intermittency. The practical impacts of this are shown in Figure 35, which shows that net loads do have more severe daytime ramp rates, but these counts are much less dramatic than if PV ramp rates were directly added to the load ramp rate counts.

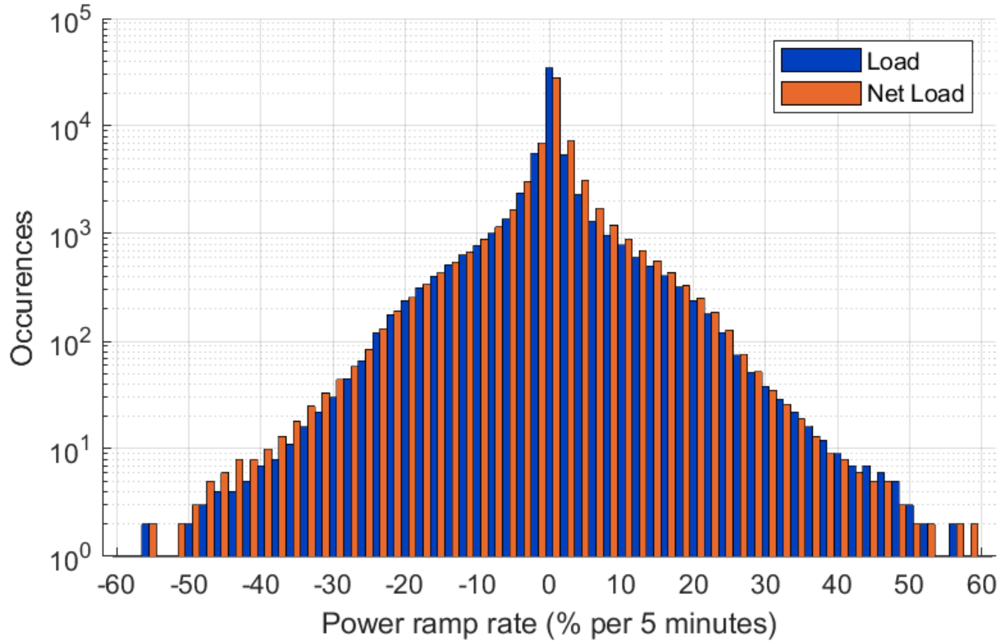

Figure 35. Original load vs net load average ramp rates for individual homes (n=588)

Since the aggregation of systems is of greater interest to the utility, and consequently electricity policy, the relative ramp rate distributions of the complete 588 home aggregation for home load and net load are shown in Figure 36. While net loads produce more severe ramp rates this change is minor, and only increases the number of ramp rates above 10% per 5-minutes by 6 (0.006% of the 5-minute intervals in a year). As more homes are added to the dataset the difference in ramp rate distributions of aggregate load and net load would likely be even smaller since the load profiles in this dataset have almost no correlation at the 5-minute timestep.

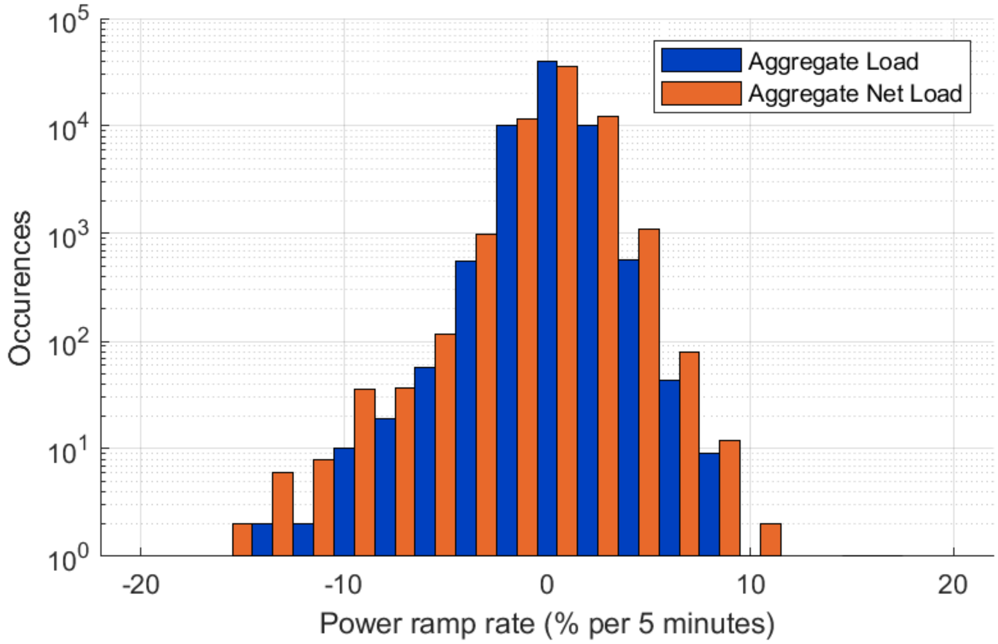

Figure 36. Original load vs net load ramp rates for an aggregation of 588 homes

7.3. Conclusions

Load profiles experience much more severe relative ramp rates and have larger peak loads than PV profiles. This means that absolute ramp rates from homes are much more impactful than ramp rates from residential PV systems. Net load intermittency of homes with PV is more severe than the original load intermittency. This increase is negligible in terms of both output variability and relative ramp rate. These findings are opposed to the application of ramp rate limits to residential PV.

Chapter 8: PV Intermittency Mitigation Using Energy Storage

The use of energy storage to mitigate the intermittency of residential PV was evaluated using a static power ramp rate limit applied to the PV profile which restricts power ramp rates to ±10% of the installed DC PV capacity per 5 minutes (example shown in Section 5.4.1, Figure 21), and a dynamic limit which prevents net load ramp rates from exceeding original load ramp rates plus 10% of the installed DC PV capacity per 5 minutes (see Section 5.4.1, Figure 22).

Since aggregation of net loads is time-sensitive, a subset of the available combinations of PV and load profiles which have data from 19-Sep-2017 to 19-Sep-2018. This subset uses 28 load profiles, and 21 PV profiles (n = 588). The required storage capacities and converter sizes were determined iteratively for both individual homes and the aggregation of all 588 available combinations of PV and load profiles.

Results for energy storage requirements were determined using brute force iteration. An initial storage capacity was applied and if the system failed to meet the ramp rate requirements the simulation was halted, the capacity was increased, and the simulation was restarted. Simulations were run with no restrictions on converter size, and the resulting converter size requirement was measured as the largest observed charge/discharge of the final simulation.

8.1. Energy Storage for Net Load Power Ramp Rate Mitigation

The rated capacity and converter size required to mitigate ramp rates for individual homes with PV and the municipal aggregate of these homes was determined using two ramp rate limits. The first limit is dynamic and is set to restrict ramp rates to within 1 kW per 5 minutes (for large systems) and 0.5 kW per 5 minutes (for small systems) in addition to the original ramp rate for each timestep (e.g. if the load ramp rate for a given timestep was 5 kW per 5 minutes, the net load ramp rate when paired with a 10 kW_{DC} PV system would be restricted to ± 6 kW per 5 minutes). This is applied to mitigate increased ramp rate severity and frequency of net loads introduced by the addition of PV generation. The second limit statically restricts ramp rates to either 1 kW per 5 minutes (for large systems) or 0.5 kW per 5 minutes (for small systems). This static limit is applied directly to the PV profile, without consideration of the net load.

Table 8 presents the average storage capacities and converter sizes needed to mitigate PV generation ramp rates, while

Table 9 presents the same results if a dynamic ramp rate limit based on the ramp rates of the residential load. Also shown are the storage requirements for an aggregate of all 588 total systems, and the per system requirements in an aggregate case. Consideration of the aggregate system is more practical since it represents larger absolute ramp rates which are of greater interest to the utility. These aggregations also stand to benefit from the intermittency benefits of system aggregation discussed in Chapter 6 and Chapter 7, leading to lower storage requirements on a per home basis.

Table 8. Energy storage requirements for PV generation ramp rate mitigation using a static ramp rate limit of 10% PV DC capacity per 5 minutes

Metric	5 kW_{DC} PV Average	10 kW_{DC} PV Average	Aggregate of 588 Systems
Storage Capacity (kWh_{DC})	1.35	2.34	112 (0.19 per system)
Converter size (kW_{AC})	2.95	5.16	540 (0.92 per system)
Power / Energy Ratio (h^{-1})	2.18	2.21	4.82

Table 9. Energy storage requirements for net load ramp rate mitigation using a dynamic ramp rate limit based on the original load ramp rate and installed PV DC capacity

Metric	Small system Average	Large System Average	Aggregate of 588 Systems
Storage Capacity (kWh_{DC})	1.29	2.06	80 (0.14 per system)
Converter size (kW_{AC})	3.01	5.17	497 (0.85 per system)
Power / Energy Ratio (h^{-1})	2.33	2.51	6.21

The impacts of including the original load in the determination of a ramp rate limit were negligible for small (5 kW_{DC} PV) systems for both storage capacity and converter size. Large (10 kW_{DC} PV) systems had an almost identical average converter size requirement, but a substantial (12%) reduction in the average capacity requirement which suggests less frequent use of the system. There was a reasonable impact on the aggregate result, where consideration of the original load ramp rates reduced the required storage capacity by 28%. The converter size was also reduced by 7%.

The resulting converter size to capacity ratio for individual system ranged from 2.18 to 2.51 kW_{AC} per kWh_{DC}, which is much smaller than the values reported in [31] and [32] (6 and 7 kW_{AC} per kWh_{DC} respectively). This can be attributed to difference in the ramp rate limits used. Results from the literature were based on a more restrictive ramp rate limit of 10% per minute, rather than the limit of 10% per 5-minutes used in this thesis. The more lenient ramp rate used in this thesis would result in a smaller converter size requirement since a sudden change in PV generation would be averaged over 5 minutes. An extreme example of this would be if a PV system generated 0 kW for 2.5 minutes, and then jumped to 10 kW for 2.5 minutes, it would result in a ramp rate of 5 kW per 5-minutes which is much less severe than the instantaneous 10 kW ramp rate.

The aggregation of systems resulted in per system requirements which were an order of magnitude smaller than when considering a single system. This would result in significant capital cost savings for the required energy storage, and is also more applicable to utility applications of energy storage for intermittency reduction which are concerned with aggregations of net load profiles (e.g. a distribution grid). Aggregation of systems also resulted in a much higher converter size to storage capacity ratio compared to individual systems. This is due to the reduced frequency of relative ramp rates exceeding 10%, while the absolute severity of ramp rates exceeding this limit is much larger.

These results are conservative, since they do not account for the fact that both PV and load profiles are duplicated within this composite dataset which increases profile correlation. While it is possible that new profiles may have more severe intermittency, as more unique profiles are incorporated the aggregate correlation is expected to decrease, resulting in smaller per system energy storage requirements.

8.2. Conclusions

Storage capacities and converter sizes required to mitigate residential PV intermittency were determined using a static ramp rate limit based on the installed DC capacity of the PV system, and a dynamic limit based on the original load ramp rates and the DC capacity of the PV system. Requirements were determined for both individual homes, and for the aggregate of all 588 homes used.

The application of either a static or dynamic ramp rate limit to individual homes had very little impact on energy storage requirements. In both cases there is a very clear benefit to considering the aggregate net load rather than individual homes. Aggregation of net loads reduces the storage requirements per home by an order of magnitude. This combined with the increased importance of aggregate ramp rates to the utility support the idea of applying centralized storage to mitigate intermittency for a large collection of homes. Alternatively, a portion of storage capacity and converter size could be commissioned from distributed energy storage assets. The remainder of the available storage capacity and converter size could be applied to other services such as energy arbitrage or solar self-consumption, depending on the electricity policy.

Chapter 9: Impact of Electricity Tariffs on PV Value

9.1. Electricity Tariffs in NS and the Impact on Generation Revenue

Generation data spanning July 10, 2018 – July 10, 2020 from 21 residential PV systems had both flat-rate and TOD tariff applied to evaluate the impacts of TOD tariffs on the expected annual economic value of PV. To visualize the differences in PV value between the two tariffs, three distinct representative days were selected for a single home and results are shown in Figure 37. The three days selected represent sunny days which have distinct TOD schemes: a winter workday which contains on-peak pricing, a summer workday where there is no on-peak, and a weekend where only off-peak rates apply.

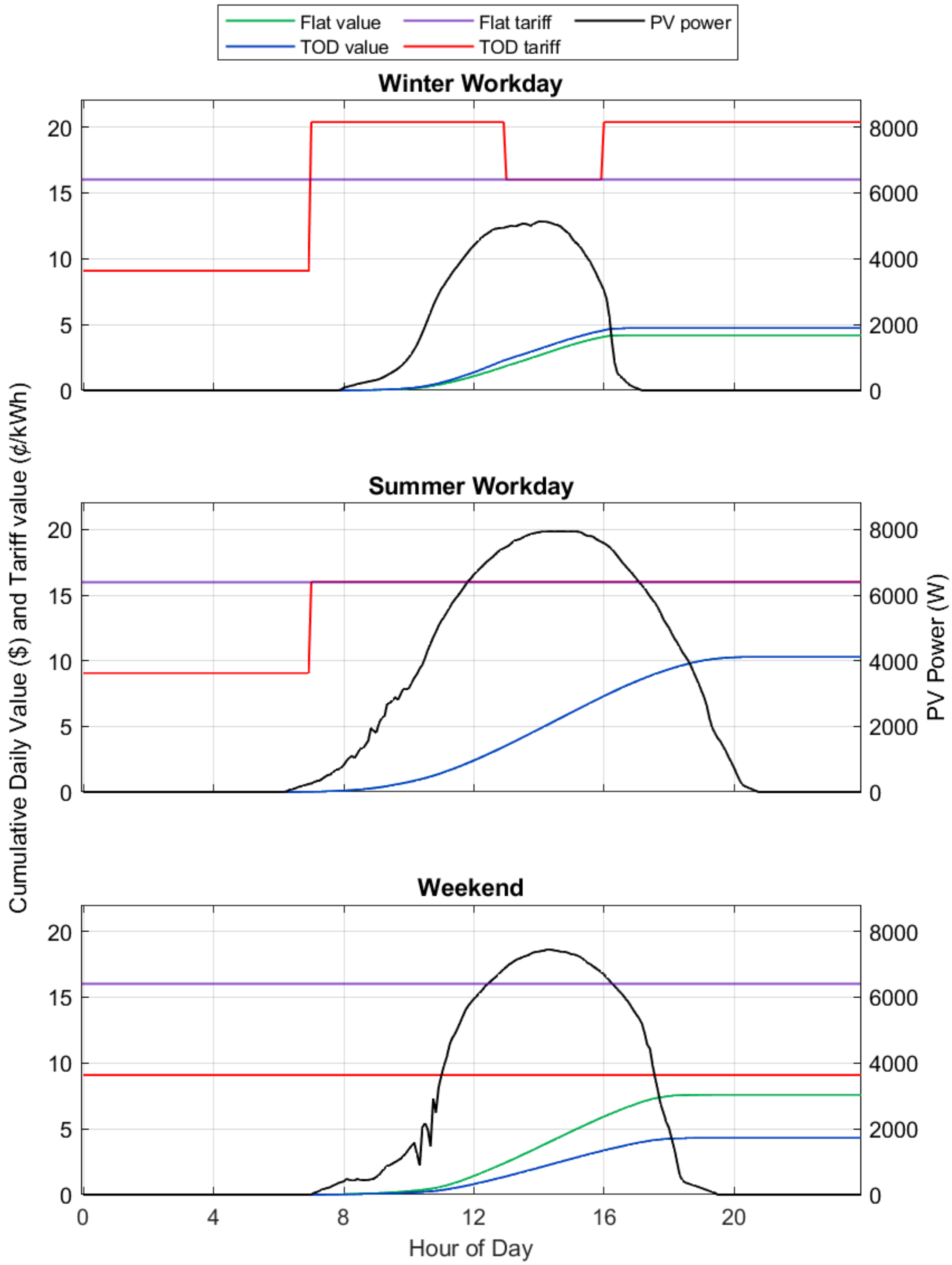

Figure 37. PV generation, cumulative PV value, and electricity rate vs time for a clear winter workday, a clear summer workday, and a clear weekend day in September

It is readily apparent that the application of TOD rates during summer workdays are negligible since almost all PV generation occurs during the mid-peak which has the same tariff as the flat-rate tariff. Winter workdays under the TOD scheme are shown to be beneficial since PV captures value during the morning on-peak pricing, but the impact of reduced daylight hours during the winter and reduced peak generation hinder the potential to take advantage of on-peak pricing. Weekends are severely detrimental to PV value since the off-peak rate is applied throughout the entire day. This is problematic to the monthly and annualized value of PV operating under the TOD scheme, since weekends represent 2 out of 7 (29%) days.

9.2. Impact of Switching From Flat-Rate to TOD

The average change in monthly economic value of all PV systems operating under the TOD scheme relative to flat rate is shown in Figure 38. The average PV system has reduced economic value under a TOD scheme compared to flat rate for all months except January. Additionally, the impacts of TOD pricing are more severe during the summer months which is especially discouraging since this is when PV is at its most productive. This was expected, since outside of January, February, and December, the loss of value incurred during the weekends cannot be mitigated by on-peak pricing.

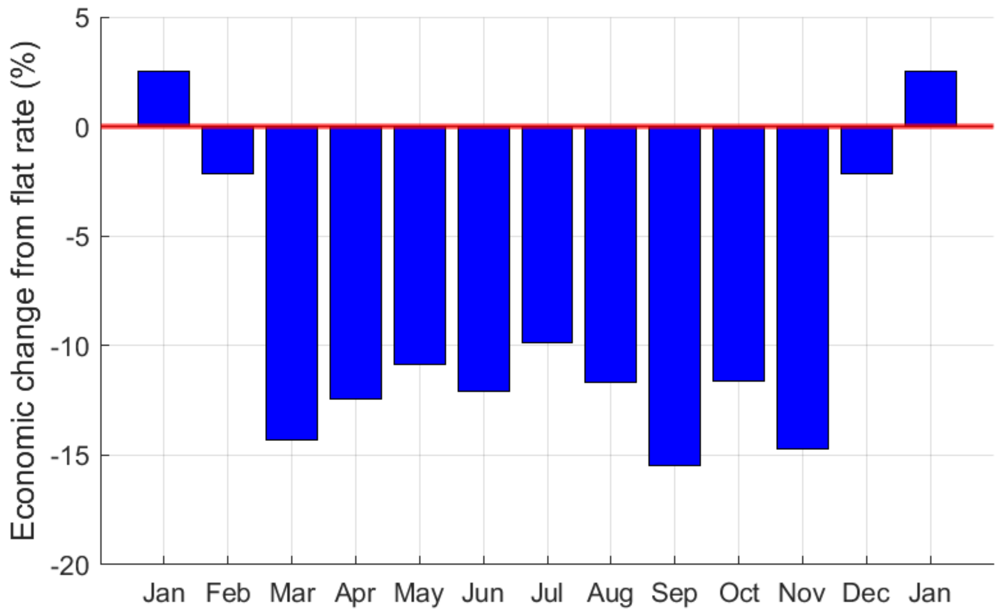

Figure 38. Average monthly economic performance of PV using TOD rates relative to flat-rate.

A breakdown of monthly PV generation value by price category is shown in Figure 39. This represents an average of all systems included in the analysis and shows that the bulk of monthly value in winter months for systems operating under a TOD scheme occurs during on-peak pricing. As previously discussed, this occurs primarily during the morning peak (from 0700 to 1200) on workdays. Also of interest is the amount of value generated during off-peak pricing. Off-peak value is accumulated almost exclusively on weekends since there is very little PV production in the early morning and none overnight. The impact of weekend pricing is especially severe during Mar to Sep, where there is increased PV generation which occurs during off-peak weekends.

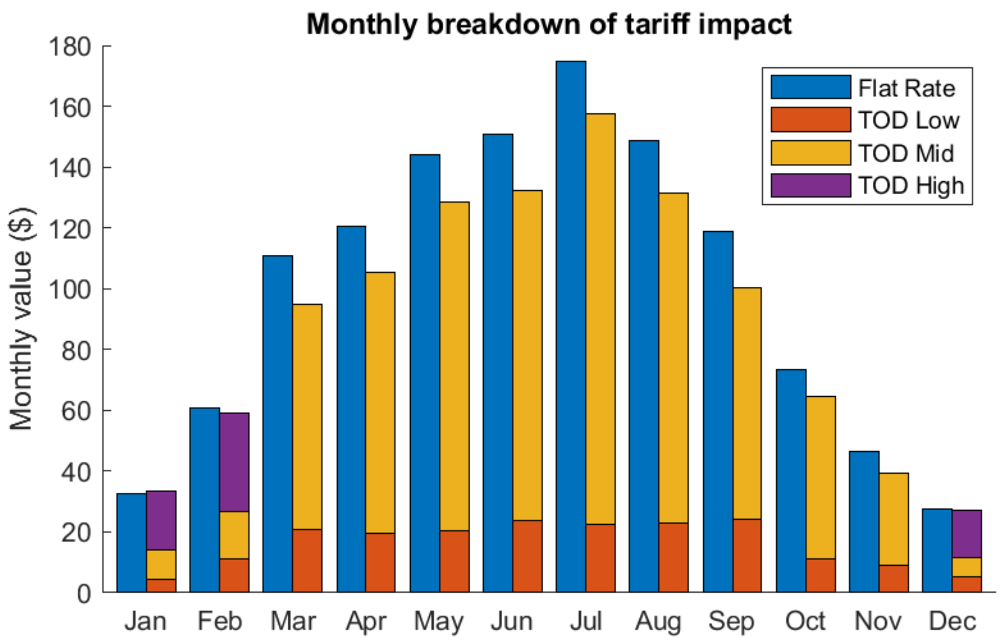

Figure 39. Impact of pricing categories on overall PV economic value

On average, switching from flat rate to TOD rates in Nova Scotia would reduce the annual generation value of residential PV systems by 11.1% on average. The reduction of value has a tight distribution, with the most severe reduction being 11.6%, and the least severe being 10.6%. This indicates that system orientation and size had an insignificant impact on the changes in generation value. The reduced value of PV systems under TOD rates was expected based on a simple calculation based on the reduced value of PV during off-peak weekends (56% value compared to mid-peak for 29% of generation days in a year yields a 16% reduction of value).

9.3. Potential Adjustments to the TOD Tariff

Provincial load profiles of workdays and weekends for summer and winter seasons were generated by taking the average load for each 5-minute period of the day. As shown in Figure 40, provincial load profiles for workdays and weekends are similar, with a small decrease in the load magnitude (<50 MW in the summer, <30 MW in the winter). This suggests that a future alternative tariff might treat weekends the same as workdays. This would be expected to substantially improve the value of PV compared to the current TOD tariff.

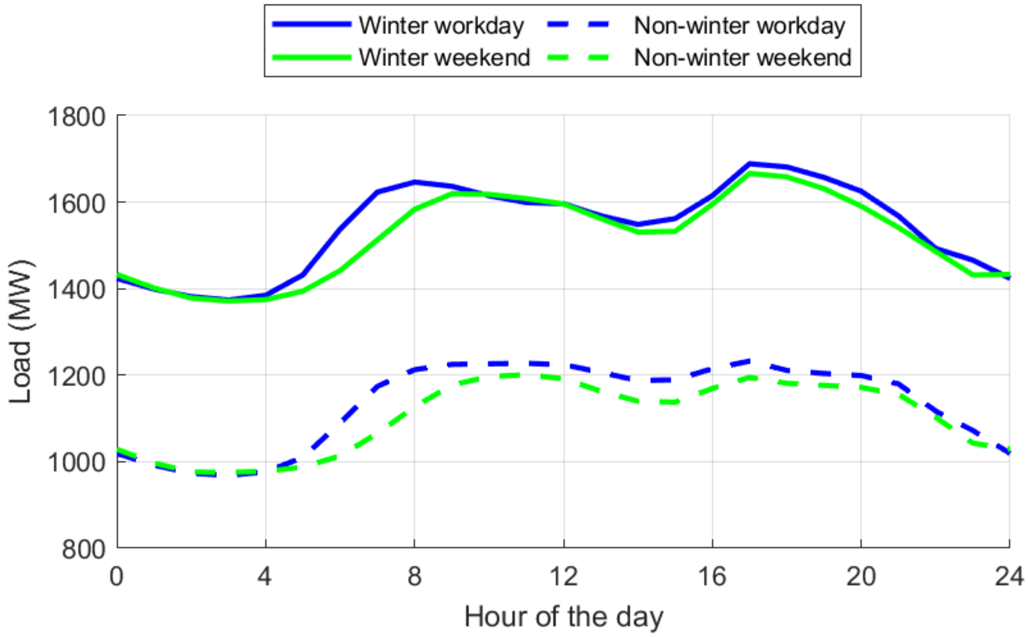

Figure 40. Comparison of hourly average grid load on workdays and weekends during the winter period (Dec – Feb, solid lines) and non-winter period (Mar – Nov, dashed lines)

There is a clear shift in terms of load magnitude, with winter loads exceeding summer ones by roughly 500 MW. Additionally, the magnitude of the evening rise in load is over triple the magnitude in the winter (150 MW) than what is observed in the summer (40 MW). While this does not provide strong support for the application of on-peak pricing outside of the winter period, the value of on-peak pricing previously discussed, and the similar load shape of winter and non-winter periods, warrants an investigation into the impact of using the winter rate scheme year-round.

The impacts of changing current TOD rate structures were evaluated using two changes to the current tariff:

- Treating weekends and workdays equally.
- Treating every day of the year as though it was a winter workday.

A summary of monthly results is shown in Figure 41, and the impacts of all TOD policies relative to flat rate are presented in Table 10.

Table 10. Impact of different Time of Day rate policies relative to flat rate

Tariff policy	Change in annual value relative to flat rate (%)
Time of Day (standard)	-11.1
Time of Day including weekends	+1.8
Time of Day winter workday all year	+17.0

As expected, removing the impact of off-peak pricing on the weekends significantly increased the value of PV generation. Treating weekends the same as workdays led to TOD rates being more attractive to PV owners based on generation value. As shown in Figure 41, this is entirely due to the inclusion of on-peak pricing during winter months. Treating everyday as a winter workday makes on-peak rates available for PV during peak generation months, which led to a significant increase in generation value.

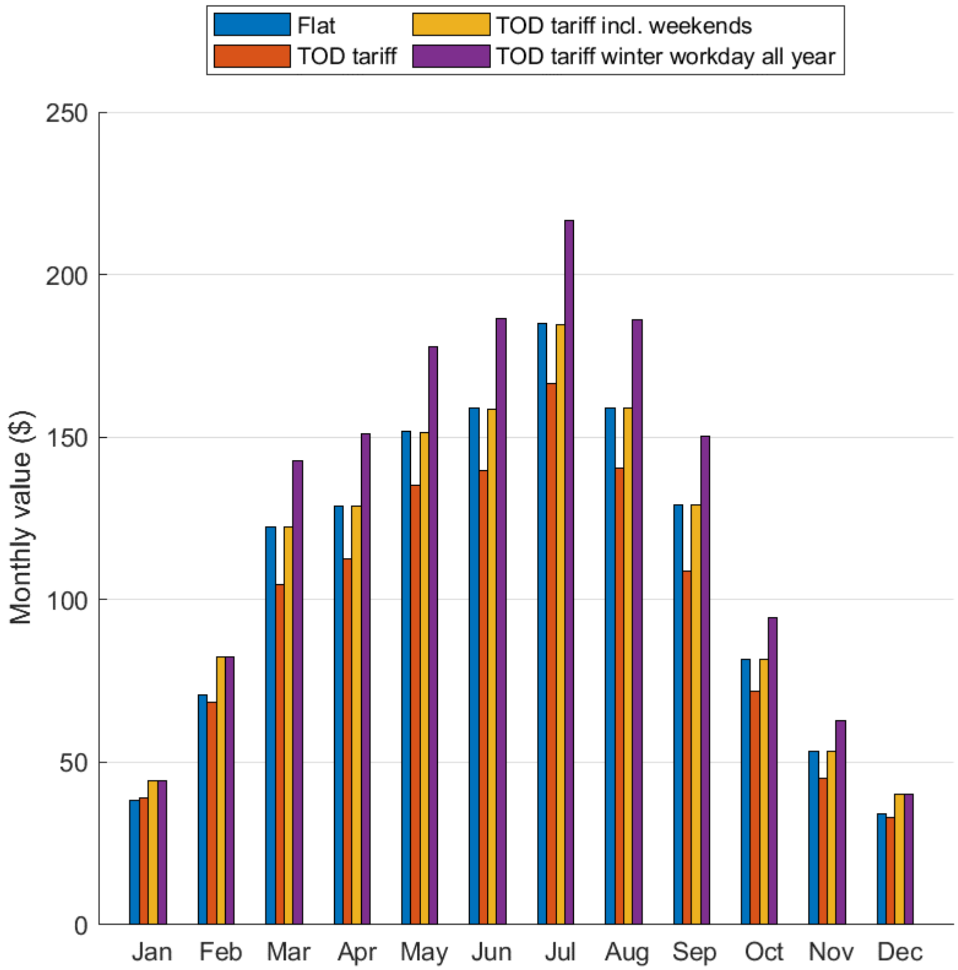

Figure 41. Monthly breakdown of the impacts of implementing different electricity tariffs

9.4. Importance of Net-Metering

Net-metering policies allow homeowners to export excess PV electricity generation at a value equal to the prevailing tariff, typically with no discount. This is beneficial to the economics of residential PV systems since the bulk of energy generation from PV systems occurs midday when homes may be unoccupied due to typical workday schedules (and so have reduced load).

Alternatively, utilities can implement a self-consumption policy which does not value excess PV generation, and in some cases may require addition capital cost to ensure exporting excess energy to the grid is not possible. There are other possible tariff possibilities between these two extremes, with the potential to discount the energy exports of a residence (e.g., exports are worth half of the current retail price of electricity). These possibilities were not addressed in this work, and focus was placed on the two extreme cases to capture the range of performance variations.

To quantify the importance of net-metering for the economic value of PV systems, the 21 PV profiles used in the previous sections were combined with 28 residential loads for the period of Sept 19, 2017 – Sept 19, 2018. The PV profiles were scaled to either 5 or 10 kW_{DC} based on the annual electricity consumption of each home. Of the 28 homes, 13 were paired with a 5 kW_{DC} PV system, and 15 were paired with a 10 kW_{DC} PV system.

The economic impacts of removing net-metering in Nova Scotia are show in Figure 42, which presents the mean value of PV generation for each PV profile using net metering or self-consumption policies. A change in policy from net-metering to self-consumption results in a mean economic value reduction of 62%.

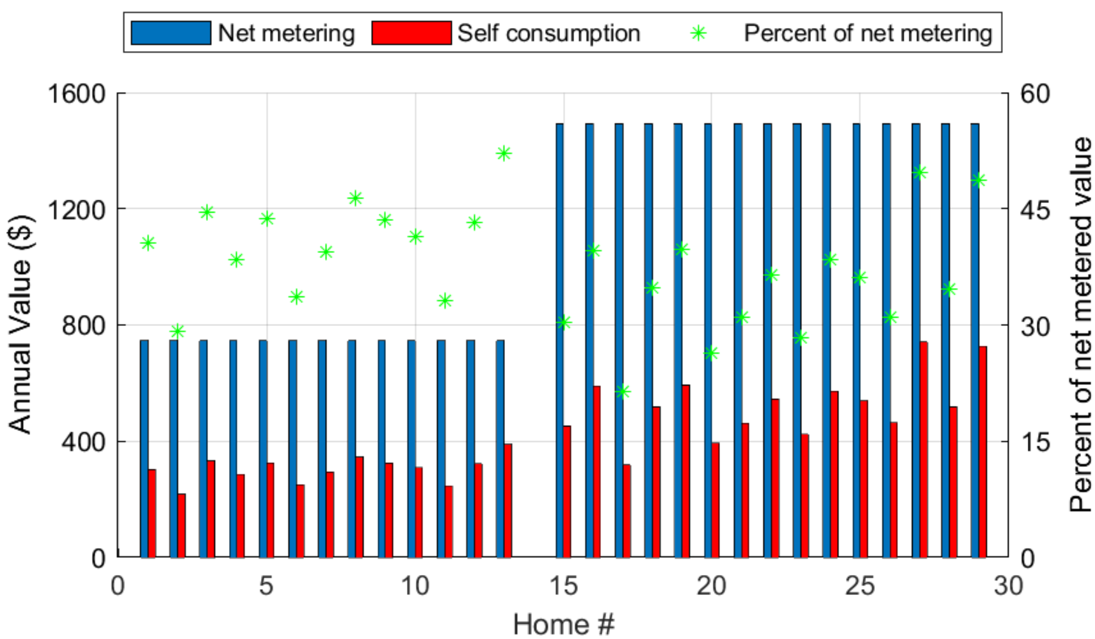

Figure 42. Average economic value of PV systems in Nova Scotia using net-metering (blue) and self-consumption (red). Homes paired with small PV system are grouped on the left, homes paired with large PV systems are grouped on the right.

Intuitively larger PV systems will be more severely impacted by a self-consumption scenario which can be seen by the larger range in net-metering values compared to self-consumption values. A self-consumption policy reduced the average economic value of a small PV systems by 59%, while reducing that of a large system by 65%. This means that the application of self-consumption to PV systems more than doubles the simple payback period for consumers. In this scenario, lost generation value would need to be made up by additional incentives to continue residential PV uptake. This also creates an opportunity to use energy storage to increase the amount of self-consumed PV and increase the value of installed PV systems.

9.5. Conclusions

The annual value of 21 PV profiles was assessed using the following electricity tariff structures:

- Flat rate. Electricity consumption has a single value year-round.
- Time of day. Electricity has three different price tiers depending on the time of day and time of year. Two pricing tiers (off-peak and mid-peak) are applied year-round while on-peak pricing is only applied during the winter period from Dec – Feb, when both the average electricity load and the difference in peak consumption and baseline consumption are larger. All weekends throughout the year are treated as off-peak.
- Time of day including weekends. Analysis of workday and weekend electricity consumption profiles show that they are essentially identical. This support equal treatment of workdays and weekends in terms of TOD pricing.
- Time of day winter workday all year. The overall load shape of winter and non-winter periods is similar and could support the application of winter TOD rates year-round.
- Self-consumption. Electricity is priced at a flat rate all year, but electricity exports are not permitted and so the value of PV generation exceeding load consumption is 0.

Switching from a flat rate to the current TOD available in Nova Scotia reduced the annual economic value of PV systems by 11%, almost certainly due to the pricing of all weekends as off-peak. Simply applying regular TOD rates to the weekends increased in value of PV relative to flat rate by 1.8%. Extending this even further and applying winter TOD rates throughout the year boosted the value of PV by 17% due to the availability of on-peak pricing. Changing the existing TOD tariff to include weekends is supported by an analysis of provincial grid loads, which show similar patterns for workdays and weekend in both the summer and winter. Doing this would encourage customers to partake in the TOD program and help shift loads, and slightly enhances the value of residential PV systems.

If substantial levels of PV capacity are reached in the province, it would be beneficial to apply a separate feed-in tariff to PV and change TOD rate structures to incentivize consumption during daytime hours, particularly in the summer. This would encourage shifting loads to periods of high PV generation (midday or afternoon) while avoiding the negative impacts of off-peak rates on PV generation value.

Applying a self-consumption requirement on PV is devastating to its annual economic value, resulting in an average decrease of 62% when using a flat-rate tariff. Applying this policy could alleviate concerns with large amounts of PV generation on the electricity grid but would need to be paired with substantial incentives to avoid crippling future developments. The importance of self-consumption could warrant the application of energy storage to shift PV electricity and increase overall system economics.

Chapter 10: Technoeconomic Performance of Energy Storage Paired With PV

In this chapter, the potential for pairing PV generation with energy storage is evaluated using 5 different tariffs. Using the rate structures/policies discussed in the previous chapter presents an opportunity for energy storage to upgrade the value of electricity. This is done by storing lower value grid electricity (off-peak) to be used in place of higher value grid electricity (mid or on-peak) later. The electricity rate scenarios are combinations of net-metering policy and TOD policies and are summarized in Table 11.

Table 11. Summary of electricity scenarios considered for energy storage

Scenario abbreviation	Net-metering (yes/no)	Flat rate, TOD, or alternate TOD
Net TOD	Yes	TOD
Self TOD	No	TOD
Net Wknd.	Yes	Wknd. TOD
Self Wknd	No	Wknd. TOD
Self Flat	No	Flat rate

All potential combinations of residential load and PV generation (n = 721) were used to estimate the actual performance of PV systems paired with battery energy storage, resulting in a total of 721 unique net load profiles. Simulations of energy storage systems with storage capacities ranging from 2 – 20 kWh in increments of 2 kWh, and storage converter ratings of 1 – 10 kW in increments of 1 kW, were conducted. PV systems were normalized to 5 and 10 kW_{DC} based on the annual electricity consumption of the home they were paired with. Both grid energy consumption and economic value were determined for the average system.

The grid consumption for each combination of storage capacity and converter size was normalized by the grid consumption of using only a PV system. This means that any combinations with a value below 1 have a larger net energy consumption than a standalone PV system, and values above 1 have less net energy consumption.

Economic value was calculated as the annual value of energy produced by the system (and/or shifted in the case of energy storage) divided by the system capital cost. This metric was normalized by the economic value of a standalone PV system of the same size. This means that values less than 1 are not as economically attractive as a PV system without storage (although they may still be economically viable). Values above 1 indicate superior economic value using a simple annual return/CAPEX measure.

The energetic value was calculated as the net electricity exports of the solar + storage (PVS) system normalized by the amount of energy which would have been exported using only a PV system. Any values less than 1 indicate an increase in grid electricity consumption, while any values above 1 mean that the home consumed less electricity from the grid. The inverse of these values could be taken to represent direct multiples of grid electricity consumption.

10.1. Energy Storage Using TOD Tariffs With Net-Metering

10.1.1 Net TOD Scenario

With net-metering present the value of energy storage is independent of PV generation, and the energy storage system is only concerned with when electricity is exported, not whether it come from PV generation or was imported from the electricity grid. In this scenario there were two distinct seasons which impacted control behaviour. During the peak season (Dec, Jan, Feb) the system was charged overnight, discharged during the morning peak, charged during the afternoon mid-peak, and then discharged again during the evening peak. Outside of the peak season, the system was charged overnight, and discharged during the day. An exception is made for weekends which are treated as off-peak for the entire day. The storage system was not discharged on these days under any circumstances.

The mean economic value and energy multipliers are shown in Figure 43. For all systems considered grid energy consumption increases. This is expected since there is no curtailment of PV exports, and the round-trip efficiency of energy storage will lead to a net increase in energy consumed by the home as it charges and discharges. Differences in the values of energy heatmaps for a 5 kW_{DC} PV system vs a 10 kW_{DC} system are attributed to the different value used to normalize the results (a larger PV system generate more electricity and so battery consumption will not have as large an impact). An important note is that converter size has very little impact on energy consumption, suggesting the amount of time spent at a given price tier exceeds the amount of time required to charge/discharge.

In terms of economic value measured no PVS systems were found to exceed the value provided by standalone PV. Discrepancies between the sizes of PV system are again attributed to the difference in normalization, where the larger PV system has a reduced cost per Watt and enhances the overall PVS value. Economic multiples below 1 for all storage configurations suggests that the energy storage used solely for arbitrage is unable to compete economically with standalone PV. The decrease in economic value (18% at best) far exceeds the increase in energy consumption (8% or less). This suggest that the capital cost of the energy storage system is more impactful than the pricing of electricity for this scenario.

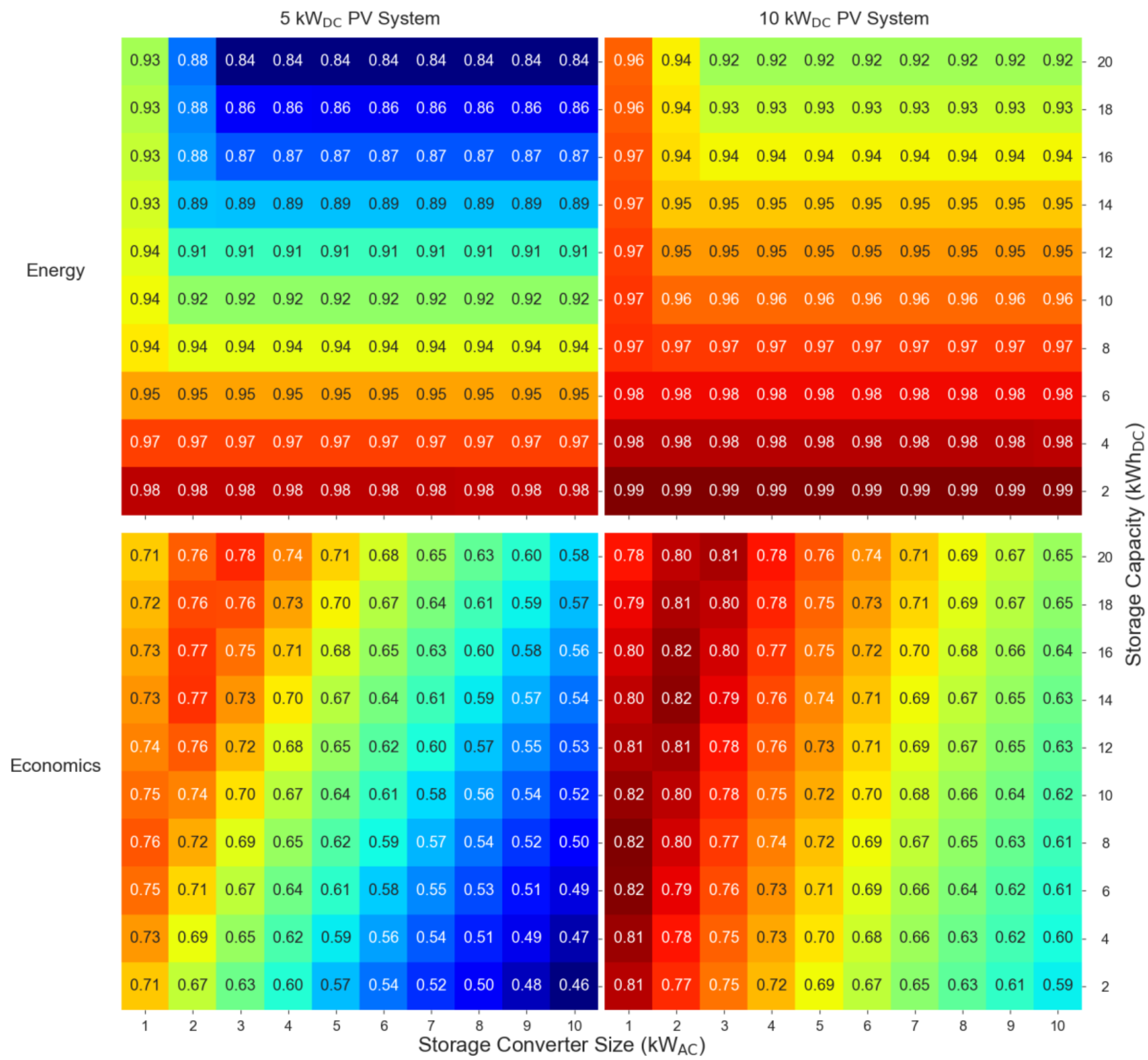

Figure 43. PV + Storage system multipliers for PV energy consumption (top) and generation value/CAPEX (bottom) for a 5 kW$_{DC}$ (left) and 10 kW$_{DC}$ (right) PV system using a TOD electricity rate with net-metering. Values normalized by PV only (e.g. PV + Storage System/PV only)

10.1.2 Net Wknd. Scenario

The inclusion of weekends in the TOD structure means that the energy storage system will have nearly 30% more opportunities to take advantage of electricity price differences, improving its economic performance.

Figure 44 shows that using the alternative TOD scheme increased the value of energy storage systems by less than 5%, with larger storage capacities seeing greater increases in value compared to smaller capacities. The increase in value was still not sufficient to equalize the revenue per capital cost of a PV + storage system with a PV only system due to the large capital cost of energy storage.

There is also less than 5% difference in the energy consumption multiples compared to the original TOD tariff. This means that the additional energy consumption caused by efficiency losses from the extra 2 days of cycling per week is small compared to the annual PV generation which was used to normalize the results.

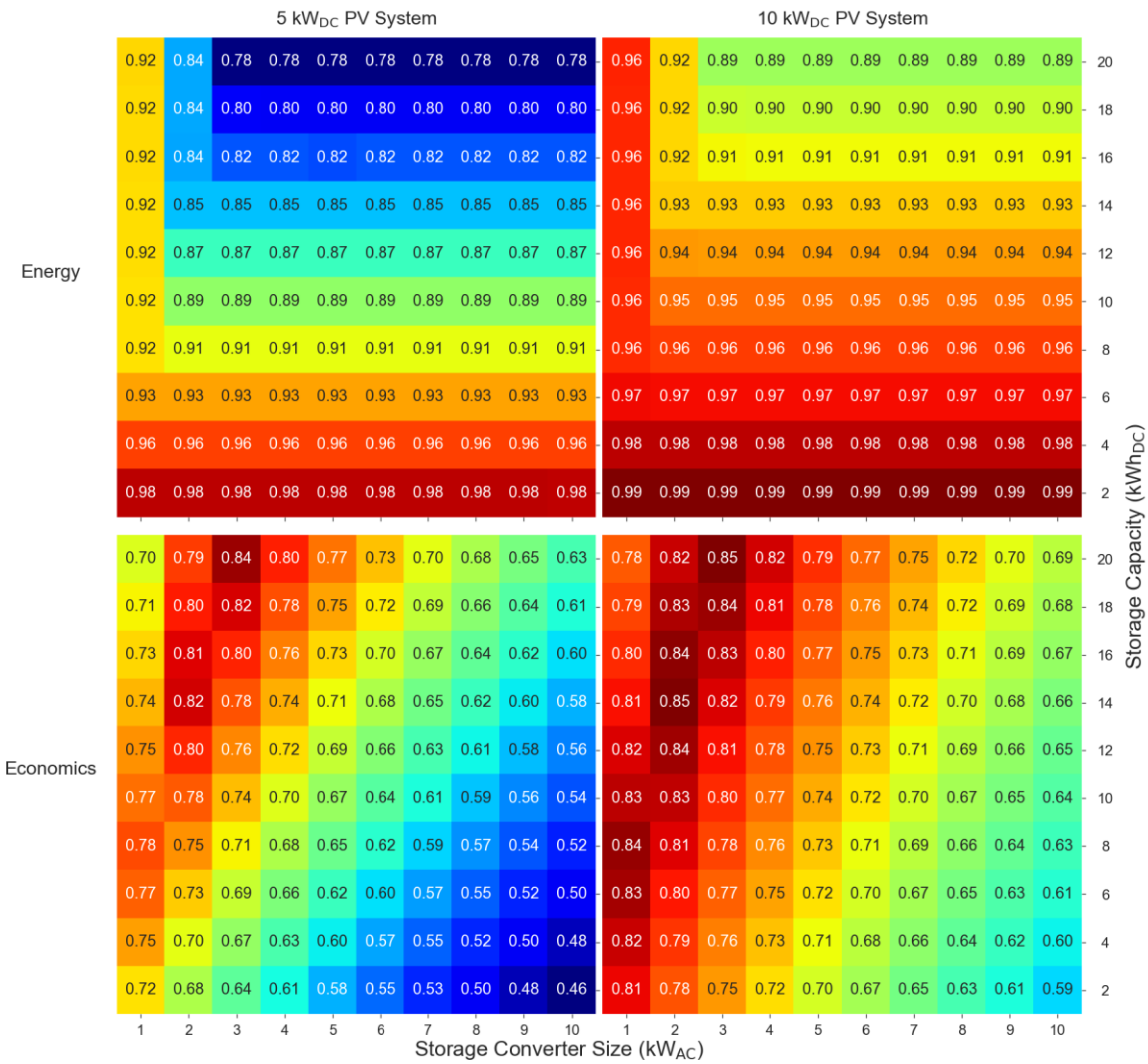

Figure 44. PVS system multiples for PV energy consumption (top) and generation value/CAPEX (bottom) for a 5 kW$_{DC}$ (left) and 10 kW$_{DC}$ (right) PV system using an alternative TOD electricity rate, which does not distinguish between weekends and workdays, with net-metering. Values normalized by PV only (e.g. PV + Storage System/PV only)

These results show that the use of battery energy storage for energy arbitrage using TOD rates available in Nova Scotia do not provide as much revenue per capital cost as PV systems. This is driven by the capital cost of energy storage, which would need to fall by approximately 18% to reach economic parity with PV.

10.2. Energy Storage Using TOD Tariffs With Self-Consumption

Results from Chapter 9 highlighted the importance of net-metering for PV economic value. Net-metering was seen to have a much more severe impact than TOD pricing and creates a difference in the value of charging energy for a PV system. Since PV generation in excess of home load cannot be exported it's economic value is 0 unless it can be upgraded by storing it for a time when load exceeds generation. This was predicted to have a significant impact on storage value (increasing) and grid energy consumption (decreasing).

10.2.1 Self TOD Scenario

Under a self-consumption scheme, priority should be given to charging the energy storage system using excess PV generation since this will upgrade its value from 0 to the mid or on-peak electricity price. PV generation predictably follows a day night cycle, so it is desirable to have a low SOE from late morning to early evening to avoid losing potential PV generation. It is still desirable to be fully charged for the morning and evening on-peak period to discharge electricity at its highest value. The strategy used for this scenario fully charges the system overnight during the off-peak except overnight on Friday and Saturday, since Saturday and Sunday are always treated as off-peak. The system is set to charge the storage system any time PV generation exceeds home load, and only discharges to meet on-peak loads during the on-peak season. Outside the peak season, the system discharges throughout the day during the mid-peak hours when load exceeds generation.

Since a self-consumption policy restricts grid exports the net grid consumption by the home is expected to increase, with energy storage allowing for recovery of otherwise lost PV generation. This is confirmed in Figure 45.

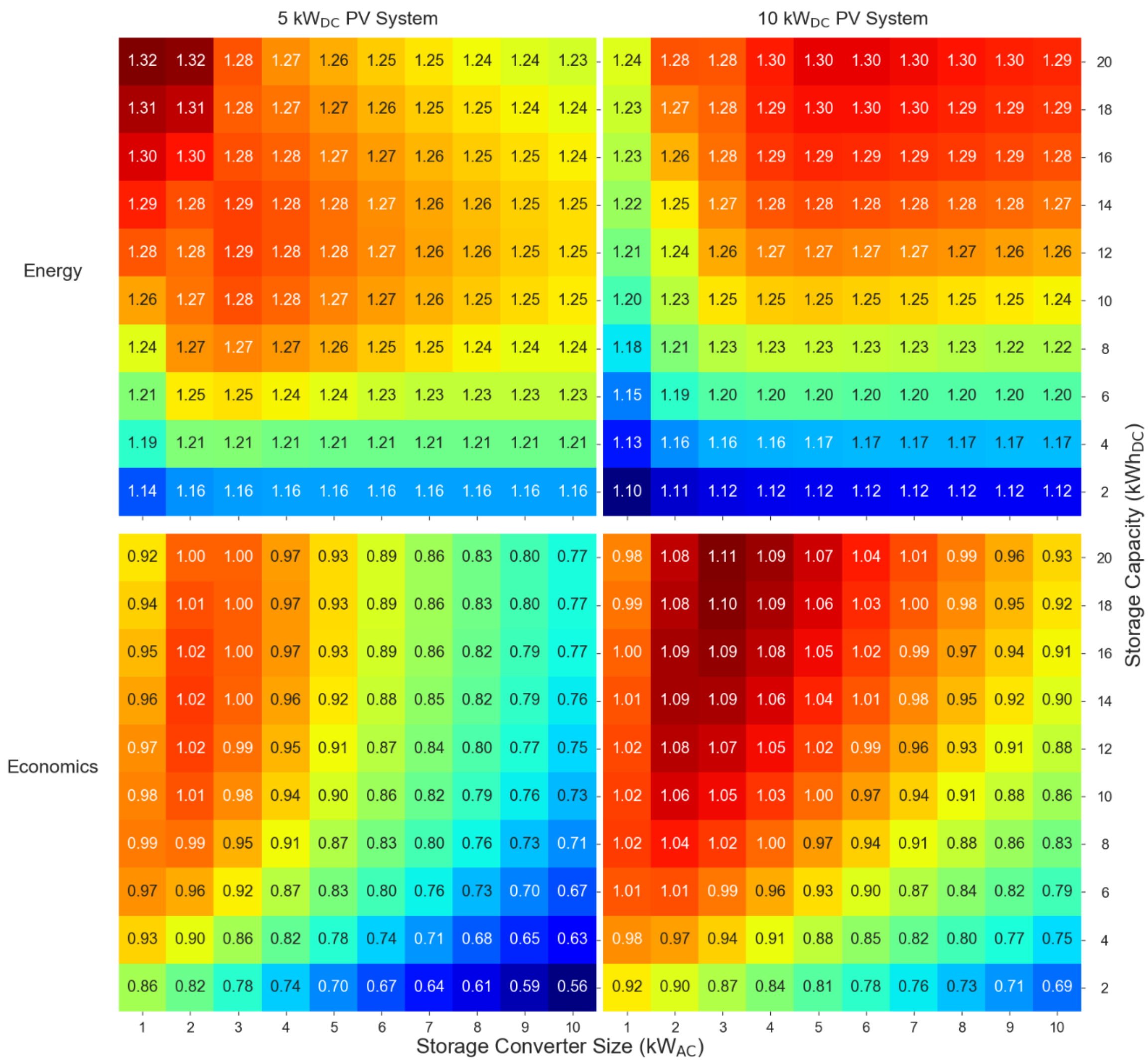

Figure 45. PVS system multiples for PV energy consumption (top) and generation value/CAPEX (bottom) for a 5 kW$_{DC}$ (left) and 10 kW$_{DC}$ (right) PV system using a TOD electricity rate with self-consumption. Values normalized by PV only (e.g. PV + Storage System/PV only)

All energy storage configurations were found to decrease the total grid electricity consumption by 16 to 32% relative to only using PV generation which has significantly reduced exports due to the self-consumption policy. Increasing storage capacity has a larger impact on energy multiples than increasing converter size, which plateaus at 4 kW$_{AC}$.

Applying a self-consumption condition was expected to increase the value of energy storage since more PV energy is used by the system and was the case for all systems tested. The economic multiples of energy storage configurations increased by 17 to 31% compared to the TOD with net-metering scenario. More importantly, there is a range of storage capacities and converter sizes which were found to be economically attractive. Converter sizes of 2 and 3 kW_{AC} paired with a range of storage capacities from 10 to 18 kWh_{DC} are shown increase the value of 10 kW_{DC} PV installations. The increased value does not offset the loss of value caused by the removal of net-metering, but does show that the additional capital cost of energy storage is warranted.

10.2.2 Self Wknd. Scenario

To investigate the impact of applying an alternative TOD rate structure, applicable storage control restrictions about weekend behaviour were removed, and results are shown in Figure 46.

There are negligible changes to the economic multiples compared to the original TOD scenario but a significant decrease in the energy multiples. This means that while the system arbitraged more electricity, the additional value generated relative to the PV only system is negligible. While there are more energy arbitrage opportunities, the value of PV generation which was used to normalize results also increased due to the availability of mid and on-peak electricity rates on weekends.

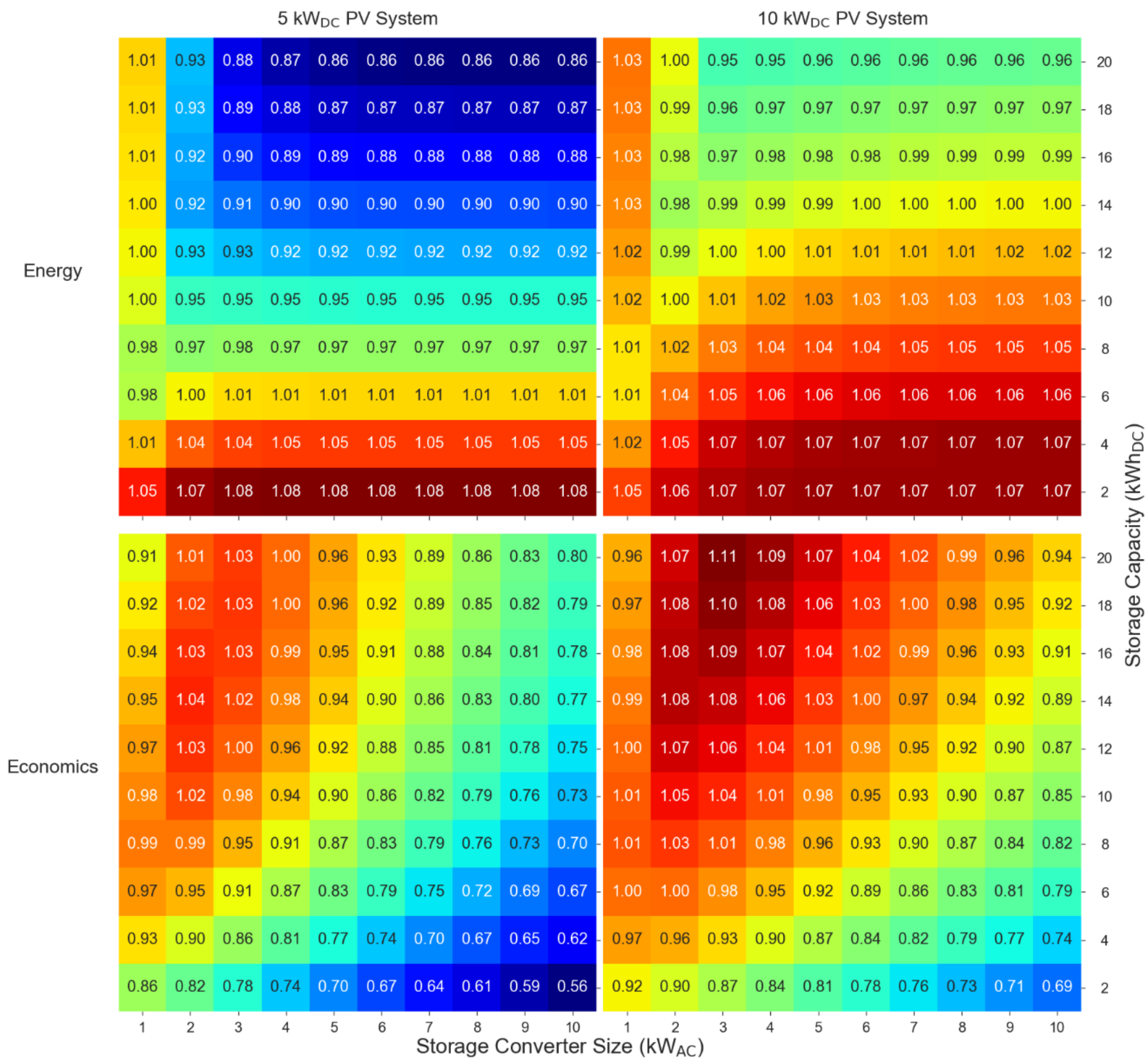

Figure 46. PVS system multiples for PV energy consumption (top) and generation value/CAPEX (bottom) for a 5 kW$_{DC}$ (left) and 10 kW$_{DC}$ (right) PV system using an alternative TOD electricity rate, which does not distinguish between weekends and workdays, with net-metering. Values normalized by PV only (e.g. PV + Storage System/PV only)

10.3. Change in Peak and Off-Peak Energy Consumption

TOD policies exist to incentivize consumers to alter their behaviour to help reduce peak demand. Since the residential loads used in this study are unaware of the conditions applied by this work, they operate as if under the general flat rate. Because of this, energy storage would operate to try and maintain the typical usage patterns of homes. To this end, this work can measure the impact of applying energy storage to the amount of grid electricity consumption during off-peak and peak times.

The mean change in off/on peak grid consumption for all battery configurations paired with a 10 kW_{DC} PV system is shown in Figure 47. There is a clear benefit to allowing systems to net-meter if the objective is to shift energy. Using either TOD tariff, energy storage systems shifted greater amounts of energy when net-metering was permitted.

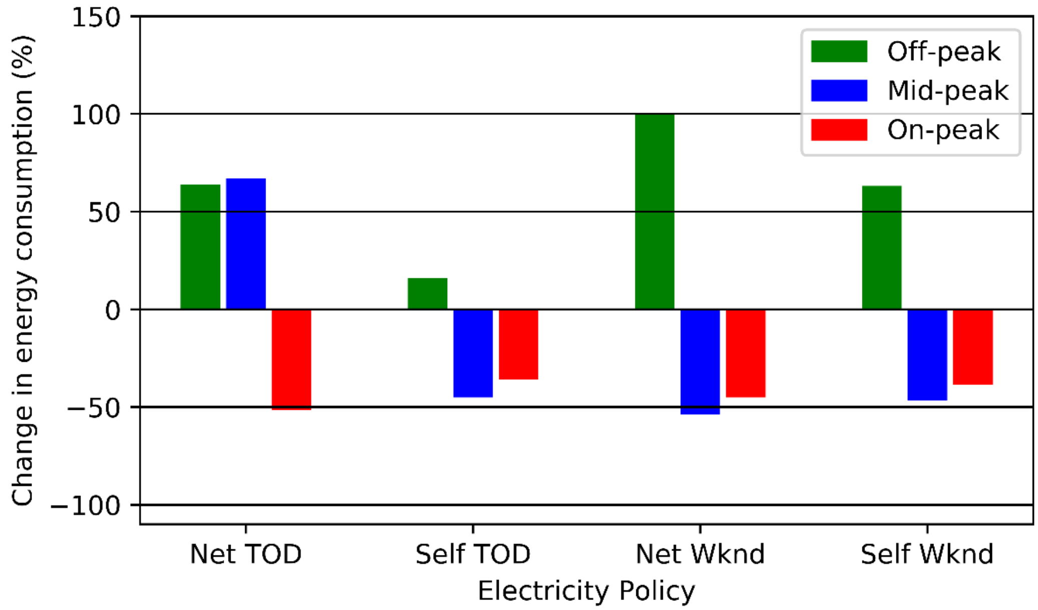

Figure 47. Average change in off-peak, mid-peak, and on-peak grid energy consumption for a 10 kW_{DC} PV system paired with all storage configurations

The increased amount of energy shifted for the net-metered scenarios can be explained by observing when off-peak energy is consumed by the energy storage system. Charging using off-peak electricity for all scenarios always occurs overnight between 23:00 and 07:00 without any opportunity to discharge. This means that any off-peak energy consumption occurs when the battery charges beginning at 23:00. A reduction in off-peak energy consumption indicates that on average the energy storage system under a self-consumption scenario does not fully discharge during the evening on-peak, and so cannot consume as much off-peak energy. This is supported by the increase in peak energy consumption when self-consumption is applied. This suggests that there are insufficient net-load opportunities present during the evening peak to fully discharge the system, which was unexpected. This could occur for two reasons; low frequency of discharge opportunities or discharge opportunities which exceed the storage converter size. In the previous section it was shown that increasing the converter size of an energy storage system past 4 kW_{AC} did not change the energy consumption of the system. This means that there are not enough discharge opportunities during on-peak times to fully discharge the battery.

Another interesting result is that the use of the Wknd. TOD tariff results in greater amounts of both off-peak and on-peak energy consumption. The increase in off-peak consumption is expected, since the system is charging for 2 additional nights during the week, but the increase in on-peak consumption is surprising. The only way for this to occur is if on-peak consumption of residential homes is larger on the weekends than on workdays, which would strengthen the argument for TOD rates to be extended to include weekends. This was confirmed using residential load data, which showed a 12.6% increase in on-peak energy consumption on weekends compared to workdays.

10.4. Energy Storage Using a Flat-Rate Tariff With Self-Consumption

In the event TOD rates are not made available to customers without electric thermal storage units and PV penetration in the market warrants removal of the net-metering incentive, energy storage may alleviate some of the economic impact to PV systems. A simple energy storage control scheme which attempts to always maintain a grid net load of zero was used to address this case. Any time home load exceeds PV generation, the battery will discharge. Conversely, any time PV generation exceeds home load, the battery will charge using the excess PV energy. Results of this scenario are shown below in Figure 48.

Energy multiples greater than 1 were expected since excess generation is captured by the battery and used when the system is in an energy deficit. Since there is no energy arbitrage occurring, the energy multiple values are a direct multiple of PV electricity used by the system (e.g. an energy multiple of 2 indicates that double the amount of PV electricity was utilized relative to a PV only system). The energy multiples for this scenario are much larger than those obtained by TOD with self-consumption schemes since no energy arbitrage is occurring.

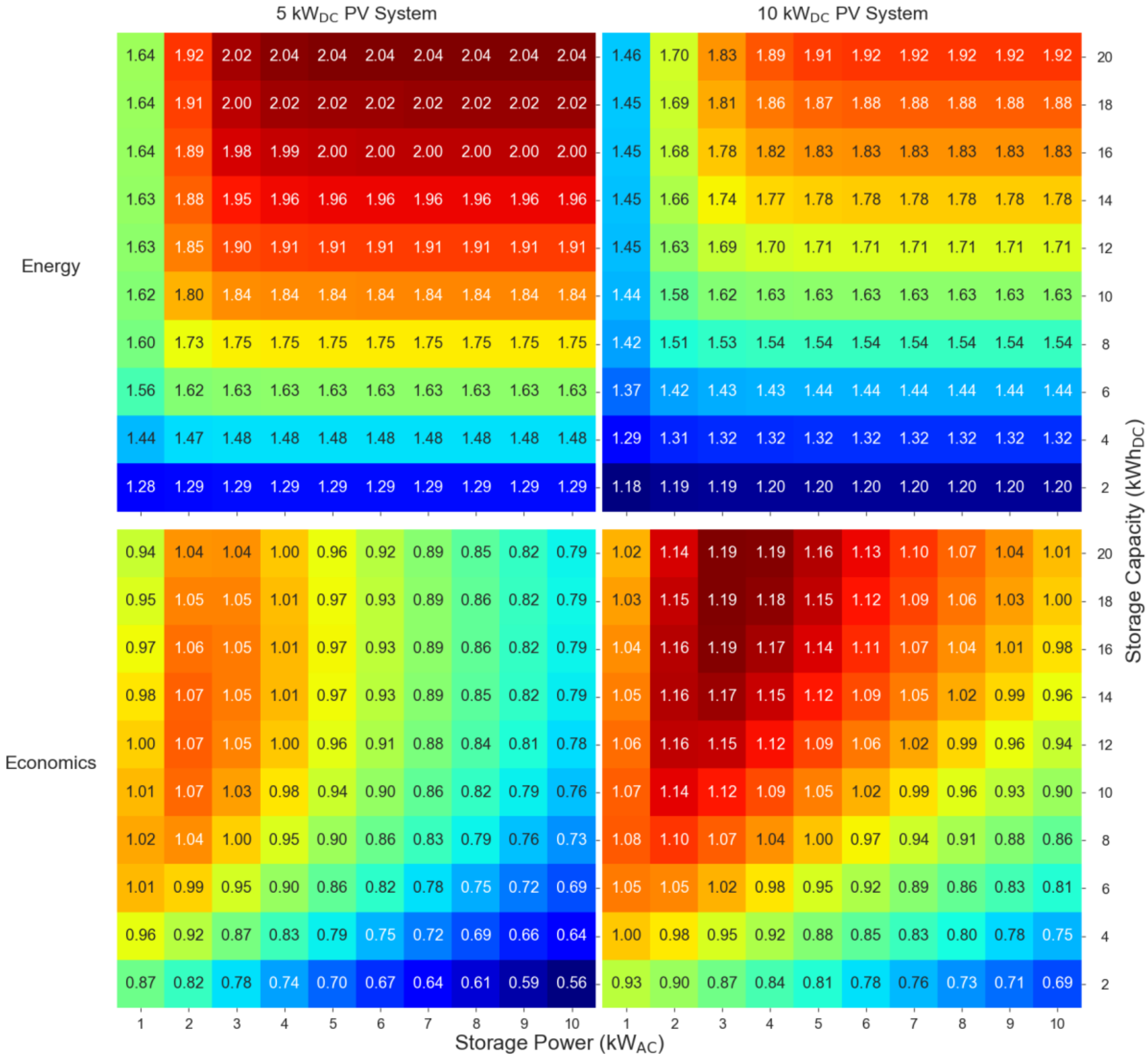

Figure 48. PVS system multiples for PV energy consumption (top) and generation Value/CAPEX (bottom) for a 5 kW$_{DC}$ system (left) and a 10 kW$_{DC}$ system (right) using a flat electricity rate with self-consumption. Values normalized by PV only (e.g. PV+Storage System/PV only)

The economic value multiplier of energy storage is larger for this scenario than it was for the TOD scenarios presented previously. For large systems values can be increased by as much as 19%, with many smaller configurations still providing improved economic performance. The increased value of energy storage for larger PV systems was expected, since they are more likely to more frequently exceed residential loads and exceed loads by a larger amount.

Converter sizes from 2 to 3 kW$_{AC}$ paired with 10 to 18 kWh$_{DC}$ storage capacities again capture a good deal of the economic value of available configurations.

Based on the evaluation of net-metering policy done in Section 9.4 the maximum achievable energy multiple would approach 3, which would indicate complete recovery of PV generation lost due to the removal of net-metering. Capacities up to 100 kWh were evaluated and reached a maximum energy multiple of 2.16, short of the theoretical maximum and only 0.2 different from the energy multiples obtained using 20 kWh. This would suggest that much of the energy lost occurs during prolonged periods of solar generation exceeding load. This would be expected during the summer when PV generation is high, and load is low, which could result in excess generation for multiple consecutive days which would fill even large energy storage capacities. Also of interest is that capacities up 60 kWh were found to be economically beneficial (have economic multiples greater than 1) to large PV systems when paired with converter sizes of 4 to 5 kW_{AC}. This storage capacity is much larger than what is available in commercially available units, but could be achieved using multiple packs.

10.5. Load Following Control Strategy for Energy Storage Using TOD Tariffs With Self-Consumption

The economic viability of adding energy storage to PV systems under a flat-rate self-consumption scenario suggest that self-consumption TOD scenarios should have greater benefits than those seen in Section 10.2. This may be due to the control strategy employed, which seeks to balance storing excess PV generation with energy arbitrage.

To evaluate the impact of energy arbitrage operations on the effectiveness of energy storage under TOD electricity rates with self-consumption, TOD rates were applied to the value calculation of simulations which used a simple load following control strategy. These results are shown in Figure 49 (Self TOD rates) and Figure 50 (Self Wknd. rates).

The application of a simplified control strategy which does not attempt any energy arbitrage has clear benefits from both an energy consumption, and economic benefit standpoint. As expected, energy multiples are identical to those seen in Section 10.4 since the control strategy is the same, but the use of a simple load following strategy results in slightly higher economic multiples compared to using an energy arbitrage strategy. This means that the use of a simple load following strategy outperforms energy arbitrage strategies both in terms of net energy consumption, and revenue generation.

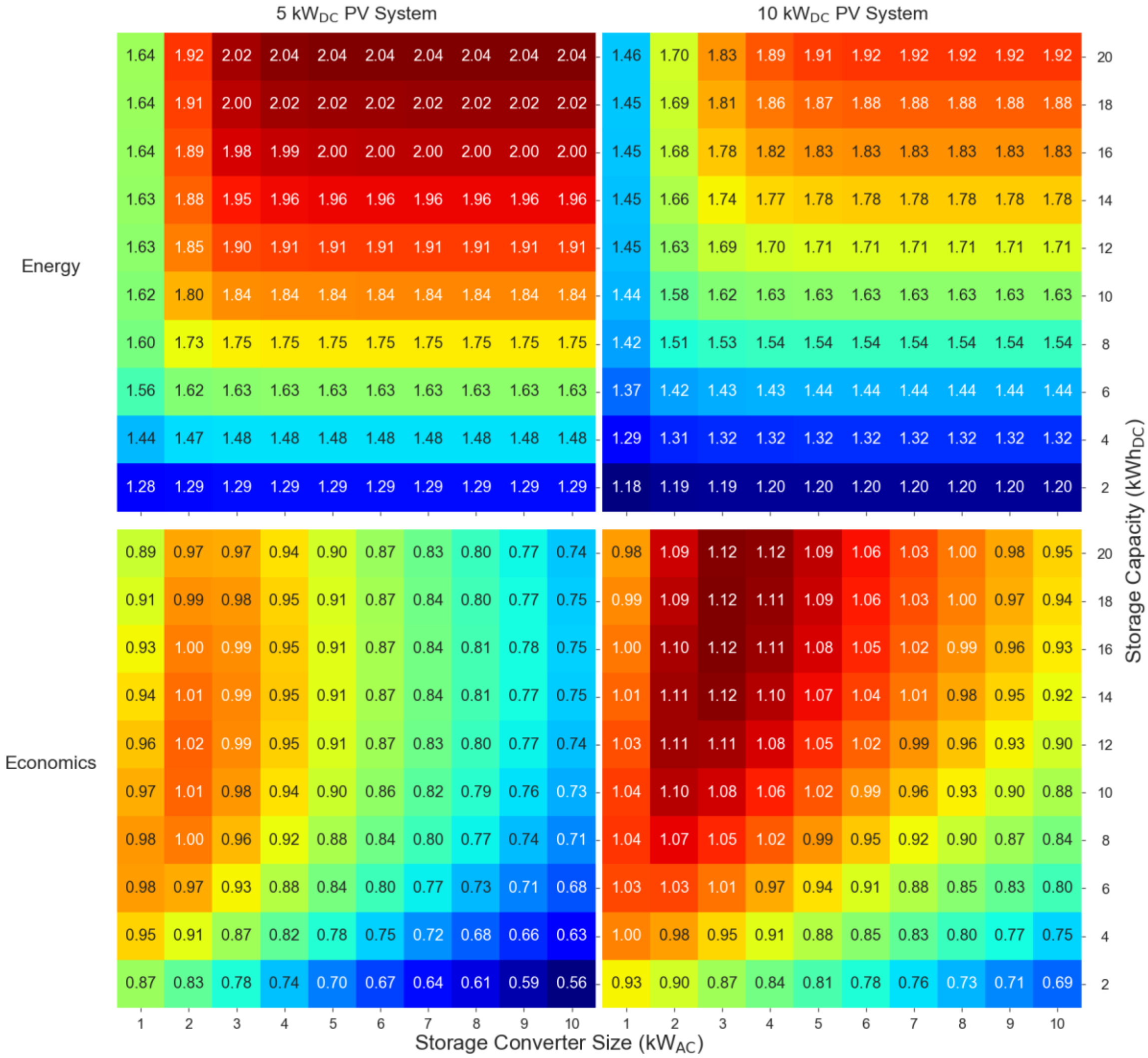

Figure 49. PVS system multiples for PV energy consumption (top) and generation Value/CAPEX (bottom) for a 5 kW$_{DC}$ system (left) and a 10 kW$_{DC}$ system (right) using a TOD electricity rate with self-consumption, and a net load following control strategy. Values normalized by PV only (e.g. PV+Storage System/PV only)

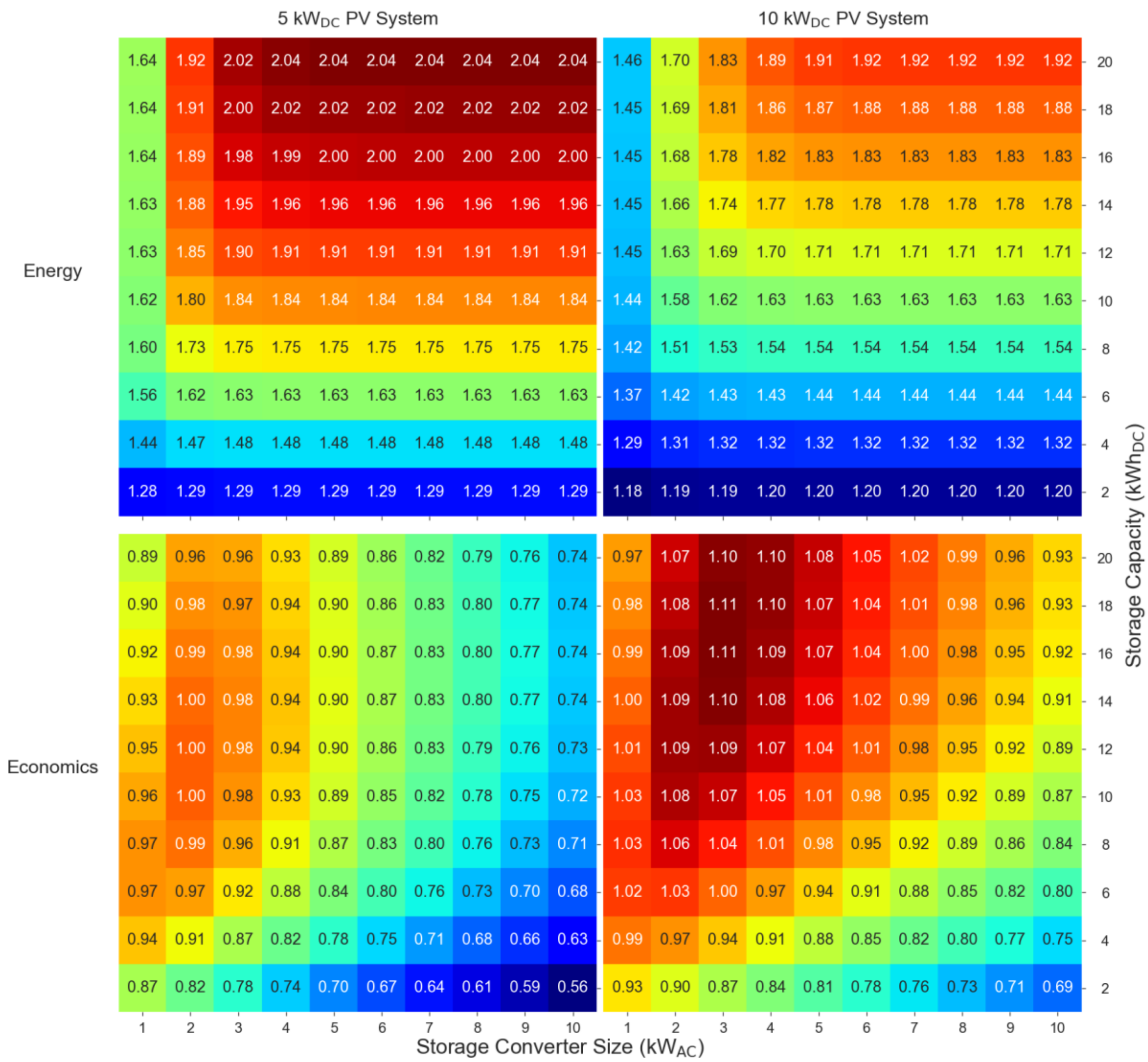

Figure 50. PVS system multiples for PV energy consumption (top) and generation Value/CAPEX (bottom) for a 5 kW$_{DC}$ system (left) and a 10 kW$_{DC}$ system (right) using an alternative TOD electricity rate, which does not distinguish weekends and workdays, with self-consumption and a net load following strategy. Values normalized by PV only (e.g. PV+Storage System/PV only)

The decreased performance of energy arbitrage strategies compared to a simple load following strategy is likely due to the assumption that the battery can sufficiently discharge in the morning prior to PV generation exceeding home load. This is important since PV generation which exceeds load has an effective cost of 0 for charging the battery, while off-peak electricity costs 9 cents/kWh. This means that any PV generation lost due to insufficient battery capacity because of the overnight charge effectively costs 9 cents/kWh of potential value.

Using a simple load following strategy does not account for TOD pricing tiers, and so the impact on energy consumption during off and on-peak times is reduced, as shown in Figure 51. While the strategy may be more economical and increase PV self-consumption more than the specific TOD strategies applied in this thesis, it is less effective at shifting grid electricity consumption from peak to off-peak times.

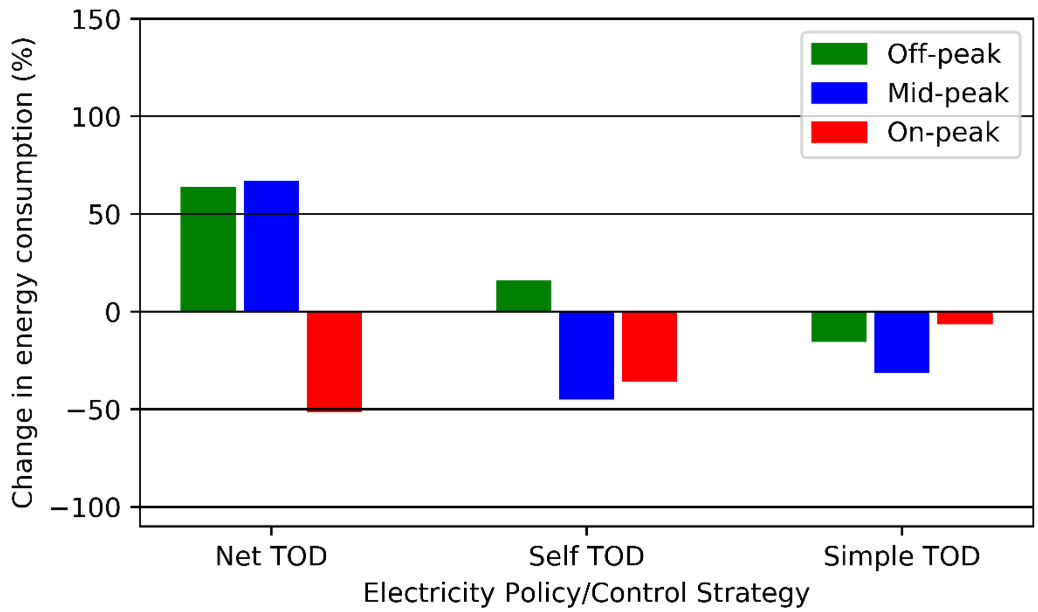

Figure 51. Impact of using a simple load following strategy on energy consumption during different pricing tiers.

10.6. Conclusions

Energy arbitrage using energy storage is not as economically attractive as standalone PV when net-metering is available based on the model used in this work. The difference in price between tiers of the TOD tariff in Nova Scotia are not large enough relative to the capital cost of storage to make arbitrage competitive for residential customers compared to PV. However, the availability of net-metering did substantially increase the amount of energy shifted from on-peak to off-peak periods and would provide additional revenue. Increasing the price differentials of the existing TOD tariff would incentivize increased residential participation in this market and shift loads. An increase in on-peak pricing would also benefit the value of PV systems, since the bulk of PV revenue during the winter months (Dec - Feb) is from on-peak generation.

Energy storage becomes both economically and energetically attractive when PV self-consumption policies are applied. When using TOD tariffs with self-consumption the energetic and economic value of storage increased considerably, and a range of energy storage configurations were shown to be economically attractive compared to standalone PV. Storage capacities from 10 to 16 kWh_{DC} paired with converters from 2 to 3 kW_{AC} produced the best results for both small and large systems. In these cases, storage was able to increase the economic value of PV and the amount of PV self-consumption.

The impacts of energy storage were greater for large PV systems which are more likely to exceed load and are more heavily impacted by self-consumption policy. Using a TOD tariff which treated weekends and weekdays equally did not improve economic results but did increase energy consumption. This occurred since there were increased arbitrage opportunities (and so more frequent cycling) but the value of this was not significant compared to the value of annual PV generation, which was also increased by the availability of mid and on-peak rates on weekends.

Using a load following strategy produced better results than the use of an energy arbitrage strategy, even when TOD rates were applied. This is because under a self-consumption condition all PV generation which exceeds load has a value of 0. If the battery was fully charged overnight using off-peak electricity, and was unable to discharge prior to PV exceeding load, then it loses 9 cents/kWh of lost PV generation. A drawback of applying the load following strategy is that it had a no impact on off-peak energy consumption but did still decrease on-peak and mid-peak consumption.

This chapter shows that under self-consumption conditions, the application of battery energy storage is both energetically and economically attractive. Storage capacities from 10 to 18 kWh_{DC} combined with converter sizes of 2 to 3 kW_{AC} were found to provide the best results in any of the scenarios examined. These converter sizes are well below the specifications of many commercial products, likely because commercially available energy storage is expected to also operate as a form of back-up power in case of outage, the value of which was not considered in this thesis. If this application were considered optimal storage capacities and converter sizes would need to be larger.

No energy storage configurations were able to recoup losses to PV value caused by the restriction of net-metering. If further incentives are required to restore value, this could be done by using energy storage for multiple services. As previously mentioned, there is some subjective value to using energy storage as a back-up power supply, but it could also be used by the utility for grid services such as load shifting and intermittency reduction. This could be done by leasing excess storage capacity and converter power to the utility, who would benefit from the aggregation of distributed storage assets. Under the right conditions, value could also be provided to other consumers within the same distribution grid during grid outages through energy sharing agreements.

An important assumption of this work is that electricity usage patterns will not change if TOD rates are implemented. If self-consumption conditions were applied residential load consumption patterns would be expected to shift in response, reducing the value of energy storage.

Chapter 11: Conclusion

The number of residential PV installations is rapidly growing across Canada and around the world due to both falling system prices, and a desire to decarbonize the electricity system. The scalability, design flexibility, and low maintenance cost of PV generation makes it accessible to residential customers. Residential rooftop PV installations are increasingly common and are set to be a major source of industry growth in the future. To support future PV development, particularly in the residential sector, this thesis used measured data from PV systems and homes from the Halifax Regional Municipality located in Nova Scotia, Canada to investigate PV intermittency, the impact of electricity tariffs on the value of PV, and the benefits of pairing PV with energy storage. Contributions from this thesis to the academic literature are presented in Sections 11.1 and 11.2, with recommendations for future research presented in Section 11.3.

11.1. Power Intermittency

The academic literature on PV intermittency rarely considers the impacts of electricity consumption, likely due to an emphasis on large utility-scale plants. Furthermore, studies typically focus either on the impacts of geographic spacing or specific control strategies for energy storage. This thesis contributes to the literature by considering residential net loads, and by incorporating both geographic smoothing (through system aggregation) and energy storage.

PV intermittency was evaluated using ramp rates and output variability. Ramp rates are a more practical evaluation of intermittency but can be subjective based on the ramp rate threshold of interest, while output variability offers a means of objectively comparing different installations.

Residential PV systems have lower intermittency than commercial systems. This may be due to the productivity of each type of system and the methodology used to normalize systems in this thesis. Commercial systems typically spend a greater amount of time near peak output due to their physical orientation. Residential system orientations are restricted by the homes roof, while commercial systems have a flat roof which allows for more design optimization. More time spent near peak production means there are more opportunities for large ramp rates due to passing clouds.

The distribution of residential PV systems across a single neighbourhood or business park (2.0 x 2.5 km), or across the municipality (48 x 57 km) was shown to decrease both the severity of relative ramp rates and output variability relative to using a single site. The distribution of systems across a neighbourhood or business park reduced the output variability by 50%, while distribution across the entire municipality reduced output variability by 78%. This finding is consistent with previous literature on geographic distribution showing decreased intermittency as geographic spacing is increased, but the final values differed significantly differs from models of dispersed intermittency. Distributed residential output variability were 3 times those predicted by a model by Hoff and Perez [20]. This is likely due to the violation of assumptions made in the model but shows that the model is not conservative, and the aggregation of real-world installations has significantly greater intermittency.

An intermediate between using models and real generation data for intermittency studies is the application of pyranometers. Pyranometers provide measured data but are much less costly than a full PV system. Comparing ramp rate measurements from pyranometers to residential PV systems found that they are very similar. Pyranometers overestimate ramp rate severity, likely due to the point measurement they represent in comparison to PV systems with a larger footprint. The use of pyranometers for intermittency studies is warranted since they provide a conservative estimate of real PV behaviour and are much less expensive than installing full systems, allowing for a larger number of deployment sites.

Comparison of PV ramp rates and output variability with those of residential loads show that PV intermittency has an insignificant impact on net load intermittency. Residential loads produce much more severe ramp rates, and so the application of ramp rate restrictions on PV systems would have a negligible impact on grid intermittency while increasing PV system costs.

11.1.1 Application of Energy Storage

Energy storage requirements for ramp rate mitigation of individual residential PV systems are an order of magnitude greater than those needed to apply ramp rate limits to an aggregation of homes on a per system basis. Aggregate systems benefit from a lack of temporal correlation and so have less severe relative ramp rates which need to be addressed by energy storage. Aggregations are also of greater interest to the utility, since they produce much larger absolute ramp rates which are more concerning. Per system requirements of 0.2 kWh_{DC} of storage capacity, and 1 kW_{AC} of converter size were required for aggregate intermittency reduction. These small values could be partitioned from larger distributed energy storage systems participating in other services. For example, a Tesla Powerwall 2 has 14 kWh_{DC} of storage capacity, and a converter size of 5 kW_{AC} [48]. The allocation of 0.5 kWh_{DC} and 1 kW_{AC} for intermittency reduction would still allow for usage of the system for PV value enhancement.

11.2. Electricity Tariffs and Residential PV Value

Previous work on the impacts of different electricity tariffs and energy storage sizing are limited by the availability of both measured PV and load data. As such this thesis contributes to the literature by using a relatively large sample size of measured PV (30 systems) and residential load (28 homes) data.

The impacts of electricity tariffs on the economic value of residential PV systems were investigated using 2-years of measured data from 21 installations located in the HRM. The prevailing tariff in Nova Scotia is a flat-rate fixed price of electricity and was used as a baseline for comparison with 3 TOD tariffs. The importance of net-metering was also examined.

The economic viability of residential PV is heavily dependant on electricity pricing and interconnection policy. The current TOD tariff available to customers with electric thermal storage units reduces the annual revenue from PV generation under a net-metering agreement by 11%. This is due to the treatment of weekends as off-peak, which is not supported by provincial load data which shows almost identical load patterns on workdays and weekends. When weekends are treated the same as workdays the value of PV is increased by 2% relative to a flat rate. This increase is due to PV generation occurring during daylight hours when mid or on-peak pricing are applied. The benefit of on-peak pricing is further supported by the 17% increase in PV value caused by applying winter rates year-round. While this adjustment is not as strongly supported by provincial load data as the equal treatment of workdays and weekends, it could be used to further incentivize residential PV generation.

Net-metering has an enormous impact on the economic value of residential PV generation. Restricting PV generation to self-consumption results in a 62% reduction in the average value of a residential PV system. This impact is more pronounced for larger PV systems which exceed building loads more frequently and by a larger amount. In the event enforcing self-consumption for PV systems was required, substantial incentives would be needed to offset the damage and enable continued industry growth.

11.2.1 Impacts of Energy Storage

Regardless of the electricity tariff employed energy storage capacities from 10 to 18 kWh_{DC} paired with converter sizes from 2 to 3 kW_{AC} were found to be optimal from an energetic and economic standpoint. These systems could be used to both shift electricity loads from off-peak to on-peak hours and increase residential PV self-consumption, depending on the prevailing tariff.

Using energy storage for energy arbitrage under a net-metered TOD tariff was not as economically attractive for consumers as standalone PV but could provide additional value to the utility by actively shifting loads from off-peak to mid/on-peak times.

If a self-consumption condition is applied to TOD tariffs, the amount of load shifting is reduced but there is an increase in the value of pairing PV with energy storage. The increased consumer value is not enough to offset the loss of PV value caused by self-consumption, and so additional incentives would be required. A drawback of the control strategy used for the TOD with self-consumption scenario is that there are insufficient discharge opportunities to complete discharge the energy storage during on-peak hours. This leads to a loss of PV self-consumption and economic value. The evaluation of net-metering based on aggregate net loads of a distribution grid rather than individual homes is recommended.

11.3. Recommendations for Future Research

Paragraphs I and II present ideas for future research into PV intermittency, while paragraphs III to V propose studies on residential energy storage.

I. The intermittency characteristics of distributed residential and distributed commercial PV generation should be compared and contrasted. Distributed residential is thought to represent an even distribution of PV installations across the municipality, while distributed commercial would have small clusters of PV generation located in business parks. Pyranometers located on the roofs of business across the HRM could be used to represent these distributed systems. The interest in commercial systems is that they tend to have lower installation costs per watt, and so would be a more economical target for incentives. This could be accomplished using pyranometers on the rooves of commercial buildings and comparing results to those found by Adye et al. [26]. Since the literature already contains a ramp rate study of residential PV using pyranometers in the HRM, funding for a second study would be better spent on incentivizing further PV installations rather than on expanding upon the pyranometer study.

II. The development of a PV intermittency model which better addresses the heterogeneity of residential PV systems should be explored. Building upon work by Hoff and Perez [20], potential models should investigate the potential for a 2 factor dispersion factor (which accounts for both system width and length), or a heterogeneity factor which may be determined by predominant roof orientations in the region.

III. Storage capacity and converter sizes prescribed in this thesis are smaller than what is available commercially, likely because commercial units are also expected to act as a source of back-up power in case of grid outage. Under normal circumstances this excess storage capacity and converter size could be used to participate in grid services markets such as load shifting, frequency regulation, and/or intermittency mitigation, increasing potential revenue streams.

IV. Energy arbitrage using TOD tariffs with self-consumption underperformed compared to a simple load following strategy. Alternative control strategies may be used to address this, and the use of solar forecasting would be expected to substantially improve results by reducing the amount of potential PV generation lost due to lack of available storage capacity.

V. The benefits of energy storage aggregation seen in intermittency studies should be evaluated within the context of PV self-consumption. Rather than apply a self-consumption condition for each residential PV system, the net load of a electrical distribution feeder would be considered. This could significantly increase PV consumption within a community since PV exports from individual homes can be used by other homes in the community.

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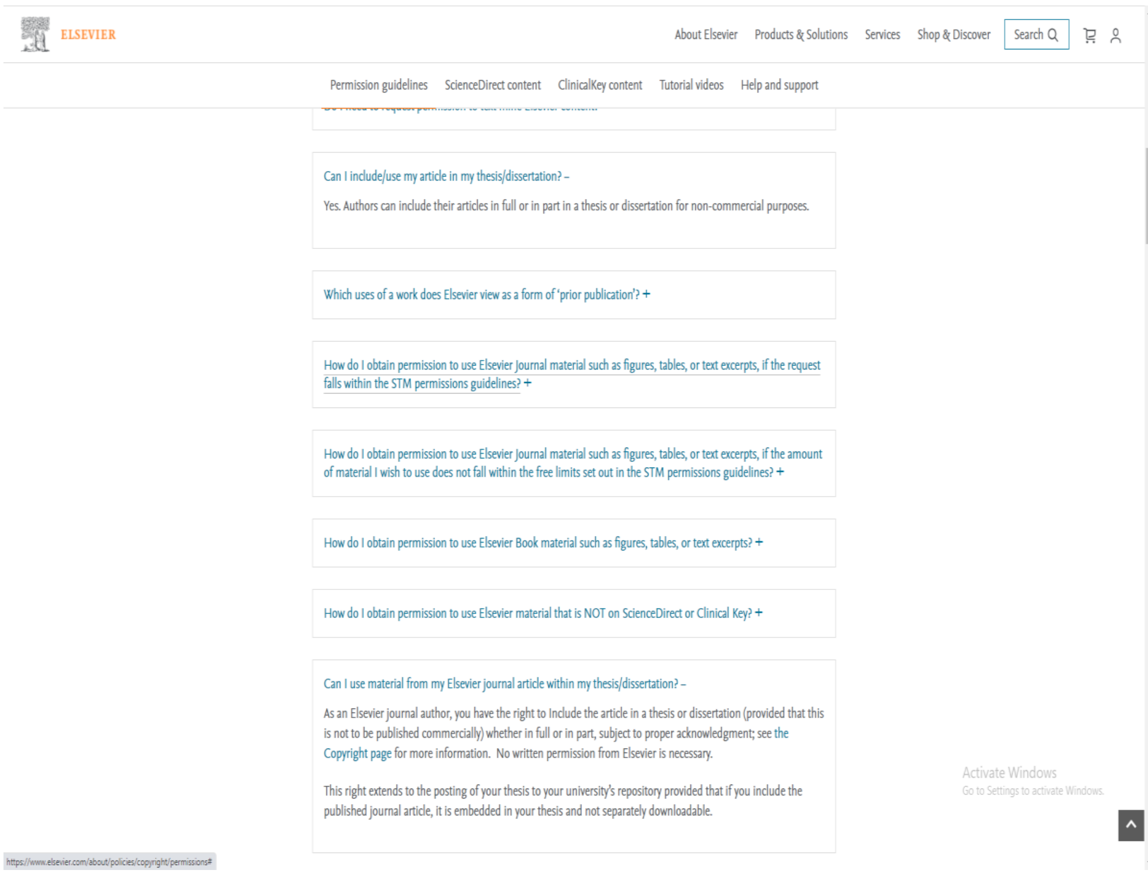
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Appendix B: Solar + Storage System Object Code

```
"""
Class definitions to represent a solar+storage system
"""

from misc import choose_dates, generate_rates
from StorageElements import Battery
from PVsystems import PVsystem
from Controller import Controller
import pandas as pd, numpy as np
from datacollection import homedata

class SolarStorageSystem:

    def
__init__(self,pvsystem=None,battery=None,load=None,control=None,feed_in=0,code_
values=None,net_override=None):
        if battery is None:
            self.battery = Battery()
        else:
            self.battery = battery

        if load is None and net_override is None:
            self.load = homedata('Home 05')
        else:
            self.load = load

        if control is None:
            self.control = Controller()
        else:
            self.control = control

        if pvsystem is None and net_override is None:
            self.pvsystem = PVsystem()
        else:
            self.pvsystem = pvsystem

        if code_values is None:
            self.code_values = pd.DataFrame(data={'Values': [0.09081, 0.16008,
0.20366]}, index=[0, 1, 2])
        else:
            self.code_values = code_values

        self.net_override = net_override
        self.rate_code = None
        self.feed_in = feed_in
        self.run_table = None

    def run_profile(self,dates=None,reset=True,control_detail=False):
        if self.net_override is not None:
            dates =
[self.net_override.index.min(),self.net_override.index.max()]
        elif dates is None:
            dates = choose_dates(self.pvsystem.data,self.load)

        self.rate_code =
generate_rates(dates=pd.date_range(dates[0],dates[1],freq='5T'),scheme=self.con
trol.rate_type)
        start_row = pd.DataFrame(columns=self.rate_code.columns)
        start_row.loc[self.rate_code.index[0] - pd.DateOffset(minutes=5)] = 0
        self.rate_code = start_row.append(self.rate_code)
```

```
        self.run_table = self.create_data_table(dates)
        start_row = pd.DataFrame(columns=self.run_table.columns)
        start_row.loc[self.run_table.index[0]-pd.DateOffset(minutes=5)] = 0
        self.run_table = start_row.append(self.run_table)
        if self.control.mode is 'Ramp':
            self.run_table = self.run_table.iloc[1:,:]

        data_length = len(self.run_table)
        cap_series = np.zeros(data_length)
        req_series = np.zeros(data_length)
        del_series = np.zeros(data_length)
        net_series = np.zeros(data_length)
        if 'Ramp' in self.control.mode:
            load_ramp = self.run_table['Load'].diff().fillna(0)

        for i, x in enumerate(self.run_table['Net Load']):
            if 'Ramp' not in self.control.mode:
                control_response = self.control.send_request(net_load=x,
battery=self.battery,timestamp=self.run_table.index[i])
            else:
                control_response = self.control.send_request(net_load=x,
battery=self.battery,timestamp=self.run_table.index[i],prev_load=net_series[i-
1],load_ramp=load_ramp[i]*-1)
                if i == 0:
                    net_series[i] = self.run_table['Net Load'].iloc[i]
                    continue

            cap_series[i] = self.battery.cap
            req_series[i] = control_response[0]
            del_series[i] = req_series[i] - control_response[1]
            net_series[i] = x - del_series[i]

        self.run_table['Capacity'] = cap_series
        if control_detail:
            self.run_table['Requested'] = req_series
            self.run_table['Delivered'] = del_series
        self.run_table['Net Energy'] = net_series
        self.run_table.loc[:,'PV'] = pd.to_numeric(self.run_table['PV'])
        self.run_table.loc[:,'Load'] = pd.to_numeric(self.run_table['Load'])
        self.run_table.loc[:,'Net Load'] = pd.to_numeric(self.run_table['Net
Load'])

        if reset:
            self.battery.reset()

        return

    def run_summary(self,summary='Full',net=True,solar_net=True):
        if self.run_table is None:
            self.run_profile()

        data = self.run_table.iloc[1:].copy()
        data = data.drop('Capacity',axis=1)
        if not net:
            if not solar_net:
                data['PVC'] = data['PV'].copy()
                data.loc[data['Net Load']>0,'PVC'] = data.loc[data['Net
Load']>0,'Load']
            data.loc[data['Net Load']>0,'Net Load'] = 0
            data.loc[data['Net Energy']>0,'Net Energy'] = 0

        if summary is 'Full':
```

```
            res = data.groupby(self.rate_code['Code']).sum()
        elif summary is 'Monthly':
            res =
data.groupby([data.index.year,data.index.month,self.rate_code['Code']]).sum()
        else:
            res = data

        res['Capacity'] = self.battery.max_cap
        res['AC_rating'] = data['PV'].max()*12

        return res

    def solar_value(self,summary='Full',net=True):
        summary = self.run_summary(summary=summary,net=net,solar_net=net)
        pv = summary['PV']/1000
        value = pv.to_frame().mul(self.code_values['Values'],axis=0).sum()

        return value

    def storage_value(self,summary='Full',net=False,normalized=False):

        summary = self.run_summary(summary=summary,net=net)
        energy_value = (summary['Net Energy'] - summary['Net Load'])/1000
        value =
energy_value.to_frame().mul(self.code_values['Values'],axis=0).sum()
        if normalized:
            value = value*1000/self.battery.max_cap # $/kWh

        return value

    def create_data_table(self,dates=None):
        if self.net_override is not None:
            self.net_override.index = pd.to_datetime(self.net_override.index)
            self.run_table = self.net_override
            return self.net_override
        elif dates is None:
            dates = choose_dates(self.pvsystem.data, self.load)

        data_table = pd.DataFrame(index=pd.date_range(dates[0], dates[1],
freq='5T'))
        data_table = data_table.join(self.load.join(self.pvsystem.data,
how='left'), how='left')
        data_table = data_table.fillna(0)
        data_table.columns = ['Load', 'PV']
        data_table['Net Load'] = data_table['PV'] - data_table['Load']

        self.run_table = data_table

        return data_table

    def clear_table(self):

        self.run_table = None

        return
```

Appendix C: PV System Object Code

```
"""
Class definitions for PV systems
"""

from pathshortcuts import solardatapath as fpath
import pandas as pd


class PVsystem:

    def __init__(self, sysid=None, normal=None,system_override=None):
        if sysid is None:
            sysid = '1012997'
            fin = fpath()+sysid+'.csv'
        else:
            fin = fpath()+str(sysid)+'.csv'

        if system_override is not None:
            self.sysid = 'Custom'
            self.data = system_override
        else:
            self.sysid = sysid
            full_data = pd.read_csv(fin, index_col=0)
            full_data.index = pd.to_datetime(full_data.index)
            full_data = full_data.sort_index()
            self.data = full_data['Energy_wh'].to_frame()

        if normal is not None:
            self.normalize(new_max=normal)

    def normalize(self,new_max=None):
        self.data = self.data/self.data.max()
        if new_max is not None:
            self.data = self.data*new_max
```

Appendix D: Battery Object Code

```
"""
Class definitions and methods for storage elements
"""

class Battery:

    def __init__(self, cap=0, max_cap=None, chg_eff=1, dis_eff=1, max_chg=None,
max_dis=None,degradation='off'):

        if max_cap is None:
            max_cap = cap # Assume starting with a fully charged battery
        if max_chg is None:
            max_chg = max_cap # 1C rate
        if max_dis is None:
            max_dis = max_cap # 1C rate

        self.cap = cap
        self.start_cap = cap # Need this for reset
        self.max_cap = max_cap
        self.start_max_cap = self.max_cap #Need this in case of degradation
implementation
        self.chg_eff = chg_eff
        self.dis_eff = dis_eff
        self.max_chg = max_chg
        self.max_dis = max_dis

    def set_size(self,new_size,charge=1):
        self.max_cap = new_size
        self.cap = self.max_cap*charge

    def reset(self):
        self.cap = self.start_cap

    def charge(self, energy=None, time=None, fade=None):
        """ Attempt to charge battery. Energy which can not be accomodated due
to rate or capacity (can't charge
        fully charged cell) is returned by this function. This is expressed in
terms of input side (so if using AC data
        deficiency is returned as AC"""
        limit = 0
        if time is not None:
            pwr = energy/time
            if pwr > self.max_chg:
                limit = (pwr-self.max_chg)*time
                energy = energy - limit
        deficiency = limit
        new_cap = self.cap + energy*self.chg_eff
        if new_cap > self.max_cap:
            deficiency = energy + limit - (self.max_cap -
self.cap)/self.chg_eff
            self.cap = self.max_cap
        else:
            self.cap = new_cap

        return deficiency # deficiency is on the "AC" side, (if asked for 5 but
system can only provide 3. deficiency = 2)

    def discharge(self, energy=None, time=None, fade=None):
        """ Attempt to discharge battery. Energy which can not be accomodated
due to rate or capacity (can't discharge
```

```
        an empty cell) is returned by this function This is expressed in terms
of output side (so if using AC data
        deficiency is returned as AC
        limit = 0
        if energy < 0:
            energy *= -1
        if time is not None:
            pwr = energy/time
            if pwr > self.max_dis:
                limit = (pwr-self.max_dis)*time
                energy = energy - limit
        deficiency = limit
        new_cap = self.cap - energy/self.dis_eff
        if new_cap < 0:
            deficiency = energy + limit - self.cap*self.dis_eff
            self.cap = 0
        else:
            self.cap = new_cap

        return deficiency # deficiency is on the "AC" side, (if asked for 5 but
system can only provide 3. def = 2)
```

Appendix E: Controller Object Code

```
"""
Define controller params (including rates) and strategies
Control descriptions are contained in each method
"""

from misc import generate_rates

class Controller:

    def
__init__(self,mode='Simple',rate_type='Flat',timestep=None,capacity_trigger=0,p
vcap=None,ramp_threshhold=0.1):

        if timestep is None:
            self.timestep = 1/12 # 5 minutes
        else:
            self.timestep = timestep

        self.pvcap = pvcap
        self.mode = mode
        self.capacity_trigger = capacity_trigger
        self.rate_type = rate_type
        self.rate_structure = None
        self.ramp_threshold = ramp_threshhold

    def generate_rate_structure(self,dates):
        self.rate_structure = generate_rates(dates=dates,scheme=self.rate_type)
        pass

    def
send_request(self,net_load,battery,timestamp,prev_load=None,load_ramp=None):
        """ Define different control strategies based on Controller mode """

        peak_months = [1,2,12]
        peak_hour = [7,8,9,10,11,16,17,18,19,20,21,22]
        off_hour = [23,0,1,2,3,4,5,6]
        weekend = [5,6]
        nights = [4,5,6]

        def simple():
            return net_load

        def tou_simple():
            req = 0
            if (timestamp.hour in off_hour) or (timestamp.weekday() in
weekend):
                req = battery.max_chg*self.timestep
            elif timestamp.month not in peak_months:
                req = -battery.max_dis*self.timestep
            elif timestamp.hour in peak_hour:
                req = -battery.max_dis*self.timestep

            return req

        def simple_alt():
            req = 0
            if timestamp.hour in off_hour:
                req = battery.max_chg * self.timestep
            elif timestamp.month not in peak_months:
                req = -battery.max_dis * self.timestep
```

```
            elif timestamp.hour in peak_hour:
                req = -battery.max_dis * self.timestep

            return req

        def tou_self():
            req = 0
            if net_load>0:
                req = net_load
            elif timestamp.hour in off_hour and (timestamp.weekday() not in
nights):
                req = battery.max_chg * self.timestep
            elif timestamp.month not in peak_months:
                req = net_load
            elif timestamp.hour in peak_hour:
                req = net_load

            return req

        def self_alt():
            req = 0
            if net_load>0:
                req=net_load
            elif timestamp.hour in off_hour:
                req = battery.max_chg * self.timestep
            elif timestamp.month not in peak_months:
                req = net_load
            elif timestamp.hour in peak_hour:
                req = net_load

            return req

        def ramp_control():
            req=0
            ramp = net_load-prev_load
            max_ramp = self.pvcap*self.ramp_threshold
            if abs(ramp) > max_ramp:
                if ramp < 0:
                    req = max_ramp+ramp
                else:
                    req = ramp-max_ramp
            elif abs(battery.cap/battery.max_cap - 0.5) > 0.1:
                if ramp > 0:
                    ramp_diff = max_ramp - ramp
                else:
                    ramp_diff = max_ramp + ramp
                if battery.cap/battery.max_cap < 0.5:
                    req = min(ramp_diff,abs(battery.cap-battery.max_cap*0.5))
                else:
                    req = -min((ramp_diff,abs(battery.cap-
battery.max_cap*0.5)))

            return req

        def pv_ramp():
            req = 0
            ramp = net_load-prev_load
            max_ramp = self.pvcap * self.ramp_threshold + abs(load_ramp)
            if abs(ramp) > max_ramp:
                if ramp < 0:
                    req = max_ramp + ramp
                else:
                    req = ramp - max_ramp
```

```
            elif abs(battery.cap / battery.max_cap - 0.5) > 0.1:
                if ramp > 0:
                    ramp_diff = max_ramp - ramp
                else:
                    ramp_diff = max_ramp + ramp
                if battery.cap / battery.max_cap < 0.5:
                    req = min(battery.max_chg*self.timestep,ramp_diff,
abs(battery.cap - battery.max_cap * 0.5))
                else:
                    req = -min(battery.max_dis*self.timestep,ramp_diff,
abs(battery.cap - battery.max_cap * 0.5))

            return req


        mapper = {
            'Simple': simple,
            'Arb': tou_simple,
            'AltArb': simple_alt,
            'TOUSelf': tou_self,
            'AltSelf': self_alt,
            'Ramp': ramp_control,
            'PVRamp' : pv_ramp
        }
        func = mapper[self.mode]

        energy_req = func()
        if energy_req <= 0:
            return [energy_req, -
1*battery.discharge(energy=energy_req,time=self.timestep)]
        else:
            return [energy_req,
battery.charge(energy=energy_req,time=self.timestep)]
```

Appendix F: Additional Code Used to Support Model

```
"""
Odds and ends for data processing and getting useful stuff
"""

import pandas as pd,numpy as np
from pathshortcuts import modelpath

def choose_dates(time_series_one,time_series_two,length=365,mode='Min'):
    # Take the most recent number of days
    def recent():
        date_max = min(time_series_one.index[-1],time_series_two.index[-1])
        date_min = date_max - pd.DateOffset(days=length) + 
pd.DateOffset(minutes=5)
        return [date_min.strftime('%Y%m%d %H:%M'), date_max.strftime('%Y%m%d 
%H:%M')]

    def minimize_zeros():
        date_max = min(time_series_one.index[-1],time_series_two.index[-1])
        date_min = max(time_series_one.index[0],time_series_two.index[0])
        check_frame = 
pd.DataFrame(index=pd.date_range(date_min,date_max,freq='5T'))
        check_frame = 
check_frame.join(time_series_one.join(time_series_two,how='outer'),
                                        how='left').fillna(0)
        check_frame['Zero'] = (check_frame[check_frame.columns[0]] != 0) & \
            (check_frame[check_frame.columns[1]] != 0)
        check_frame['Sum'] = 
check_frame['Zero'].rolling(length*24*12).sum().shift(-length*24*12)
        check_max = check_frame['Sum'].max()
        date_min = check_frame[check_frame['Sum'] == check_max].index.max()
        date_max = date_min + pd.DateOffset(days=length) - 
pd.DateOffset(minutes=5)
        return [date_min.strftime('%Y%m%d %H:%M'), date_max.strftime('%Y%m%d 
%H:%M')]

    mode_select = {
        'Recent': recent,
        'Min': minimize_zeros
    }

    mode = mode_select[mode]
    date_range = mode()

    return date_range

def hourofyear(dates):
    if isinstance(dates, pd.Timestamp):
        doy = dates.dayofyear
        hoy = (doy-1)*24 + dates.hour
    else:
        doy = dates.dt.dayofyear
        hoy = (doy-1)*24 + dates.dt.hour

    return hoy

def getmatchingsolar(home):
    home_list = pd.read_csv(modelpath()+'generatedFiles/ENS Data 
Length.txt',index_col=0)
    pv_frame = pd.read_csv(modelpath()+'generatedFiles/Solar Data 
Timespans.csv',index_col=0)
```

```
    min_start = pd.to_datetime(home_list['End'][home]) - pd.Timedelta(days=365)

    pv_list = []
    for pv_row in pv_frame.itertuples():
        if pd.to_datetime(pv_row.Start) < min_start:
            pv_list.append(pv_row[0])

    return pv_list

def generate_rates(dates=None,scheme='Flat'):
    def timeofuse():
        structure = pd.DataFrame({'Code': 0}, index=dates)
        weekend_idx = structure.index.weekday.isin([5, 6])
        month_idx = structure.index.month.isin([1, 2, 12])
        peak_idx = structure.index.hour.isin(np.concatenate([np.arange(7, 12),
np.arange(16, 23)]))
        mid_idx = structure.index.hour.isin(np.arange(12, 16))
        low_idx = np.logical_not(peak_idx) & np.logical_not(mid_idx)
        structure.loc[(weekend_idx | low_idx), :] = np.array([0])
        structure.loc[((month_idx & mid_idx) |
            (np.logical_not(month_idx) & (peak_idx | mid_idx))) &
np.logical_not(weekend_idx), :] \
            = np.array([1])
        structure.loc[(month_idx & np.logical_not(weekend_idx) & peak_idx), :]
= np.array([2])

        return structure

    def alternate_tou():
        structure = pd.DataFrame({'Code': 0}, index=dates)
        month_idx = structure.index.month.isin([1, 2, 12])
        peak_idx = structure.index.hour.isin(np.concatenate([np.arange(7, 12),
np.arange(16, 23)]))
        mid_idx = structure.index.hour.isin(np.arange(12, 16))
        low_idx = np.logical_not(peak_idx) & np.logical_not(mid_idx)
        structure.loc[low_idx, :] = np.array([0])
        structure.loc[((month_idx & mid_idx) |
                       (np.logical_not(month_idx) & (peak_idx | mid_idx))), :]
\
            = np.array([1])
        structure.loc[(month_idx  & peak_idx), :] = np.array([2])

        return structure

    def flat():
        structure = pd.DataFrame({'Code': 1}, index=dates)
        return structure

    mapper = {
        'Flat': flat,
        'TOU': timeofuse,
        'AltTOU': alternate_tou,
        'Ramp': flat
    }
    func = mapper[scheme]
    rate_structure = func()

    return rate_structure
```