Multi-stakeholder Control Modelling for Distributed Behind-the-Meter Battery Energy Storage Systems

by

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Submitted in partial fulfilment of the requirements
for the degree of Master of Applied Science

at

Dalhousie University
Halifax, Nova Scotia
December 2021

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Abstract

To support local electricity distribution companies (LDC) develop technically justified and economically efficient energy management strategies, this thesis evaluates traditional single-stakeholder and novel multi-stakeholder battery energy storage system (BESS) control techniques.

An electricity distribution system consisting of three stakeholder categories (residential, commercial, and LDC) was modelled with behind-the-meter energy systems at the residential and commercial facilities. Both systems consist of energy storage, while the residential energy systems also utilize solar photovoltaic (PV) modules. Model architecture and system sizes are maintained while operational strategies and policy scenarios are varied over numerous simulations. Both traditional single-stakeholder and novel multi-stakeholder control strategies were developed to create value by capitalizing on the structure of electricity tariffs. Model simulation results were analyzed to identify the strategy scenarios which provide the greatest value to an individual stakeholder and to all stakeholders combined.

It was found that the monetary value obtainable from behind-the-meter BESS at residential and commercial facilities can be increased by as much as 73% and 42% respectively by implementing a coordinated, multi-stakeholder control regime and evaluating performance at a system level.

List of Abbreviations and Symbols Used

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AC	Alternating Current
AV	Annual Value
BEC	Berwick Electric Commission
BEIS	U.K. Department for Business, Energy & Industrial Strategy
BESS	Battery Energy Storage System
BTM	Behind-the-meter
CCP	Centralized Control Platform
CEA	Constrained Energy Arbitrage
CES	Commercial Energy System
C1°	Commercial Single Stakeholder
C2°	Commercial Multi-Stakeholder
CPS	Commercial Peak Shaving
DC	Direct Current
E	Energy
EA	Energy Arbitrage
ESS	Energy Storage System
HV	High Voltage
KMCC	Kings Mutual Century Center
LDC	Local Distribution Company
LFP	Lithium Iron Phosphate (Chemical Abbreviation: LiFePO4)
NRCan	Natural Resources Canada
NS	Nova Scotia
P	Power
PFC	Power Forward Challenge
PS	Demand Peak Shaving
PV	Photovoltaic
RES	Residential Energy System
R1°	Residential Single Stakeholder
R2°	Residential Multi-Stakeholder
RESL	Dalhousie Renewable Energy Storage Lab
RDG	Renewable Distributed Generation
SO	System Operator
SOE	State of Energy
SPS	Stacked Peak Shaving
t	Timestep
TOU	Time of Use
TAP	Transmission Access Provider
TH	Town Hall
UPS	Utility Peak Shaving

Acknowledgments

I would like to thank my supervisor Dr. Lukas Swan for his ongoing mentorship and for the opportunity to study at his lab. I am thankful for the guidance provided while conducting my thesis research, the opportunity to gain valuable battery system hardware testing experience and his encouragement to build relationships which may advance my career throughout my master's education.

It has been a pleasure to work with the team at RESL. Their inquisitive minds combined with their unique interests and experiences, helped facilitate an excellent learning and working environment for all things renewable energy and energy storage. I would like to thank (in no particular order) Mark, Riley, Chris, Bryan, David. K, David. T, Mitch, and Nat.

This work was made possible by the data collected and shared by the Alba Nova consortium, consisting of Equilibrium Engineering, StorTera and the Town of Berwick. I would especially like to thank members of Equilibrium Engineering: Jeremy Lutes, Tyler Yorke, and Will Marshall; and members of StorTera: Gavin Park, Pas Pallawela, Mihika Pallawela, Scott Ledingham and Katie Inthavong.

I would like to thank my parents and my sister for their support in keeping me fed, caffeinated and sane over the course of my master's journey.

Chapter 1 Introduction

The global share of electricity produced by renewable distributed generation (RDG) sources is rising rapidly, collectively predicted to surpass coal as the largest source of electricity generation by 2025 [1].

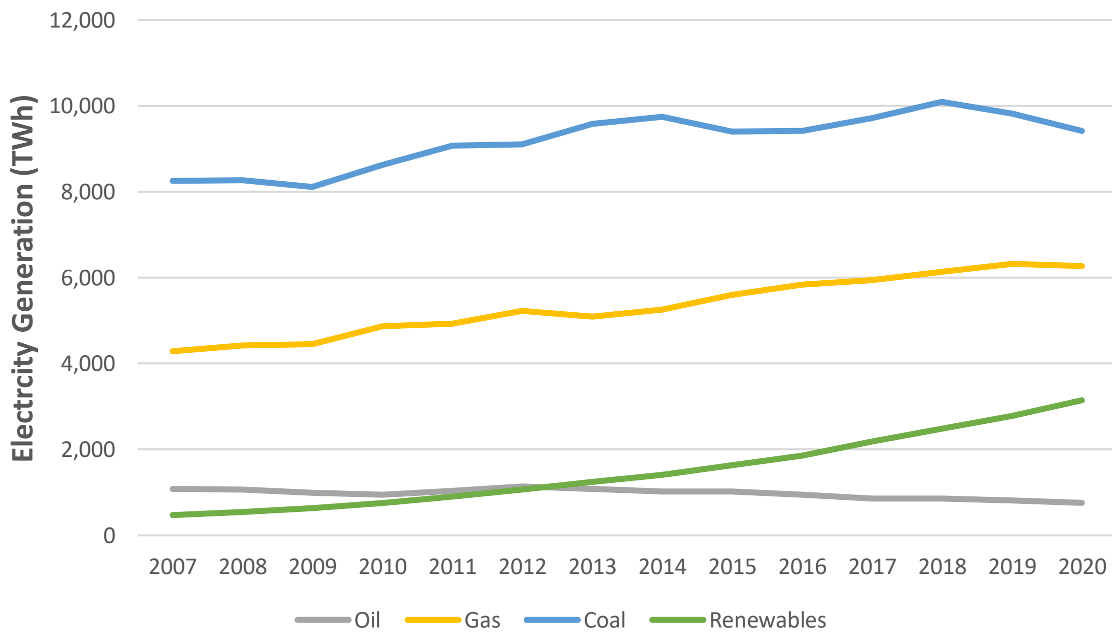


Figure 1. Electricity generation by source from 2007 to 2020 [2]

While some renewable energy projects, such as solar photovoltaic (PV) and onshore wind turbine installs are adopted purely on their ability to provide electricity at competitive rates, the accelerated pace of renewable energy adaptation is additionally motivated by long term temperature and carbon neutrality goals such as the ones set in the 2015 Paris Agreement, and COP 26 conference proceedings, which require displacing large amounts of carbon based energy generation to limit global warming to 1.5 ℃ [2, 3]. In addition to emission reduction policies, born from aforementioned climate concerns, energy security concerns are also driving electricity systems to incorporate increased amounts of renewable electricity [4, 5].

While RDG is increasingly sought after, introducing high levels of renewable generation into existing electrical systems introduces a variety of challenges including reduced system reliability, grid congestion, grid stability issues, increased power reserve requirements and increased ancillary service requirements. These challenges are driven by the intermittent and variable output of renewable generators [6, 7]. Energy storage systems (ESS), such as batteries, are a tool for energy management in high-renewable-penetration power systems, particularly due to the wide range of applications in which they are applicable. Popular uses of ESS include mapping the variable outputs of renewable electricity generators to match system demand, providing capacity reserve, and providing ancillary services. ESS can also be used to manage the extremes of system demand by charging during troughs and discharging during peaks [9].

Despite recent declines in the cost of energy storage, high capital costs continue to be a major obstacle to widespread deployment and single use ESS control is often not financially viable [10]. Control strategies which serve multiple energy storage applications simultaneously can potentially reduce this barrier by taking advantage of multiple revenue streams [11]. The technical and financial complexity of sharing the benefits of an energy storage system between two stakeholders makes it a rare occurrence [12].

1.1 Research Objectives

The focus of this research is the development and evaluation of novel multi-application, multi-stakeholder battery energy storage system (BESS) control strategies. An electricity distribution system consisting of three stakeholder categories (residential, commercial, and utility) is modelled with energy systems installed onsite, behind-the-meter (BTM), at the residential and commercial facilities. The commercial energy systems consist of energy storage, while the residential energy systems consist of energy storage and solar photovoltaic (PV) modules. Multi-stakeholder BESS control, in the context of this thesis, is defined as an operational strategy with the objective function of providing value to an end-user of electricity (either a residential or commercial consumer) and the local distribution company (LDC) which operates the local electricity distribution system. Model architecture and system sizes are maintained while operational strategies and policy scenario are varied over different simulations.

This system model provides insight to the value of residential and commercial BTM-BESS on individual stakeholders (private value) and the system as a whole (system value). By evaluating the private and system values which result from traditional single-stakeholder and novel multi-stakeholder ESS control regimes, this work supports LDC, or other aggregators of load and distributed generation, to develop technically justified and economically efficient energy management strategies and integrated resource plans which involve energy storage. This topic is of particular interest to electric utilities concerned about end-users lessening their reliance on the electricity grid, leaving remaining customers to bear a greater portion of the system costs [13].

The objectives of this thesis are:

1. **Create System Model:** This model will simulate actual operation of distributed BTM-BESS and the resultant impact on the three stakeholder groups (residential, commercial, and utility).
2. **Develop BESS Control Strategies:** Both traditional single-stakeholder and novel multi-stakeholder control strategies are developed, designed to create value by capitalizing on the structure of electricity tariffs.
3. **Private and System Value Analysis:** The model simulation results will be analyzed to determine which strategy scenarios provide the greatest amount of private and system value, and how the generated value is distributed across stakeholder groups. Results will be discussed, and conclusions will be drawn to inform development of potential ESS energy management platforms and business models.

This thesis is organized as follows:

- **Chapter 2:** Fundamental background information
- **Chapter 3:** Literature review focusing on recent work in the field
- **Chapter 4:** Methodologies used to generate results
- **Chapter 5:** An introduction to, and analysis of, the data used to execute the model
- **Chapter 6:** Numeric results, key observations, and analysis and discussion of residential control simulations

- **Chapter 7:** Numeric results, key observations, and analysis and discussion of commercial control simulations
- **Chapter 8:** Summary of conclusion and recommendations for future study

Chapter 2 Background

2.1 Electricity Systems

Electric utilities are organizations which specialize in the generation, distribution, and sale of electricity to commercial, industrial, and residential customers. Depending on the jurisdiction, generation, transmission, and distribution assets may be owned and operated by one or multiple entities. In Nova Scotia (NS), Nova Scotia Power (NSP) is a vertically integrated electric utility, which means they own assets on all levels of the electricity grid. Utility companies which operate and maintain areas of the distribution network are know as local distribution companies (LDC) (also known as distribution system operators (DSO) in other parts of the world). In NS, there are six such LDC in operation, which use NSP as their transmission access provider (TAP). The electrical substation which connects a LDC distribution network to the TAP is known as an intertie. All other distribution networks are owned and operated by NSP. In some electricity markets, such as in Ontario which has over 60 LDC, utility companies do not have distinct jurisdictions and compete with each other.

This section describes the role that utility companies provide with a highlight on challenges faced, and how challenges are exacerbated by increased adoption of RDG. This background information is beneficial when discussing how energy storage systems provide value to electricity systems.

2.1.1 Scheduling and Dispatch

Electricity demand is transient and matching demand with supply is one of the main functions and challenges of electric system operators (SO). Maintenance of the balance of supply and demand requires planning the operational hours of generators ahead of time (scheduling) and controlling generators in real time (dispatch). Historically, electricity demand has been supplied by centralized, large capacity, fossil-fuel based power generation plants such as coal or natural gas fired power plants. These conventional forms of generation, often referred to as dispatchable generation, produce electricity on demand using stockpiled fuels or sources and their outputs can be carefully controlled [14]. Generated electricity is injected into a transmission network at very high voltages where it can travel distances with relatively small power losses. The high voltage transmission network is then transformed to medium and low voltages as it is fed to distribution networks and to end-users respectively.

This centralized, top-down paradigm for electricity generation and distribution is evolving as larger proportions of electricity generation begin to come from RDG, such as onshore wind turbines and PV modules, which can be connected at various voltage levels of distribution networks [14, 15]. While introducing RDG into a distribution system can reduce system carbon emissions and lessen reliance on transmission access providers, the outputs of RDG are highly variable and independent of system demand which makes it difficult for SO to balance the supply of dispatchable generation with the remaining demand for electricity, particularly in systems with high penetration of RDG [8]. Failure to adequately match supply and demand may result in system reliability and stability issues, such as brown or blackouts, particularly on the distribution network [16].

2.1.2 System Peaks

Another challenge of electric utilities is the maintenance of sufficient generation and transmission capacity to meet peak system demand. As the number of end-users with uncontrolled loads in an electricity distribution system grow, so too will the systems peak demand, thus utilities are always concerned with managing peak demand. Often, utilities use smaller capacity generation plants ('peaker' plants) to manage peak demand; however these plants have low utilization factors and disproportionately high costs for the quantity of energy and power delivered, which raises the marginal cost of supply [17]. It is difficult to rely on variable RDG to meet demand peaks and natural gas plants, diesel generators or combined cycle gas turbines are often used [16, 6].

2.1.3 Operational Reserves

In the advent that demand increases sharply or that a generation facility suddenly drops off-line, system operators must have spare capacity that is ready to be brought online to compensate. Surplus capacity maintained for this purpose is referred to as capacity reserve. Spinning reserves represent the amount of additional capacity that can be extracted from a generating asset that is already on-line, which typically has short response times. Due to the quick response times, batteries, are increasingly utilized as spinning reserves. Non-spinning reserves represent capacity from offline generators which could be brought online, if necessary, however with a longer response time associated with system start up. The greater the proportion of variable electricity generation that exists in a power system; the more operating reserve is needed to compensate for potential generation drops. This leads to increased system integration costs [7].

2.1.4 Grid Stability

As mentioned previously, failure to adequately match supply and demand of electricity result in grid stability issues [16]. Grid frequency is an important measure of the balance of electricity supply and demand and must be maintained at the systems nominal value (60 Hz in North America) with tolerances typically below 0.05 Hz. Historically, when a dispatchable generator fails and drops offline, other rotating generators briefly compensate for the loss in power by converting kinetic energy into useful power. This helps maintain system frequency, giving SO time to dispatch operating reserves to balance supply and demand and maintain system stability [18]. RDG interface with the grid through power electronic converters and have little or no inertia. Studies such as [18] and [19] indicates that it is possible to maintain grid frequency in systems with low or no inertia; however, the solutions required increase system complexity.

2.1.5 Cost Recovery and Electricity Pricing Structures

To avoid electric utility companies possessing monopolies and setting unreasonable prices, regulatory authorities regulate the pricing mechanisms used by utilities. A key principle guiding tariff development are that the utilities must be able to fully recover the costs associated with generating and delivering electricity to customers while make enough profit to enable the necessary investments required for the continued provision and improvement of their services. The costs to each customer should be representative of the relative burden that the customer has on the system and determined in a fair and economically efficient manner [5].

Although electricity pricing structures vary across jurisdictions and the world, there is commonality. Electricity tariffs usually incorporate up to three different charges:

1. **Service Charge:** A flat fee paid by customers, implemented to recover the costs of connecting customers to the distribution network. This fee is unaffected by the quantity of energy consumed or unique consumption patterns of a customer [5].
2. **Energy Charge:** A fee paid by customers per unit of energy consumed. This charge is implemented to recover the costs associated with generating and transporting electricity to customers [5].
3. **Demand Charge:** A fee paid by customers per unit of power, applied to the maximum customer demand within a billing period (typically monthly or annually). Demand charges are implemented to recover costs associated with the maintenance and operation of the infrastructure required to provide the system with power during times of maximum demand (peak demand) rather than average demand (as with the energy charge) [17].

Typically, different customer types are offered different electricity tariffs and sometimes, in the case of very large consumers, custom tariffs are designed. Most electricity tariffs, regardless of customer type, include a service charge and an energy charge. Demand charges generally only apply to customers who have large electrical power requirements such as commercial and industrial customers. Residential consumers are not considered sophisticated customers, and it is often assumed they will be less likely to change their consumption dynamics to adapt to demand charges. As an alternative to demand charges for residential customers, utilities may offer tariffs that have multiple pricing tiers for different times of day, which is known as a time-of-use (TOU) tariff. In a TOU tariff, the price per unit of electricity is decreased for periods of low demand and increased for periods of high demand, which incentivizes ratepayers to shift electricity consumption away from times of high system demand which helps relieve stress on the system [4, 16].

TAP often treat LDC customers similarly to a large commercial or industrial customer, with tariffs that include both an energy charge and a demand charge. With large customers such as LDC, TAP may apply a ratcheted demand charge. When subjected to a ratcheted demand charge, the electricity customer will typically continue to pay a demand charge each month, however instead of the demand charge being applied to the maximum demand for the current month, it is applied to the greater of maximum demand of the current month or the maximum demand which occurred in the most recent ratcheted demand period, which typically span two or more months. The ratcheted demand period is set to encompass the period in which the TAP experiences its greatest system demand. In winter peaking systems (which are typical in cold climates due to high heating loads), the ratcheted demand period will encompass the winter months such as from the start of December to the end of February. As with non-ratcheted demand charges, the intention of the TAP is to recover costs associated with maintaining and operating the infrastructure necessary to meet demand peaks; however, ratcheted charges place more emphasis on the costs associated with meeting the annual system demand peak, which can be very capitally intensive. LDC purchase electricity from a TAP and resell to customers on their distribution network. The LDC can set its own electricity tariffs (in compliance with regulatory bodies) which it applies to its customers. To ensure cost recovery, the LDC will typically offer their customers energy charges equal to the TAP energy charge plus a profit margin, as well as applying their own demand charges to commercial and industrial customers.

A significant portion of the costs recovered by electric utilities comes from energy charges, leaving them vulnerable to BTM RDG, such as rooftop PV, which cause declines in demand for electricity from utility owned assets. Utilities have a large amount of fixed costs, such as costs associated with maintaining generation capacity and transmission capacity; if electricity demand falls, utilities may be forced to increase the cost of electricity to recover sufficient revenue to maintain their infrastructure. By increasing electricity prices, rate payers who have not deployed RDG are left to bear an increased portion of the utility’s expenses and are further incentivized to pursue RDG deployment of their own or grid defection. This creates a positive feedback loop referred to as a utility death spiral [4, 16]. Renewable energy subsidies and policies such as net-metering agreements, which value the grid exports of electricity generated BTM, may exacerbate this issue [20]. While some authors argue that the possibility of utility death spirals is greatly exaggerated [21], there is legitimate concern with regard to how a rapid increase in RDG may impact the legacy business model of electric utilities.

2.2 Energy Storage Applications

Energy storage system (ESS) technologies can serve a wide number of applications. A study conducted by the Sandia National Laboratories for the United States Department of Energy identified 17 grid-related electric energy storage applications which apply to different stages of the grid from generation, transmission, distribution to end-use [12]. As discussed in the preceding section, increased deployment of RDG in distribution networks generates a portfolio of challenges to SO, resulting in an increased need for active energy management at the local and distribution level [3]. As such, this thesis examines BESS applications which apply at the distribution and end-use consumer level.

Pricing signals passed from the TAP to the LDC, and from the LDC to end-use customers, such as demand charges and TOU tariffs, exist to incentivize customers to alter their demand in ways that lower their impact on the system and lower overall system costs [22]. At the same time, end-use customers can purchase their own RDG, lessening their reliance on utilities altogether. This thesis examines three BESS applications, the first two were developed to take advantage of TOU and demand charge tariffs, respectively, while the third was developed to maximize the value of a BTM PV system.

1. **Energy Arbitrage (EA):** Reducing energy charge costs by purchasing and storing electricity during the low-pricing period of a TOU electricity tariff for use or sale during the tariffs high-pricing period. This application is available to residential customers with bi-directional energy meters on TOU tariffs.
2. **Demand Peak Shaving (PS):** Reducing demand charge costs by discharging electricity from storage at strategic times to decrease a building's maximum net power draw over a billing period. This application is available to commercial and LDC customers.
3. **PV Self Consumption (SC):** Reducing energy charge costs by maximizing the amount of BTM PV electricity generation that gets consumed BTM. This practice

maximizes the value of PV systems in policy environments which do not value grid exports. This application is available to residential customers with BTM PV systems, particularly those in policy environments which do not offer net-metering agreements.

Note that the energy arbitrage and demand peak shaving applications are enabled by electricity tariffs which are designed to pass system costs to consumers thus would not be expected to have adverse negative repercussions on the utility business model, although studies such as [23] found that traditional electricity tariffs become more inefficient as the amount of distributed energy resources (sch as RDG and BESS) increases. The PV self consumption application is more likely to negatively impact utilities as it will decrease residential demand for utility electricity.

Chapter 3 Literature Review

In this chapter an overview of academic literature which is relevant to the work conducted in this thesis is provided. The focus points of this literature review are:

- BESS demand peak shaving control algorithms and techniques
- BESS application stacking:
    - BESS application stacking theory
    - Proposed BESS application stacking algorithms and techniques

The findings presented in these studies helped guide this work and provide a point of comparison for the results obtained from this work.

3.1 Energy Storage Demand Peak Shaving

Many studies have investigated ways to optimally conduct demand peak shaving with BESS [17]. Conventional approaches to demand peak shaving involve setting a fixed power threshold (peak shaving threshold). If load exceeds the threshold, a battery discharge is triggered to displace the excess loads, and if load falls below the threshold, the battery is allowed to charge, unless it cannot do so without causing the threshold to be exceeded [24]. It has been shown that electricity peaks are highly variable by time of year and that by simply setting individual thresholds for different seasons, value can be increase by as much as 8% [25]. This alludes to the potential for a dynamic peak shaving threshold, which is set and adjusted in the context of the current time of year, to further increase value.

Rahimi et al. [26] present a method for dynamically setting a peak shaving threshold using load forecasting and a novel control algorithm. At the beginning of each hour, load is forecasted for the upcoming 24-hour period at a one-hour resolution. The peak shaving threshold is then set as the average load of the 24-hour forecast. A battery charge or discharge command is then calculated to maintain the load at the peak shaving threshold which the battery holds for one-hour. After the hour, a new 24-hour load forecast is performed, and the process repeats. The result is a ‘sliding’ 24-hour window of forecasted load data which continuously adjusts the peak shaving threshold to account for expected loads. To allow tuning of the model, a utilization factor was introduced. The utilization factor is a number between zero and one which gets multiplied by the charge and discharge commands before they get sent to the battery (e.g. with a utilization factor of 0.5, if load exceeds the threshold by 10 kW, the battery is discharge at 5 kW). The control was tested on an Institute of Electrical and Electronics Engineers distribution feeder model and a maximum peak reduction of 9% was observed, which was 75% of the maximum theoretically possible reduction considering the converter size modelled. The method presented in this study was proven to be effective; however, required extensive load forecasting capabilities unlikely to be possessed by potential adaptors outside of the utility stakeholder group. Furthermore, the control was only tested over a one-week period, which is insufficient to properly test the method's ability to account for normal week to week variation, much less the large seasonal impacts on electricity consumption. This thesis will utilize a full year of data to evaluate developed controls strategies, ensuring that seasonal effects are accounted for.

Barzkar et al. [27] developed and evaluated a method for dynamically adjusting the peak shaving threshold, which does not rely on load forecasting. In their proposed algorithm, the peak shaving threshold is set to the average load that has occurred within the previous 24-hours. To accomplish this, a trailing data set is continuously adjusted such that it contains only the most recent data; in this study, which utilized ten-minute data, the trailing dataset consisted of the most recent 144 data points. At each timestep, the average load of the trailing data set is calculated and applied as the threshold. This dynamic algorithm was simulated and evaluated through comparison to a solution which was obtained via a shortest path optimization algorithm. The results obtained though an optimization algorithm will inherently overpredict the capabilities of a system operating dynamically in real time. The dynamic and optimized scenarios were simulated using a variety of input load profiles from different building types. The dynamic algorithm was concluded to be a success due to its ability to achieve similar demand reductions to the optimized solution. The dynamic algorithm was found to achieve demand peak reductions 10%, 1% and 4% less than the optimized solution when applied to a residential, hotel and office building load profile respectively. A major shortcoming of this analysis is that the lengths of the tested data profiles were all less than a month.

3.2 Combining Energy Storage Applications

The International Energy Agency's Renewable Energy Technology Development collaboration programme (IEA-RETD), facilitated a scoping study of policy considerations for energy storage, authored by Hart et al. [10]. This study introduces the changing requirements of electricity grids and the need for flexibility as the proportion of RDG increases; energy storage technologies are presented as a tool for providing flexibility. The importance of policies which allow the services of energy storage to be monetized is highlighted, and it is explained that energy storage systems often need to tap into multiple value streams by combining (or 'stacking') applications to reach commercial viability. Hart et al. explain that some of the value provided by energy storage is "hidden value" which is not, or is not properly, valued in the current state of electricity markets. This hidden value includes environmental benefits from avoided power plant emissions, ability to defer grid investments, and ability to improve power quality. The study suggests that the value of energy storage systems must be considered from a system perspective and value streams which are often reserved for only system operators should be made available to other actors in the market. In accordance with recommendations from this study, this thesis takes a system perspective in evaluating energy storage and investigates scenarios in which BESS stack applications serving separate stakeholder groups.

Numerous researchers have used models to evaluate the potential of combining various ESS applications. Englberger et al. [28] explore three different methods of combining ESS applications, sequential, parallel and dynamic stacking. In sequential stacking, the ESS allocates itself to only one application at a time, however at each timestep the application can be changed. In parallel stacking, a fixed portion of the ESS energy capacity is dedicated to a single application and multiple applications are served simultaneously. In dynamic stacking, multiple applications are served simultaneously but the amount of energy capacity dedicated to a given application is variable. Dynamic stacking requires external control to dictate the amount of energy capacity to dedicate to a given application at any time. To contrast the performance of the various stacking types, Englberger et al. modelled a BESS and simulated various stacked control scenarios, consisting of different combinations of the self consumption, frequency reserve, and peak shaving applications. Each stacked control scenario was simulated using sequential, parallel, and dynamic stacking using a mixed-integer linear programming solver to optimize the solution. It was found that dynamic stacking consistently provided the highest value, followed by sequential stacking and lastly parallel stacking. These findings suggest that dividing an ESS energy capacity into portions, which each serve a separate application is inefficient and focusing on one application at a time while switching between applications, provides more value. When the amount of energy capacity dedicated to an application can be adjusted in real-time, serving simultaneous applications becomes significantly more efficient and generates more value than switching between single applications. These findings provided key insight into how to efficiently combine ESS applications and the principles of sequential, parallel, and dynamic stacking guided the multi-application control strategy development of this thesis.

Many of the multi-application ESS scenarios in the literature involve a community energy storage system. Lombardu et al. [29] developed a community energy storage model for benefit sharing in a commercial and industrial environment. The system model used in this study was developed to represent a centralized storage system installed in a commercial or industrial business park providing a variety of customers with peak shaving, PV self consumption and adherence to the day-ahead market. Input data profiles were used from 2 commercial sites (one with 80 kW rooftop solar), one industrial facility, a 1 MW solar park and an 11 MW wind park. Note that the solar and wind park are separate stakeholders, both participating in the day-ahead energy market. The applications were first simulated without sharing to provide a point of reference. Next a shared scenario was modelled in which the energy storage operation was dictated by an application hierarchy. At each timestep the model evaluated the opportunity to conduct each application and selected the most profitable of the applications as determined by the results of the single application simulations (a.k.a sequential stacking). Lombardu et al. discovered that it was necessary to implement a capacity reservation for the industrial facility to ensure that enough energy was available for peak shaving during its peak demand hours. This was done by prohibiting discharge and favouring charging applications for the hours directly preceding the industrial peak demand period. By implementing this measure, the maximum system benefit was obtained.

Ultimately, it was found that the combined application scenario generated almost double the value of the single application scenarios. A major take away from this study is the challenge associated with combining demand peak shaving with other applications. Abandoning a site's peak shaving threshold for any period, which would occur in sequential stacking, may set a new site demand peak and negate demand charge savings for the whole billing period. This implies that peak shaving cannot be combined with other applications sequentially without additional system intervention such as the capacity reservation method implemented by Lombardu et al. The capacity reservation method used in this study could be considered as a form of dynamic stacking as an amount of capacity is reserved for a specific application, but this amount of capacity is variable. This study also highlights the large potential for increasing the value of ESS by servicing multiple applications for multiple stakeholders in the industrial and commercial sectors.

Parra et al. [11] studied the impact of combining residential energy storage applications, considering PV self-consumption, demand load shifting, PV curtailment avoidance and residential peak demand shaving. Each application was simulated individually, and then each possible combination of two applications was simulated using a simulation-based optimisation method. Demand profiles measured from 100 homes, all from the same community in London UK, and simulated PV generation data were used as model inputs. The PV generation data was simulated using irradiance and temperature data measured near the community. Combining the ESS applications increased system profitability in each scenario when compared to single-use scenarios, resulting in net present values per unit of capital expenditure as high as 0.21. No attempt was made to quantify the impact of the 100 distributed PV with ESS on the upstream grid stakeholders such as the LDC. Additionally, no scenarios were explored in which the residential ESS provided a service for another stakeholder group. Despite this article's focus solely on the residential stakeholder group, establishing that the value of residential ESS can be increased through application stacking in a single-stakeholder scenario alludes to the potential for multi-stakeholder stacking scenarios.

Schram et al. [30] studied the potential of using distributed residential batteries, which were optimally sized for PV self consumption, to provide coordinated neighbourhood peak shaving in the Netherlands. A simulation model was developed which was tested using very high-resolution data with timesteps of 10 s. Three single application scenarios were simulated, residential PV self consumption, a heuristic neighbourhood peak shaving algorithm (fixed charge and discharge windows), and a 'perfect forecast' neighbourhood peak shaving algorithm. They found that, for the homes examined, the distribution of optimal storage size for PV self consumption was normally distributed with a median of 3.5 kWh. A net present value above zero was found for 70% of the homes operating on PV self consumption. When the heuristic and perfect forecast peak shaving algorithms were conducted, neighbourhood demand peaks were reduced by 22% and 51% respectively. Peak shaving benefits were only reported as percent reductions with no attempt to apply economic value. Although their study did not directly investigate combining applications, Schram et al. illustrated the potential of aggregating BTM residential BESS systems for use in applications other than for what they were sized, which has large implications. In addition, the added benefit of 'smart' controls was emphasised with the perfect foresight scenario increasing peak shaving potential by almost 30% when compared to the simple rule-based heuristic scenario. This study could be extended by investigating methods which could sequentially switch the objective function of the BESS between the two applications (PV self consumption and neighbourhood peak shaving).

Stephan et al. [31] developed a techno-economic model of lithium-ion storage to assess the attractiveness of battery investment for single applications and various combinations of applications. Applications were selected which are typically reserved for separate stakeholder types, including, industrial/commercial peak shaving, residential PV self consumption, and utility applications including grid investment deferral, frequency regulation, secondary reserve capacity and tertiary reserve capacity. When stacking applications, each application was deemed either 'primary' or 'secondary', with the secondary application only being provided while the primary application was idle. They found that combining applications can significantly increase system benefit with the largest synergy found between end consumer energy arbitrage paired with frequency regulation, and transmission and distribution investment deferral paired with frequency regulation. While net present values of the batteries were presented under the various scenarios, little discussion was given to how the value was distributed across stakeholders. Additionally, the impact of end user savings on LDC revenue was not analyzed and neglected in net-present value calculation.

3.3 Summary

The literature on optimal operation of BESS for demand peak shaving emphasises the importance of dynamic peak shaving thresholds and presents a variety of methods which utilize load forecasting or trailing data sets to adjust a threshold dynamically. It has been shown that a simple and effective method for adjusting a dynamic peak shaving threshold involves recording a trailing data set of historic timestep load data and setting the threshold to the average of the trailing data. No work was found on an ESS control algorithm which defends more than one peak shaving threshold simultaneously.

The literature on combining ESS applications emphasises the importance of evaluating the ESS at a system level and the potential inherent in allowing distributed BTM ESS to serve applications typically reserved for utility companies. The literature justifies three methods used to combine ESS applications, sequentially, parallel, and dynamic stacking. Study findings suggest that parallel and sequential stacking of peak shaving is often ineffective and stacking peak shaving requires a dynamic approach. It has been shown that the value of BTM ESS can be increased via stacking and that coordinating BTM ESS can be used to create value for upstream grid stakeholders such as LDC.

While there are a variety of academic articles which study combining ESS applications, there are clear gaps in the literature with respect to multi-stakeholder control of ESS:

- Most studies rely on optimization algorithms to calculate the theoretical value potential of combining application, while failing to offer ESS control strategies which would facilitate the combining of applications in practice.
- Few studies take a systems approach to evaluating ESS, quantifying value to single stakeholders, neglecting the impact on other stakeholders such as LDC.

- The stacking of peak shaving for two stakeholders (peak shaving stacked with peak shaving) has yet to be adequately described in the literature.
- Stacked control strategies propose in the literature tend to be tested on short periods of data, neglecting large seasonal variations in demand.

This thesis contributes to the literature by developing and evaluating multi-stakeholder ESS controls strategies using a system approach and a full year of real-world load data, PV generation data and electricity tariffs.

Chapter 4 Methods

This chapter presents the methods used to evaluate the private and system value of distributed BTM residential and commercial energy systems under single-stakeholder and multi-stakeholder control regimes.

The contents of this chapter are as follows:

- **Section 4.1:** Development of a system model comprised of residential, commercial, and LDC entities using the MATLAB programming platform.
- **Section 4.2:** Development of single stakeholder control strategies for the residential energy systems
- **Section 4.3:** Development of single stakeholder control strategies for the commercial energy systems
- **Section 4.4:** Development of multi-stakeholder control strategies for the residential and commercial energy systems
- **Section 4.5:** Metrics used to evaluate the economic value of the various control scenarios
- **Section 4.6:** Additional performance metrics

4.1 Model Development

A system model containing interconnected components and subcomponents was developed. The system model components comprise of:

- **A local distribution company (LDC):** consisting of load and net load profiles and residential and commercial subcomponents
- **Residential energy systems (RES):** consisting of load, PV generation, BESS power and BESS energy profiles
- **Commercial energy systems (CES):** consisting of load, BESS power and BESS energy profiles
- **A cloud-based, centralized control platform (CCP):** Which connects all system components, allowing data sets to be shared and system control to be coordinated

These system components are interconnected as shown in Figure 2, and their various sub-components are detailed in the following sections.

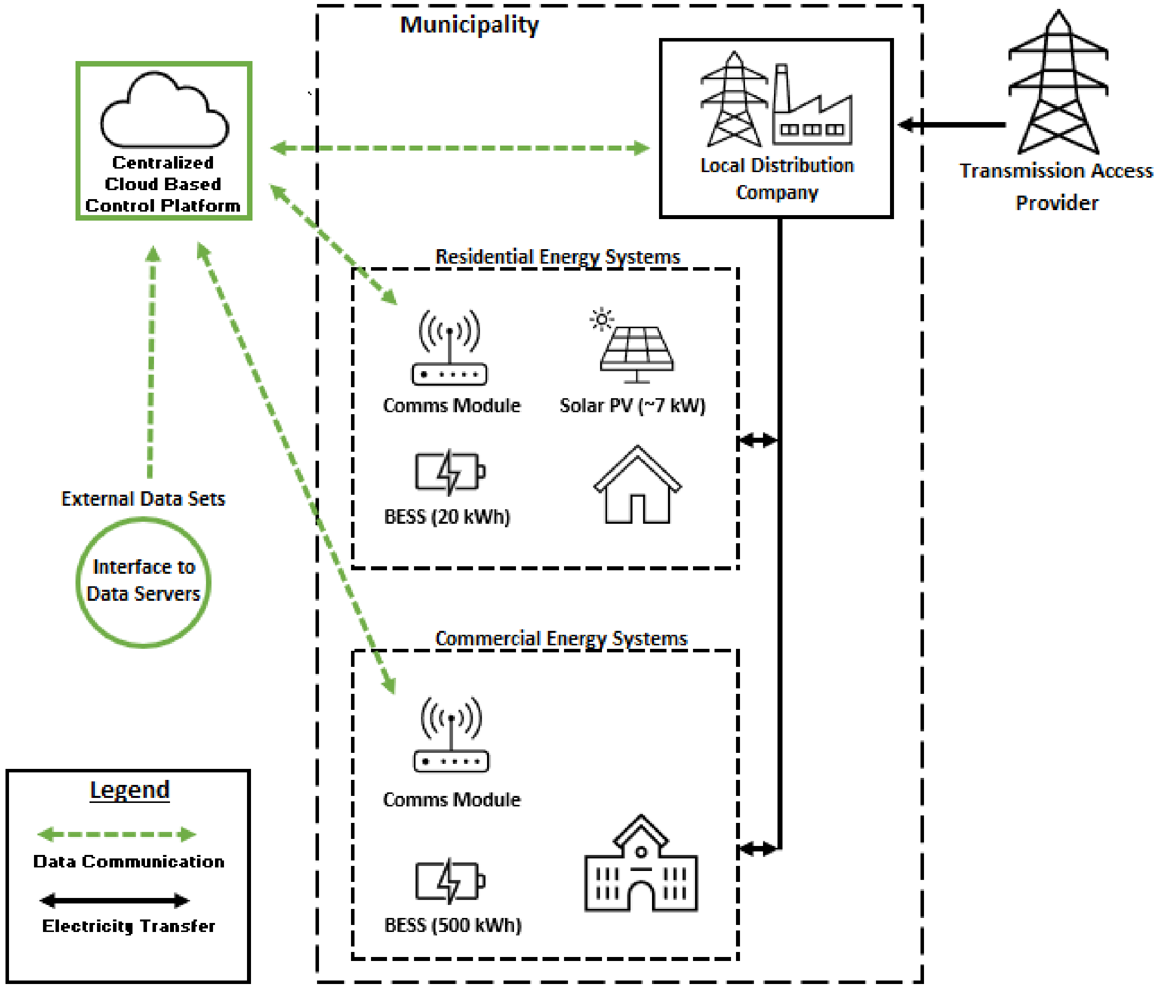


Figure 2. System model architecture

4.1.1 Local Distribution Company

The LDC is the highest-level system component and was modelled using two timestep data profiles.

1. **LDC load:** An input profile, measured and recorded at the intertie between a LDC and their TAP, which represents the combined loads of all customers on the LDC distribution network.

2. **LDC net-load:** An output profile, which is initially identical to LDC load but is dynamically updated by interactions with model sub-components.

Differences between the original LDC load and the resulting LDC net-load are used to quantify the impact that the lower-level model components have on the LDC. LDC load is also used as an input profile to inform the operation of some of the developed control strategies. A diagram showing how the LDC interacts with other model components is shown in Figure 3.

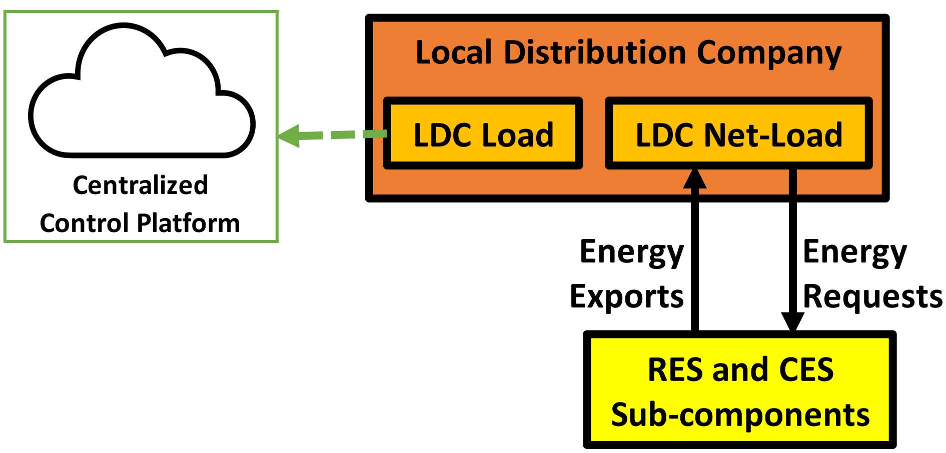


Figure 3. Local Distribution Company interaction with other model components

4.1.2 Residential Energy System

A residential energy system (RES), consisting of BTM-BESS and PV, was developed. A simplified schematic showing RES configuration is shown in Figure 4.

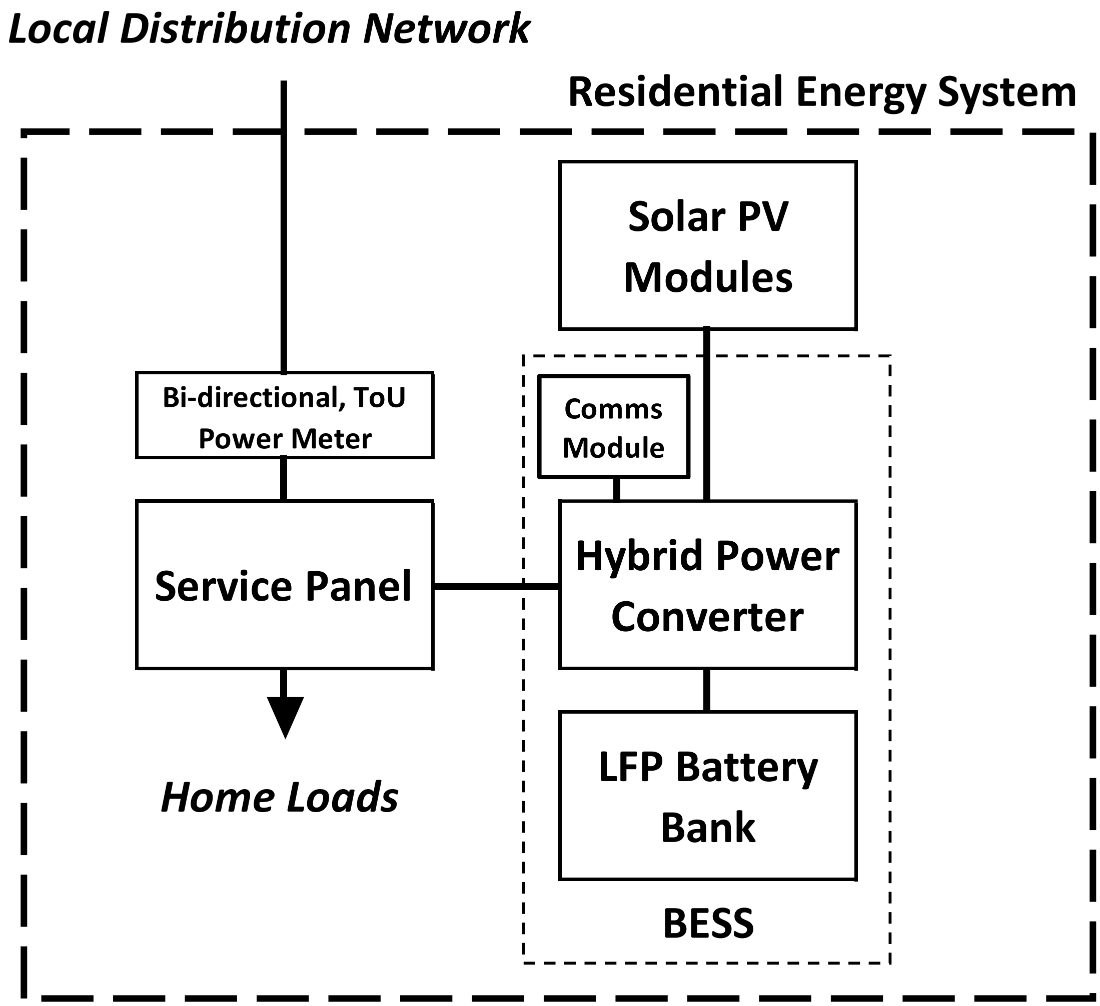
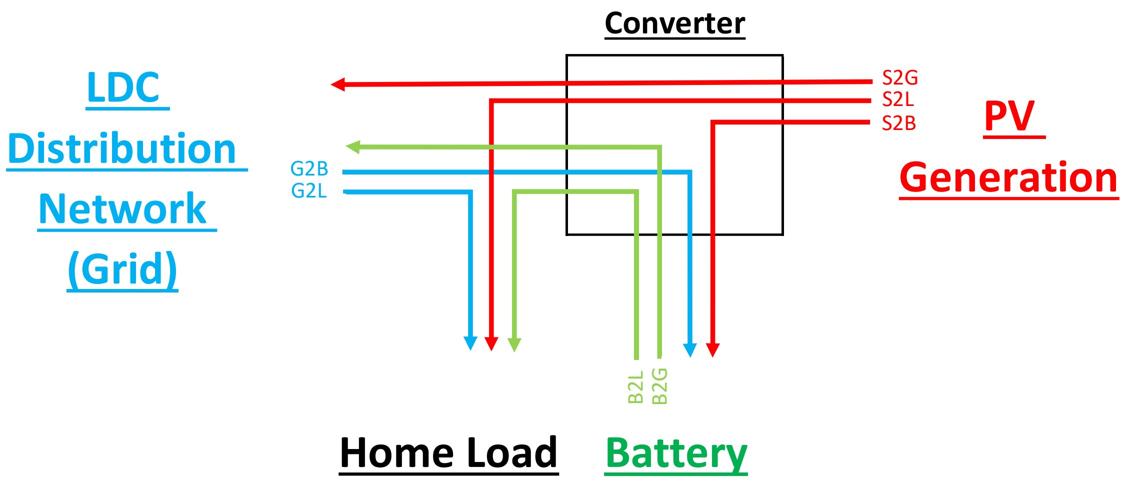


Figure 4. Simplified diagram of residential energy system configuration

The RES shown above was modelled and requires two input timestep data profiles.

1. **Home electrical load:** measured at a home's electric utility service entrance
2. **PV Generation:** measured on the DC side of a PV system

The RES model utilizes the home load and PV generation input profiles to execute rule-based control strategies and generate seven different output power profiles. Each output power profile represents one of seven possible paths that electrical power can travel through the RES, from source (grid, battery, or PV) to destination (load, battery, or grid). A diagram showing the seven output power profiles and the nomenclature used to describe them is shown in Figure 5.



Where:

S2G = Solar to Grid
S2L = Solar to Load
S2B = Solar to Battey
G2B = Grid to Battey
G2L = Grid to Load
B2L = Battery to Load
B2G = Battery to Grid

Figure 5. RES model output profiles and nomenclature

Note that giving each possible power flow its own individual profile enabled an increased ability to analyse system performance and simplified the calculation of system performance metrics. For example, instead of using one 'battery discharge' profile, there are 'battery to load' and 'battery to grid' profiles; this allows the proportion of discharge which meets loads to be distinguished from battery exports to the grid leading to potentially useful findings.

The seven output power profiles are analysed and used to quantify the value generated to the residential stakeholders. Additionally, any changes to the electricity demand of the residential customers have an equal effect on the LDC electricity demand, thus the relevant power profiles are sent the LDC layer of the model to update the LDC Net-Load accordingly. A diagram showing how the modelled RES interacts with other model components is shown in Figure 6.

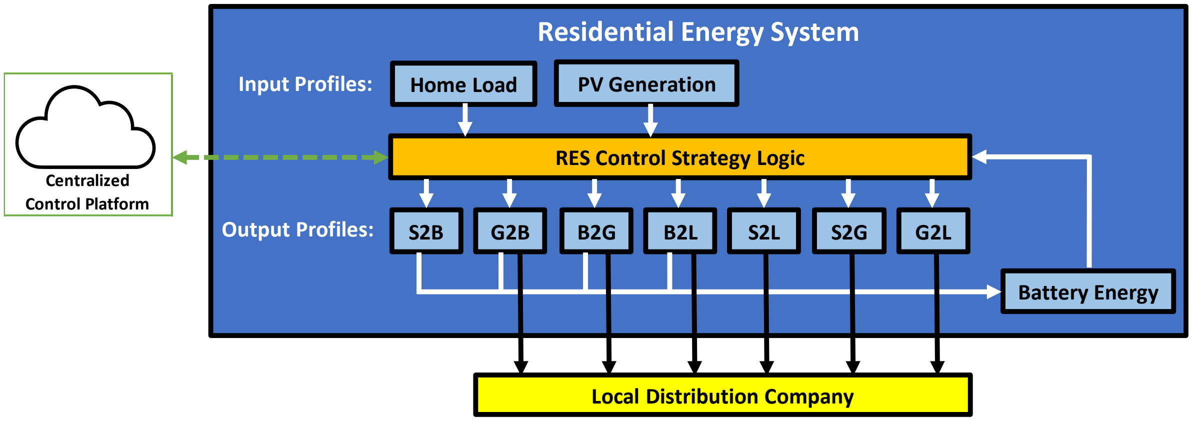


Figure 6. RES model interaction with other model components

All output power profiles are initialized as empty (all zero) column matrices. Generalized equations were developed to calculate and fill the output power profiles vectors. These equations contain shared terms; to improve readability and reduce repetition, all shared terms are first shown in EQ1 through EQ5.

$$Remaining\ Load = Load(t) - B2L(t) - S2L(t) - G2L(t) \tag{1}$$

Where t represents the current timestep and $Remaining\ Load$ represents the amount of household load which has not already been displaced by another source, in kW.

$$Remaining\ Converter\ Capacity = P_{Rated\ Capacity} - B2L(t) - B2G(t) \tag{2}$$

Where $Remaining\ Convert\ Capacity$, represents the available converter capacity in kW and $P_{Rated\ Capacity}$ represents the rated converter capacity in kW.

$$Remaining\ Solar = Solar(t) - \frac{S2G(t)}{n_{S2AC}} - \frac{S2L(t)}{n_{S2AC}} - S2B(t) \tag{3}$$

Where $Remaining\ Solar$ represents the quantity of PV generation which has not already been consumed by an end-use in kW and n_{S2AC} represents the converter efficiency associated with converting PV energy from DC to AC.

$$Remaining\ Charge\ Room = E_{Rated\ Capacity} - \left[E(t) + \left(G2B(t) \times dt \times n_{Charge}\right) + \left(S2B(t) \times dt \times n_{PV\ Charge}\right)\right] \quad (4)$$

Where $Remaining\ Charge\ Room$ represents the additional quantity of energy the battery can absorb, $E_{Rate\ Capacity}$ represents the rated energy capacity of the BESS, E represents the current amount of energy in the BESS, dt represents the timestep resolution of the data, $n_{PV\ Charge}$ represents the converter efficiency associated with converting PV energy to the DC voltage level of the battery modules, and n_{Charge} represents the converter efficiency associated with converting AC power to DC for battery charging.

$$Remaining\ Energy = E_{Rated\ Capacity} - \left[\left(B2L(t) + B2G(t)\right) \times dt \times n_{Discharge}\right] \quad (5)$$

Where $Remaining\ Energy$ represents the quantity of usable energy remaining in the battery and $n_{Discharge}$ represents the converter efficiency associated with converting the battery DC power to AC.

The above terms were used to construct the generalized equations which calculate the RES output profiles, shown in EQ6 through EQ12. Depending on the control strategy utilized, the order of execution of these equations varies (e.g. in a solar-self consumption strategy, S2L power flow is first priority, thus the S2L equation will appear first in the control strategy logic script). In certain strategies, only a portion of these equations are used (e.g. in a solar-self consumption strategy, B2G exports are undesired thus do not appear in the script and remains all zeros).

$$S2L(t) = min\ [(Remaining\ Load)\ (Remaining\ Converter\ Capacity)\ (Remaining\ Solar \times n_{S2AC})] \quad (6)$$

$$S2B(t) = min\ [(Remaining\ Solar)\ (Remaining\ Converter\ Capacity)\ (Remaining\ Charge\ Room)] \quad (7)$$

$$S2G(t) = min\ [(Remaining\ Solar \times n_{S2AC})\ (Remaining\ Converter\ Capacity)] \quad (8)$$

$$B2L(t) = min\ [(Remaining\ Load)\ (Remaining\ Converter\ Capacity)\ (Remaining\ Energy)] \tag{9}$$

$$B2G(t) = min\ [(Remaining\ Converter\ Capacity)\ (Remaining\ Energy)] \tag{10}$$

$$G2B(t) = min\ [(Remaining\ Converter\ Capacity)\ (Remaining\ Charge\ Room)] \tag{11}$$

$$G2L(t) = Remaining\ Load \tag{12}$$

LDC Net Load and RES state of energy (SOE) are updated as show in EQ13 and EQ14 respectively. Note that the residential data sets used in this thesis were obtained from the same jurisdiction as the LDC load profile. As such the LDC Load profile already accounted for meeting the home loads. To obtain the LDC Net Load, any power profile which displaced loads, which would have otherwise been met by the LDC, is subtracted from the original Load profile; the only profile which is added to the equation is the grid to battery profile.

$$LDC\ Net\ Load = LDC\ Load - B2L(t) - B2G(t) - S2L(t) - S2G(t) + G2B(t) \tag{13}$$

$$E(t) = E(t-1) + \left[\left(G2B(t) \times n_{Charge} + S2B(t) \times n_{PV\ Chagre} \right) - \frac{B2L(t) + B2G(t)}{n_{Discharge} \times n_{battery}} \right] \times dt \tag{14}$$

Table 1 contains the input parameters dictating the capabilities of the modelled BTM-BESS+PV system.

Table 1. Residential BESS parameters

Parameter	Description	Value
Maximum Charge Rate	Maximum power (AC) which can be used to charge the battery	5 kW
Maximum Discharge Rate	Maximum power (AC) which the battery can discharge	5 kW
Rated Capacity	The batteries nominal capacity when fully charged	20 kWh
Charge Efficiency	Efficiency of converting AC energy to DC energy for storage in the battery	87 %
Solar Charge Efficiency	Efficiency of converting DC energy from PV to battery voltage for storing in the battery	95 %
Discharge Efficiency	Efficiency of converting DC energy from the battery to AC energy	88 %
Battery Efficiency	Efficiency of battery electrochemistry	96 %
Solar to AC Conversion Efficiency	Efficiency of converting DC energy from the PV modules to AC energy	90 %

4.1.3 Commercial Energy System

A commercial energy system (CES), consisting of BTM-BESS was developed. A simplified schematic showing CES configuration is shown in Figure 7.

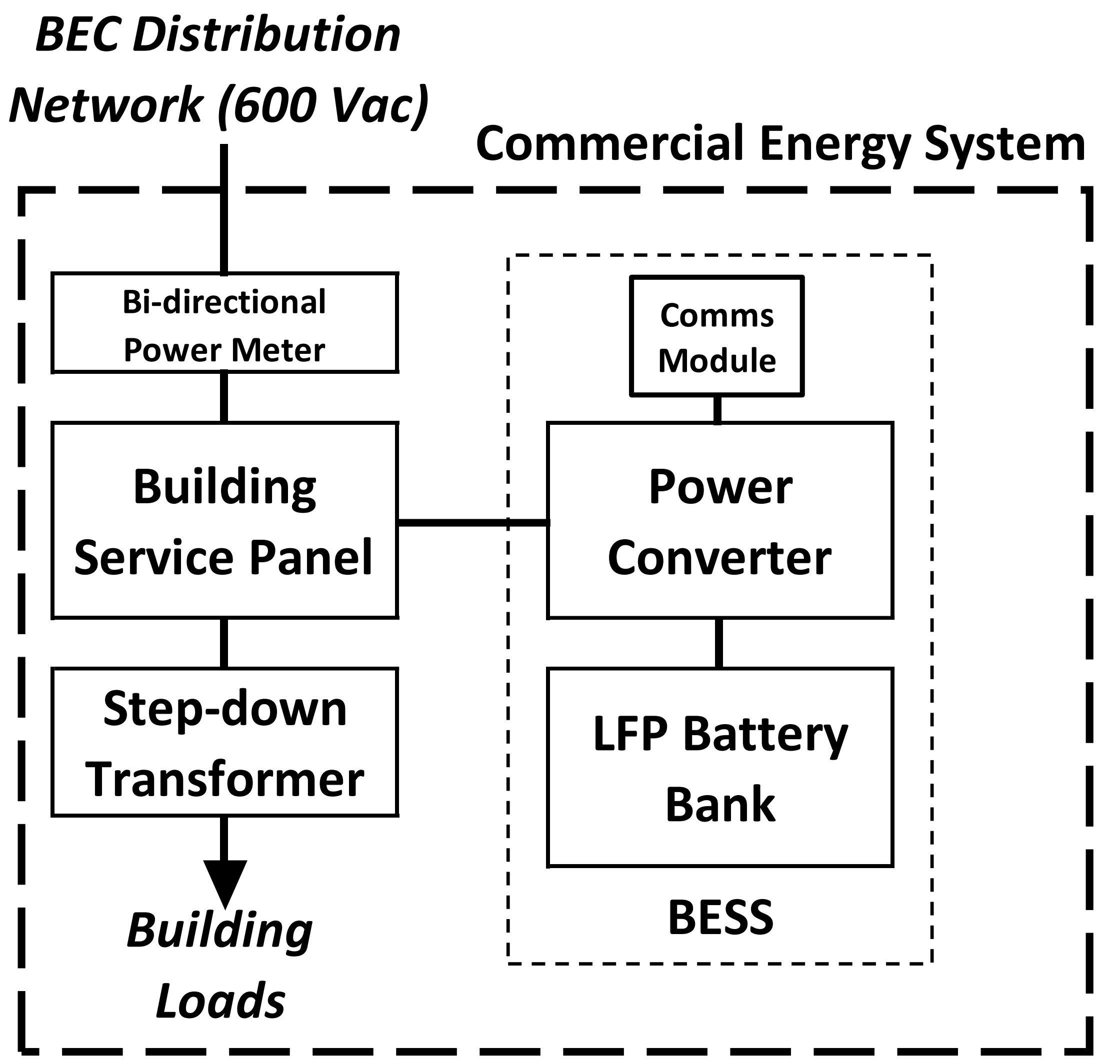


Figure 7. Simplified diagram of commercial energy system configuration

The CES shown above was modelled for each commercial site. The model requires one input timestep building load profile, which should be measured at a building's electric utility service entrance. The CES model utilizes the building load profile to execute rule-based control strategies and to generate four different output power profiles, each corresponding to a different power flow. A diagram showing the seven output profiles and the nomenclature used to describe them is shown in Figure 8.

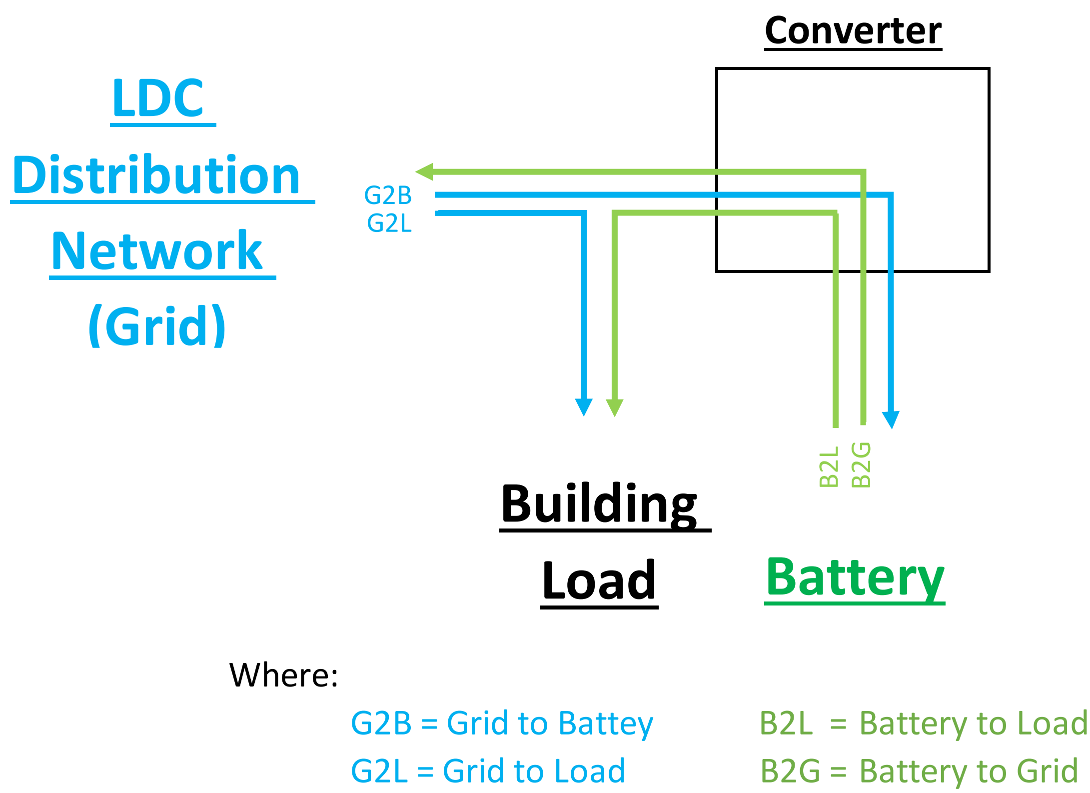


Figure 8. CES model output profiles and nomenclature

The four output power profiles, and the building load input profile, are used to quantify value generated by the commercial stakeholder owning the BTM-BESS. Any changes to the electricity demand of the commercial customers have an equal effect on the LDC electricity demand, thus the relevant power profiles are sent the LDC layer of the model to update the LDC Net-Load accordingly. A diagram showing how the modelled CES interacts with other model components is shown in Figure 9.

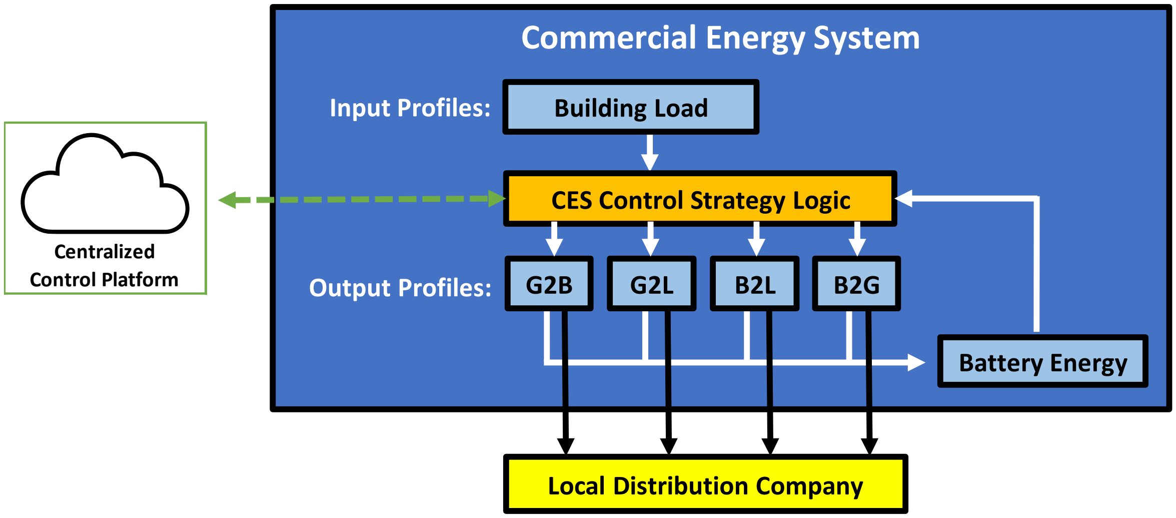


Figure 9. CES model interactions with other model components

As with the RES, generalized equations were developed to calculate the CES output power profiles and are shown in EQ15 through EQ18, where the $Discharge\ Command$ and $Charge\ Command$ terms are operational commands determined by the control strategy, which are explained in later sections. In a multi-stakeholder scenario, these terms may be calculated by the LDC and passed to the CES.

$$B2L(t) = \min\left[(Remaining\ Load)\ (Remaining\ Converter\ Capacity)\ (Remaining\ Energy)\ (Discharge\ Command)\right] \quad (15)$$

$$B2G(t) = \min\left[(Remaining\ Converter\ Capacity)\ (Remaining\ Energy)\right] \quad (16)$$

$$G2B(t) = \min\left[(Remaining\ Converter\ Capacity)\ (Remaining\ Charge\ Room)\ (Discharge\ Command)\right] \quad (17)$$

$$G2L(t) = Remaining\ Load \quad (18)$$

The LDC Net Load and CES SOE are updated as show in EQ19 and EQ20 respectively. Note that the commercial data sets used in this thesis were obtained from the same jurisdiction as the LDC load profile. As such, the LDC Load profile already accounted for meeting the building loads. To obtain the LDC Net Load, any power profile which displaced loads, which would have otherwise been met by the LDC, is subtracted from the original LDC Load profile; the only profile which is added is the grid to battery profile.

$$LDC\ Net\ Load = LDC\ Load - B2L(t) - B2G(t) + G2B(t) \tag{19}$$

$$E_{Capacity}(t) = E_{Capacity}(t) + \left[\left(G2B(t) \times n_{Charge}\right) - \frac{B2L(t) + B2G(t)}{n_{Discharge} \times n_{battery}}\right] \times dt \tag{20}$$

Table 2, contains the input parameters dictating the capabilities of the modelled CES system.

Table 2. Commercial BESS parameters

Parameter	**Description**	**Value Used**
Maximum Charge Rate	Maximum power (AC) which can be used to charge the battery	250 kW
Maximum Discharge Rate	Maximum power (AC) which the battery can discharge	250 kW
Rated Capacity	The batteries nominal capacity when fully charged	500 kWh
Charge Efficiency	Efficiency of converting AC energy to DC energy for storage in the battery	90 %
Discharge Efficiency	Efficiency of converting DC energy from the battery to AC energy	90 %
Battery Efficiency	Efficiency of battery electrochemistry	96 %

4.1.4 Centralized Control Platform

The LDC, RES and CES are all connected to a centralized control platform (CCP). In practice this could be achieved using wireless communication or a wired network connection. Data communication is bi-directional, allowing the CCP to receive data from, and transmit operational commands to, the system components. The specific hardware and software that comprise a CCP are not modelled; however, the CCP is important conceptually as it explains how the RES, CES and LDC share and receive information that dictates operation. Functions enabled by the CCP in this thesis include, LDC load prediction, RES and CES system aggregation, and passing of operational commands (battery charge and discharge) from LDC to CES and RES. These functionalities are explained in more detail throughout this thesis.

4.2 Residential Single-Stakeholder Strategies

Four different residential single-stakeholder (R1°) control strategies were developed:

1. **Energy Arbitrage (EA) Control:** which shifts energy according to the TOU tariff structure at maximum charge and discharge rates
2. **Constrained Energy Arbitrage (CEA) Control:** which shifts energy according to the TOU tariff structure with discharge constrained to avoid battery to grid exports
3. **PV Self-Consumption (SC) Control:** which maximizes solar energy consumed behind the meter by storing excess PV energy and releasing it later to displace home loads
4. **Residential Stacked (RS) Control:** which combines the functionality of CEA and SC Control

The following sections display the logic utilized by each control strategy using flow charts. As explained in section 4.1.2, generalized equations are used to calculate the various power flows of the RES, the order of execution of these generalized equations are shown in brackets within the flowcharts. Recall that these generalized equations ensure that all system constrains such as rated converter capacity and battery energy capacity are abided by.

4.2.1 Energy Arbitrage Control

Under the TOU tariff used in this thesis, explained in more detail in section 4.5.2, there are two cost schemes, a scheme for winter months (Dec – Feb) and non-winter months (Mar-Nov). In the winter TOU scheme, there are three levels of pricing, low-price (off-peak), medium-price (shoulder-peak) and high price (on-peak); in the non-winter months, only the low and medium rate are used. In non-winter months there is one cycling opportunity per day (charge at night, discharge through daily medium price period). In winter months, there are two cycling opportunities per day as a high pricing period follows both the overnight low-price period and a mid-day medium-price period. A flowchart of the EA Control logic is shown in Figure 10.

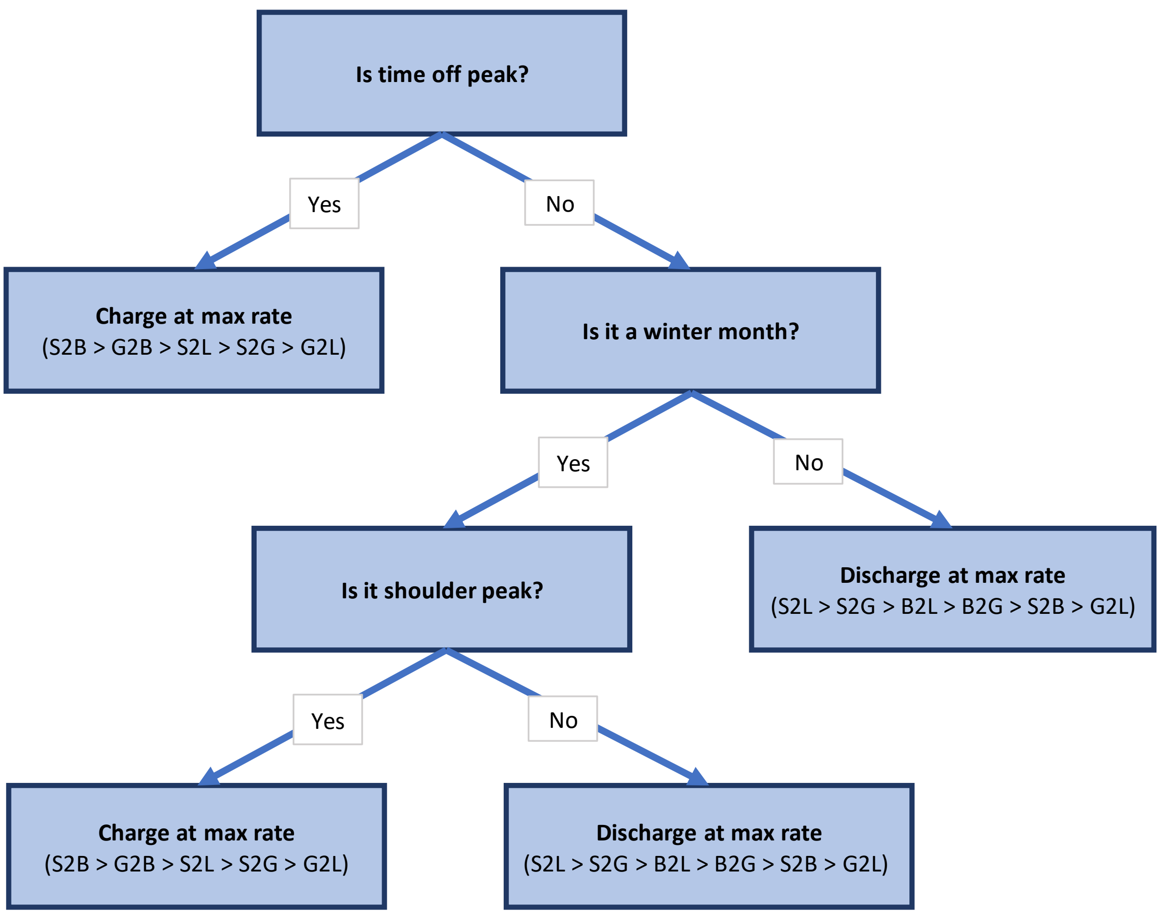


Figure 10. Flow chart representing the Energy Arbitrage control strategy

4.2.2 Constrained Energy Arbitrage Control

Homes on a TOU electricity tariff with no net-metering agreement can still arbitrage energy; however, to avoid wasting energy, battery discharging is constrained by the current household load to avoid discharging to the grid. The strategy logic is similar to that of EA Control except that during on-peak pricing, the B2G term is removed and S2B is prioritized over S2G. A flowchart of the CEA Control logic is shown in Figure 11.

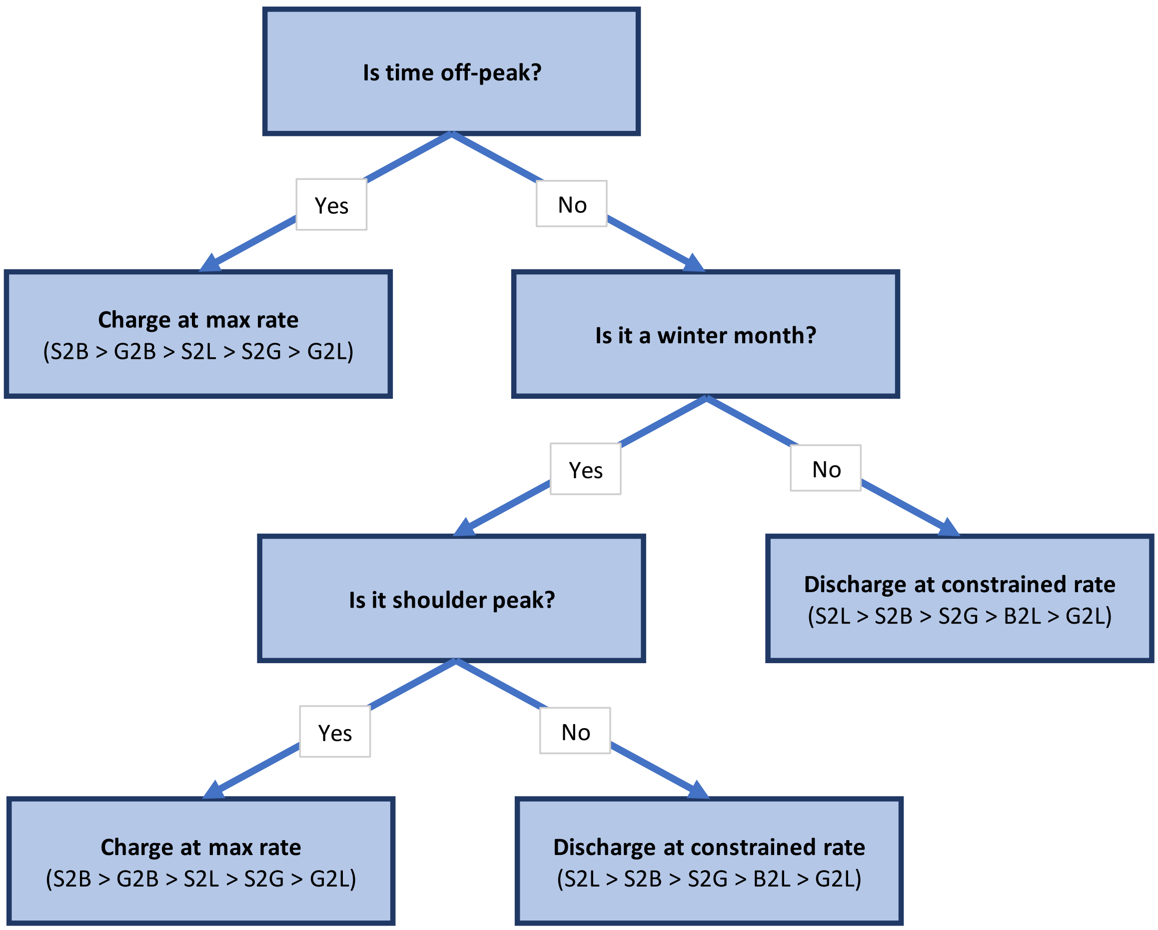


Figure 11. Flow chart representing the Constrained Energy Arbitrage control strategy

4.2.3 Self Consumption Control

The objective of this strategy is to maximize the amount of PV generation self consumed at the residential sites. This strategy maximizes the value of rooftop PV in policy environments which have no net-metering agreement, hence no value for grid exports. When PV generation is greater than load, the battery charges to absorb the excess PV energy; when PV is less than load the battery discharges to displace as much remaining load as possible. A flowchart of the SC Control logic is shown in Figure 12. Note that regardless of whether PV generation is greater or less than load, the strategy logic is the same.

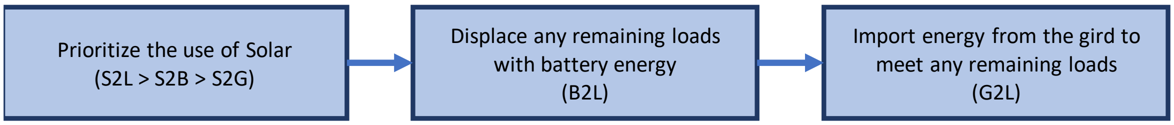


Figure 12. Flow chart representing the Self Consumption control strategy

4.2.4 Residential Stacked Control

Homes on a TOU rate with no net-metering agreement can utilize both the constrained energy arbitrage and PV self consumption battery applications. The residential stacked (RS) control was developed to combine the benefits of constrained energy arbitrage and self consumption into one strategy, by adding an overnight charging window to the SC control algorithm. During this window, the battery will be charged to a target SOE value. The target SOE value is determined by the CCP, which forecasts household demand and PV generation to make its decision. When high loads or low PV generation are predicted, a higher target SOE will be passed to the RES to prioritize energy arbitrage. Conversely when low loads or good PV generation are predicted, a lower target SOE is passed, to limit grid charging and prioritize PV self consumption. During all other times when the system is not in the overnight charging window, power flows are directed based on the pre-set priorities of the SC Control algorithm. A flowchart of the RS Control logic is shown in Figure 13.

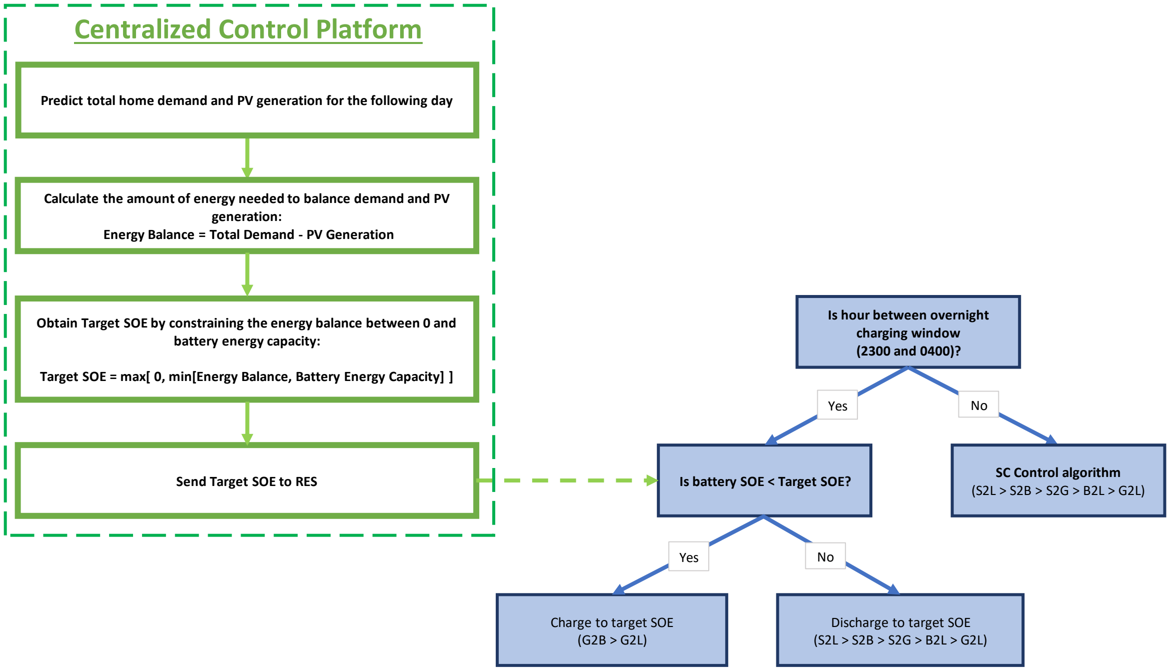


Figure 13. Flow chart representing the Residential Stacked Control

Setting an optimal target SOE value for each overnight charging window requires forecasting the expected household demand and PV generation for the following day. In practice an artificial neural network (ANN) with the correct input data streams (such as weather forecasts, time of year and historic load data) could facilitate this role. To mimic the ability of an ANN to forecast electricity demand and PV generation, the model is provided with known values of daily electricity demand and daily PV generation (both in kWh). This is a generous assumption as ANN predictions are likely to have a degree of error when forecasting daily demand and PV generation. This is not 'perfect forecasting' as the control strategy does not know how demand and PV generation are distributed throughout the daily TOU pricing periods or if the system will run into converter power constraints.

4.3 Commercial Single-Stakeholder Control Strategies

A commercial single-stakeholder (C1°) control strategy was developed, designed purely for the commercial stakeholder group, to mitigate peak demand charges.

4.3.1 Commercial Peak Shaving

The Commercial Peak Shaving (CPS) Control strategy has the objective of minimizing the monthly demand charge costs of the commercial sites through peak demand shaving. CPS Control uses a dynamic peak shaving threshold which is similar to the one presented in [27] and discussed in section 3.2. CPS Control utilizes a trailing data set of four days of load data. With five-minute data, this amounts to 1152 data points. At each timestep, the average of the trailing data set is taken, multiplied by a tuning factor, and applied as the peak shaving threshold. As a precaution, the maximum net load which has occurred each month is also recorded, and if it is higher than the peak shaving threshold, the threshold is overridden with this value. This second term accounts for the case in which a peak shaving threshold has already been exceeded due to a depleted battery, as there is no point defending a threshold which is less than the monthly demand peak which has already been set. The equation used to calculate the dynamic peak shaving threshold is shown in EQ21, where TD is the trailing dataset, y is a tuning factor, and P_{Net} is a dataset containing the net load of the current month.

$$Dynamic\ Commercial\ Threshold = max\left[avg(TD) \times y, \max\left(P_{Net,month}\right)\right] \tag{21}$$

Figure 14 shows an example of the dynamic threshold.

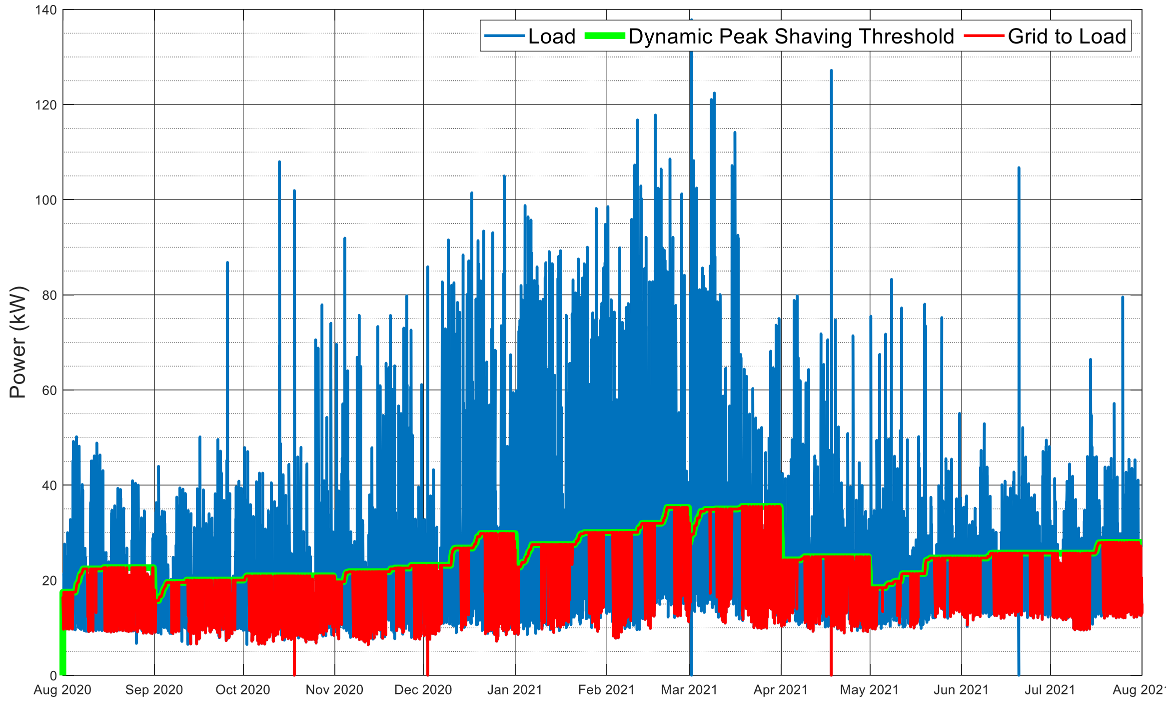


Figure 14. CPS Control dynamic peak shaving threshold example

The dynamic threshold raises and falls in response to the seasonal dynamics of electricity consumption. As an example, the value of the dynamic threshold is 60% higher in March than in August. Step changes in the threshold are observed at the beginning of some months as a new billing period begins and the BESS no longer must defend the previous months peaks. The threshold then falls to the average value of the trailing data sets. If load exceeds the dynamic peak shaving threshold the battery is discharged to meet excess load; if load falls under the threshold the battery is allowed to charge. This is represented in Figure 15.

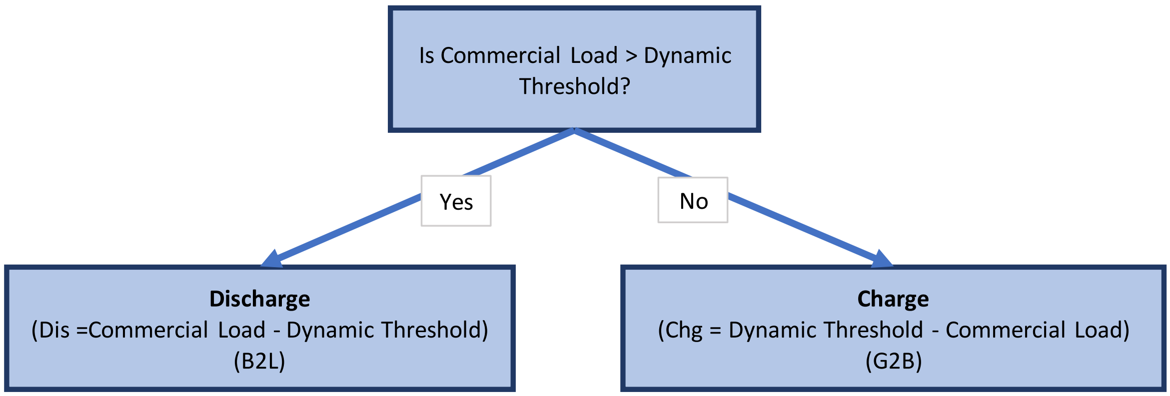


Figure 15. Flow chart representing the Commercial Peak Shaving Control

A trialing data set was chosen experimentally through trial and error, with four days being found to be the 'sweet spot' which allowed the threshold to respond to seasonal dynamics in electricity consumption without overcompensating for outlier days such as weekends and holidays. The tuning factor, y, used for the TH and KMCC were 1.1 and 1.3 respectively, which were also obtained experimentally. To avoid confusion with peak shaving thresholds for other stakeholders, the dynamic thresholds used at the commercial sites is referred to as the commercial threshold.

4.4 Multi-Stakeholder Control

In this section, residential multi-stakeholder (R2°) and commercial multi-stakeholder (C2°) control strategies were developed. R1° and C1° control strategies were stacked with a utility peak shaving algorithm, with the aim of providing the LDC ratcheted demand charge reductions, while continuing to generate value for the original stakeholder group. Section 4.4.1 introduces a LDC load forecasting technique and a dynamic LDC peak shaving threshold, which are used in the multi-stakeholder control strategies. The R2° and C2° control strategies are presented in sections 4.4.2 and 4.4.3 respectively.

4.4.1 Utility Peak Prediction and Dynamic Threshold

A utility peak prediction (UPP) algorithm was developed, designed to predict the magnitude of the daily LDC demand peaks. By predicting the magnitude of daily peaks, the LDC can decide whether it will need to initiate peak shaving and prepare accordingly. Daily peak demand predictions are made using a correlation between the maximum LDC load occurring between 06:00 and 07:00 and the daily LDC demand peak. Each day, the maximum load which occurs between 06:00 and 07:00 is recorded and at 07:00 is entered into the correlation to obtain a daily peak prediction. This correlation, derived from historic data, is shown in Figure 16.

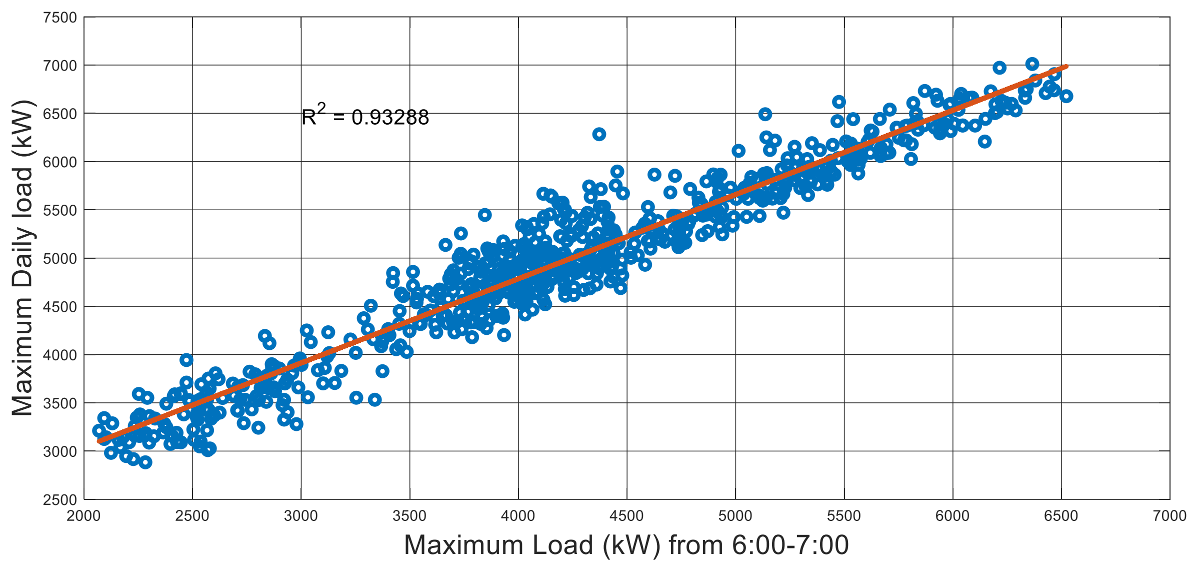


Figure 16. Correlation between daily LDC peak and maximum load between 06 and 07

In practice an artificial neural network (ANN) with the correct input data streams (such as historic load and weather forecast data) could also accomplish the LDC peak prediction.

An LDC dynamic peak shaving threshold was developed which serves two functions. To avoid confusion with peak shaving thresholds for the commercial sites, the dynamic threshold used for the LDC is referred to as the LDC threshold. The LDC threshold is used to dictate battery charging and discharging to facilitate peak shaving. If LDC load exceeds the threshold, the LDC send discharge commands, via the CCP, to the distributed RES and CES to displace the excess loads; if load falls under the threshold, charging commands are sent. The secondary function of the LDC threshold is to provide a point of reference to put the daily peak demand predictions in context. If the daily peak prediction exceeds the current value of the dynamic LDC threshold, a 'peak day' is predicted. When a peak day is predicted, prior to the peak occurring, the LDC has an opportunity to send charging commands to the RES and CES to prepare their SOE for peak shaving. If the UPP fails to properly forecast a peak day, the LDC can still conduct peak shaving with the RES and CES but will have to make do with their current SOE when the LDC load exceeds the LDC threshold.

The methodology for setting the LDC threshold was designed specifically to identify annual ratcheted demand peaks as opposed to monthly peaks as is the case with the commercial threshold. LDC peak load can vary substantially year to year and a universally set threshold could under or over evaluate the number of peak days, resulting in unnecessary peak shaving measures being taken or missing peak days entirely. The LDC threshold is initialized at zero in August, which is outside of the ratcheted demand period and typically has the lowest annual demand. The threshold is then continuously adjusted such that it is equal to the maximum net load experienced by the LDC since initialization. The result is a dynamic threshold which begins low and increases with the seasonal increase of LDC demand as it enters the heating season. Figure 17 provides an example of the moving threshold and the daily demand peak predictions. Note that peak demand predictions are only needed during the ratcheted demand period and thus aren't shown for other months.

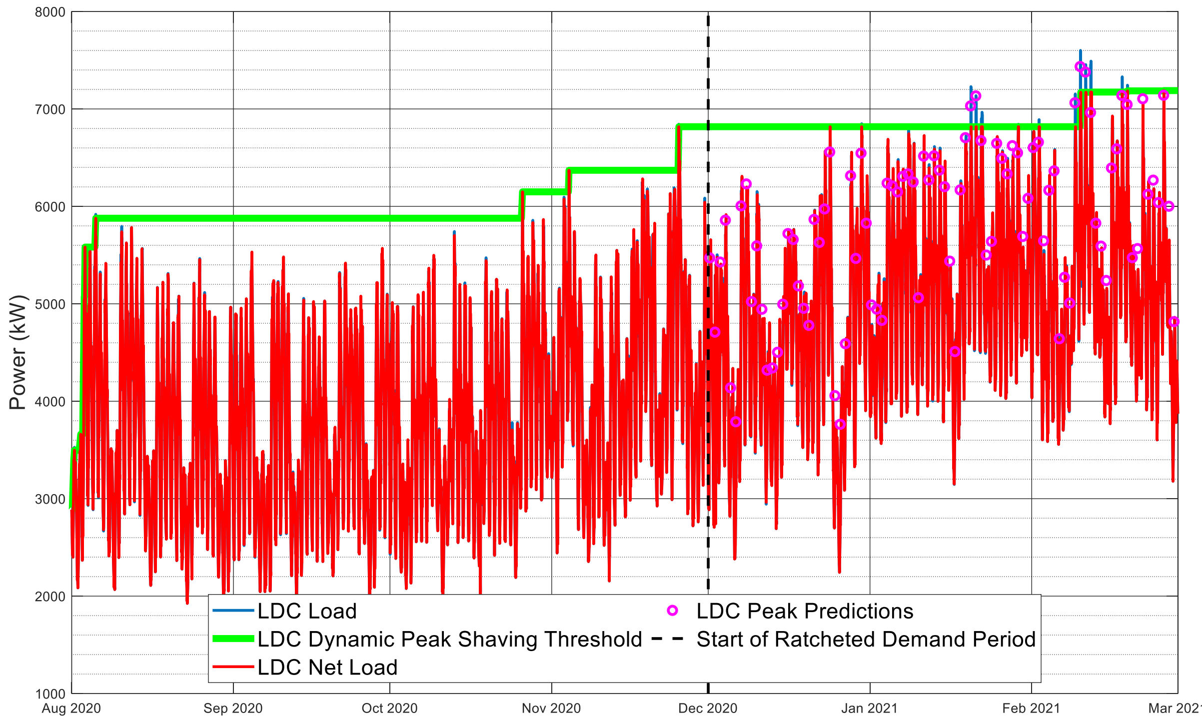


Figure 17. LDC dynamic threshold and daily peak predictions

4.4.2 Residential Utility Peak Shaving Control

R2° control strategies were developed to share the benefit of the distributed RES with the LDC by stacking residential applications with utility peak shaving. While studies have show that peak shaving is often unconducive to sequential application stacking [28], our research found that in the case of the LDC peak shaving, a sequential stacking approach was effective. Since the LDC is subject to a ratcheted demand charge, the LDC experiences only one true peak day a year, which falls within the ratcheted period (Dec – Feb). Ideally, the RES would operate purely for homeowners every day except the LDC ratcheted peak day. The UPP, introduced in the previous section, is used to predict LDC peak days; if a peak day is predicted, the LDC takes control of the RES an operates them for peak shaving for the full day, disregarding the residential BESS application. On all non LDC peak days, the RES operates purely for the homeowners on a R1° control strategy. The more accurate the UPP algorithm, the lower the number of days the RES systems would be interrupted from normal behaviour by the LDC. The value lost by the residential stakeholders for each missed day of normal RES operation is small in comparison to the value which can be gained by the LDC via demand charge reduction. Due to the sequential nature of stacking used, the utility peak shaving application can be staked with any of the R1° control strategies. The algorithm used by the LDC to operate the RES for utility peak shaving is referred to as the residential utility peak shaving algorithm (RES_{UPS}). On peak days the RES are used to defend the LDC threshold; while otherwise they are left to R1° operation as shown by the flow chart in Figure 18. The phrase '+ UPS' will be used to identify the residential control strategies which have been stacked with RES_{UPS} (e.g. SC + UPS control identifies self consumption control stacked with RES_{UPS}).

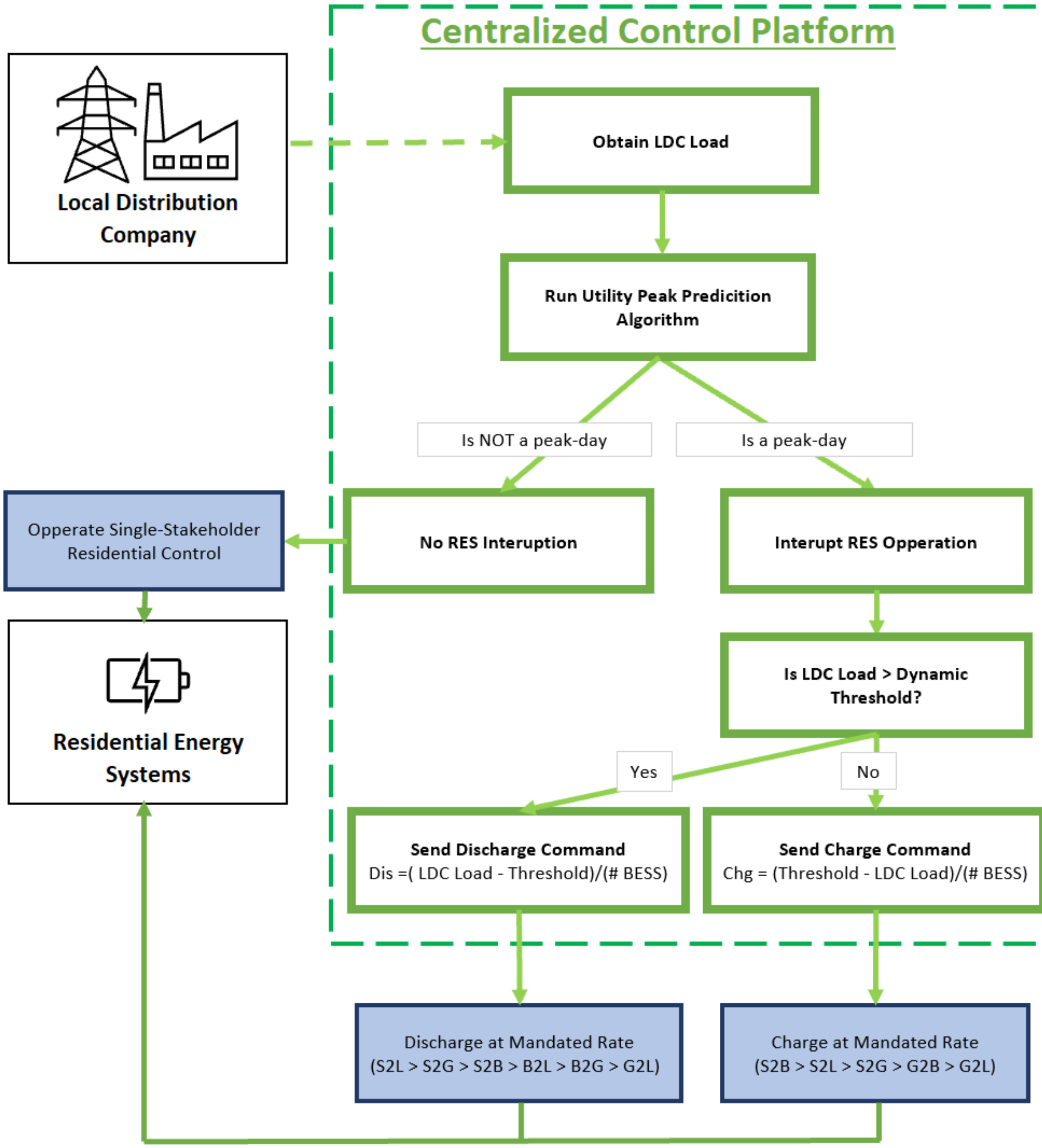


Figure 18. Flow chart representing the Residential Utility Peak Shaving Control

4.4.3 Commercial Stacked Peak Shaving Control

A C2° control strategy was developed to share the benefit of the distributed CES with the LDC by stacking the C1° CPS Control with utility peak shaving; this control is referred to as Stacked Peak Shaving (SPS) Control. In contrast to the R2° control strategies discussed in the previous section; sequential stacking could not be utilized for the C2° strategy. The LDC experiences a relatively few number of peak days and only needs to utilize the CES on an irregular basis; however, the commercial sites are subject to monthly demand charges and utilize the CES storage much more frequently. Abandoning the commercial threshold for any period may set a new monthly demand peak at the commercial sites, negating a month worth of peak shaving effort and providing sub-optimal value to the commercial stakeholders. To provide peak shaving for the commercial and LDC stakeholders simultaneously, a dynamic stacking approach was used where the CES defend two thresholds, the commercial threshold and the LDC threshold.

At each timestep throughout the LDC ratcheted demand period, the charge and discharge commands of the CES are calculated such that they consider the loads and thresholds of both the LDC and the commercial sites. If either (or both) the LDC or commercial loads are above their respective thresholds a discharge is mandated to shave the demand peak. In the case that both the loads of the LDC and commercial site exceed their respective thresholds, the discharge power is set to the greater of the two power values need to peak shave each party. If both the LDC and commercial loads are below their respective thresholds, a charge is mandated, constrained such that the charge power does not cause either stakeholder's net load to exceed their threshold. This approach is dynamic as specific values of energy capacity are not reserved for either stakeholder, instead the CES will spend capacity to defend both thresholds indiscriminately. A flow chart showing the logic for SPS Control is achieved is shown in Figure 19.

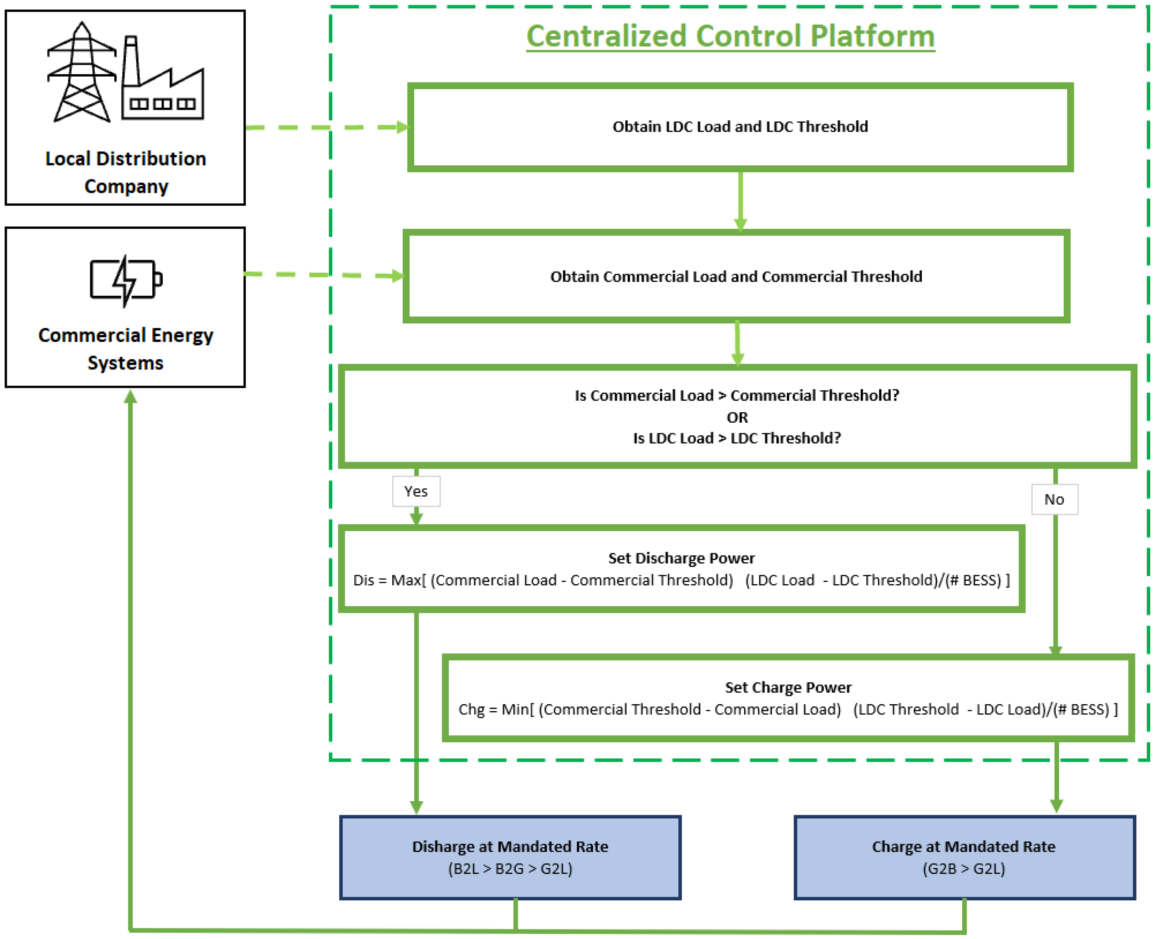


Figure 19. Flow chart representing the Commercial Stacked Peak Shaving Control

4.5 Economic Evaluation

The system model provides insight to the value of RES and CES on individual stakeholders (private value) and the system as a whole (system value). The private and system value of the energy systems is evaluated over a one-year period to ensure seasonal impacts are accounted for. The equations used to calculate the private value of the energy systems depend on the application that the system is serving and the policy scenario being considered. Generalized equations are used to calculate the annual value of the residential, commercial and LDC stakeholder groups, referred to as AV_{Resi}, AV_{Comm} and AV_{LDC} respectively. The annual value of the system, AV_{System}, is obtained by summing the private values of all stakeholders considered in the scenario.

4.5.1 Annual Value Equations

A generalized equation for the annual value provided to a residential stakeholder, AV_{Resi}, is shown in EQ 22, where t is used to represent each 5-minute timestep in a year (105120 timesteps), $Price_t$ is the price of electricity at each timestep, and $Price_{net-meter\ credit,t}$ is the value of grid exports at each timestep.

$$AV_{Resi} = \sum_{t}^{n=105120} \left[(S2L_t + B2L_t - G2B_t) \times dt \times Price_t + (B2G_t + S2G_t) \times dt \times Price_{net-meter\ credit,t} \right] \tag{22}$$

A generalized equation for the annual value provided to a commercial stakeholder, AV_{Comm}, on a monthly demand charge is shown in EQ 23, where m represents each month of the year, and $Load_{Com}$ and $NetLoad_{Com}$ represents the commercial site load and net load respectively.

$$AV_{Comm} = \sum_{t}^{n=105120} [(B2L_t - G2B_t) \times dt \times Price] + \sum_{m}^{n=12} \left[\left(max\left(Load_{Com,m}\right) - max\left(NetLoad_{Com,m}\right) \right) \times Demand\ Charge \right] \tag{23}$$

A generalized equation for the annual value provided to a LDC stakeholder, A_{LDC}, on a ratcheted demand charge is shown in EQ 24, where $Peak\ Reduction_m$ is the LDC peak reduction of month m, and $Peak\ Reduction_{ratcheted}$ is the peak reduction during the ratcheted demand period. As explained in section 2.1.5, all savings achieved by the residential and commercial stakeholders represent lost revenue for the LDC.

$$AV_{LDC} = \sum_{m}^{n=12} [max(Peak\ Reduction_m, Peak\ Reduction_{ratcheted}) \times Demand\ Charge] - Lost\ Residential\ Revenue - Lost\ Commercial\ Revenue \tag{24}$$

The lost residential revenue experienced by the LDC comes in the form of reduced energy charge income. Due to inefficiencies, BESS act as a net load and increase behind the meter consumption, however these increases in consumption are small in comparison to the amount of home loads which are displaced by rooftop PV and the net effect of the RES is a significantly reduced demand for LDC electricity. To calculate the lost LDC revenue resultant from displaced residential loads, the quantity of displaced loads is multiplied by the LDC energy charge profit margin. The lost (or gained) LDC revenue due to residential electricity exports is calculated by multiplying the quantity of exports by the difference between the price that the TAP charges for electricity and what the LDC has agreed to pay the residential stakeholders for grid exports. If the LDC values residential exports at a lower price than which it buys electricity from the TAP, then the LDC profits from residential exports. If the LDC does not offer net-metering, then all residential exports are profits for the LDC as it is ‘free’ energy that it will sell to customers without having to purchasing from the TAP. The formula for calculating lost residential revenue is shown in EQ 25.

$$Lost\ Residential\ Revenue = \sum_{t}^{n=105120} \left[\left(S2L_{RES,t} + B2L_{RES,t} - G2B_{RES,t}\right) \times \left(Price_{LDC,t} - Price_{TAP}\right) + \left(B2G_{RES,t} + S2G_{RES,t}\right) \times \left(Price_{TAP} - Price_{net-meter,t}\right)\right] \times dt \quad (25)$$

Where $Price_{TAP}$ is the price the TAP charges the LDC for electricity, $Price_{LDC,t}$ is the price the LDC charges the residential stakeholders for electricity and $Price_{net-meter,t}$ is the agreed upon price which the LDC pays the residential stakeholder for grid exports.

The lost commercial revenue experienced by the LDC comes in the form of lost commercial demand charge income. Reductions in commercial demand charges are directly absorbed by the LDC as losses. As with the RES, the BESS of the CES are a net load and increase BTM consumption, and since there is no PV at the commercial sites, the reliance of the commercial sites on LDC electricity is increased. However, the increases in energy charge revenue due to increased consumption are small in comparison to the losses in commercial demand charge revenue. The formula for calculating lost commercial revenue by the LDC is shown in and EQ 26.

$$Lost\ Commercial\ Revenue = \sum_{t}^{n=105120} \left[\left(B2L_{CES,t} - G2B_{CES,t}\right) \times \left(Price_{Commercial} - Price_{LDC}\right)\right] \times dt - \sum_{m}^{n=12} \left[\left(max\left(Load_{Com,m}\right) - max\left(NetLoad_{Com\ new,m}\right)\right) \times Demand\ Charge\right] \quad (26)$$

Where, $Load_{Com,m}$ and $NetLoad_{Com,m}$ are the commercial load and net load profiles respectively.

4.5.2 Electricity Tariffs

The LDC modelled in this thesis is the Berwick Electric Commission (BEC), whose transmission access provider is Nova Scotia Power (NSP). All rate payers within the BEC distribution network pay tariffs set by the BEC, found at [32]. The BEC itself can purchase electricity from NSP, according to the NSP municipal tariff structure, found at [33]. The electricity tariffs used in this work were obtained from these two entities; tariffs from the BEC were used for the residential and commercial tariffs and the NSP municipal tariff was used as the LDC tariff.

The residential Flat and TOU tariffs used in this thesis are shown in Table 3. The TOU rate contains three different pricing levels: low-pricing (or off-peak), medium-pricing (or shoulder-peak) and high-pricing (or on-peak). The TOU rate in 'non-winter months' (Mar-Nov), uses only shoulder and off-peak pricing, while in 'winter months' (Dec-Feb) all three levels of pricing are used. The TOU shoulder-peak energy charge is equivalent to the Flat rate energy charge.

Table 3. Residential electricity tariffs (Berwick Electric Commission Rates [32]**)**

Tariff category	**Conditions**	**Energy Price ($/kWh)**	**Service Cost ($/month)**
Flat rate	Applies throughout entirety of the year	0.1405	20.19
TOU off-peak	22:00 - 07:00 all year All Weekends and Holidays	0.0975	23.19
TOU shoulder-peak	07:00 - 22:00 on workdays from Mar-Nov 13:00 - 16:00 on workdays from Dec - Feb	0.1405	
TOU on-peak	07:00 - 13:00 & 16:00 - 22:00 on workdays from Mar-Nov	0.2583	

In all scenarios, the homes are allowed to export to the LDC grid, however exports are only credited in the net-metering scenario. The residential net-metering agreement policies used in this thesis are summarized in Table 4.

Table 4. Residential net-metering agreement considered

No net-metering	**Net-metering**
Exports to the grid are allowed but valued at $0.00/kWh	Exports to the grid are valued at the current $/kWh price of the applicable tariff (Flat or TOU)

The commercial tariff used in this thesis contains an energy charge and a monthly demand charge. The commercial tariff is summarized in Table 5.

Table 5. Commercial electricity tariffs (Berwick Electric Commission Rates [32]**)**

Tariff category	**Conditions**	**Energy Price ($/kWh)**	**Demand Charge ($/kW/month)**
General Service Commercial	Applies throughout entirety of the year	0.1040	18.88

The municipal (LDC) electricity tariff used in this thesis is shown in Table 6. Note that the $/kW price presented includes a $0.32 reduction available to customers who own their own substation transformer. It is assumed that the LDC modelled in this thesis owns their own stepdown transformer.

Table 6. Municipal electricity tariffs (NSP Rate [33]**)**

Tariff category	**Conditions**	**Energy Price ($/kWh)**	**Demand Charge ($/kW/month)**
Municipal Tariff	Monthly demand charge is applied to the greater of maximum demand of the current months, or the maximum demand of the previous Dec, Jan, or Feb occurring in the previous eleven months.	0.09171	12.125

4.5.3 Residential Policy and Strategy Scenarios

As introduced in section 4.5.2, there are two electricity tariffs used for the residential stakeholders, a Flat and a TOU tariff. Both tariffs can be offered with or without a net-metering agreement. This creates several different policy environments for the residential stakeholders, three of which are used in this work:

I. Flat tariff, no net-metering
II. TOU tariff, no net-metering
III. TOU tariff, and net-metering

Each policy scenario lends itself to certain residential BESS applications. The four R1° control strategies, developed in section 4.2, were paired with policy environments, ultimately resulting in five R1° scenarios, which are shown in Table 7, color coded by policy environment.

Table 7. Summary of residential single-stakeholder scenarios

Scenario Abbreviation	**BESS Control Strategy**	**Policy Environment**
SC_{Flat}	PV Self-Consumption	Flat Tariff, No Net-Metering
SC_{TOU}	PV Self-Consumption	TOU Tariff, No Net-Metering
CEA_{TOU}	Constrained Energy Arbitrage	
RS_{TOU}	Residential Stacked Control	
$EA_{TOU, NM}$	Energy Arbitrage	TOU Tariff with Net-Metering

In some jurisdictions, TOU tariffs are offered only to rate-payers who operate load shifting technologies. In the advent that a jurisdiction expands their TOU tariff to ratepayers with BTM-BESS, savings associated with switching tariffs should be included in analysis. As such, extra variations of the R1° scenarios were developed which also include a tariff switch from a Flat to TOU tariff. These scenarios are shown in Table 8.

Table 8. Summary of residential single-stakeholder scenarios with tariff switching

Scenario Abbreviation	BESS Control Strategy	Policy Environment
SC_{F2TOU}	PV Self-Consumption	Flat to TOU Tariff switch, No Net-Metering
CEA_{F2TOU}	Constrained Energy Arbitrage	
RS_{F2TOU}	Residential Stacked Control	
$EA_{F2TOU, NM}$	Energy Arbitrage	Flat to TOU Tariff switch with Net-Metering

As explained in section 4.4.2, R2° control strategies were developed by stacking the R1° strategies with a RES_{UPS} algorithm. The private and system impact of the R2° strategies will also be dependent on the residential policy environments, so one R2° control strategy was developed for each of the three policy environments by stacking RES_{UPS} functionality with SC Control, RS Control and EA Control as shown in Table 9.

Table 9. Summary of residential multi-stakeholder scenarios

Scenario Abbreviation	BESS Control Strategy		Policy Environment
	Non LDC Peak Day	LDC Peak Day	
SC_{Flat} + UPS	PV Self-Consumption	Residential Utility Peak Shaving	Flat Rate, No net-metering
RS_{TOU} + UPS	Residential Stacked Control	Residential Utility Peak Shaving	TOU Rate, No net-metering
$EA_{TOU, NM}$ + UPS	Energy Arbitrage	Residential Utility Peak Shaving	TOU Rate, With Net-metering

4.6 Additional Performance Metrics

Two additional performance metrics were used to analyze system performance, percent solar self consumption and battery full cycle equivalents, introduced in sections 4.6.1 and 4.6.2, respectively.

4.6.1 Percent Solar Self Consumption

The RES includes rooftop PV modules which generate electricity. The generated electricity can displace home loads, charge the battery, or be exported to the grid. In a no net-metering jurisdiction, grid exports are undesirable (or at least have no benefit to the homeowner). The metric used in this thesis to gauge the RES systems and accompanying control strategy's ability to keep PV generation BTM. EQ 27 is used to calculate the percentage of PV generation that is consumed internally within the home.

$$Solar\ Charge\ Factor\ (SCF) = \frac{\sum \int (S2B) dt}{\sum \int (S2B + G2B) dt}$$
$$\%\, Solar\ Self\ Consumption = \frac{\sum \int \left(S2L + (B2L \times SCF)\right) dt}{\sum \int (S2L + S2G + (B2L \times SCF)) dt} \tag{27}$$

The above equations account for solar power flowing directly to loads and solar energy which gets stored in the battery and later discharged to loads. The Solar Charge Factor (SCF) is the proportion of total battery charging (from solar and grid) that comes from solar generation. Both numerator and denominator are DC thus SCF is unitless. The calculated percentage excludes conversion losses from DC to AC power as all terms in the equation are in AC with efficiency losses already accounted for.

4.6.2 Battery Full Cycle Equivalents

Both the RES and CES include BESS; depending on the control strategy utilized, the amount of energy that passes through the BESS will vary. The metric used in this thesis to gauge battery energy throughput is battery full cycle equivalents which is calculated by dividing the total quantity of discharged energy (AC) by the rated energy capacity of the system, as shown in EQ 28.

$$Full\ Cycle\ Equivalents = \frac{\sum \int (B2L + B2G)dt}{Battery\ Capacity} \tag{28}$$

Chapter 5 Data Sources and Analysis

All input data sets used in this thesis were recorded to use for the Natural Resources Canada (NRCan) funded Alba Nova project which took place in Berwick, NS as a part of the Power Forward Challenge [34].

The contents of this chapter are as follows:

- **Section 5.1:** Introduced to the Alba Nova project and Berwick, NS
- **Section 5.2:** Introduction and analysis of residential load and PV generation profiles
- **Section 5.3:** Introduction and analysis of commercial load profiles
- **Section 5.4:** Introduction and analysis of commercial LDC profile

5.1 The Alba Nova Project and Berwick Nova Scotia

In October 2018, NRCan and the UK Department for Business, Energy & Industrial Strategy (BEIS) put out a call for proposals for companies to compete in the Power Forward Challenge (PFC). The Alba Nova team was one of seven project finalists, and accordingly conducted a smart grid pilot project, implementing a centralized energy storage control platform controlling over 1 MWh of battery energy storage systems distributed across 10 residential sites and 2 commercial sites in Berwick, NS. As a member of the project consortium, Dalhousie's Renewable Energy Storage Lab (RESL) was granted access to all the data collected over the course of the project, which was completed in October 2021. These data sets were used to execute the model developed in this thesis.

Berwick is a town in the Annapolis Valley of Nova Scotia, approximately one-hour drive from Nova Scotia's capital city of Halifax. In 2016, the population of Berwick was 2,509 people [35]. The Town of Berwick is the owner of its own LDC, the Berwick Electric Commission (BEC). Berwick, along with the municipalities of Mahone Bay and Antigonish, share ownership of the Alternative Energy Resource Authority, which owns and operates a 23.5 MW wind farm in Ellershouse, NS [36]. The remainder of Berwick's electricity needs are purchased through an intertie (69 kV sub-station) with the Nova Scotia Power (NSP) transmission network. A total of thirteen electricity demand profiles were recorded in Berwick:

1. Ten Residential demand profiles (with matching rooftop PV generation profiles)
2. Two Commercial facility demand profiles
    i. A municipal town hall (TH)
    ii. A hockey rink / community center (KMCC)
3. One Local Distribution Company (LDC) profile

An aerial view of the Berwick Municipality is shown in Figure 20. The commercial sites and BEC substation are marked. To protect the privacy of the homeowners, the ten residential sites were not marked; however, all ten homes are located within this boundary.

Figure 20. Aerial view of Berwick, NS [37]

5.2 Residential Load and PV Generation Data

The RES load and PV generation input profiles were measured and recorded from 10 homes within Berwick, with a timestep resolution of 5 minutes. Load and PV generation data were recorded starting in Sep 2019 and Aug 2020 respectively. Data from both sets was collected until Aug 2021 as shown in Figure 21, where the horizontal lines represent points which load data was available for each of the 10 homes. To create anonymity for the homes, each home was assigned a number one through ten; and the homes are referred to by the letter H followed by the homes number.

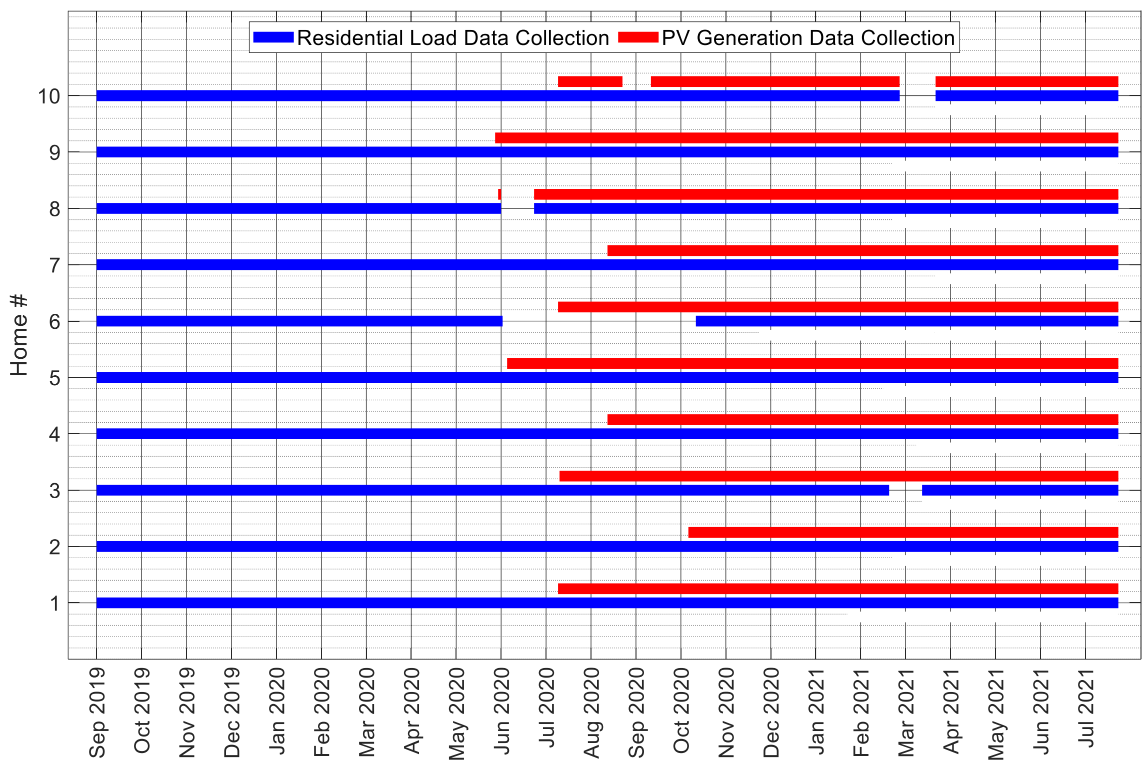


Figure 21. Timeline of residential load and PV generation data

Only five large data gaps (longer than a day) were observed:

- H3: Load from Feb 28 to Mar 23, 2021
- H6: Load from Jun 15 to Oct 23, 2020, and PV generation from Jun 15 to Jul 23rd, 2021
- H8: Load and PV generation from Jun 15 to Jul 7, 2020

- H10: PV generation from Sep 2 to Sep 23, 2020, and Load and PV Generation from Mar 07 to Apr 2021

There are two causes of the residential data gaps: i) internet outages at the homes which prevented the metering equipment from uploading data to the data server and ii) metering equipment being temporarily uninstalled to allow electrical work in the homes. **A one-year period, ranging from Aug 1st, 2020, to Aug 1st, 2021, was identified as having a full year of both the residential load and PV generation profiles with the least amount of data gaps.** This is an important finding as it proves to be the limiting factor dictating the timespan of data used to evaluate the system model. H2 was the only home which had less than a full year of both load and PV generating data, as PV generation only began at this home during October 2020. The entirety of each load profile was plotted to check for any data quality issues. Figure 22 shows a representative residential load profile.

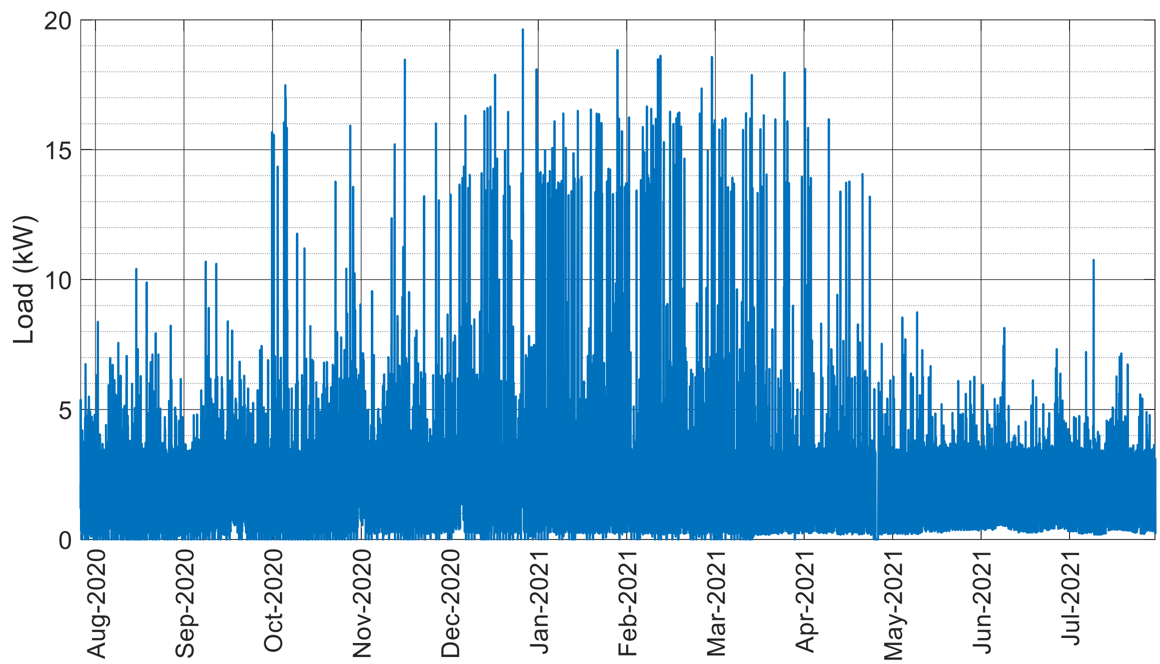


Figure 22. Representative residential load profile (Aug 2020 to Aug 2021)

A clear seasonal pattern in electricity consumption can be observed, where demand increases substantially during the heating season. For the majority of the year loads largely remain between 0.5 kWh and 5 kW, with some spikes reaching as high as 10 kW. In the winter months, loads routinely exceed 10 kW, reaching as high as 20 kW.

The entirety of each PV generation profile was plotted to check for any data quality issues. Figure 23 displays three sample days of PV generation profile.

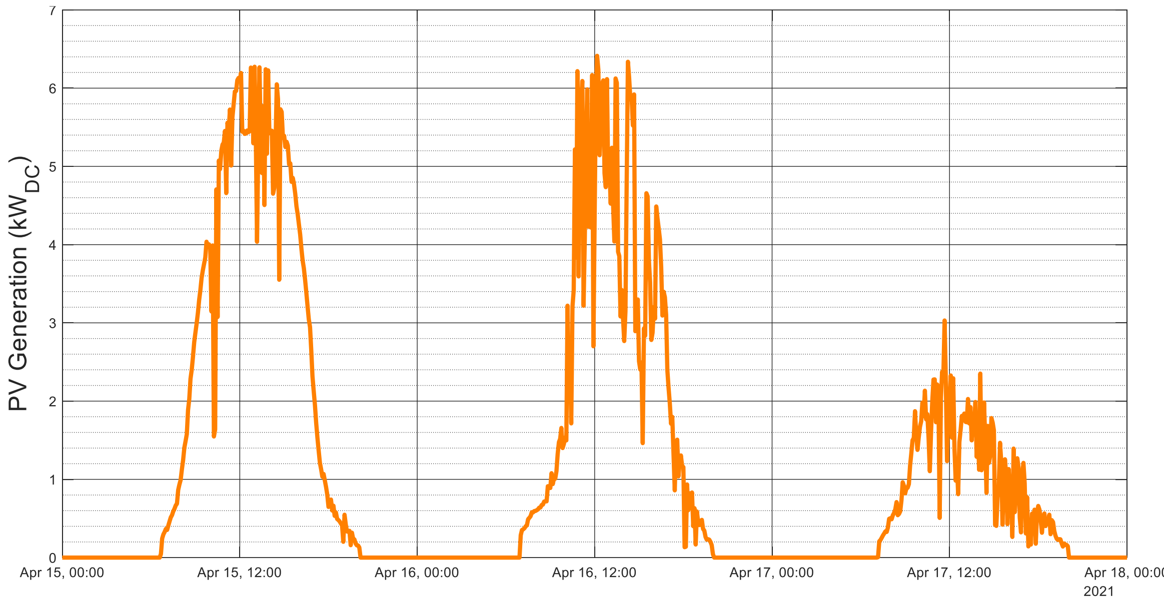


Figure 23. Representative days of PV generation profile

It can be seen that the PV generation profiles vary significantly by day. On April 15th, 2021, PV generation started at 07:00, peaked at 13:00 and ends at 20:00. On April 17th, PV generation was significantly less, likely due to unfavourable weather conditions.

5.2.1 Metadata Analysis

The 10 homes were selected by Alba Nova, who noted that their intention was to select homes with a variety of characteristics such as primary heating types, occupancy, and historic electricity consumption, for the 10 homes to be representative of other homes within the region. The monthly electricity consumption of each home for a representative year are shown in Figure 24.

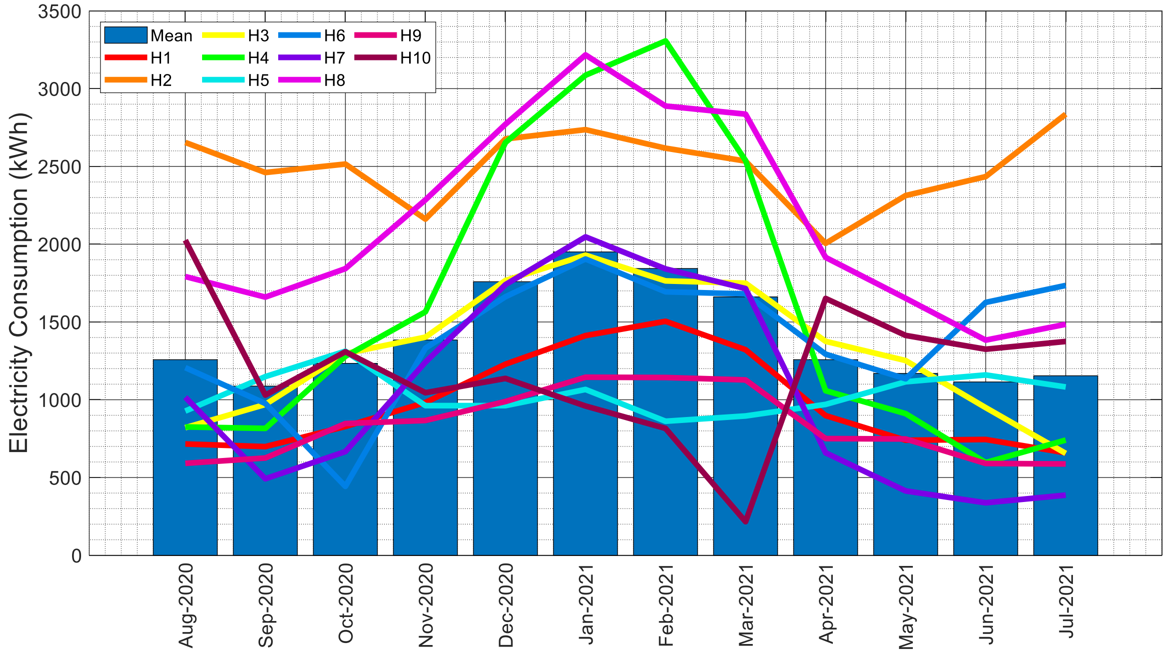


Figure 24. Electricity consumption by home (Aug 2020 to Aug 2021)

While the mean electricity consumption of the 10 homes follows a clear seasonal pattern, with high consumption during the heating season and low consumption during the summer, a few homes do not follow this trend, such as H2 (orange), H5 (light blue) and H10 (maroon). H5 and H10 do not utilize electric heating thus their electricity consumption has less seasonal correlation. H2, which utilizes electric heating, was observed to also have high loads in the summer months, conceivably due to substantial air-cooling loads, although this was unable to be confirmed. A summary of the meta data for the ten residential sites is given in Table 10.

Table 10. Residential site meta data

House ID	Approximate Age (years)	Full Time Occupants	Primary Heating Source	Secondary Heating Source	2018 Electricity Consumption (kWh)
1	77	2	Electric Heat Pump	Wood	4526
2	32	5	Electric Resistive	Wood	28003
3	15-20	4	Electric Heat Pump	Oil	13019
4	65	2	Electric Heat Pump	Wood	9182
5	23	3	Oil	Wood	11151
6	36	2	Electric Heat Pump	N/A	19608
7	34	1	Electric Resistive	N/A	12590
8	46	4	Electric Heat Pump	Wood	10413
9	155	2	Electric Heat Pump	Wood	10766
10	30-40	2	Oil	Wood	17430

Of the ten homes, eight utilize some form of electric heating, either electric resistive (baseboard) or an electric heat pump. The remaining two homes (H4 and H10) utilize oil as their primary heat source. Seven homes identified that they use wood as a supplementary, secondary heating source.

Approximately 7 kW_{DC} of solar modules were installed on each home. The modules were installed with various orientations which was dictated by the geometry of the home's roofs. The monthly PV generation of each home for a representative year are shown in Figure 25.

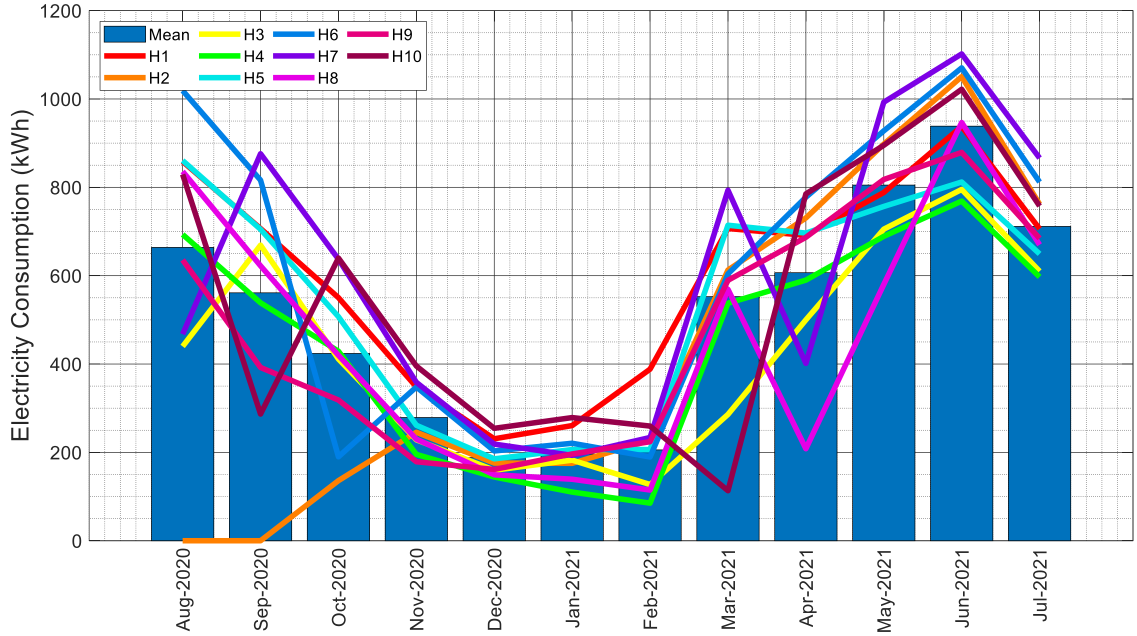


Figure 25. Representative year of PV generation by home (Aug 2020 to Aug 2021)

As expected, PV generation follows a clear seasonal pattern with generation highest in the summer months and lowest in the winter months. Maximum PV generation occurred in June, with monthly generations as high as 1,100 kWh. Minimum monthly PV generation occurred in February with values as low as 85 kWh. Table 11 shows the installed capacity and PV module orientation of the 10 PV generation profiles.

Table 11. Installed solar photovoltaic capacity, slope and azimuth angle

House ID	Solar PV Capacity (kWdc)	PV Module Slope	PV Module Azimuth
1	6.93	30	-13
2	6.93	30	78
3	6.93	30	-105
4	6.93	18	-17
5	5.78	18	-18
6	6.55	18	0
7	6.93	18	-12
8	6.93	25	-103
9	6.93	40	-5
10	6.93	18	0

5.2.2 Data Capture Manipulation and Validation

All residential load data was measured and recorder using Generac W1-HEM Neurio home energy monitoring kits (+/- 1% accuracy @ 1-Watt resolution) and split-core current transducers (CT) (+/- 1% accuracy, 110-240 V, 2-264 A, 50/60 Hz). The Neurio sensor monitors both current and voltage, calculates instantaneous demand and transmits the data to a cloud network. The data was then accessed as comma delimited (*.csv) files with timestamped demand values (watts) through individual Generac accounts for each homeowner.

Originally, 2 CT (one per phase) were installed to monitor the residential properties inter-connection with the BEC to capture home load. In Aug 2020, residential BESS were installed in each home; to continue recording home load, an extra set of CT were installed to monitor the BESS AC circuits. Home load was then obtained by summing the profile of all four CTs. The locations of the Neurio CT measurements used to obtain home load are shown in Figure 26, prior to installation of the BESS (left) and after (right).

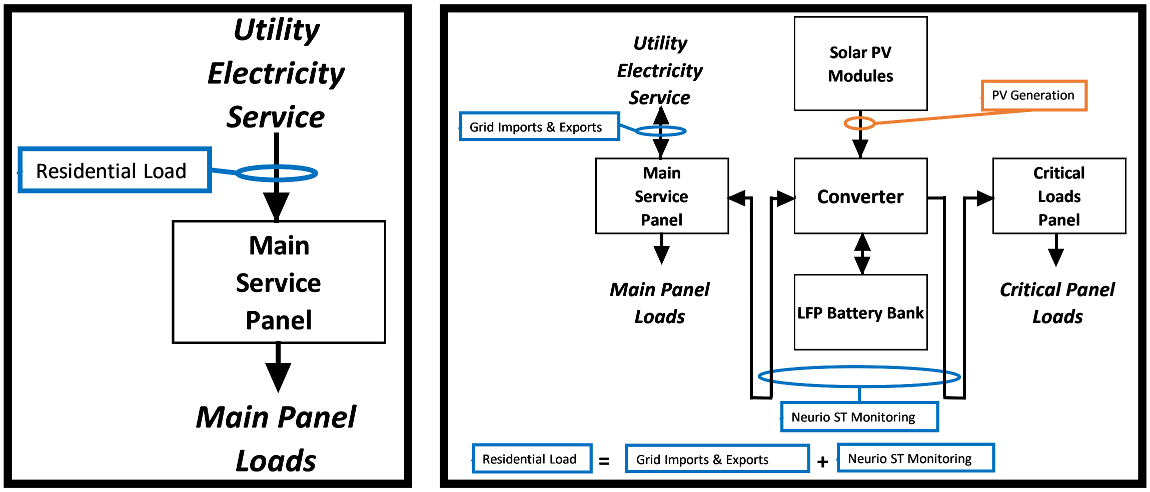


Figure 26. Location of Neurio CT before (left) and after BESS installation (right)

Also included in Figure 26 (right tile), is the location of PV generation measurement. This data set was measured and recorded by sensors within the BESS power converter, after maximum power point tracking (MPPT) and before conversion from DC to AC.

All data sets were timestamped with Coordinated Universal Time (UTC) values. These timestamps were converted to Atlantic Standard Time (AST) and then daylight savings time was accounted for (ADT). All profiles were visually examined for data gaps and other data issues.

Data gaps were filled using the following methodology:

- All data gaps ranging from several hours to 2 days were filled with replacement data.
- The replacement data came from the nearest full days of data recorded on the same day of the week. For example, if a Tuesday had significant data gaps, the whole day was replaced with the average load profile of the previous and the following Tuesday.
- Data gaps larger than 2 days were left blank. Resulting partial days were removed.
- Data gaps under the 1-hour range were filled using linear interpolation.

The data profiles were validated as follows:

- The 2 CT monitoring the residential properties inter-connection with the BEC were validated against BEC billing data.

- All Neurio data sets were validated through on-site ‘spot-checks’ using high accuracy handheld measurement equipment supplied by RESL.

5.3 Commercial Load Data

The CES input load profiles used in this thesis were measured and recorded with a timestep resolution of 1 minute from 2 commercial sites in Berwick:

1. **The Berwick town hall (TH):** Town administration building and library
2. **The Kings Mutual Century Center (KMCC):** Town community center and hockey rink

Data collection for the TH and KMCC began in Aug 2019 and Oct 2019 respectively and data was collected until Aug 9th, 2021. Note that the available time span of reliable residential load and PV generation data was found to be Aug 1st, 2020, to Aug 1st, 2021. To keep a consistent period of analysis between stakeholders, the commercial data profiles were shortened to this period. The entirety of each profile was plotted to check for any data quality issues such as data gaps or irregularities. Since the timestep resolution of the data is shorter than what is available for the other datasets, the commercial data was down sampled to 5-minute intervals by averaging all data points which shared the same nearest 5-minute value (e.g. the average of 5 data points from 11:58 to 12:02 were used to represent 12:00). Figure 27 and Figure 28 shows the TH and the KMCC electricity demand profiles respectively, for the one-year period.

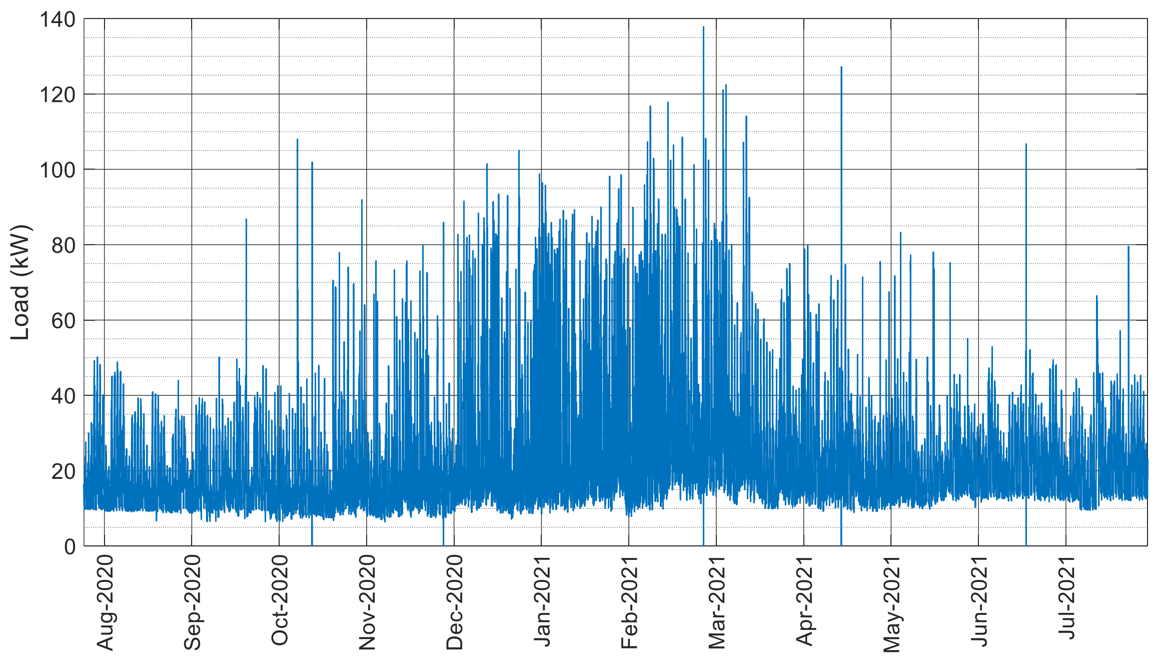


Figure 27. Town Hall load profile (Aug 2020 to Aug 2021)

The TH follows a clear seasonal pattern in which demand is highest in the winter, gradually declines through Spring, is smallest in Summer and rises in the Fall. In the summer months, demand peak are mostly below 60 kW, however reach as high as 80 kW on isolated instances such as on July 24th. On June 20th, a demand peak over 100 kW was observed, however on inspection, immediately prior to the peak, building loads fell to zero, which implies that this peak is associated with restarting equipment after an outage; another such event was observed on April 17th. In October, demand peaks are observed to rise, reaching above 100 kW on two separate occasions. By December, demand peaks are observed to routinely exceed 80 kW. The Town hall was observed to have its largest peaks in February and early March, with a maximum peak of 137 kW. In mid-March, demand is observed to fall and demand peaks seldom exceed 80 kW.

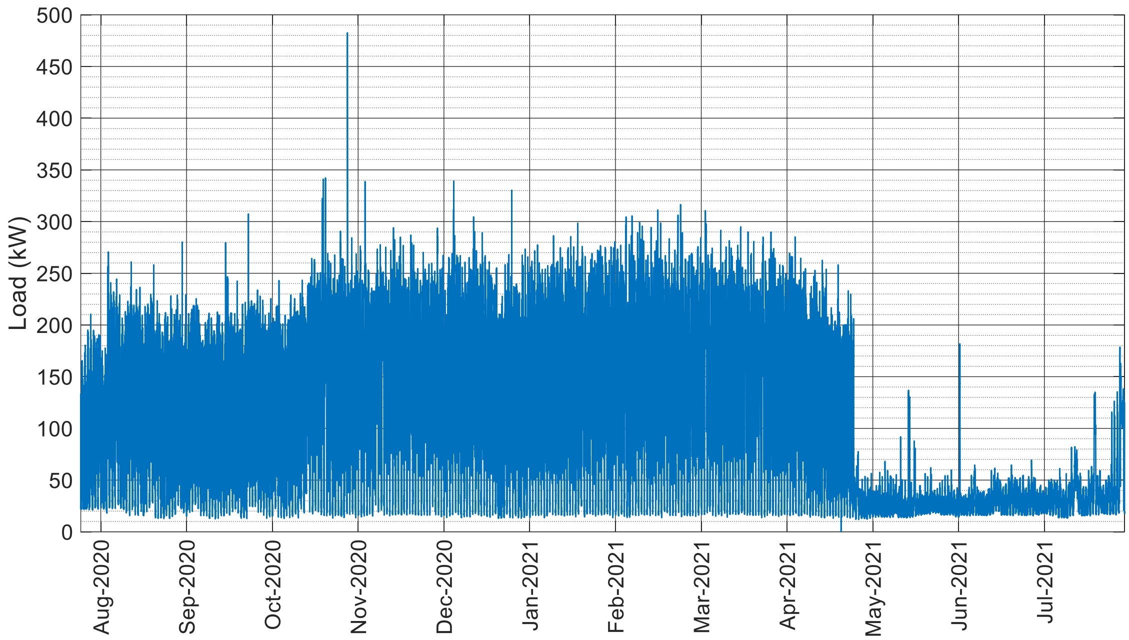


Figure 28. Kings Mutual Century Center load profile (Aug 2020 to Aug 2021)

A very strong seasonal pattern is observed in the KMCC load profile. A large portion of the KMCC load is associated with the building ice rink. For summer months, outside of the hockey and skating season, a significant portion of the building's equipment is turned off (including ice making machines) and building demand drops to approximately 25% of on-season consumption. A sharp drop in load is observed on Apr 28th, 2021, and loads remain low for 3 months, before beginning to rise again on Jul 27th, 2021, in accordance with the rink closure.

5.3.1 Metadata Analysis

The KMCC is a much larger consumer of electricity than the TH. Even in the 'offseason' of the KMCC when the ice hockey rink is inactive, the KMCC still consumes more energy than the TH. Figure 29 display the monthly energy consumption of the 2 sites.

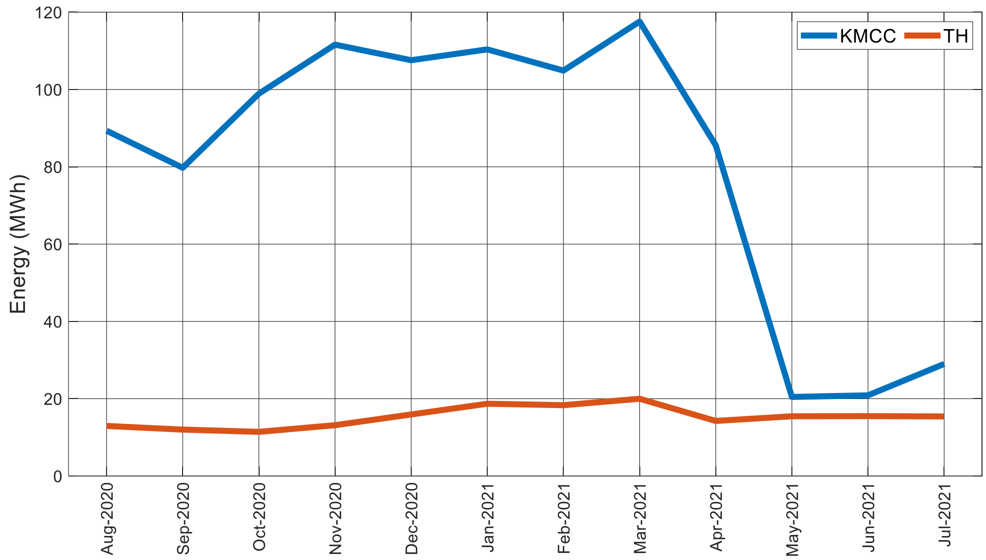


Figure 29. Monthly energy consumption of CES input profiles (Aug 2020 to Aug 2021)

Both the TH and KMCC follows a clear seasonal pattern in which demand is highest in the winter and lowest in the summer. This pattern is much more dramatic for the KMCC which sees consumption drop to approximately 25 % of winter levels in the summer months. Figure 30 shows the distribution of demand of both sites over the course of a one-year period.

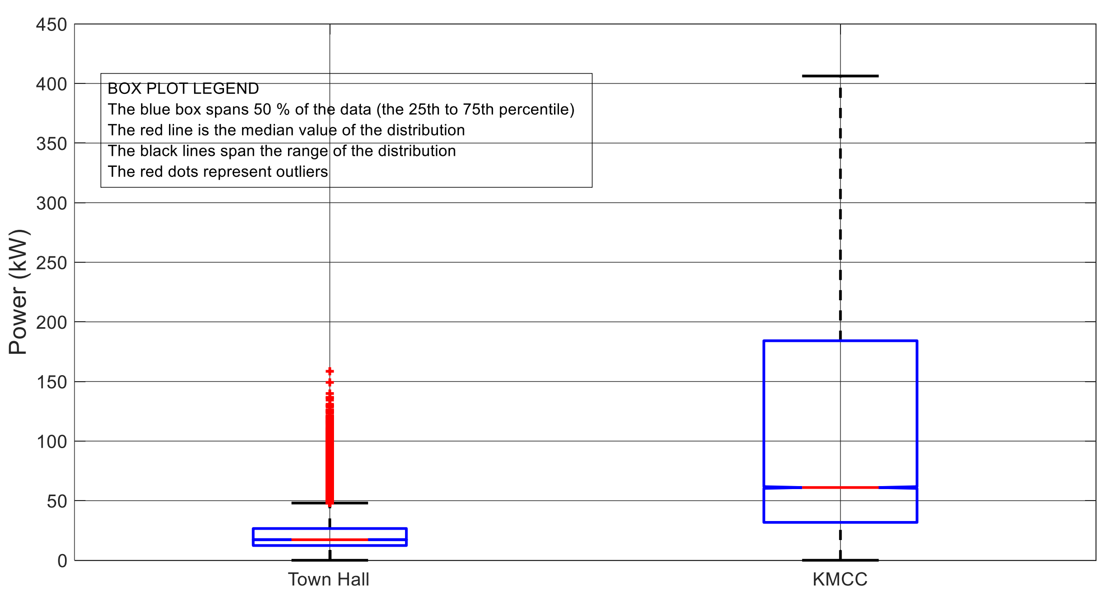


Figure 30. Distribution of commercial demand (Aug 2020 to Aug 2021)

The median KMCC electricity demand is approximately three times that of the TH. Both sites see maximum demand values over 500% greater than their annual mean consumption. The KMCC has the largest absolute difference between its median and maximum loads, which alludes to greater peak shaving potential than at the TH. The TH never experiences loads above 225 kW, which is the discharge capability of the CES used in this thesis. This means that no matter how effective of a peak shaving strategy is deployed at the TH, the TH demand peak will never be able to be reduced by the CES full converter power capacity. At the KMCC, it would be theoretically possible to obtain peak shavings equal to the full power capacity of the CES; however, ability to do so would depend upon how much energy is required. The wider the demand peak, the more energy is needed to peak shave by the same amount of power.

5.3.2 Data Capture Manipulation and Validation

All commercial load data was measured and recorded using Onset UX120-006M analog data loggers (+/- 0.1% accuracy) and Onset CTV-E current transducers (CT) (+/- 2.1% accuracy, 600 VAC, 60-600 A, 50/60 Hz) monitoring each of the three phases of the 600 VAC supplied to each site. Exported from the loggers were comma delimited (*.csv) timestamped electrical current data. 2 assumptions were made when calculating load:

1. Nominal 600 VAC L-L three phase (voltage not measured directly)
2. Power factors of 1.0 at both sites

It is possible that this power factor assumption slightly inflates the real power calculation (kW), and corresponding energy consumption characteristics (kWh). Electrical power was calculated by averaging the three currents, multiplying by the assumed L-L voltage, and multiplying by the square root of three to account for the three-phase system. Figure 31 shows data loggers being installed in the electrical service bay of the KMCC three-phase (600 VAC L-L, 3Y-N-G) step-down transformer.

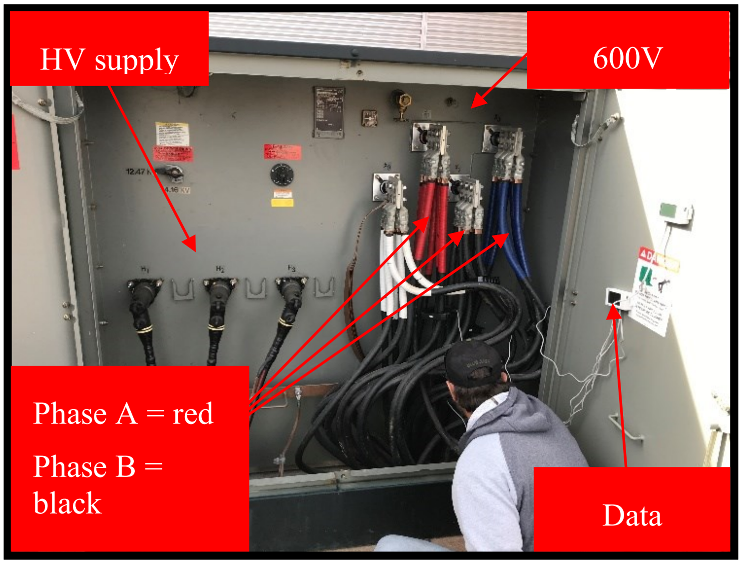


Figure 31. KMCC step-down transformer

The commercial data sets were timestamped with Coordinated Universal Time minus 3 hours (UTC-3) values. These timestamps were converted to Atlantic Standard Time (AST) and then daylight savings time was accounted for (ADT). All profiles were visually examined for data gaps and other data issues.

In Aug 2021, BTM-BESS were installed at both commercial sites and the profiles captured by the Onset data loggers became a combined profile of site load and battery operations (after conversion to AC). To monitor the BESS operations and to allow site load to be isolated, RESL deployed an independent metering system consisting of a Continental Control Systems LLC 600 Vac Wattnode power and energy meter working in conjunction with a DataTaker DT80 series stand-alone datalogger and Continental Control Systems Accu-CT split core current transducers. This system is shown in Figure 32.

Figure 32. RESL commercial BESS monitoring system

Commercial load could then be deduced by subtracting the data from the RESL metering system from the original Onset data profile. This is visualized in Figure 33, which shows how KMCC load was deduced using the 2 data sets; on this day, the BESS system was undergoing a sinusoidal charge and discharge curve to test system functionality.

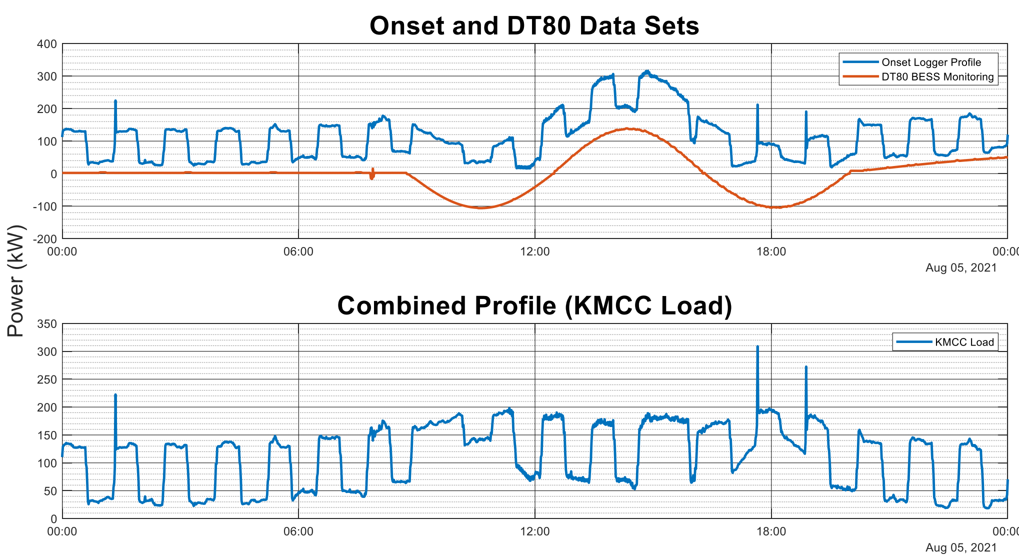


Figure 33. Deduced commercial load profile using external energy monitoring system

5.4 Local Distribution Company Load Data

The input LDC dataset used in this thesis was measured and recorded at the BEC intertie with the NSP transmission network, with a timestep resolution of 15 minutes using commercial revenue grade metering equipment. Data from 2017 to 2021 was shared. Note that the available time span of reliable residential load and PV generation data was found to be Aug 1st, 2020, to Aug 1st, 2021. To keep a consistent period of analysis between stakeholders, the LDC data profile was shortened to this period. The timestep resolution of the LDC data was larger than what is available for the other datasets, thus was up sampled to 5-minute intervals using linear interpolation. The entirety of the profile was visually examined to check for any data quality issues such as data gaps or irregularities, though none were found. The resulting data is shown in Figure 34.

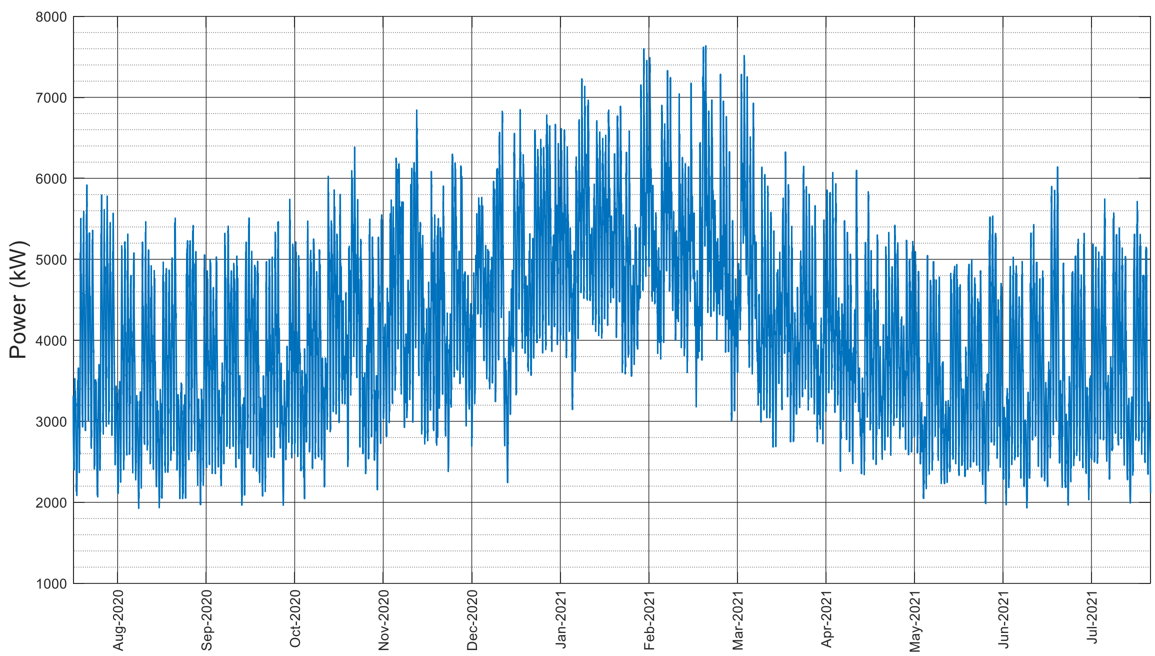


Figure 34. Input LDC electricity demand profile

A clear seasonal pattern can be observed in the LDC load profile. The system is a winter peaking system with loads as high as 7.5 MW in January, February, and March.

Chapter 6 Residential Energy System

A system model was used to evaluate the annual value of ten distributed RES operating single-stakeholder (R1°) and multi-stakeholder (R2°) control strategies. Value was assessed at the single-stakeholder level, and at the system level.

The residential and LDC stakeholder groups each have their own vested interests. The homeowners are concerned with which policy environment allows them to maximize the value of their RES; and whether a R2° scenario would compromise their value. The LDC is concerned with which R1° scenario maximizes their own value, considering both resultant losses in energy charge revenue, and how the RES impacts the peak demand of their distribution network. The LDC is also interested in whether they can obtain additional value by encouraging (or incentivizing) R2° operation. Scenarios which provide more value to the system than to any single stakeholder group alludes to the potential for new policies and cooperative business models which could more efficiently monetize RES and facilitate increased system penetration. How the value of the RES is distributed across stakeholder groups is also of interest.

The contents of this chapter are as follows:

- **Section 6.1:** Numerical results, and key observations of the simulated R1° control strategies
- **Section 6.2:** Numerical results, and key observations of the simulated R2° control strategies
- **Section 6.3:** Detailed analysis and discussion of the results given in sections 6.1 and 6.2

6.1 Residential Single-Stakeholder Control Results

In this section, numerical results, and key observations of the simulated R1° control strategies are presented. The contents of this section are divided into seven result subsections, followed by one summary subsection. The results displayed in each subsection are as follows:

- **Section 6.1.1:** Monthly residential value of Flat to TOU tariff switch

- **Section 6.1.2:** Monthly residential value by R1° scenario
- **Section 6.1.3:** Annual residential value by R1° scenario
- **Section 6.1.4:** Annual LDC value by R1° scenario
- **Section 6.1.5:** Annual system value by R1° scenario
- **Section 6.1.6:** Percentage of PV self consumption by R1° scenario
- **Section 6.1.7:** Battery full cycle equivalents by R1° scenario

Recall that ten RES were modelled; the results displayed are the aggregate results of all ten systems.

6.1.1 Impact of Flat and TOU Electricity Tariff

The aggregate monthly savings of the ten residential stakeholders obtained by changing from the Flat to TOU tariff are shown in Figure 35.

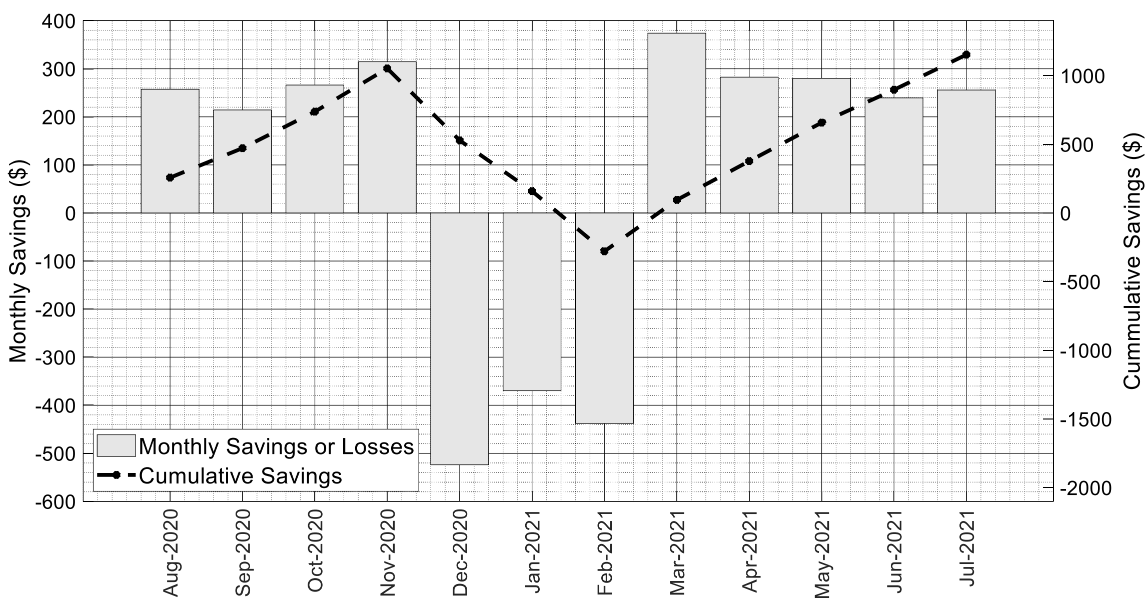


Figure 35. Monthly aggregate residential value from changing from Flat to TOU tariff

Observations:

- Switching homeowners, in the absence of RES, from the Flat to TOU tariff provided savings in all non-winter months (Mar – Nov) and losses for the winter month (Dec – Feb), resulting in a net benefit exceeding $100 per home.

- This comparison does not consider any behavioural changes that may occur in electricity consumption when a customer is switched to a TOU tariff.
- An educated electricity customer could maximize the benefit of the TOU rate by running high load appliances during off-peak pricing hours.

6.1.2 Monthly Value Analysis

The aggregate monthly value generated by the ten RES are plotted by scenario in Figure 36 and Figure 37. For clarity, the monthly values for scenarios with and without tariff switching (Flat to TOU tariff), are shown in separate figures, Figure 36 and Figure 37 respectively.

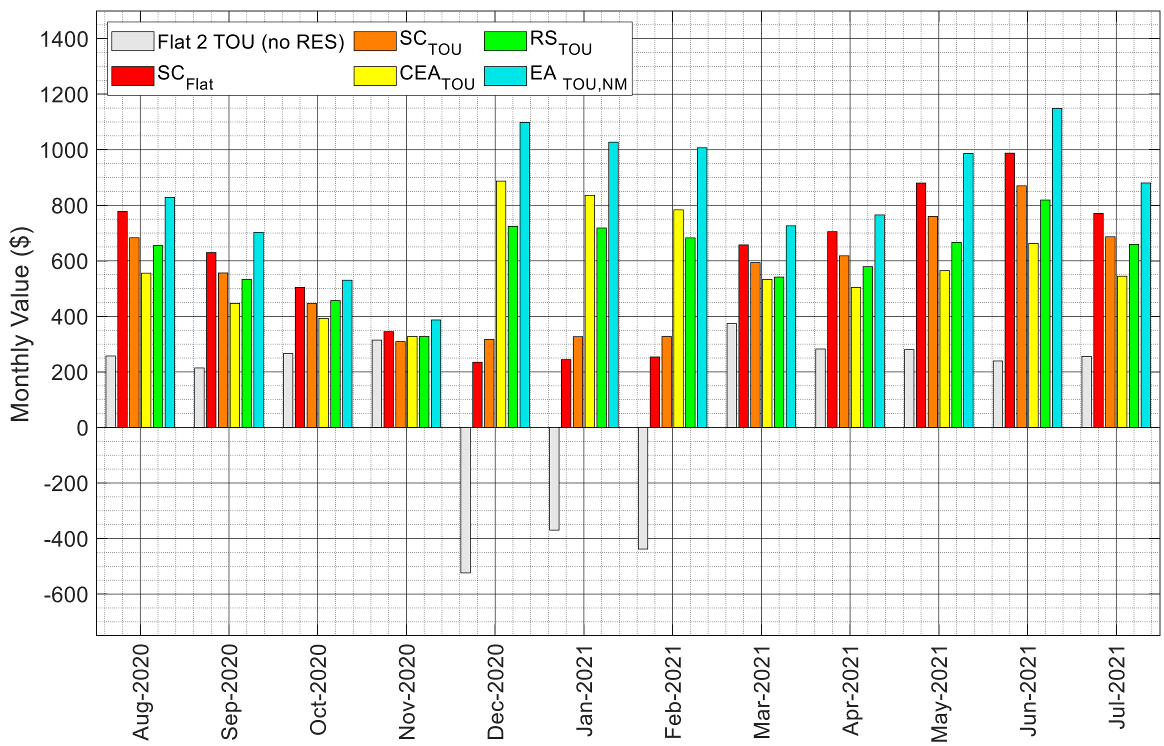


Figure 36. Monthly aggregate residential value by R1° scenario (no tariff switching)

Observations:

- Both SC scenarios provide the greatest value in the non-winter months (Mar-Nov).
- Unlike the SC scenarios, CEA_{TOU} and $EA_{TOU,NM}$ have greater value generation ability in the winter months (Dec – Feb).

- The RS_{TOU} scenario, which combines the benefits of SC and CEA, generates more value than SC_{TOU} and SC_{Flat} across all months. RS_{TOU} outperforms CEA_{TOU} in non-winter months but not in the winter-months.
- $EA_{TOU, NM}$ generated the most residential value for all twelve months.

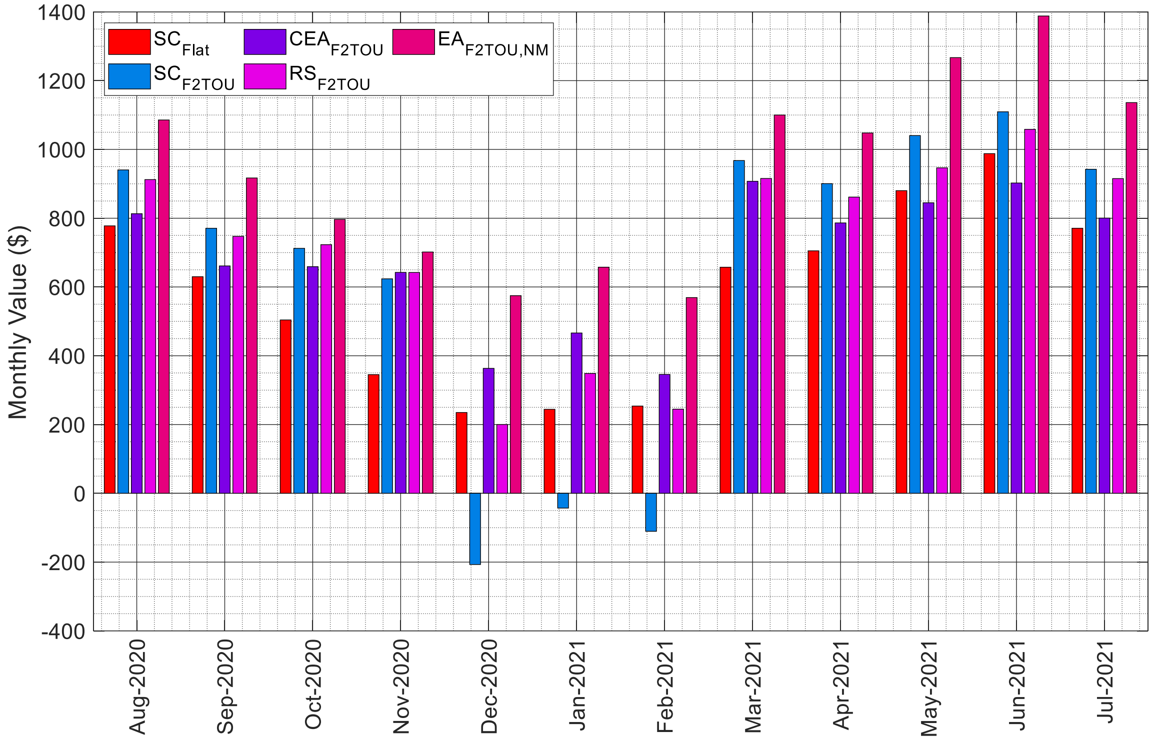


Figure 37. Monthly aggregate residential value by R1° scenario (with tariff switching)

Observations:

- Switching the homeowners from a Flat to TOU tariff reduced residential value in the winter months, but increases value for all other months, providing a net benefit.
- The SC_{TOU} scenario was found to generate less value than SC_{Flat}; however, the SC_{F2TOU} scenario creating more value than SC_{Flat}.

6.1.3 Residential Annual Value

The R1° control strategies were simulated on the system model and the resulting annual residential values, AV_{Resi}, were calculated and are shown in Figure 38.

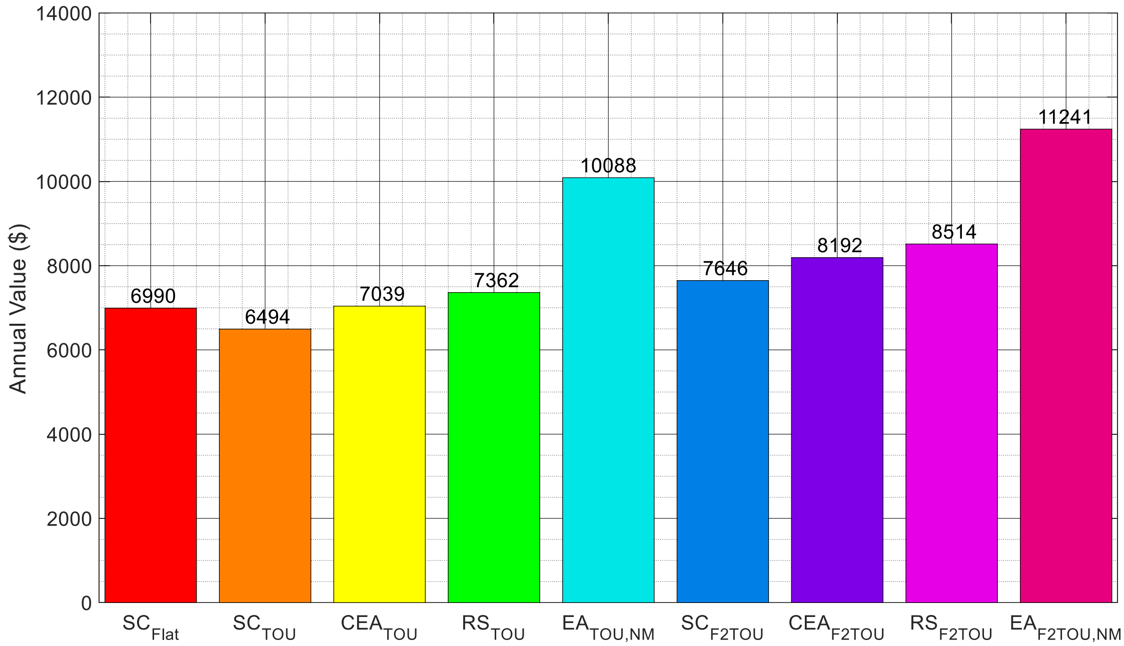


Figure 38. Aggregate residential annual value by R1° scenario

Observations:

- The R1° scenarios which provided the largest AV_{Resi} were scenarios which utilised EA Control, followed by RS, CEA, and SC Control scenarios, respectively.
- SC Control added more value when added to a TOU than the Flat rate; however, SC_{F2TOU} outperformed both SC_{Flat} and SC_{TOU}

6.1.4 Impact on Local Distribution Company

As homeowners deploy RES (which include rooftop PV generation and load shifting battery), they lessen their reliance on the LDC for electricity which reduces the amount of revenue the LDC receives from residential energy charges. Although the R1° strategies do not actively consider their impact on the LDC, the RES may passively mitigate (or increase) the LDC peak demand resulting in LDC savings (or deficit). The impact of the RES paired with R1° control strategies on the LDC are shown in Figure 39.

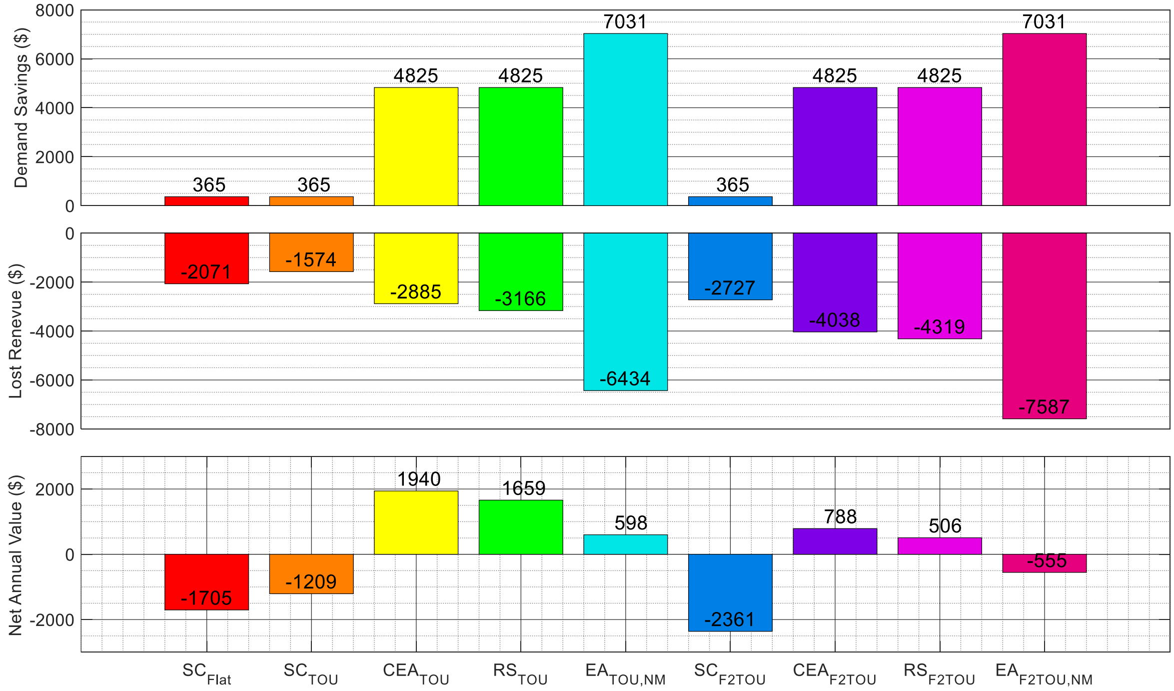


Figure 39. LDC annual value by R1° scenario

Observations:

- SC Control was found to provide almost no LDC demand savings
- CES and RS Control were observed to provide the LDC with identical demand charge savings at $4,850
- EA control, which allows itself to export energy to the LDC grid, had the largest impact on LDC demand savings with over $7,000 in savings
- A trend was observed that the scenarios which resulted in the greatest LDC peak shaving, also resulted in the most lost LDC revenue
- As expected, when the residential tariff switch is considered, LDC revenue losses are greater
- Five scenarios were found to provide positive AV_{LDC} values, CEA$_{TOU}$, RS$_{TOU}$, EA$_{TOU}$, CEA$_{F2TOU}$, and RS$_{F2TOU}$ control.

6.1.5 System Annual Value

The annual value of the system provided by R1° scenarios was obtained by summing the values of the individual stakeholder groups (residential and LDC). The individual and system AV values are presented in Figure 40.

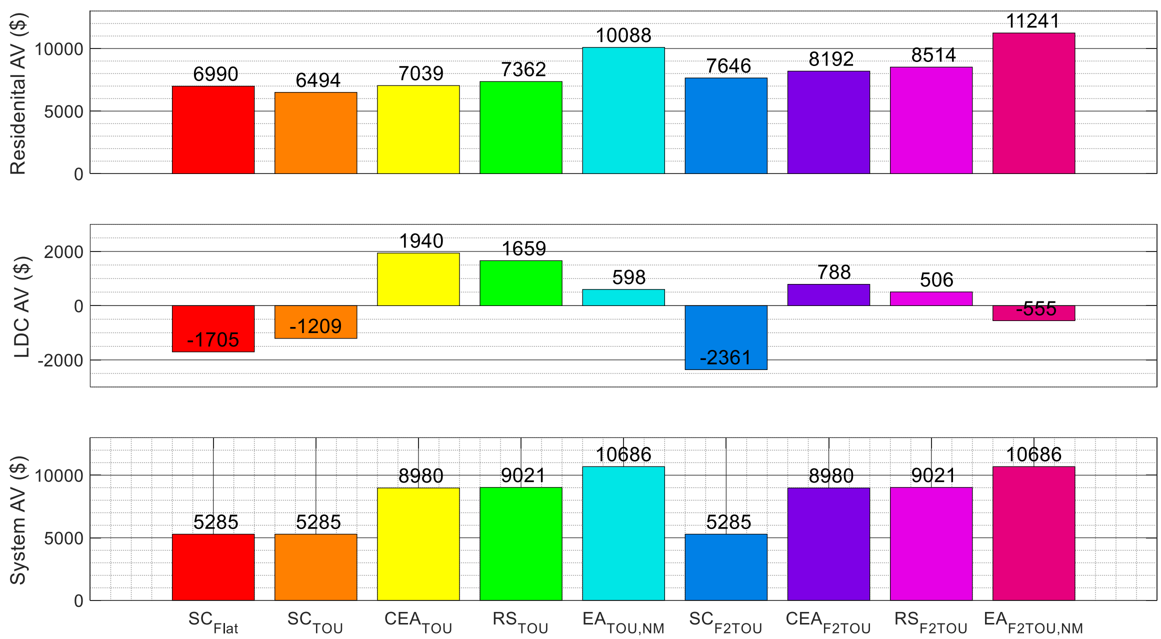


Figure 40. System annual value by R1° scenario

Observations:

- All nine scenarios were observed to provide positive AV_{System}, indicating that the negative impact of certain scenarios on the LDC were smaller in magnitude than the positive impact provided to the residential stakeholders.
- $\mathrm{AV}_{\mathrm{System}}$ was largest for the EA Control scenarios, followed by the RS, CEA and lastly SC Control scenarios
- $\mathrm{AV}_{\mathrm{System}}$ were the same for all TOU scenarios regardless of whether the switch from the Flat to TOU tariff was considered in the value calculation. This is because the value obtained by the residential stakeholders when changing tariffs is equal to the value lost by the LDC, thus the tariff switch has a neutral net impact on the system.

The distribution of value amongst stakeholders would, however, change when considering the tariff switch.

6.1.6 PV Self Consumption

The rooftop PV of the RES can displace home loads, charge the BESS, and export power to the grid. The quantity of PV generation consumed BTM is referred to as percent self consumption. The average percent self consumption of the ten homes operating on each of the four R1° control strategies is shown in Figure 41.

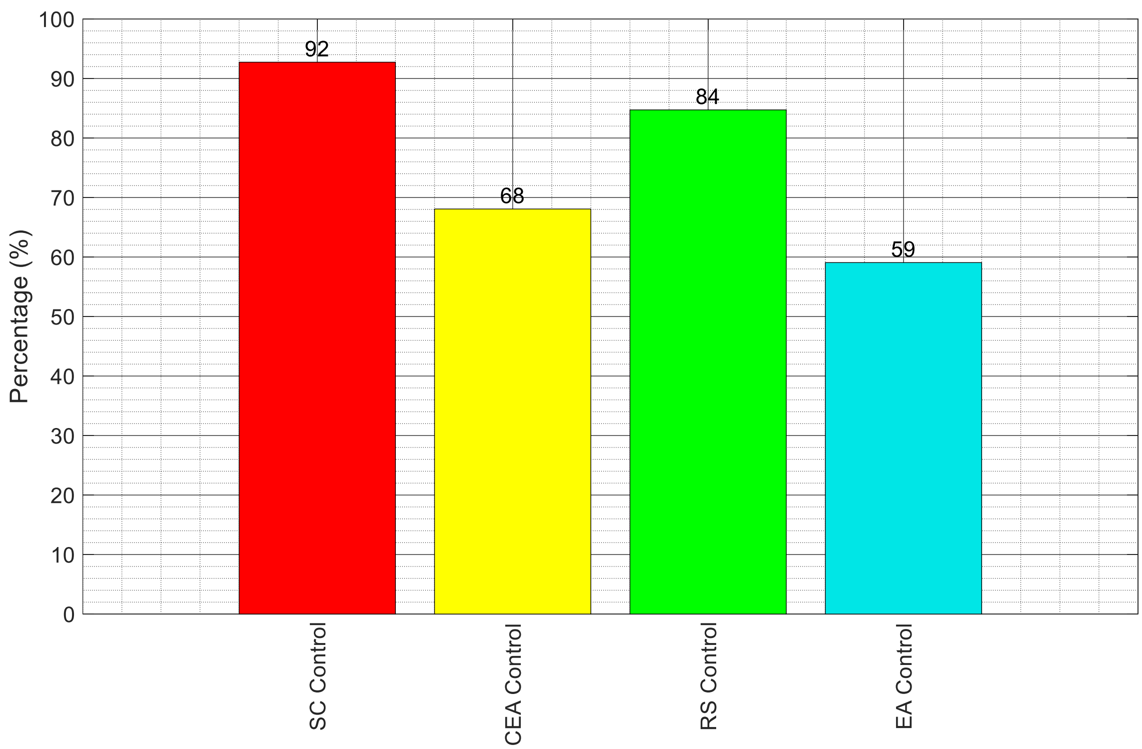


Figure 41. Average residential solar self consumption percentage by R1° control strategy

Observations:

- SC Control was observed to have the highest rate of PV generation self consumed at 93% consumption
- CEA Control had considerably less solar consumed internally at 68% self consumption

- RS Control, which leverages benefits of both SC and CEA Control, was able to retain the self consumption rate of SC Control at 92% self consumption
- EA Control, which was designed for and takes advantage of, valued grid exports, consumed the least amount of PV generation internally at 59% self consumption

6.1.7 Battery Full Cycle Equivalents

The energy throughput experienced by the RES batteries varies depending on the control utilized. The aggregate full cycle equivalents of the ten homes resulting from each of the four strategies is shown in Figure 42.

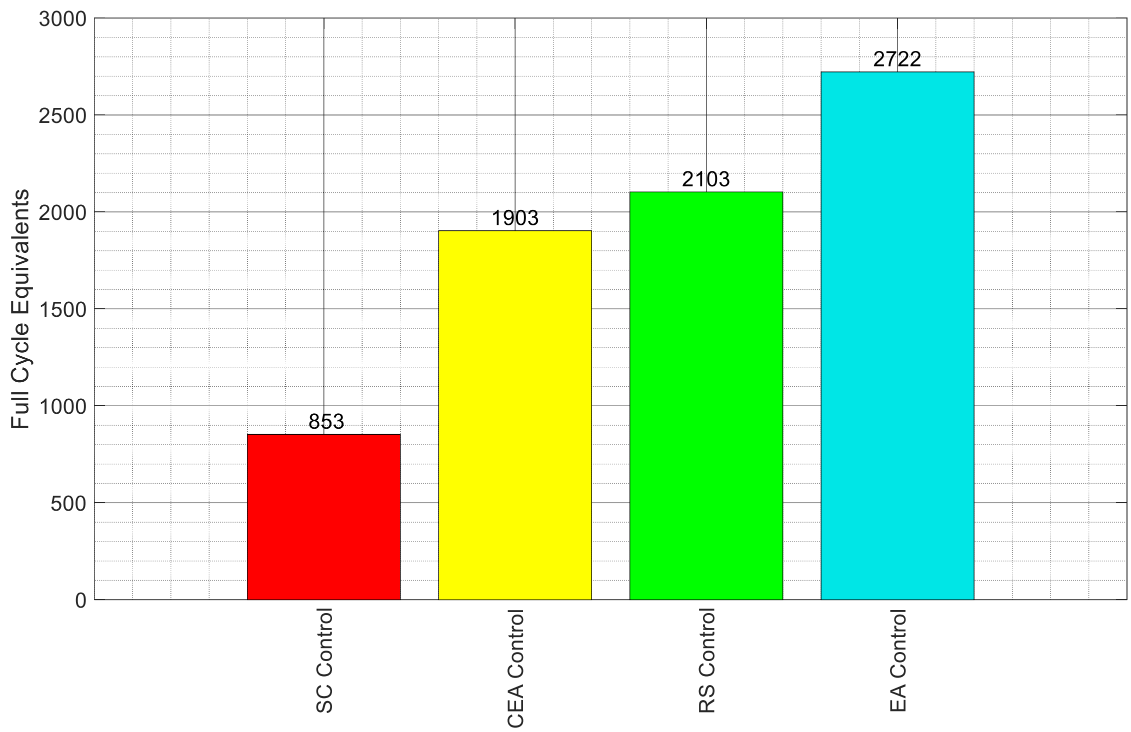


Figure 42. Aggregate residential battery full cycle equivalents by R1° control strategy

Observations:

- SC Control was found to cycle the BESS significantly less than the other three strategies with an average of 85 full cycle equivalents a year per home
- CES and EA Control had the most cycles with average household cycles of 190 and 272 respectively. By allowing an energy arbitrage system to export to the grid, cycling increases dramatically

- RS Control resulted in an average of 210 cycles per home, 10% and 146% greater than the CEA and SC control strategies which share the same policy environment

6.1.8 Summary

Switching residential stakeholders, in the absence of any BESS and PV, from a Flat to a TOU tariff provided savings in all non-winter months (Mar – Nov) and losses for the winter month (Dec – Feb), resulting in a net benefit exceeding $100 per home. All scenarios which included the tariff switch from the Flat to the TOU tariff generated more value than their counterparts which did not consider the switch.

The R1° policy environment which created the most private value for the homeowners was found to be the TOU tariff and net-metering agreement. The next most favourable policy was the TOU tariff with no net-metering, in which case, RS Control was found to generate the most value. The least desirable policy environment from the homeowner perspective was the Flat tariff an no net-metering. All R1° strategies resulted in LDC residential revenue losses, while only some provided the LDC with passive demand charge savings. CEA_{TOU}, RS_{TOU} and $EA_{TOU, NM}$ all had a positive net benefit on the LDC; however, when a tariff change from Flat to TOU is also considered, $EA_{F2TOU, NM}$ did not result in positive net LDC impact. A summary of the AV_{Resi}, LDC demand charge savings, LDC lost residential energy charge revenue, the AV_{LDC} and the AV_{System} of each R1° scenario is shown in Table 12.

Table 12. Summary of annual values by R1° scenario (All values in $)

	SC_{Flat}	SC_{TOU}	CEA_{TOU}	RS_{TOU}	$EA_{TOU,NM}$	SC_{F2TOU}	CEA_{F2TOU}	RS_{F2TOU}	$EA_{F2TOU,NM}$
Annual Residential Value	6991	6494	7039	7362	10089	7647	8192	8515	11241
Annual LDC Demand Charge Savings	365.5	365.5	4825	4825	7032	365.5	4825	4825	7032
Annual LDC Revenue Loss	-2070	-1574	-2885	-3166	-6433	-2726	-4037	-4319	-7586
Annual LDC Value	-1705	-1208	1941	1660	598.1	-2361	788	506.8	-554.6
Annual System Value	5286	5286	8980	9022	10687	5286	8980	9022	10687

6.2 Residential Multi-stakeholder Control Results

In this section, numerical results, and key observations of the simulated R2° control strategies are presented. As explained in section 4.4.2, the R2° control strategies were developed by stacking the R1° strategies with a residential utility peak shaving algorithm referred to as RES_{UPS}. The R2° results are presented next to selected R1° results for the sake of comparison (the R1° results are shown in grey while the R2° results are shown in color). A detailed discussion of the results with comparisons between the R1° and R2° scenarios is provided in section 6.3. The contents of this section are divided into three result subsections, followed by one summary subsection. The results displayed in each subsection are as follows:

- **Section 6.2.1:** Annual residential value by R2° scenario
- **Section 6.2.2:** Annual LDC value by R2° scenario
- **Section 6.2.3:** Annual System value by R2° scenario

Recall that ten residential stakeholders were modelled; the results displayed are the aggregate results of all ten homes.

6.2.1 Residential Annual Value

The R2° control strategies were simulated on the system model and the resulting annual residential value, AV_{Resi}, of the RES were calculated and are shown in Figure 43.

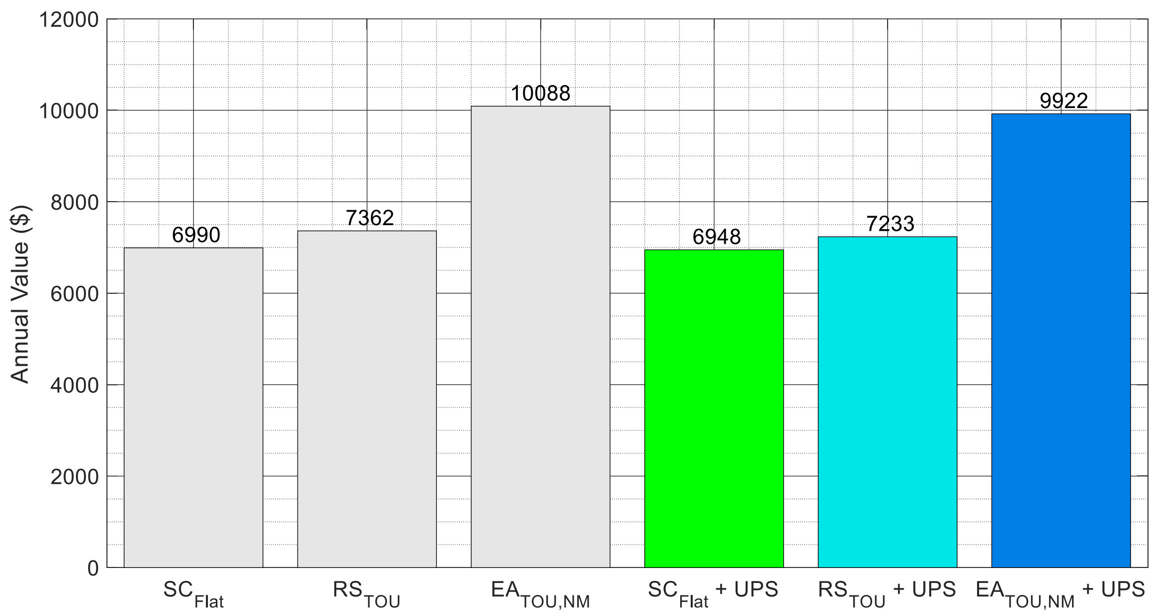


Figure 43. Aggregate residential annual value by R2° scenario

Observations:

- The R2° control strategies provided the residential stakeholders with less savings than the R1° control strategies as the RES now sacrifice days of normal operation to help the LDC mitigate demand charges.
- The reduced cost savings experienced by the residential stakeholders was found to be small (~2% for each of the residential strategy)

6.2.2 Impact on Local Distribution Company Annual Value

The impact of each R2° control strategy on the LDC was analyzed. The RES can impact the LDC in two ways. Energy cost savings achieved by the residential stakeholders correspond to losses in LDC revenue; while the RES can mitigate LDC demand charges paid to the transmission access provider by displacing system loads during LDC demand peaks. The impact of the R2° scenarios on the LDC are shown in Figure 44.

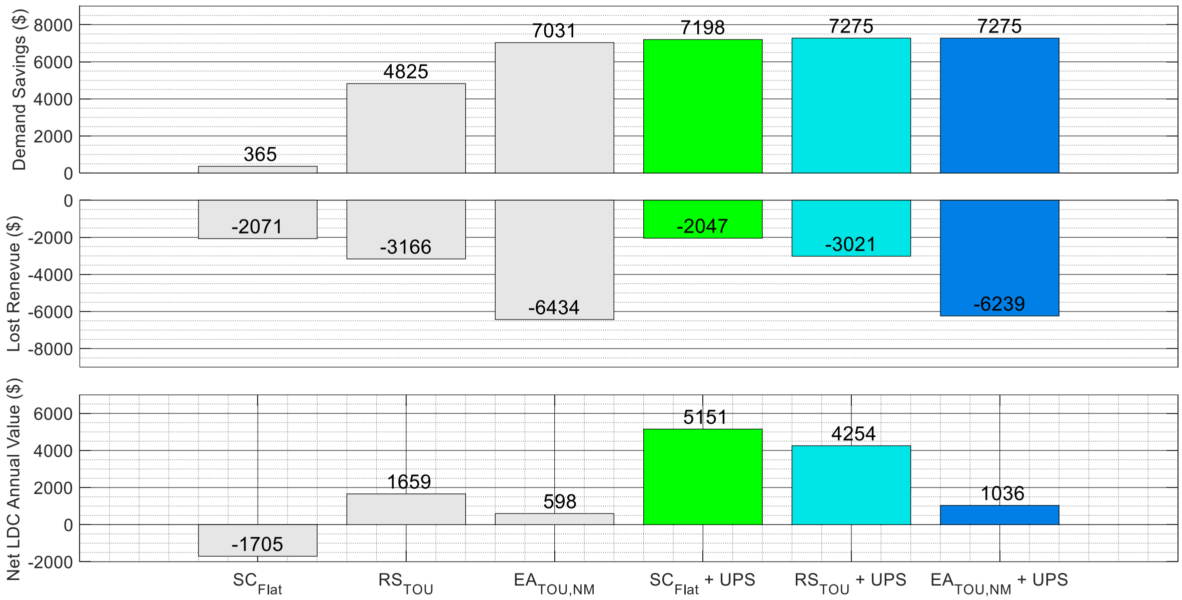


Figure 44. LDC annual value by R2° scenario

Observations:

- Each R2° control strategy was observed to provide the LDC with annual demand charge savings of more than $7,200.
- SC_{Flat} + UPS Control provided slightly less LDC demand charge reduction than the other R2° control strategies
- The lost LDC revenue was observed to be similar between the R1° and R2° control strategies. Of the R2° strategies, SC_{Flat} + UPS Control resulted in the least lost revenue for the LDC, followed by RS_{TOU} + UPS Control and EA_{TOU} + UPS Control.
- The resultant AV_{LDC} values of the R2° control strategies follow a separate trend than the R1° strategies. SC Control, which negatively impacted the LDC, was observed to become the most favourable strategy when paired with UPS functionality.
- SC_{Flat} + UPS Control provided almost as much LDC peak shaving benefits as the other R2° strategies, but when considering the lower LDC revenue losses, the SC_{Flat} scenario provided the largest AV_{LDC} ($5,200) of all R2° scenarios.

- Although $EA_{TOU, NM}$ + UPS Control provided high LDC demand savings, it also created the highest LDC lost revenue figure, collectively resulting in the lowest AV_{LDC} off all the 2°R control scenarios.

6.2.3 System Annual Value

The System Annual value, AV_{System}, provided by the RES paired with R2° control strategies was obtained by summing the benefit provided to the residential and LDC stakeholder groups, AV_{Resi} and AV_{LDC} respectively. The individual and system AV values are presented in Figure 45.

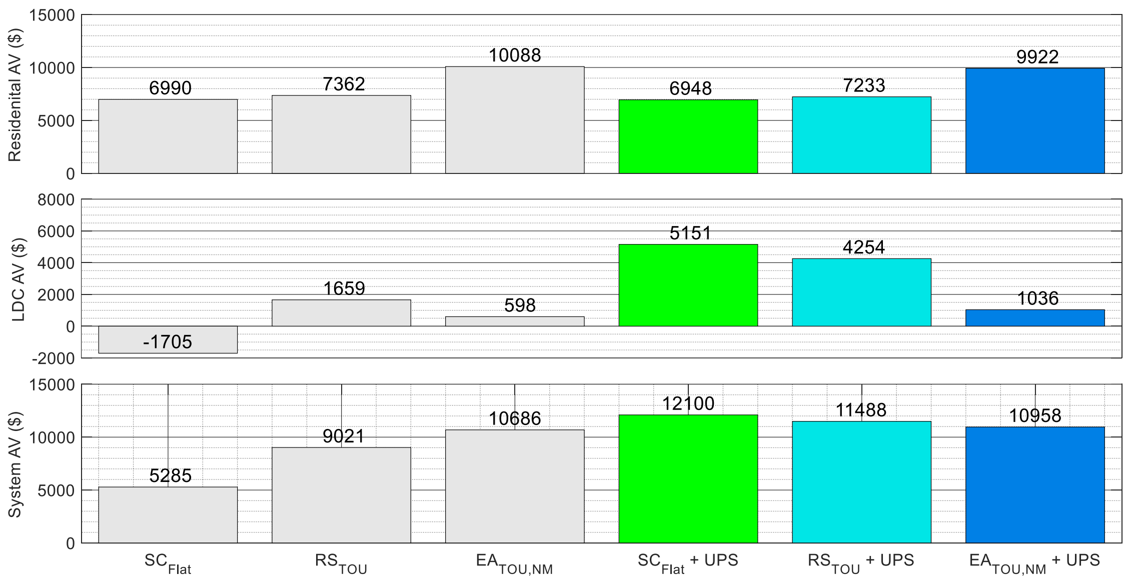


Figure 45. System annual value by R2° scenario

Observations:

- A trend was observed for the R2° control strategies that strategies which provided the highest AV_{Resi} provided the lowest AV_{LDC} and vice-versa. This alludes to the impact that the lost residential energy charge revenue has on the LDC.
- Each R2° scenario was found to provide similar AV_{System} values, with the aggregate annual residential impact of the ten homes ranging from \$10,000-\$12,000 by scenario.

- All R2° AV_{System} values were higher than their R1° counterparts. SC Control gained the largest increase in AV_{System} when paired with UPS functionality. The system value of EA Control was only minorly affected by adding UPS functionality.

6.2.4 PV Self Consumption

The rooftop PV of the RES can displace home loads, charge the BESS, and export power to the grid. The quantity of PV generation consumed BTM is referred to as percent self consumption. The average percent self consumption of the ten homes resulting from the R1° and R2° scenarios are shown in Figure 46.

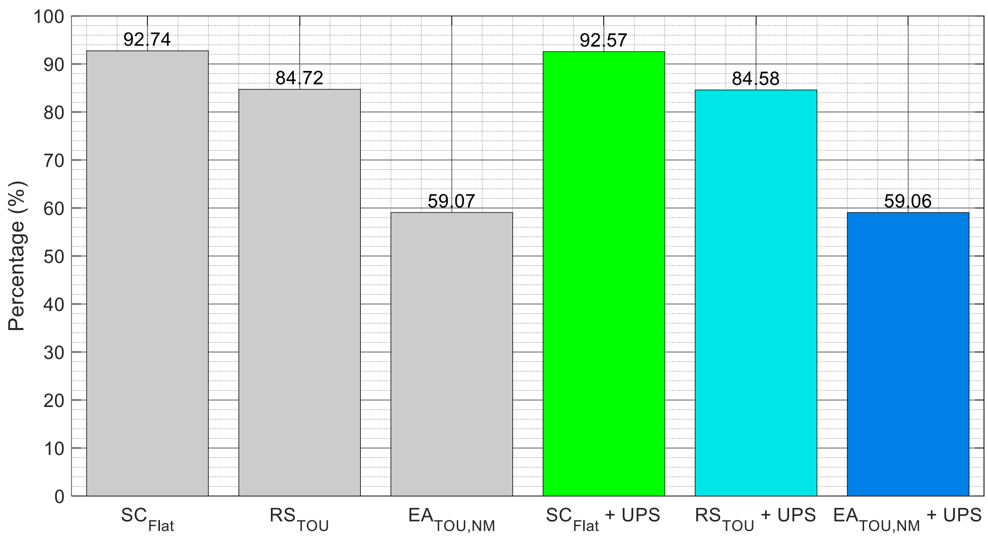


Figure 46. Average residential solar self consumption by R1° and R2° scenario

Observations:

- Adding the RES_{UPS} algorithm to the R1° scenarios was found to have a negligible impact on the precent of PV self consumed, with reductions under 1%.

6.2.5 Battery Full Cycle Equivalents

The energy throughput experienced by the RES batteries varies depending on the control utilized. The aggregate full cycle equivalents of the ten homes resulting from the R1° and R2° scenarios are shown in Figure 47.

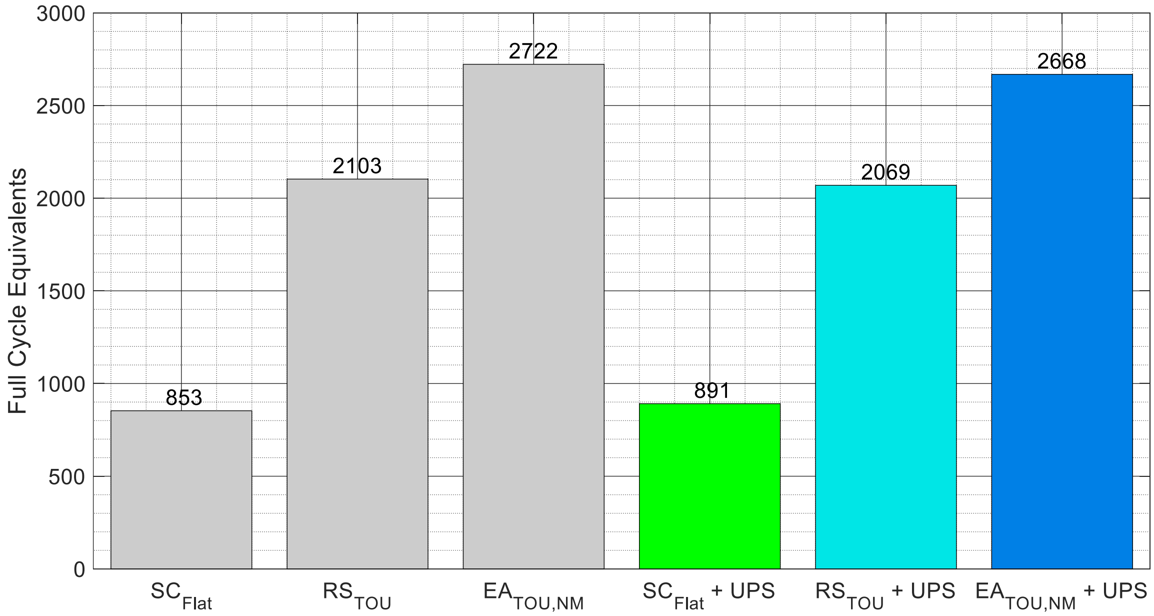


Figure 47. Aggregate residential battery full cycle equivalents by R1° control strategy

Observations:

- Adding the RES_{UPS} algorithm to the R1° scenarios was found to have an impact on battery cycling.
- The° RS_{TOU} + UPS and $EA_{TOU,\,NM}$ + UPS scenarios were shown to decrease the annual cycling of the RES by an average of 3.4 and 5.4 cycles per homes, when compared to their respective R1° counterparts.
- The SC_{Flat} + UPS scenario was shown to increase RES annual cycling by an average of 3.8 cycles per home.

6.2.6 Summary

The R2° scenarios provided the residential stakeholders with less value than their R1° scenario counterparts. The reduced AV_{Resi} experienced by the residential stakeholders was found to be small (~2% for each of the residential strategy). Both the $EA_{TOU,\,NM}$ + UPS and RS_{TOU} + UPS scenarios were observed to achieve demand charge savings of $7,275. The SC_{Flat} + UPS scenario was found to provided slightly less LDC demand charge savings than the other R2° scenarios at $7,200. The SC_{Flat} + UPS scenario resulted in the highest AV_{LDC}, followed by RS_{TOU} + UPS and then $EA_{TOU,\,NM}$ + UPS. Each R2° strategy was found to provide similar AV_{System} values, ranging from \$10,000 – 12,000. All R2° AV_{System} values were higher than their R1° counterparts. The SC_{Flat} scenario gained the largest increase in AV_{System} when paired with RES_{UPS} functionality, while the increase to system value from adding the RES_{UPS} functionality to the $EA_{TOU,\,NM}$ was minor. A summary of the AV_{Resi}, LDC demand charge savings, LDC lost residential energy charge revenue, the AV_{LDC} and the AV_{System} of each R2° scenario is shown in Table 13.

Table 13. Summary of annual values by R2° scenario (All values in \$)

	SC_{Flat} + UPS	RS_{TOU} + UPS	$EA_{TOU,NM}$ + UPS
Annual Residential Value	6949	7234	9922
Annual LDC Demand Charge Savings	7198	7275	7275
Annual LDC Revenue Loss	-2046	-3020	-6239
Annual LDC Value	5152	4255	1036
Annual System Value	12100	11489	10959

6.3 Analysis and Discussion

As shown in sections 6.1.1, a residential tariff switch from Flat to TOU generated an annual average value of \$100 of per home. All the R1° scenarios which included the tariff switch in the value calculation, generated 15% more value on average compared to the scenarios in which the homes were assumed to begin on TOU tariff. The TOU tariff used in this study offers a discounted overnight rate year-round, and only implements high price tier in the three winter months. Although value was decreased in the winter months, it was more than accounted for over the course of the nine summer months.

As expected, the R1° control which created the most private value for the homeowners was EA control which takes advantage of a TOU tariff and a net-metering agreement ($EA_{TOU, NM}$ scenario). Access to a TOU tariff with a discounted overnight window allowed the homeowners to buy cheap off-peak electricity, store it in the battery and sell it back to the LDC during the on-peak pricing period. Net-metering effectively decouples the homeowner's battery operation from its load, alleviating the homeowners from having to constrain discharge rates, or reserve battery energy capacity to store excess PV energy (unless to shift the PV energy to a higher tier of TOU pricing). Due to the favourable policy environment, this scenario provided the most residential value across all months of the year. If the homes were offered a TOU tariff but no net-metering agreement, operating on RS Control would provide the homeowners with the most private value (RS_{TOU} scenario). With the exclusion of a net-metering agreement, energy arbitrage must be constrained to avoid unvalued grid exports. Homeowners in this situation become incentivized to self consume as much PV generation as possible. RS control takes advantage of both applications (CEA and SC) and uses load and PV predictions to shift the objective of the system between applications in real time. As shown in section 6.1.2, the CEA_{TOU} scenario generated more value than SC_{TOU} in the winter months and vice-versa for the summer months. This highlights how RS Control can maximize homeowner value in climates with seasonal dynamics in electricity consumption; RS Control would, however, require a 'smart' control platform which could increase the initial cost of investment. If the more complex RS Control was unavailable, it was found that CEA control provided more value than SC Control in this policy environment; although only marginally. The residential policy environment with the least potential for value generation is a flat rate with no net-metering. Without a TOU tariff or a net-metering agreement, homeowners lose the ability to shift consumption between TOU pricing tiers and take advantage of cheap off-peak electricity. SC Control is used to self consume as much PV generation as possible and minimize the amount of electricity purchased from the LDC.

The impact of the R1° scenarios on the LDC varied by scenario as shown in section 6.1.4. A trend was observed where the scenarios which resulted in the largest amounts of LDC revenue losses, also provided the LDC with greatest amount of demand charge savings. This is not a coincidence as, from the homeowner perspective, the R1° scenarios which generated the most value involved shifting load from on-peak to off-peaks hours on a TOU tariff. By shifting loads, the RES are likely to provide the LDC with passive peak shaving value, even without coordination between the RES and the LDC. Whether the net impact of the R1° scenarios on the LDC was positive or negative, depended on whether the resulting LDC demand charge savings were greater or less than the accompanying revenue losses. To help visualize this concept, Figure 48 shows the LDC demand charge savings as a percentage of the accompanying LDC revenue losses for each R1° scenarios. Percentages above 100%, represent scenarios in which the LDC demand savings exceeded LDC revenue losses, providing a net benefit to the LDC.

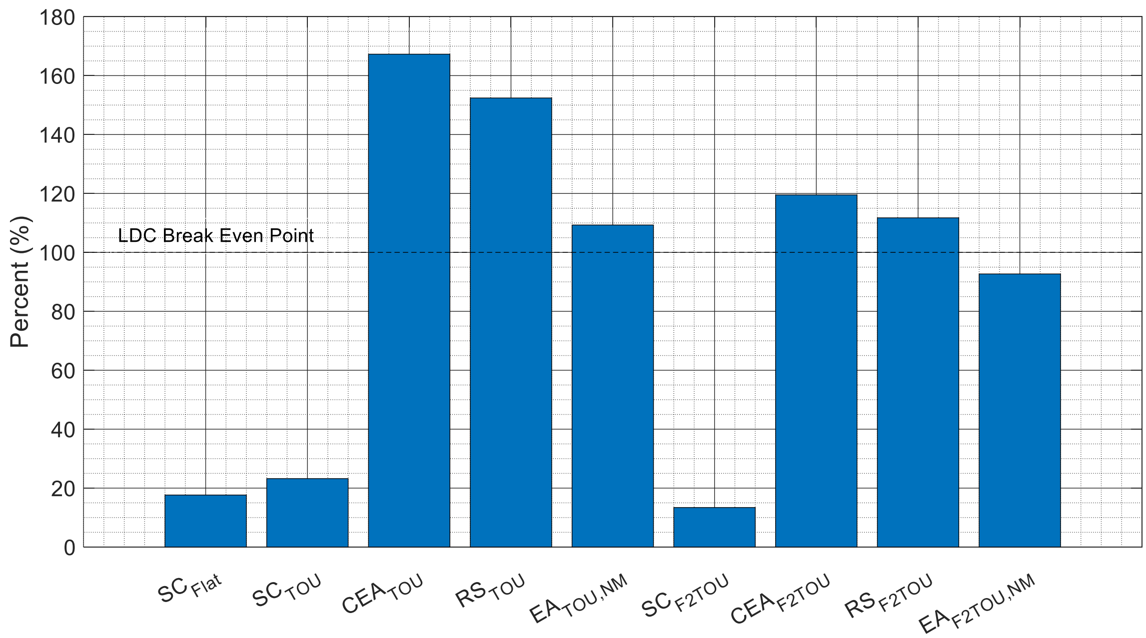


Figure 48. LDC demand savings as a percentage of lost LDC revenue by R1° scenario

All of the R1° control strategies which shift loads from on-peak to off-peak hours on a TOU tariff (CEA, RS and EA Control), at the penetration level examined, were shown to provide the LDC with enough passive demand charge savings to offset the associated LDC energy charge revenue losses, and in certain cases add extra value. The one exception being $EA_{F2TOU,NM}$, implying that the EA Control is only beneficial to the LDC when offered to residential customers already on a TOU tariff. Although the SC_{Flat} and SC_{TOU} scenarios resulted in the smallest amount of LDC revenue losses, they also provided the least LDC demand savings and failed to offset their associated LDC energy charge revenue losses.

These findings suggest that from the LDC perspective, offering the residential stakeholders a TOU tariff without net-metering is the policy ‘sweet-spot’. SC Control provided the residential stakeholder with the least amount of value, so when given access to a TOU tariff, an informed residential stakeholder would choose instead to conduct CEA or RS Control; this would eliminate the negative impact that SC Control has on the LDC and as shown, would provide additional benefit for the level of penetration examined. Offering a net-metering agreement and valuing grid exports was found to tip the scale and result in a neutral or negative AV_{LDC} impact. Although certain R1° control scenarios provide some value to the LDC, they are not significant enough that the LDC would be inclined to further incentivize the residential stakeholders to deploy RES, apart from creating the policy environment which enables the control strategies.

It should also be noted that, in BESS peak shaving applications there is a point of diminishing returns, in which increased energy capacity (and associated cost) is needed to provide the same incremental kW of demand peak reduction. An implication of this is that after a certain level of RES penetration, each incremental RES added to the LDC distribution network will not provide the same LDC peak demand savings as all previous RES. As such, the benefit achieved by the LDC will not increase linearly as additional RES are deployed; at a certain penetration level, the lost LDC energy charge revue will exceed the LDC demand charge savings.

Three R2° residential scenarios (SC_{Flat} + UPS, RS_{TOU} + UPS, and $EA_{TOU, NM}$ + UPS) were developed by stacking R1° control strategies with RES_{UPS}. A sequential stacking approach was used, in which the RES would operate either entirely for homeowners or entirely for the LDC on any given day. Sacrificing one day of normal RES operation results in minimal losses to homeowners and has no lasting impact on the homes ability to resume normal operation the following day. The UPP utilized in the R2° strategies predicts LDC peak days with high accuracy so the RES only sacrifices a small number of days of normal operation and, as shown in section 6.2.1, lost value experienced by homeowners when moved from the

R1° to R2° control strategies is minimal, with AV_{Resi} reductions less than 2%. These findings allude to the success of the sequential stacking method used to construct the R2° control strategies with regards to its ability to serve the interests of the LDC, while maintaining the private value of the residential stakeholders.

While the impact on LDC demand charge savings varied significantly by R1° scenario, similar LDC demand charge savings were found for all three R2° scenarios. Both the $EA_{TOU, NM}$ + UPS and RS_{TOU} + UPS scenarios were observed to achieve the maximum theoretical value of LDC demand charge savings of $7,275, when considering the converter power constraints ($\mathit{10}$ systems $\times$ $\mathit{5}$ kW $\times$ $\mathit{12.125\$}$/kW/month $\times$ $\mathit{12}$ months). SC control does not prioritize starting each day at a full SOE and thus is at a disadvantage when called on to provide LDC peak shaving and the SC_{Flat} + UPS scenario was found to provide, at $7,200, slightly lower LDC demand charge savings than the other R2° scenarios. Since the LDC can obtain similar demand charge savings regardless of which R2° scenario is utilized, the factor dictating which scenario was the most beneficial to the LDC became the amount of LDC lost revenue associated with the given scenario. As shown in section 6.1.4, scenarios which utilize SC control generate the least value for the homeowners and thus the smallest amount of LDC revenue losses. From the LDC perspective, this makes SC Control the most suitable for pairing with RES_{UPS}. To highlight the impact that adding RES_{UPS} functionality to the R1° scenarios has on the LDC, Figure 49 shows the LDC demand charge savings as a percentage of LDC revenue losses for the R1° scenarios (left) and their corresponding R2° scenarios (right). Percentages above 100%, represent scenarios in which the LDC demand savings exceeded LDC revenue losses.

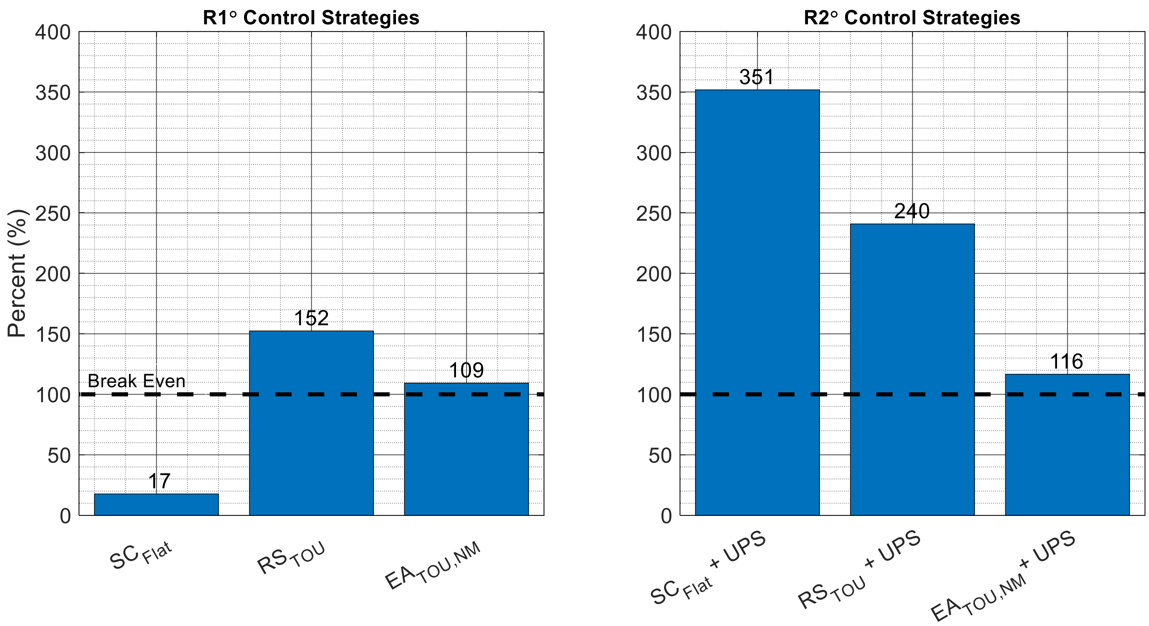


Figure 49. LDC demand savings as a percentage of LDC lost revenue by R1° and R2° scenario

Prior to stacking RES_{UPS}, the SC_{Flat} scenario only provided LDC demand charge savings equal to 17% of the resulting lost revenue; stacking RES_{UPS}, the SC_{Flat} + UPS scenario resulted in LDC demand savings of 350% of the lost revenue. The RS_{TOU} scenario, which already had a positive impact on the LDC, also saw a large increase in AV_{LDC} when stacked with RES_{UPS}. Contrary to the other two scenarios, the $EA_{TOU,\,NM}$ + UPS scenario provided marginal additional benefit to the LDC than the $EA_{TOU,\,NM}$ scenario, because the R1° scenario already provided the LDC with close to the maximum obtainable demand charge savings, leaving little opportunity for an additional benefit from being stacked with RES_{UPS}. The marginal value increase of going from $EA_{TOU,\,NM}$ to $EA_{TOU,\,NM}$ + UPS is unlikely to justify the capital cost of implementing the necessary CCP infrastructure required for the R2° strategy; however, the value of going from R1° to R2° control for the other two policy environments is much more significant. The SC_{Flat} + UPS and RS_{TOU} + UPS scenarios result in AV_{LDC} that are 497% and 410% higher than that of $EA_{TOU,\,NM}$ + UPS, respectively; giving the LDC much more incentive to pursue R2° control.

These findings suggest that operating distributed RES on R2° control strategies, at the penetration level examined, can ensure that the LDC obtain sufficient demand charge savings to fully offset any losses in residential energy charge revenue, and can provide substantial additional benefit. From the LDC perspective, policy environments which offer low value to the residential stakeholders are ideal for R2° control, as the LDC can obtain the same amount of demand charge savings while sacrificing smaller revenue losses. The LDC should consider, however, that the policy environment must offer enough value to the residential stakeholders to rationalise their involvement.

As mentioned above, there is a point of diminishing returns associated with BESS peak shaving. While this phenomenon will still occur in the R2° scenarios, it will do so at a slower rate than with the R1° scenarios. The ability to coordinate the RES charge and discharge commands will utilize energy more efficiently, resulting in an enhanced ability for each incremental RES deployed to provide as much or close to, the LDC peak shaving of prior RES.

RES control scenarios which result in AV_{System} greater than the annual values of any of the individual stakeholders suggest a potential for new policies and cooperative business models which could more efficiently monetize RES. Traditionally, RES is purchased by the residential stakeholder and operated on a R1° control strategy, disregarding impact on the LDC. In a R2° scenario, the residential stakeholders allow the LDC to make use of their RES on LDC peak days. While this practice has been shown to increase the AV_{System}, without incentivization the residential stakeholders are unlikely to willingly participate. To inform the development of a business agreement between parties it is of interest to know how the value of the RES is distributed between stakeholders. Figure 50 shows the percent contribution of each stakeholder toward the system value for the R1° scenarios (left) and the corresponding R2° scenarios (right). This is calculated by dividing the annual value of a single stakeholders (AV_{Resi} and AV_{LDC}) by the annual value of the system (AV_{System}). Note that for scenarios which have a negative impact on AV_{LDC} (and by extension AV_{System}), the percent contribution of the LDC will be negative.

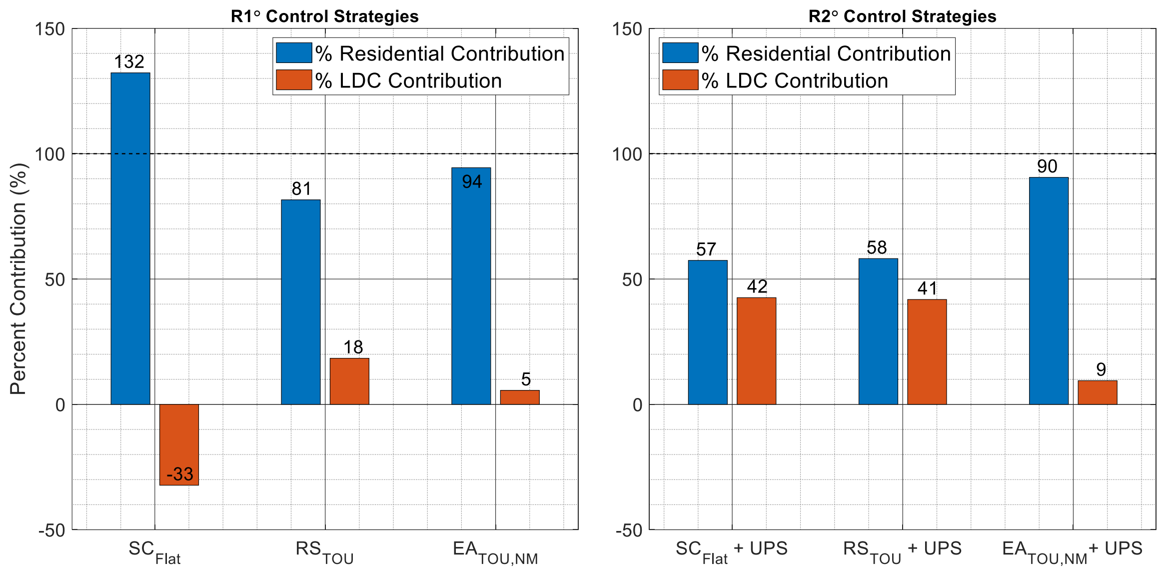


Figure 50. Percent contribution of each stakeholder to system value by R1° and R2° scenario

As expected, most of the value generated by the R1° strategies is attributed to the residential stakeholders. The R2° strategies result in a more even distribution of value when compared to their R1° counterparts. Stacking RES_{UPS} with R1° control strategies in non-net-metered policy environments (SC_{Flat} + UPS and RS_{TOU} + UPS) resulted in an approximate value split of 60:40 between the residential and LDC stakeholders. In a net-metered environment ($EA_{TOU, NM}$ + UPS) the value is tilted much more in favour of the residential stakeholders at approximately a 90:10 value split between the residential and LDC stakeholders respectively.

As shown in section 6.2.1, implementing R2° control comes at a cost to the residential stakeholder of roughly 2% of their R1° AV_{Resi}. This lost AV_{Resi} is a small fraction of the gained AV_{System} and could easily be reimbursed by the LDC, with possibly further incentivization, while still leaving the LDC with significant added value. Considering that, in the SC_{Flat} + UPS and RS_{TOU} + UPS scenarios, 40% of the AV_{System} is achieved by the LDC, the residential stakeholders may be entitled to expect the LDC to share some of the upfront capital cost of the RES. Further analysis could determine the level at which the subsequent value gained by the LDC from the R2° control would offset the capital investment required to implement the CCP.

Chapter 7 Commercial Energy System

A system model was used to evaluate the annual value of two distributed CES operating single-stakeholder (C1°) and multi-stakeholder (C2°) control strategies. Value was assessed at the single-stakeholder level, and at the system level.

The commercial and LDC stakeholder groups each have their own vested interests. The commercial sites are concerned with whether a C1° control strategy can minimize their monthly demand charges; and whether a C2° scenario would compromise their ability to do so. The LDC is concerned about how a C1° control strategy affects their own value, considering both resultant losses in commercial demand charge revenue, and how the CES impacts the peak demand of their distribution network. The LDC is also interested in whether they can offset the potential negative impacts of a C1° control, or obtain additional value, by encouraging (or incentivizing) C2° operation. Scenarios which provide more value to the system than to any single stakeholder group, alludes to the potential for new policies and cooperative business models which could more efficiently monetize CES and facilitate increased system penetration. To inform development of a potential business agreement between parties, how the value of the CES is distributed across stakeholder groups is also of interest.

The contents of this chapter are as follows:

- **Section 7.1:** Numerical results, and key observations of the simulated C1° control strategies
- **Section 7.2:** Numerical results, and key observations of the simulated C2° control strategies
- **Section 7.3:** Detailed analysis and discussion of the results given in sections 7.1 and 7.2

7.1 Commercial Single-Stakeholder Control Results

In this section, numerical results, and key observations of the simulated C1° control strategy, Commercial Peak Shaving (CPS) Control, are presented. The contents of this section are divided into five result subsections, followed by one summary subsection. The results displayed in each subsection are as follows:

- **Section 7.1.1:** Monthly commercial value of C1° control
- **Section 7.1.2:** Annual commercial value of C1° control
- **Section 7.1.2:** Annual LDC value of C1° control
- **Section 7.1.3:** Annual system value of C1° control
- **Section 7.1.5:** Battery full cycle equivalents of C1° control

7.1.1 Monthly Value Analysis

The monthly peak shaving revenue of each commercial site is shown in Figure 51.

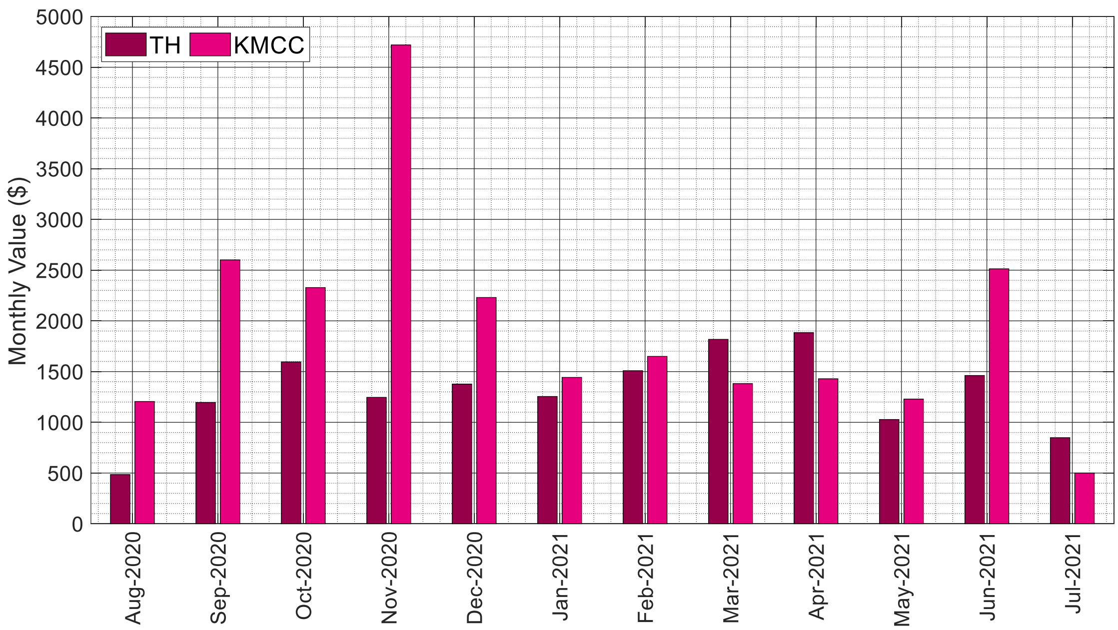


Figure 51. Monthly commercial value by site for CPS control

Observations:

- No strong seasonal pattern was observed for commercial demand charge savings for either site.
- The monthly value generated through peak shaving was observed to vary significantly by month, especially for the KMCC which received over $4,500 in demand charge savings in November, while the savings of all other months were under $3,000.
- The largest monthly demand charge savings achieved by the TH occurred in June, resulting in $2,000 of savings.

7.1.2 Commercial Annual Value

CPS Control was simulated on the system model and the resulting annual commercial value, AV_{Comm}, of both sites are shown in Figure 52.

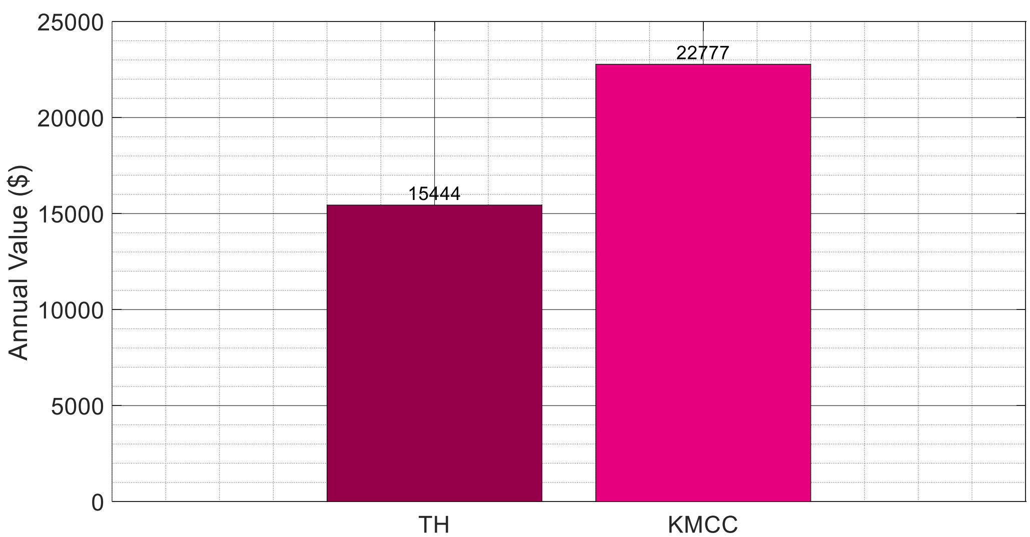


Figure 52. Commercial annual value by commercial site: CPS control

Observations:

- The KMCC was observed to obtain 40% more annual value than the TH despite using the same sized CES

- As discussed in section 5.3.1, the KMCC was expected to obtain larger demand charge savings than the TH

7.1.3 Impact on Local Distribution Company

Demand charge savings achieved by the commercial stakeholders are directly absorbed by the LDC as lost revenue. Although the C1° strategy, CPS control, does not actively consider its impact on the LDC, it may passively mitigate (or increase) the LDC peak demand resulting in LDC savings (or deficit). The impact of the CES paired with CPS control on the LDC is shown in Figure 53.

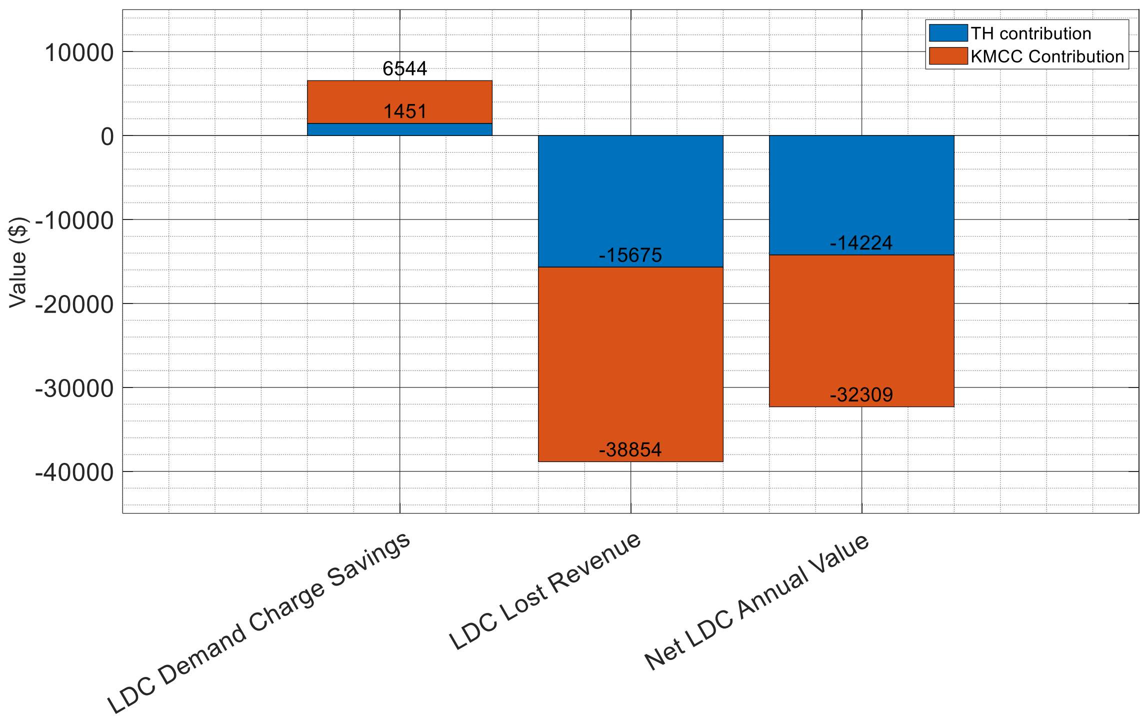


Figure 53. LDC annual value by commercial site: CPS control

Observations:

- Two CES paired with CPS control were found to collectively provide $6,500 of demand charge reduction for the LDC. Most of this peak shaving (77%) was a result of the CES at the KMCC

- Combined, the two commercial sites provided over $38,800 in LDC revenue losses. The majority (59%) of the LDC revenue losses came from the KMCC
- The loss of LDC revenue is much greater than peak demand reduction savings, resulting in total LDC losses exceeding $32,000. The TH and KMCC contributed 44% and 56% to the total AV_{LDC} respectively

7.1.4 System Annual Value

The annual value of the system, AV_{System}, provided by CPS Control was obtained by summing values of the individual stakeholders (commercial and LDC). The individual and system annual values are presented in Figure 54.

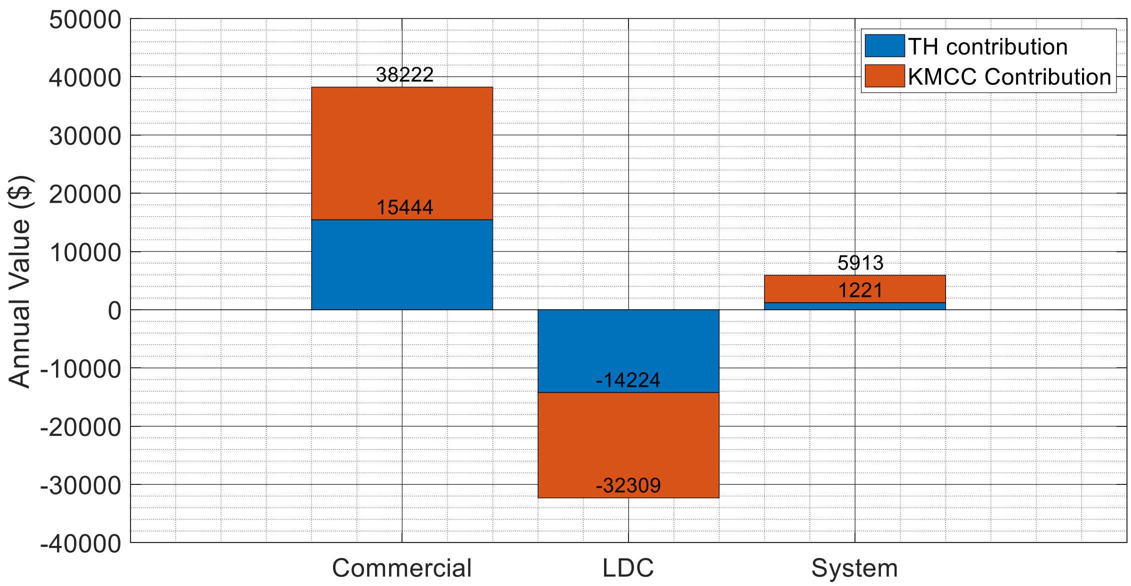


Figure 54. System annual value by stakeholder group: CPS control

Observations:

- The AV_{Comm} of the two commercial sites is larger than the negative AV_{LDC} resulting in a positive AV_{System} value, albeit of small magnitude
- CPS control has a significant, negative impact on the LDC and results in an AV_{System} which is only 15% of the AV_{Comm}.

7.1.5 Battery Full Cycle Equivalents

The annual battery full cycle equivalents for both commercial sites are shown in Figure 55.

Figure 55. Commercial battery annual full cycle equivalents by commercial site on CPS control

Observations:

- The KMCC was observed to cycle 75 % more than the TH
- The TH and KMCC batteries go through an average 0.08 and 0.14 cycles per day respectively which is low usage.

7.1.6 Summary

The C1° control strategy, CPS Control, was found to successfully providing both commercial sites with monthly demand charge reductions. Although no strong seasonal pattern was observed for commercial peak shaving value for either site; significant variations between monthly savings were observed. AV_{Comm} at the KMCC was found to be over 40% greater than at the TH; consequentially, the KMCC resulted in more LDC revenue losses than the TH. It was found that the KMCC provided the LDC with more passive demand charge reduction than the TH, though neither site provided enough LDC demand savings to offset the lost revenue experienced by the LDC due to the reduced commercial demand charges.

The individual impacts of the TH and KMCC on the LDC were similar with each site contributing 46% and 54% to the total AV_{LDC} respectively. Total AV_{Comm} was greater than the LDC losses, however only marginally, resulting in a small AV_{System} of just over $7,000. A summary of the AV_{Com}, LDC demand charge savings, LDC lost commercial revenue, AV_{LDC} and the AV_{System} of SPS Control for each site is shown in Table 14.

Table 14. Summary of CPS control annual values by commercial site (All values in $)

	Town Hall	KMCC	Combined
Annual Commercial Value	15445	22777	38222
Annual LDC Demand Charge Savings	1451	5093	6544
Annual LDC Revenue Loss	-15674	-23179	-38853
Annual LDC Value	-14223	-18086	-32309
Annual System Value	1221	4692	5913

7.2 Commercial Multi-stakeholder Control Results

In this section, numerical results, and key observations of the simulated C2° control strategy, Stacked Peak Shaving (SPS) Control, are presented. The contents of this section are divided into four result subsections, followed by one summary subsection. The results displayed in each subsection are as follows:

- **Section 7.2.1:** Annual commercial value of C2° control
- **Section 7.2.2:** Annual LDC value of C2° control
- **Section 7.2.3:** Annual system value of C2° control
- **Section 7.2.4:** Battery full cycle equivalents of C2° control

7.2.1 Commercial Annual Value

SPS Control was simulated on the system model and the resulting annual commercial value, AV_{Comm}, of both sites are shown in Figure 56.

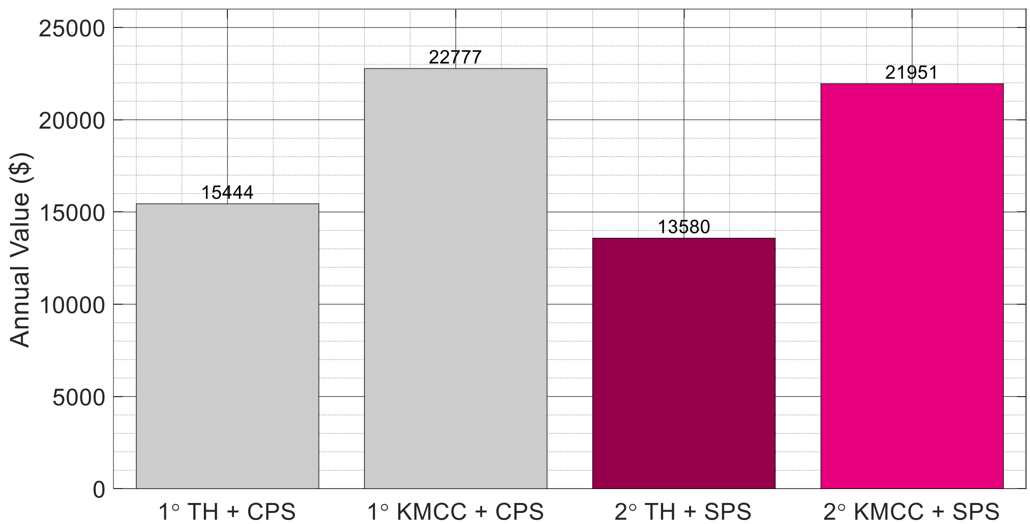


Figure 56. Commercial annual value by commercial site: SPS control

Observations:

- Very slight reductions in AV_{Comm} were observed between the C1° and C2° control strategies.
- The TH and KMCC experienced a 12% and 3% decrease in AV_{Comm}, respectively.
- The combined AV_{Comm} of the two commercial sites decreases by 8% when moved from the C1° and C2° control strategies

7.2.2 Impact on Local Distribution Company

On LDC peak days, SPS Control is fed operational demands by the LDC, via the CCP. The charge and discharge commands are calculated as to facilitate demand peak shaving of both the commercial and LDC peaks, mitigating demand charges for both stakeholder groups. While this control provides the LDC benefit via peak shaving, it also decreases the amount of revenue that the LDC collects from the commercial stakeholders. The combined impact of CPS Control on LDC peak demand savings and revenue loss was evaluated as shown in Figure 57.

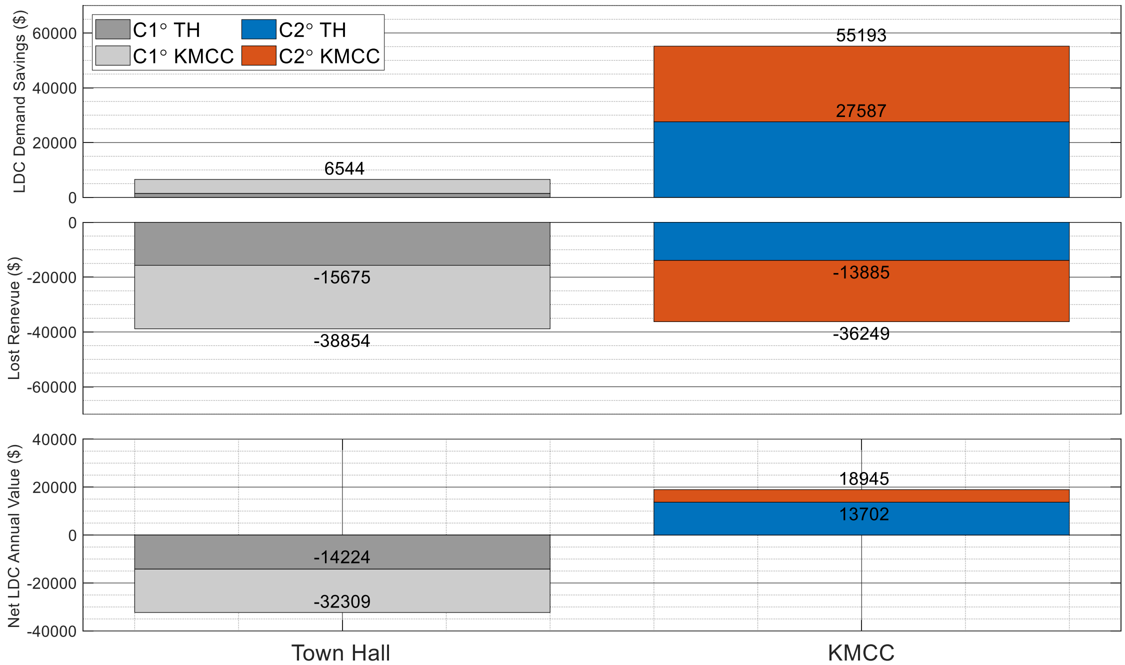


Figure 57. LDC annual value: SPS control

Observations:

- As expected, SPS Control provided the LDC with substantial peak demand savings, providing the LDC with a 630% increase in demand savings when compared to CPS Control.
- In the SPS Control, both commercial sites contributed evenly to the LDC demand charge reduction.
- SPS Control still resulted in significant losses in commercial revenue; decreasing losses by 6% compared to CPS control.
- SPS Control resulted in a positive AV_{LDC} of $19,000

7.2.3 System Annual Value

The annual system value, AV_{System}, provided by the CES paired SPS Control was obtained by summing the benefit provided to the commercial and LDC stakeholder groups, AV_{Comm} and AV_{LDC} respectively. The individual and system AV values are presented in Figure 58.

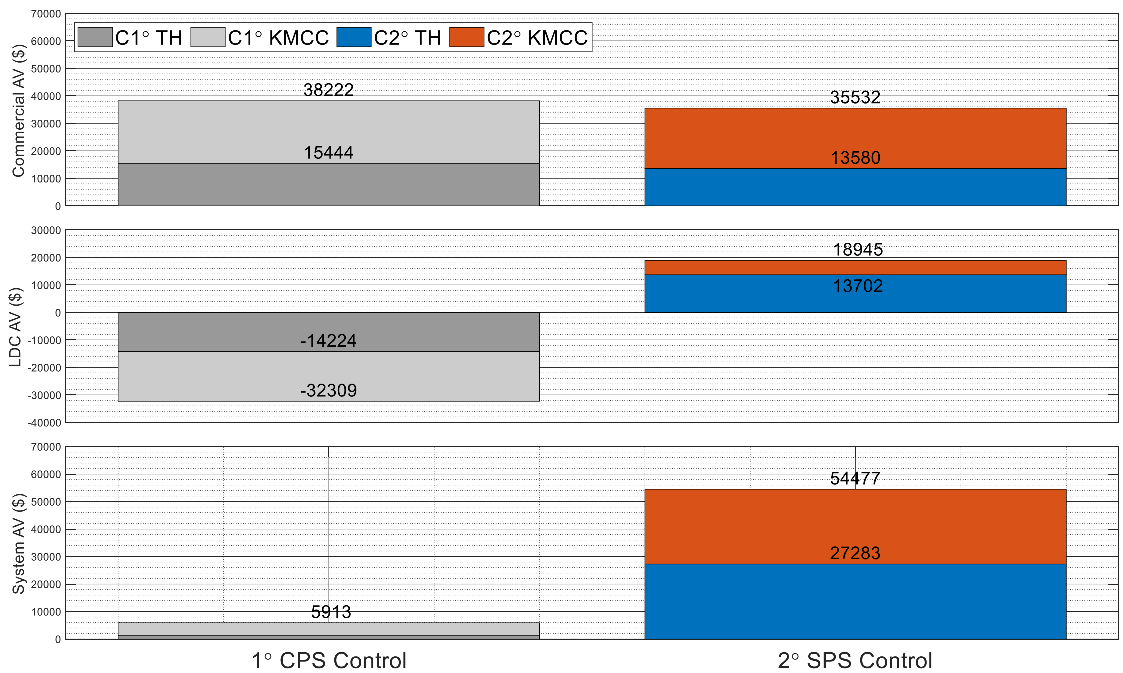


Figure 58. System annual value: SPS control

Observations:

- SPS Control provided benefit to both the commercial sites and the LDC, resulting in a AV_{System} of \$54,500, which is an 820% increase compared to the AV_{System} of CPS Control
- Under SPS Control, the contribution of each commercial site to the AV_{System} was very evenly distributed

7.2.4 Battery Full Cycle Equivalents

The battery full cycle equivalents for both commercial sites are shown in Figure 59.

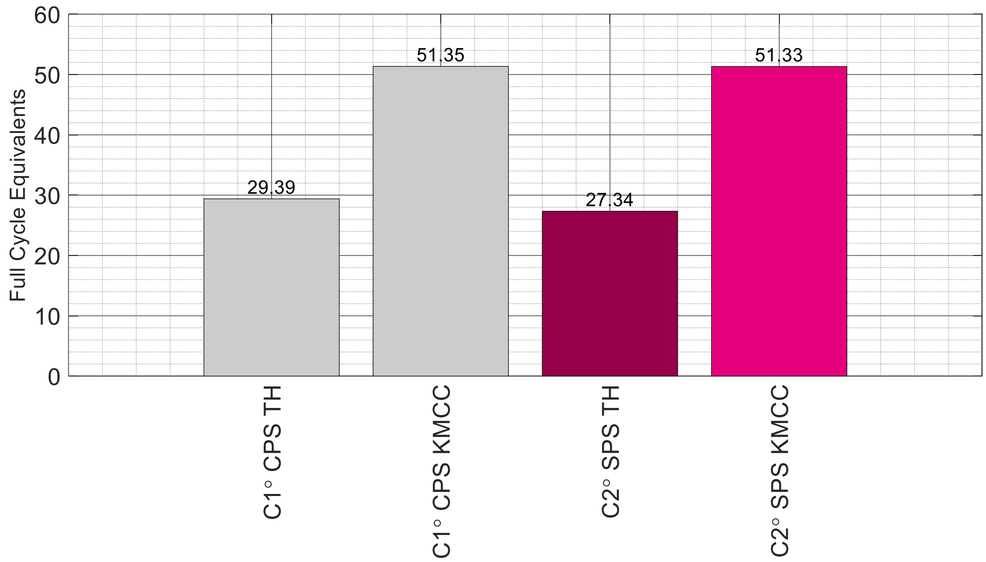


Figure 59. Commercial battery full cycle equivalents by commercial site on SPS control

Observations:

- Battery cycling at both sites was observed to decrease when switched to SPS Control.
- The impact of SPS Control on battery cycling at the KMCC was negligible (< 0.1%), while cycling at the TH decreased by 7%

7.2.5 Summary

The C2° control strategy, SPS control, was found to provide the commercial stakeholders with less value than the C1° control strategy, with a combined reduction in AV_{Comm} of 8% across both sites. Moving the CES from C1° to C2° control slightly reduced the revenue losses experienced by the LDC; however, the major impact of the SPS control strategy was a 630% increase in LDC demand charge savings. The demand savings experienced by the LDC were great enough to offset all lost commercial demand charge revenue and provide a positive AV_{LDC}. Since the commercial and LDC stakeholders all received positive value from SPS control, the AV_{System} was higher than of the individual AV. The AV_{System} of SPS control was found to be a 700% increase to the C1° CPS control. A summary of the AV_{Comm}, LDC demand charge savings, LDC lost commercial revenue, AV_{LDC} and the AV_{System} of SPS Control at each site is shown in Table 15.

Table 15. Summary of SPS control annual values by commercial site (All values in $)

	Town Hall	KMCC	Combined
Annual Commercial Value	13581	21951	35532
Annual LDC Demand Charge Savings	27587	27606	55193
Annual LDC Revenue Loss	-13884	-22364	-36248
Annual LDC Value	13703	5242	18945
Annual System Value	27283	27194	54477

7.3 Analysis and Discussion

As shown in section 7.1.1 and 7.1.2, the C1° CPS Control successfully provided both commercial sites demand charge savings for all months of the year, amounting to AV_{Comm} of $15,400 and $22,700 for the TH and KMCC respectively. As noted in section 5.3.1, it was expected for the KMCC to achieve more savings than the TH as the KMCC exhibited a larger difference between the maximum and median demand and had larger absolute peaks.

By mitigating commercial demand charges, the two commercial sites caused substantial revenue losses to the LDC. In contrast to the relationship between the residential stakeholders and the LDC, the reductions in LDC revenue caused by the CES are caused by a loss of demand charge ($/kW) revenue, as opposed to energy charge ($/kWh) revenue. When a residential stakeholder reduces energy purchase, the LDC losses revenue equal to the reduction of energy purchased (in kWh) multiplied by the LDC energy charge margin. In the case of commercial demand charge savings, the LDC bears the full brunt of commercial savings as lost revenue. The lost LDC revenue can be offset if the CES operations also reduce the LDC ratcheted demand peak, providing the LDC with demand charge savings; however, CPS Control at both commercial sites failed to do in a meaningful way. CPS Control at the TH and KMCC only resulted in enough LDC demand charge savings to offset 9% and 21% of their associated LDC revenue losses, respectively. The result was a significant negative impact on the $\mathrm{AV_{LDC}}$. This finding suggests that while commercial facilities can achieve significant demand charge reductions via CES and C1° control strategies, the impact on the LDC is very negative, giving cause for concern to the LDC. Another implication of this finding is the latent inefficiency of commercial demand charges to recover LDC costs associated with managing system peak demand. Although commercial demand charges can create substantial revenue for the LDC for commercial sites without CES.

When moved to the C2° control strategy, SPS Control, the TH and KMCC saw respective reductions in AV_{Comm} of 12% and 3%. This finding suggests volatility in how SPS control impacts a commercial site's ability to manage local demand peaks. A dynamic stacking approach was used to develop SPS Control (as explained in section 4.4.3). Dynamically sharing an ESS for peak shaving is more suitable between stakeholders with similar dynamics in load profile, such as demand peaks occurring at the same time of day. In ideal situations, the two stakeholders would have similar demand profiles, and the battery commands desired by one stakeholder would also benefit the other with minimal need to compromise. The opposite is also true in that two stakeholders with drastically different load profiles may be at odds with each other in terms of desired BESS operation. Operating on CPS Control, the KMCC was found to provide the LDC with passive demand charge savings over 300% greater than the TH. Although the magnitude of the passive peak shaving was small, this finding suggests that the KMCC is more conducive to being dynamically stacked with the LDC, than is the TH. This conclusion is strengthened by the finding that the AV_{Comm} of the KMCC was less negatively affected than that of the TH when switched from the C1° CPS Control to the C2° SPS Control.

Switching the CES to the C2° SPS Control provided a significant increase on LDC demand charge savings. To highlight the impact that switching the CES from C1° to C2° control has on the LDC, Figure 60 shows the LDC demand charge savings as a percentage of the accompanying LDC revenue losses for both CPS and SPS Control. Percentages above 100%

represent scenarios in which the LDC demand charge savings exceed LDC revenue losses providing LDC benefit.

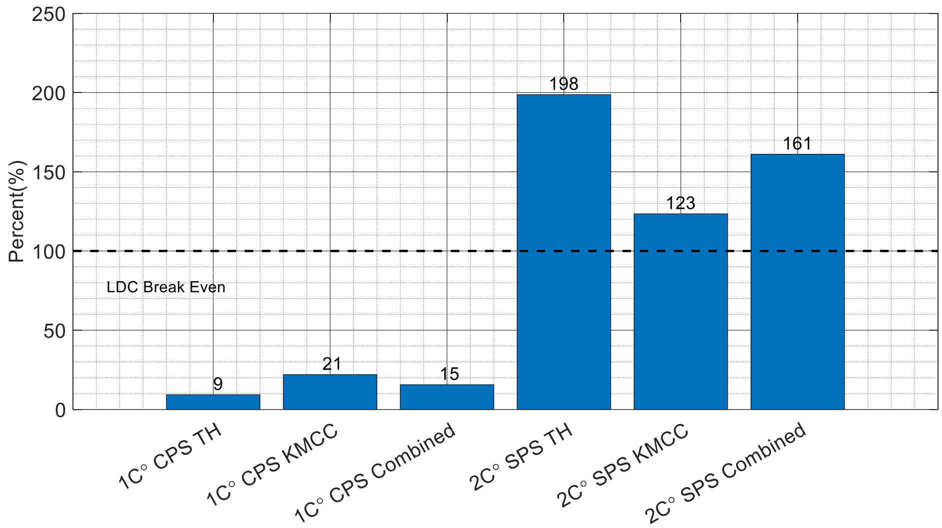


Figure 60. LDC demand savings as a percentage of lost LDC revenue by C1° and C2° control

The LDC demand charge savings obtained from SPS Control not only offset the lost LDC revenue but provided substantial additional benefit. On CPS Control and SPS Control, the two commercial sites resulted in LDC demand charge savings equal to 15% and 160% of the associated LDC revenue losses respectively. Not only does C2° control remove the negative impact of C1° control, but it provides significant added benefit. This finding suggests that the LDC is largely incentivized to pursue C2° control, especially if commercial sites in their jurisdiction plan on deploying CES regardless of LDC coordination.

While the passive peak shaving provided to the LDC by each commercial site varied significantly in the C1° scenario, both sites provided the LDC with identical demand charge savings in the C2° scenario. Since SPS Control allows the LDC to obtain identical demand charge savings regardless of site, the determining factor determining which site has the largest beneficial impact on AV_{LDC} is the amount of LDC revenue losses that the sites generate. From the LDC perspective, commercial sites which are less effective at generating their own demand charge savings are ideal for SPS Control. Further study should be given to this concept as two commercial load profiles provides a limited ability to examine what specific load profile characteristics are more conducive for SPS Control. The LDC should consider that the CES control regime (or other incentive scheme) must provide sufficient value to the commercial stakeholders to rationalize their involvement.

CES scenarios which have a positive impact on the LDC result in AV_{System}, greater than the value provided to any individual stakeholder. Traditionally, CES would be purchased by the commercial stakeholder group and operated on a C1° control strategy, disregarding impact on the LDC. In a C2° scenario, the commercial stakeholders allow the LDC to make use of their CES on LDC peak days. While this practice has been shown to increase the CES system value it provides little benefit to the commercial stakeholders, who, without proper incentivization, are unlikely to willingly participate. To inform the development of a business agreement between parties it is of interest to know how the value of the CES is distributed between stakeholders. To exhibit the benefit received by each stakeholder group, Figure 61 shows the percent contribution of each stakeholder toward the system value for CPS Control (left) and the SPS Control (right). This is calculated by dividing the annual value of a single stakeholders (AV_{Comm} and AV_{LDC}) by the annual value of the system (AV_{System}). Note that CPS Control had a negative impact on AV_{LDC} (and by extension AV_{System}), so the percent contribution of the LDC will be negative.

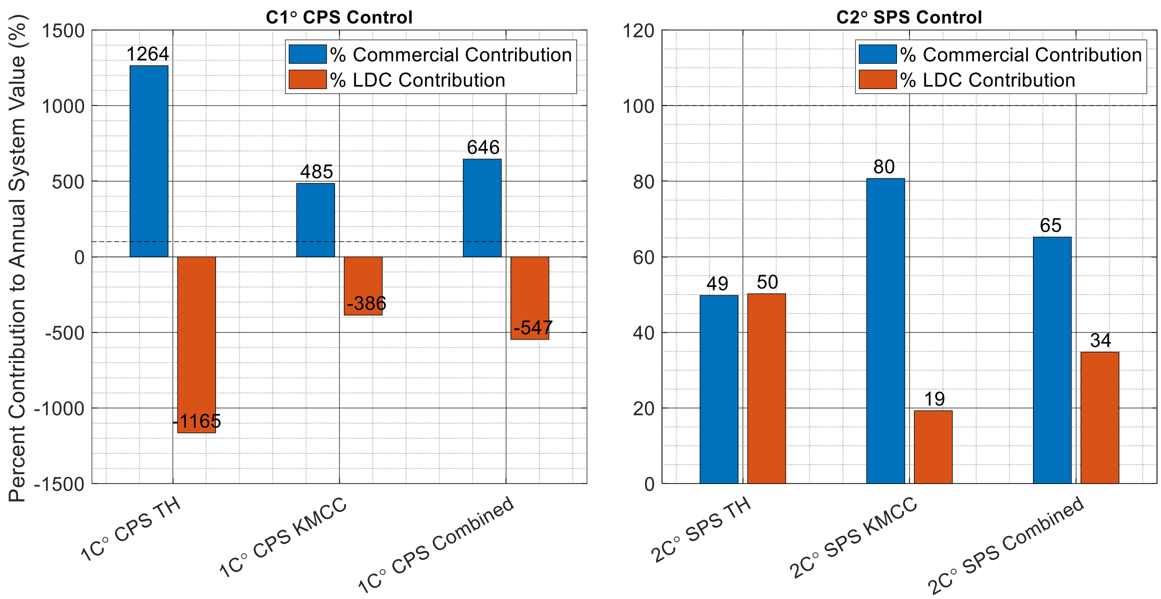


Figure 61. Percent contribution of each stakeholder to system value by C1° and C2° scenario

As expected, all of the value generated by C1°, CPS Control is attributed to the commercial stakeholders as the impact of C1° CPS Control on the LDC was negative. SPS Control resulted in a more even distribution of value between the commercial and LDC stakeholders. SPS Control at the TH and KMCC resulted in value splits of 50:50 and 80:20 between the commercial site and the LDC respectively.

As shown in section 7.2.1, the TH and KMCC were found to lose 12% and 3% of their AV_{Comm}, respectively, when switched from CPS Control to SPS Control. As concluded in this section, the TH load profile was less conducive for dynamically stacking with the LDC profile than that of the KMCC. As such, the distribution of value across stakeholders ends up being even between the TH and the LDC, while the KMCC received 80% of its contribution to the AV_{System}. The lost AV_{Comm} is a small fraction of the gained AV_{System} and could easily be reimbursed by the LDC, (or an alternative incentive can be offered), while still leaving the LDC with significant added value. Considering that 34% of the AV_{System} of the two CES is achieved by the LDC, the commercial stakeholders may be entitled to expect the LDC to share some of the upfront capital cost of the CES. A complication arises as the amount of value that the LDC achieves from the two commercial sites varies significantly. Further analysis could determine the level at which the subsequent value gained by the LDC from the C2° control would offset the capital investment required to implement the CCP.

The issues regarding the diminishing returns of BESS peak shaving, discussed in section 6.3, apply to the C2° control strategy and there will be a point where each incremental CES will have a smaller ability to provide the LDC with demand charge reduction. The coordination of the C2° strategy will become increasingly important with increased saturation of CES.

Chapter 8 Conclusion and Recommendations

ESS technologies, such as batteries, are a promising tool for energy management in high penetration rate renewable energy systems. Despite recent declines in the high capital cost of energy storage, it continues to be a major obstacle to widespread deployment. Control strategies which serve multiple energy storage applications simultaneously can more effectively monetize the ESS and justify increased deployment. While there are a variety of academic articles which study the combining of ESS applications, there are clear gaps in the literature with respect to multi-stakeholder control of ESS. Most studies evaluate the theoretical value of combining applications, while failing to offer ESS control strategies which would facilitate the combining of such applications in practice. Studies also fail to take a systems approach to evaluating ESS, quantifying value to single stakeholders and neglecting the impact of the ESS on other stakeholders throughout the electricity supply chain such as LDC.

The major research contribution of this thesis is the creation of a system model which consists of residential, commercial and LDC stakeholders to simulate the impact of distributed RES and CES, operating on single and multi-stakeholder control strategies, on individual stakeholders (private value) and the system as a whole (system value).

The system model was used to derive the following conclusions on the impact of distributed RES operating R1° control strategies under different policy environments:

A. Flat tariffs without net-metering incentivize PV self consumption and was found to be the least profitable R1° scenario. TOU tariffs enable residential stakeholders to incorporate energy arbitrage and increase private value. Net-metering agreements significantly enhance the residential value of a TOU tariff allowing energy arbitrage to be unconstrained.
B. At the penetration level examined, a TOU tariff with no net-metering is a policy 'sweet-spot' for the LDC.
    i. Flat tariffs with no net-metering incentivizes PV self consumption which is detrimental to the LDC ability to sustain energy charge revenue.

ii. When offering TOU tariffs, residential RES stakeholders are incentivized to abandon PV self consumption controls for the more beneficial energy arbitrage controls. This practice, at the level of penetration examined, was shown to increase LDC energy charge revenue losses but provide enough passive LDC peak demand savings to offset all negative impact and add additional value.

iii. Offering net-metering significantly increases lost LDC revenue without a reciprocal increase in passive LDC demand charge reduction, resulting in a net neutral or negative RES impact.

C. Although certain R1° control scenarios provide value to the LDC, they are not significant enough that the LDC would be inclined to incentivize the residential stakeholders to deploy RES, apart from creating the policy environment which enables the control strategies.

D. Due to diminishing returns in peak shaving, the benefit achieved by the LDC will not increase linearly as additional RES are deployed. At a certain penetration level, the lost LDC energy charge revue will likely exceed the LDC demand charge savings.

The system model was used to derive the following conclusions on the impact of distributed RES operating R2° control strategies under different policy environments:

E. A sequential stacking approach to combining residential BESS applications with LDC peak shaving was found to result in minor reductions to residential private value (< 2%)

F. R2° control provided the LDC with the greatest value in policy environments which offer low value to the residential stakeholders, as the LDC could obtain the same amount of demand charge savings, regardless of policy, while sacrificing smaller revenue losses.

G. Implementing R2° in a TOU tariff and net-metered environment ($EA_{TOU, NM}$ + UPS) provided the LDC with only a marginal increase in value.

i. The marginal value increase of going from $EA_{TOU, NM}$ to $EA_{TOU, NM}$ + UPS is unlikely to justify the capital cost of implementing the necessary CCP infrastructure required for R2° control
ii. The R1° scenario ($EA_{TOU, NM}$) already provided the LDC with 96% of the maximum obtainable demand charge savings, leaving little opportunity for additional benefit from being stacked with LDC peak shaving

H. Implementing R2° in a Flat tariff, non-net-metered (SC_{Flat} + UPS Control) or TOU tariff, non-net-metered (RS_{TOU} + UPS Control) policy environment provides significant added benefit to the LDC and results in the greatest system value of all R1° and R2° scenarios considered.
i. Given considerable increase in LDC and system value, these scenarios give the LDC much more incentive to pursue R2° control
ii. The SC_{Flat} + UPS scenario provided the greatest value to the LDC and resulted in the highest system value
iii. The lost residential value is a small fraction of the gained system value and could easily be reimbursed by the LDC, with possibly further incentivization, while still leaving the LDC with significant added value
iv. 40% of the system value generated in these scenarios is achieved by the LDC and the residential stakeholders may be entitled to expect the LDC to share some of the upfront capital cost of the RES
v. Further analysis could determine the level at which the subsequent value gained by the LDC from the R2° control would offset the capital investment required to implement the CCP

I. As with R1° control scenarios, the benefit achieved by the LDC will not increase linearly as additional RES are deployed. However, returns will diminish at a slower pace in the R2° controls scenarios as coordination allows for more efficient use of energy, enhancing the ability of each incremental RES to provide as much, or close to, the LDC peak shaving of prior RES.

J. Monetary value obtainable from RES can be increased by as much as 73% by implementing a coordinated, multi-stakeholder control regime and evaluating performance at a system level.

The system model was used to derive the following conclusions on the impact of distributed CES operating C1° control strategies:

K. By reducing commercial demand charges, C1° control has a significant negative impact on the LDC
    i. The passive LDC demand peak shaving resulting from C1° control were negligible when compared to the amount of resulting LDC revenue loss occurred
    ii. The substantial negative impact on LDC value gives the LDC cause to pursue C2° control

The system model was used to derive the following conclusions on the impact of distributed CES operating C2° control strategies:

L. A dynamic stacking approach to combining commercial peak shaving with LDC peak shaving resulted in losses to commercial value ranging from 3% to 12%
    i. The variability in lost commercial value was concluded to be the due to different compatibilities of each commercial load profile with the LDC load profile.

M. Implementing C2° control provided the LDC with significant demand charge savings, resulting in a large positive LDC and system impact
    i. Moving from C1° to C2° control turned the impact of the CES on the LDC from strongly negative to strongly positive which gives the LDC strong incentive to pursue C2° control, especially if commercial sites plan to deploy CES regardless of LDC cooperation
    ii. The lost commercial revenue is a small fraction of the gained system value and could easily be reimbursed by the LDC, with possibly further incentivization, while still leaving the LDC with significant added value

iii. Between 20% and 50% of the system value generated in these scenarios is achieved by the LDC and the commercial stakeholders may be entitled to expect the LDC to share some of the upfront capital cost of the CES

iv. Further analysis could determine the level at which the subsequent value gained by the LDC from the C2° control would offset the capital investment required to implement the CCP

N. Due to diminishing returns in peak shaving, the benefit achieved by the LDC will not increase linearly as additional CES are deployed; at a certain penetration level, the lost LDC revue from commercial demand charge reductions will likely exceed the LDC demand charge savings. C2° control will mitigate but not remove this phenomenon.

O. Monetary value obtainable from CES can be increased by 42% by implementing a coordinated, multi-stakeholder control regime and evaluating performance at a system level.

The system model was used to derive the following conclusions, comparing the impact of distributed RES and CES on single and multi-stakeholder control:

P. At the penetration level examined, certain R1° scenarios were found to have a positive impact on the LDC, while the C1° scenario had a significant negative impact on the LDC.

Q. The commercial stakeholders are more susceptible to losing private value when moved from single to multi-stakeholder control than the residential stakeholders.

R. Variability in the value lost between stakeholders is greater for the commercial stakeholder group than the residential stakeholder group.

8.1 Recommendations for Future Research

The model and analysis have several areas in which they could be improved:

I. The effect of market saturation should be investigated by utilizing more residential and commercial input load profiles. Distributed RES and CES provide value to the LDC via passive or deliberate LDC peak shaving. It is well understood that the greater the reduction in demand peak desired, the longer the duration of the peaks become, and the more energy storage capacity is required to make the same demand peak reduction. At a certain level of BESS penetration, each incremental BESS added to the grid will be able to provide a smaller amount of LDC peak shaving, thus providing less LDC value than all previous systems. It is expected that returns will diminish at a significantly slower pace in the multi-stakeholder control scenarios as coordination allows for more efficient use of energy. However, this phenomenon should be investigated further.

II. Future analysis should investigate the effect of BESS sizing in the ability of RES and CES to create value. One should expect that the optimal sized BESS for residential and commercial applications differs from the optimal size for LDC peak shaving. Conceivably, there exists an optimal BESS size which maximizes system value. This optimal size may change for each incremental BESS added to the system.

III. Further study should incorporate the value placed on carbon emission reductions, imposed by climate change policies. It is likely that the economic results would improve.

IV. With the availability of additional data, commercial rooftop PV systems, LDC owned solar farms and LDC owned onshore wind turbines could also be modelled. This would increase the number of BESS applications which could be examined and stacked, including ramp rate mitigation and renewable capacity firming. Investigating the ability of distributed BESS to facilitate increased penetration of renewables in distribution networks, in an effectively monetized, multi-stakeholder manner could amount to a large contribution to academic literature.

V. The impact of front of the meter (FTM) BESS should be investigated and contrasted against the results of this analysis. A FTM BESS serving only the LDC could provide value through LDC peak shaving, without resulting in residential or commercial LDC revenue losses. However, this system would only have access to LDC revenue streams, and there would be no one for the LDC to split the capital cost of the system with.

VI. Further study should incorporate the hardware test findings presented in Appendix A: StorTower Performance Testing. Experimental testing of a residential energy storage system found that the system's energy capacity and converter power capacity were nominal values which differed from rated values. By adjusting the residential input parameters to match the experimentally obtained values showed strong agreement between a cycle of experimental and simulated data.

8.2 Limitations and Additional Considerations

The main limitations of this thesis are:

- One-year of test data
- Availability of time-synced data
    - Low sample size of commercial buildings (2)
    - Medium sample size of residential buildings (10)
    - No large (> 10 kW) scale renewable generation profiles
- Lack of experimental validation data
- Model sensitivity analysis not conducted
- The electricity tariffs used in this thesis do not necessarily represent all jurisdictions

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Appendix A: StorTower Performance Testing

Appendix A
StorTower Performance Testing
Baseline Performance

Work conducted by Byrne Campbell (BEng) and Lukas Swan (PhD)

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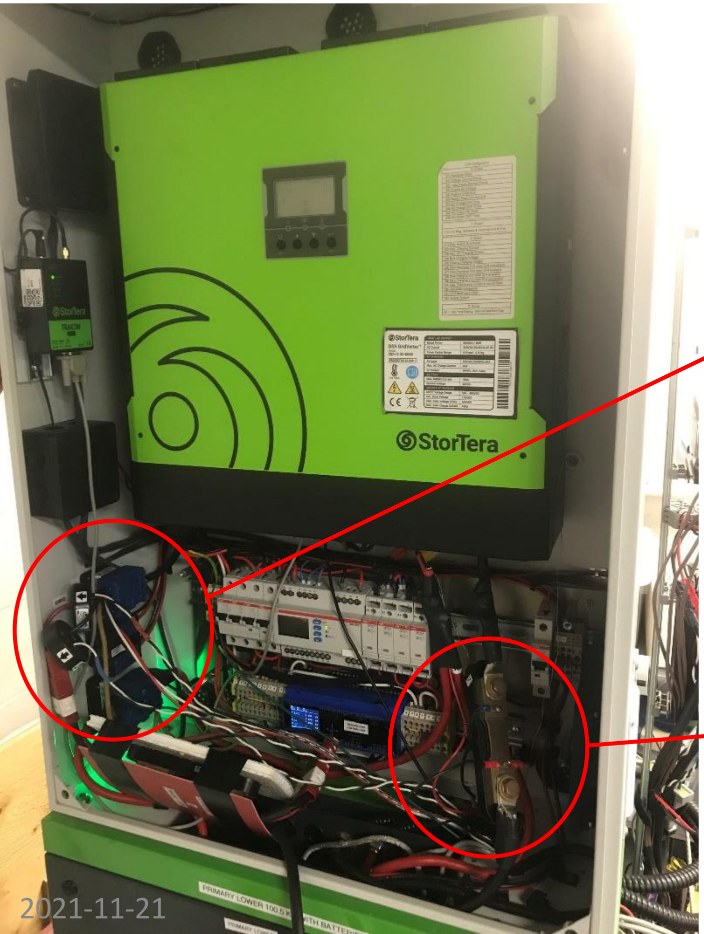
Intro and Objective

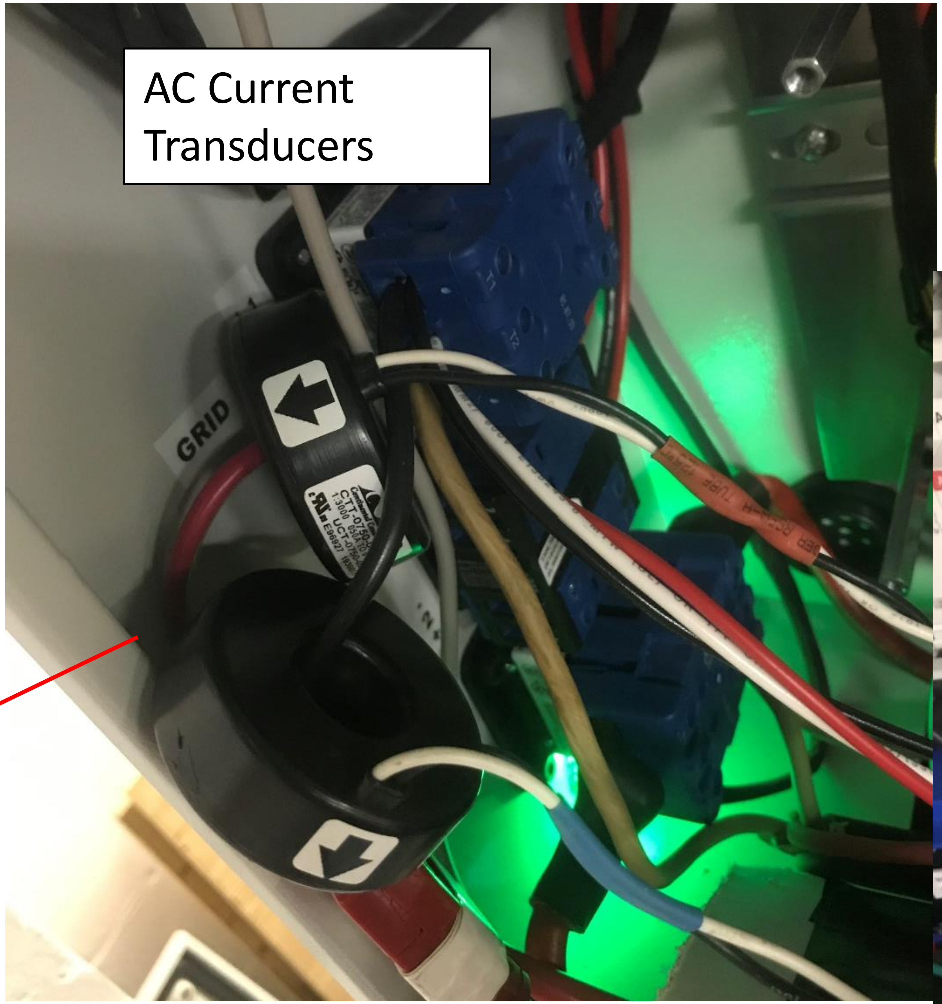
- The StorTower is a residential battery energy storage system designed and manufactured by StorTera, a UK based tech company
- Objectives
  - Apply independent metering to a StorTower
  - Measure AC and DC side performance along with temperature
    - Calculate energy capacity and energy efficiency over standardized cycles
    - Determine true converter charge and discharge power capacities
  - Compare one cycle of experimental data with modelled data for the Energy Arbitrage use case
- Not investigated
  - StorTower solar to battery charge efficiency

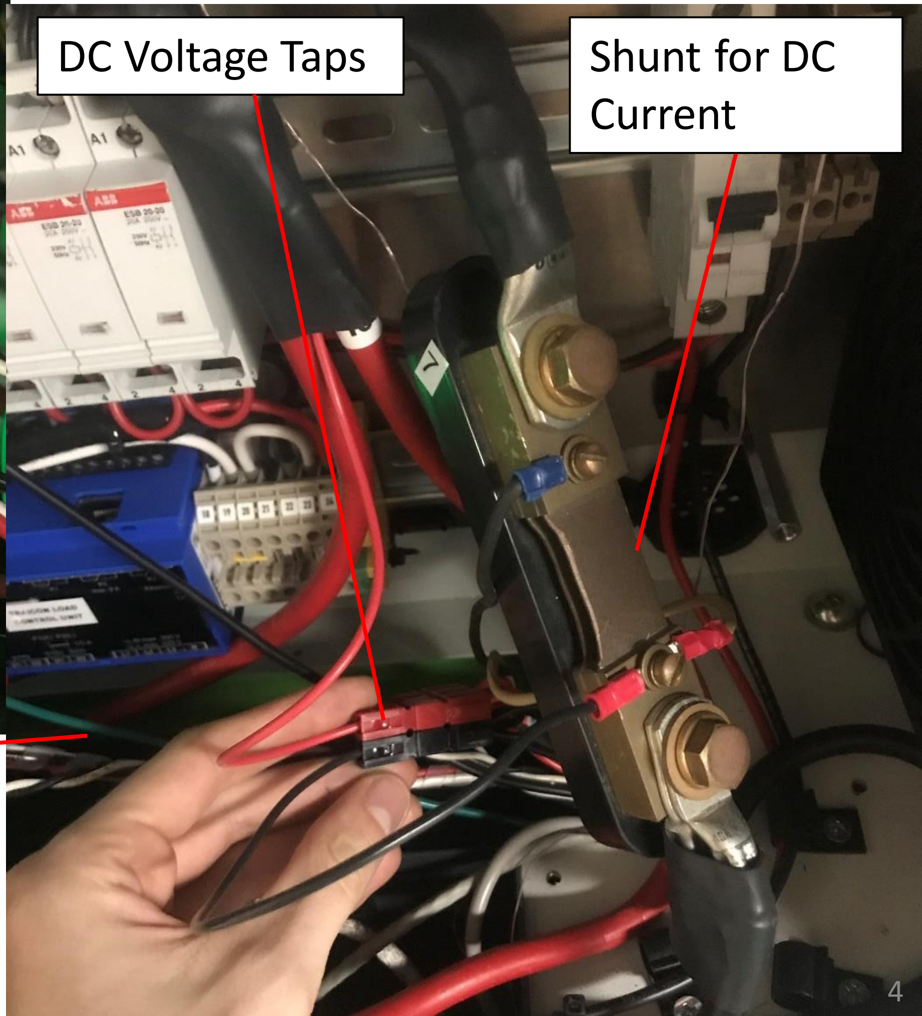
Equipment

- A variety of voltage, current, and temperature sensors were applied
- AC and DC side measurements are made
- Equipment locations, models, and connection order are given on the following slides

Electricity measurement locations



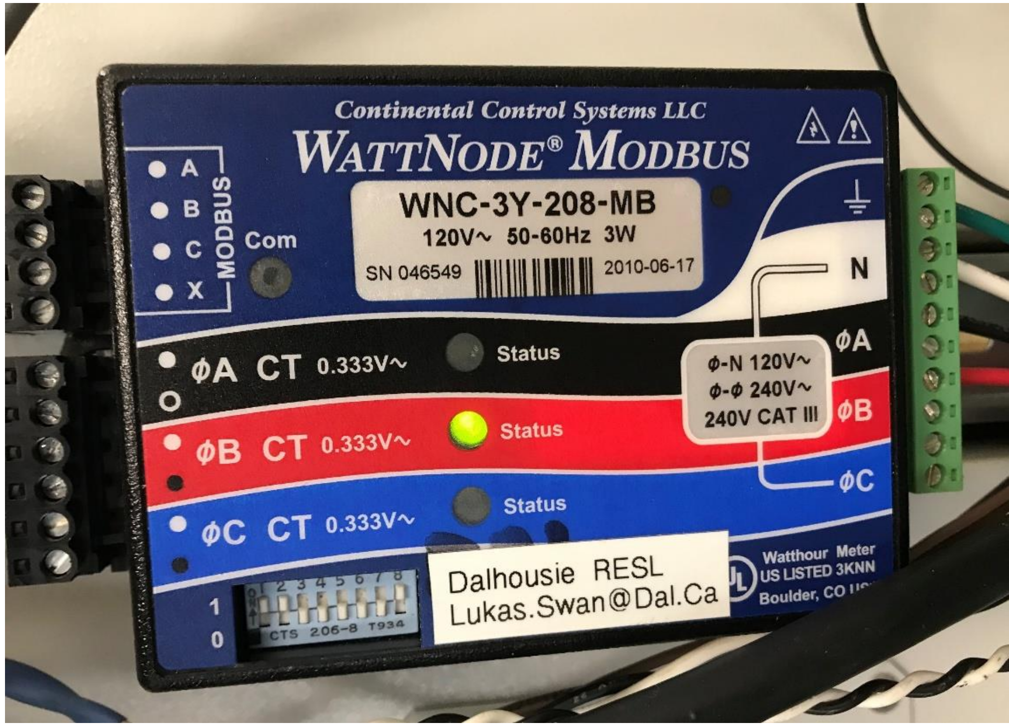


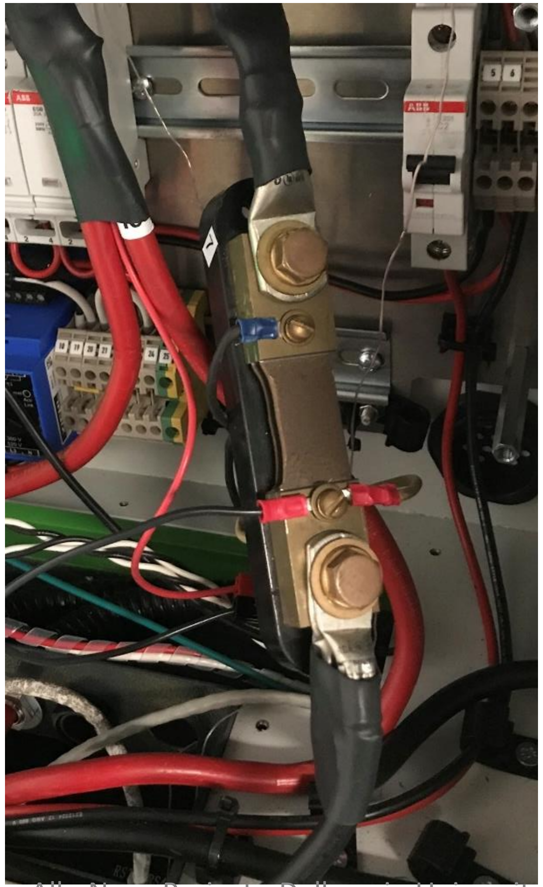


Electricity instruments

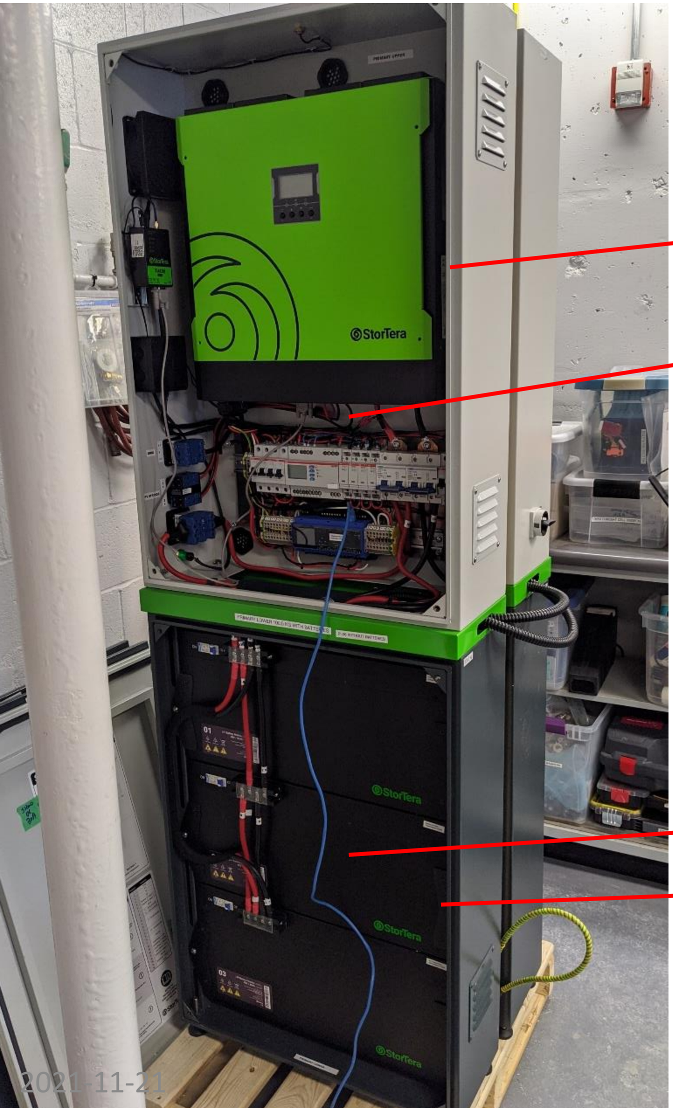
- Campbell Scientific CR1000 datalogger
- Continental Control Systems WattNode ModBus WNC-3Y-208-MB power meter
- DC current shunt (150 A, 50 mV)
- AC current transducers (50 A)

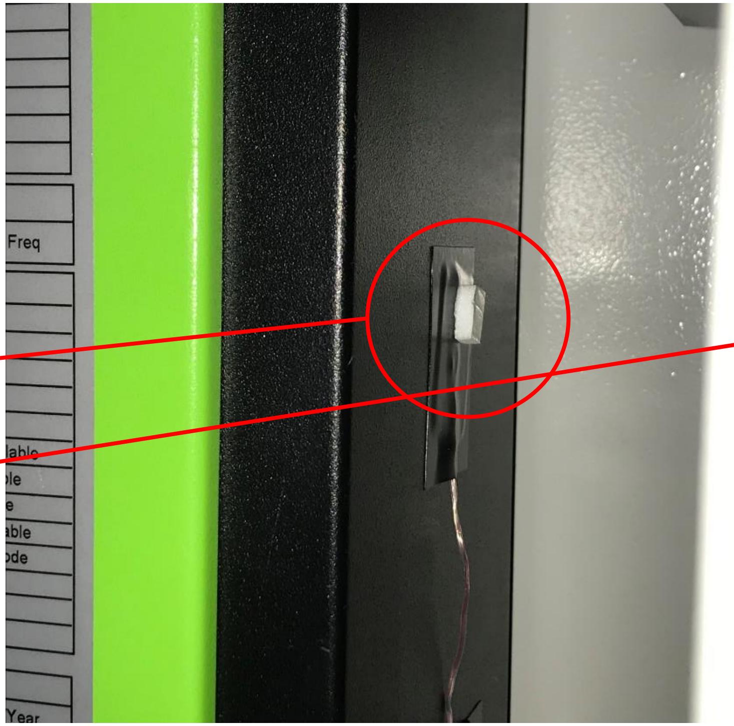
- Additionally an AC current shunt (50 A, 50 mV) was applied for further validation

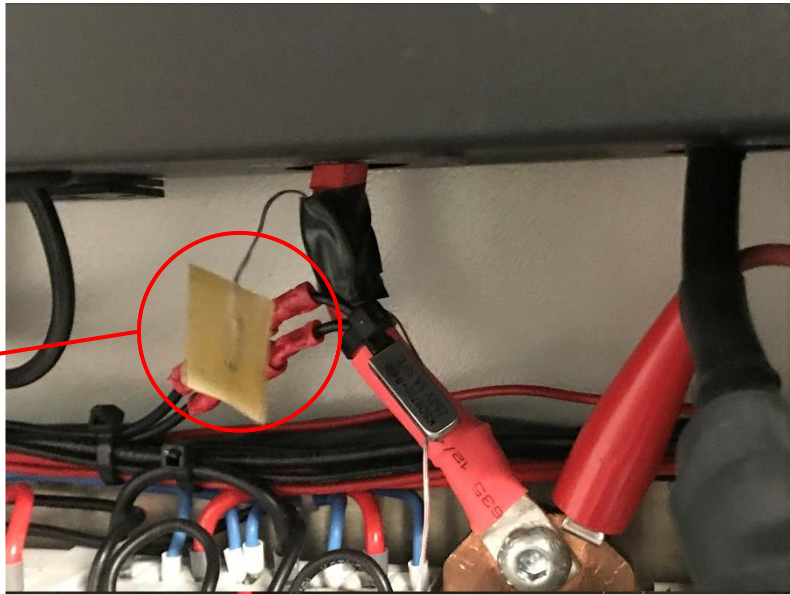


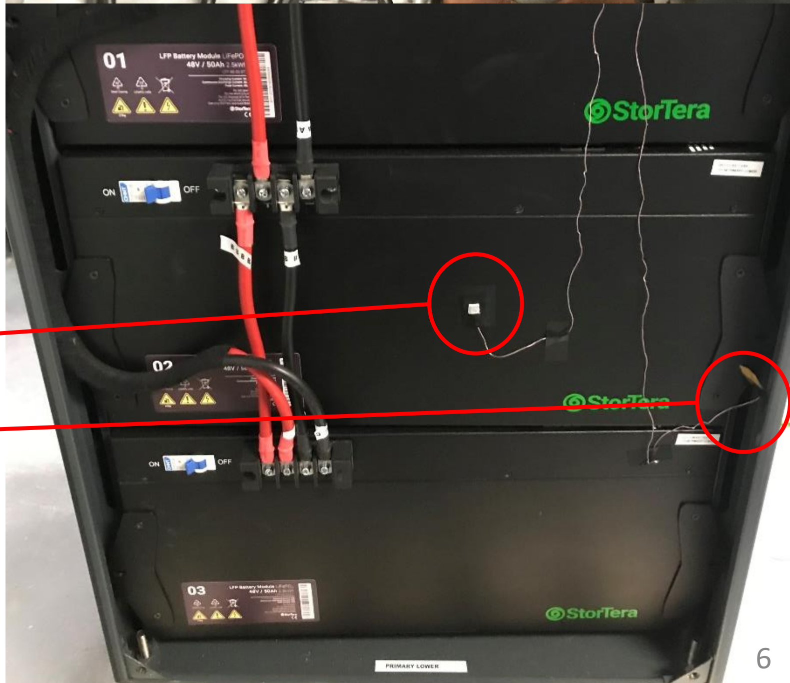


Temperature measurement (type T thermocouple)



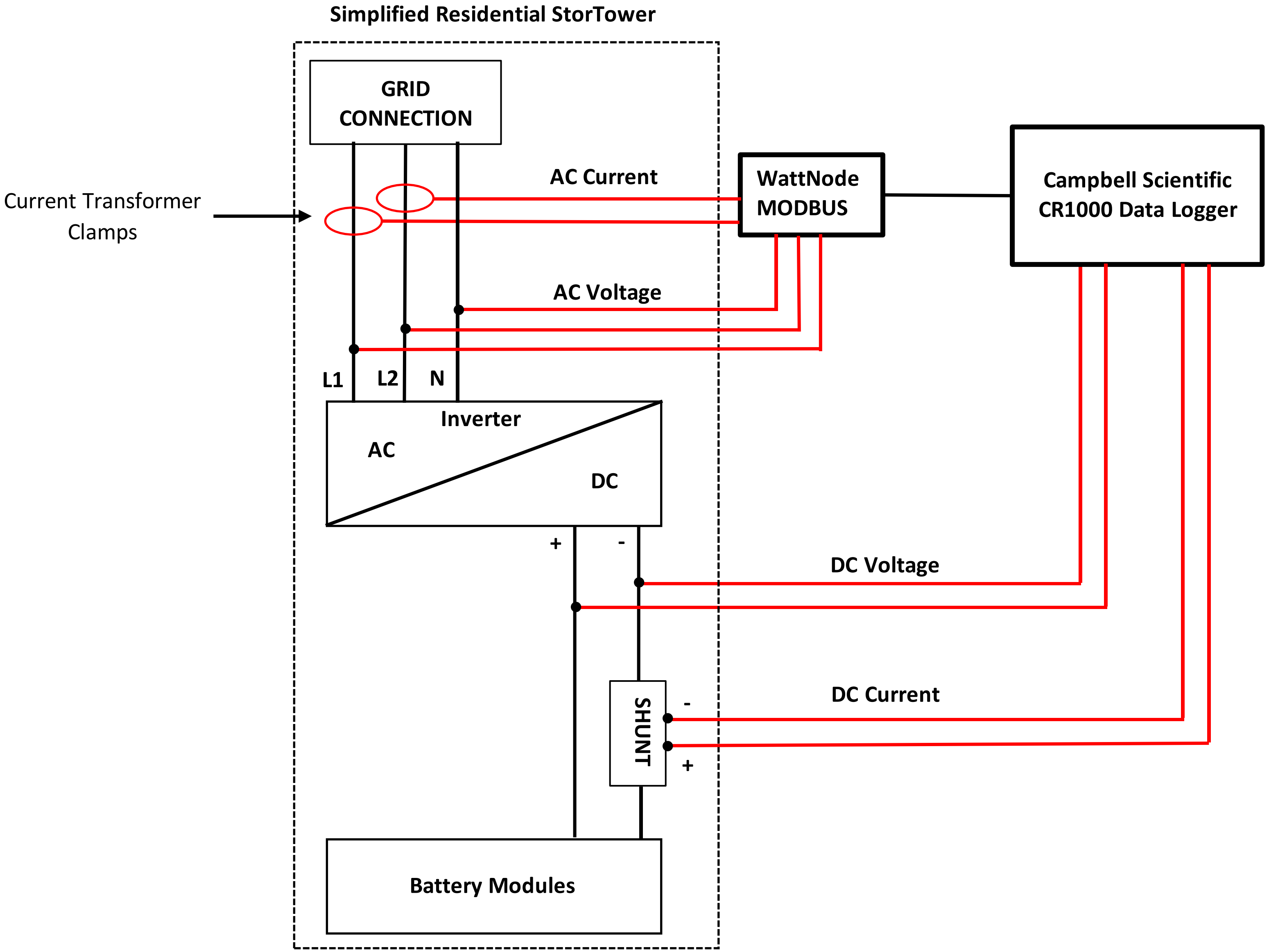






Single line diagram

- AC voltage and current measurements made at the incoming 208 VAC grid connection
- DC voltage and current measurements made at converter output terminals near the connection blocks.
- No PV input was used
- No internal loads were used
- Data was collected at a ten second rate



Test protocol

- A common test protocol is developed using standardized settings
- Three cycles are conducted prior to analysis
- Cycles are defined as discharge first (from a fully charged reference point) followed by a charge second

Cycle settings

- Battery cycled with settings for three cycles
- Subsequent rounds of cycles were also conducted.
- Analysis was conducted on data from the third cycle
  - First cycle recovers from previous tests
  - Second cycle allows the system to thermally acclimate
  - Third cycle is for data

Parameter Settings	
Max. feed-in grid power	5000 W
Max. charging current	60 A
Bulk charging voltage	52 V
Floating charging voltage	52.5 V
Battery re-discharging voltage when grid is available	50 V
Battery cut-off discharging voltage when grid is available	46.1 V
Battery float charge above voltage (10 A for 15 min)	50 V

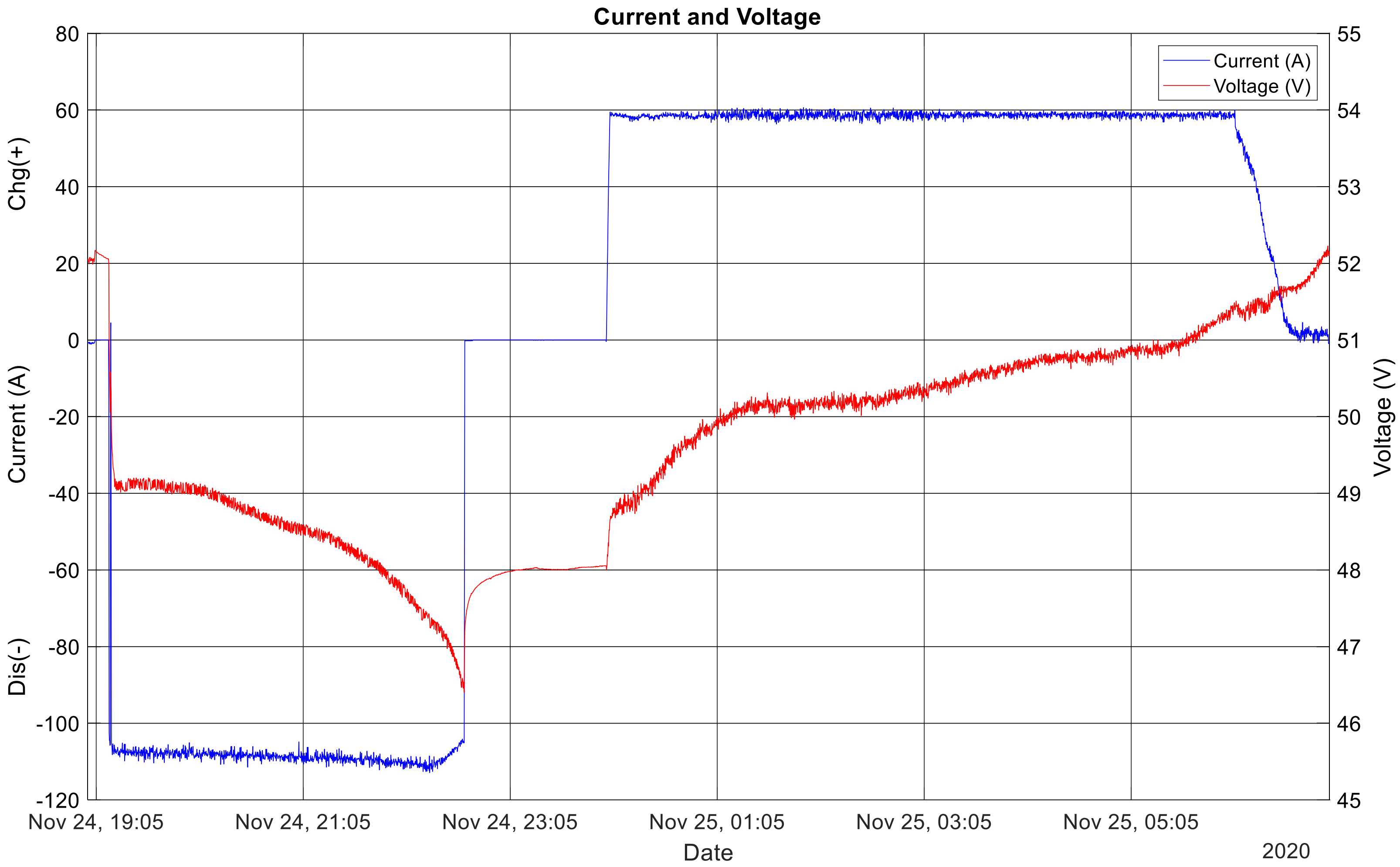
Results at the converter and battery level

- Treats the converter and the battery as whole items
- Examines AC and DC sides
- Examines temperature response

Battery current and voltage

- Figure is presented as timestep data.
- Discharge occurs first from 24 Nov 19:00-22:30
- Rest occurs from 24 Nov 22:30 to 25 Nov 00:00
- Charge occurs second from 25 Nov 00:00-07:00

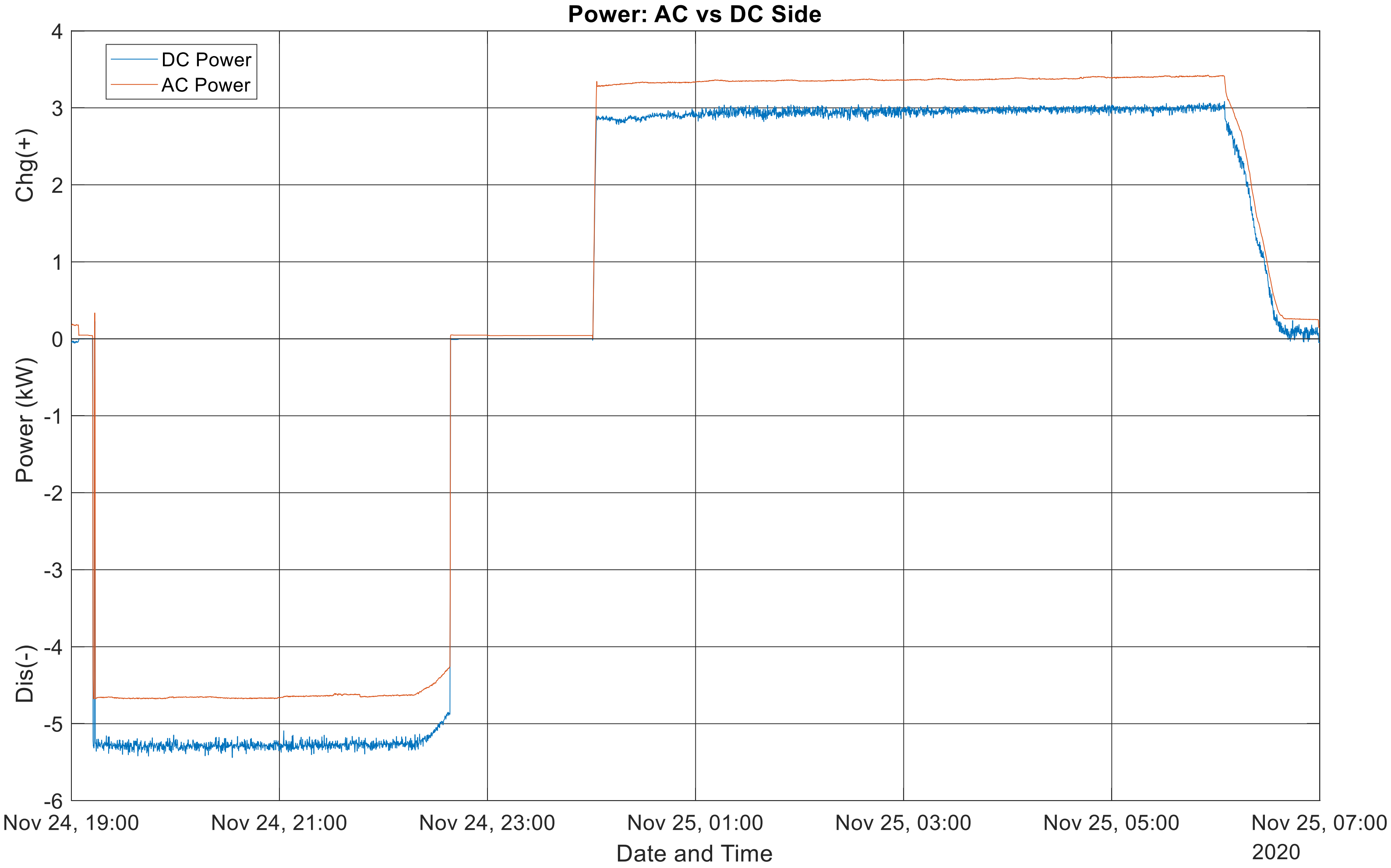
- Discharge at 110 ADC until voltage reaches 46.1 VDC cut-off.
- Note there is a small reduction in current magnitude at the end of discharge – it is speculated this is due to thermal limitations of the converter.
- Bulk charge at 60 ADC until voltage reaches 51.5 VDC. This is less than the setpoint due to differences in the measurement location of the converter and the independent system.
- Charge current tapers at this voltage
- Float charge begins and voltage rises until 52.5 V as expected.



AC and DC power

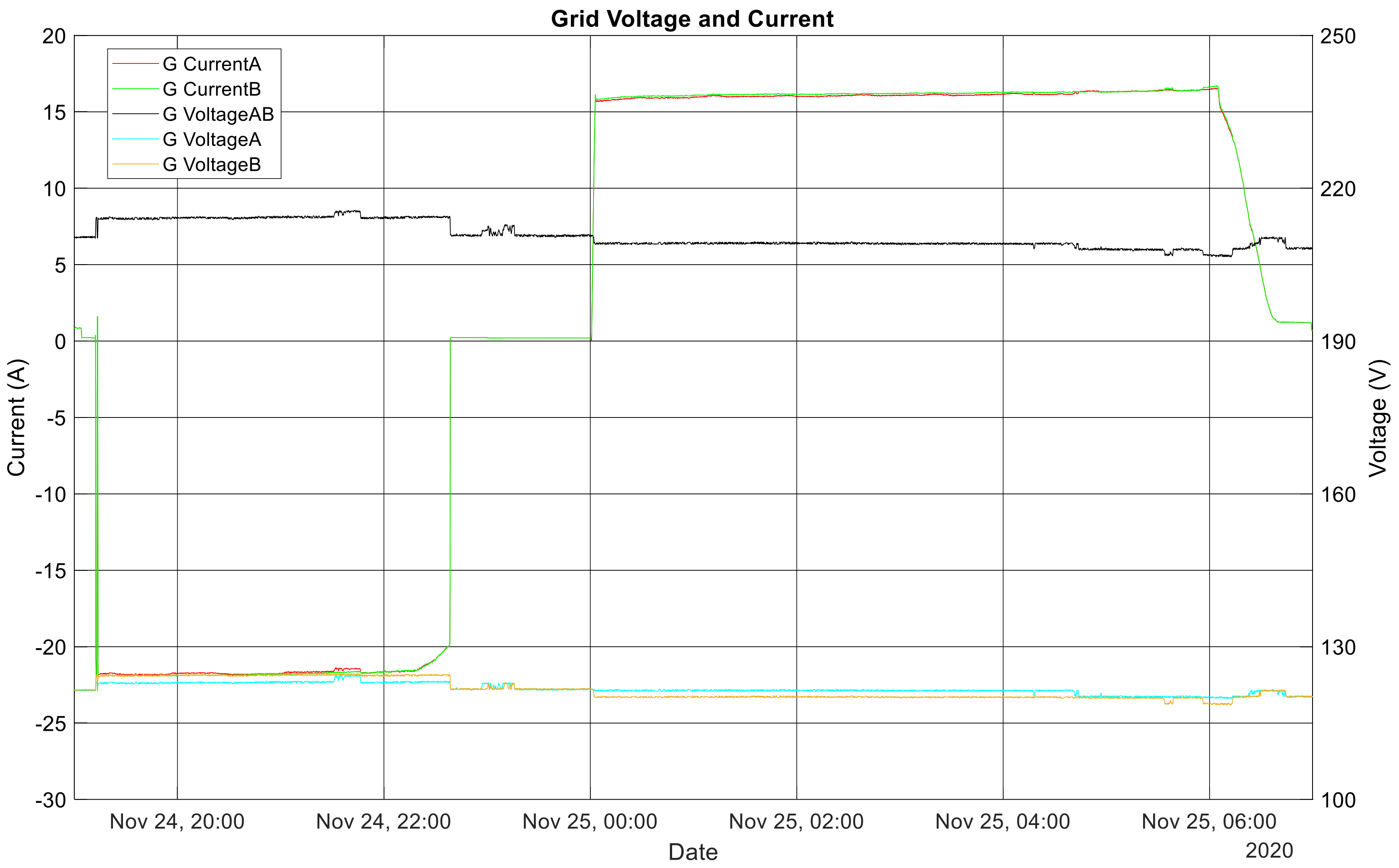
- **DC discharge power slightly higher than 5 kW, with resulting AC discharge power of 4.7 kW**
- **AC charge power greater than 3 kW (3.3 kW) to allow a 3 kW DC charge rate including efficiency.**

- AC power stays on after charge.
  - This is the period of 25 Nov 06:30-07:00
  - We have validated that this AC power is present with additional metering
  - It is speculated this is due to fans and requires further investigation
- The difference between AC and DC power is more prominent during discharge due to higher power levels



AC voltage and current

- Grid voltages steady at 208 (L-L) and 120 (L-N) throughout cycles
- Small AC voltage rise during discharge, and small AC voltage drop during charge, as expected due to bi-directional power transfers.
- Current A and Current B are equal as expected (this validates the CTs are reading correctly).



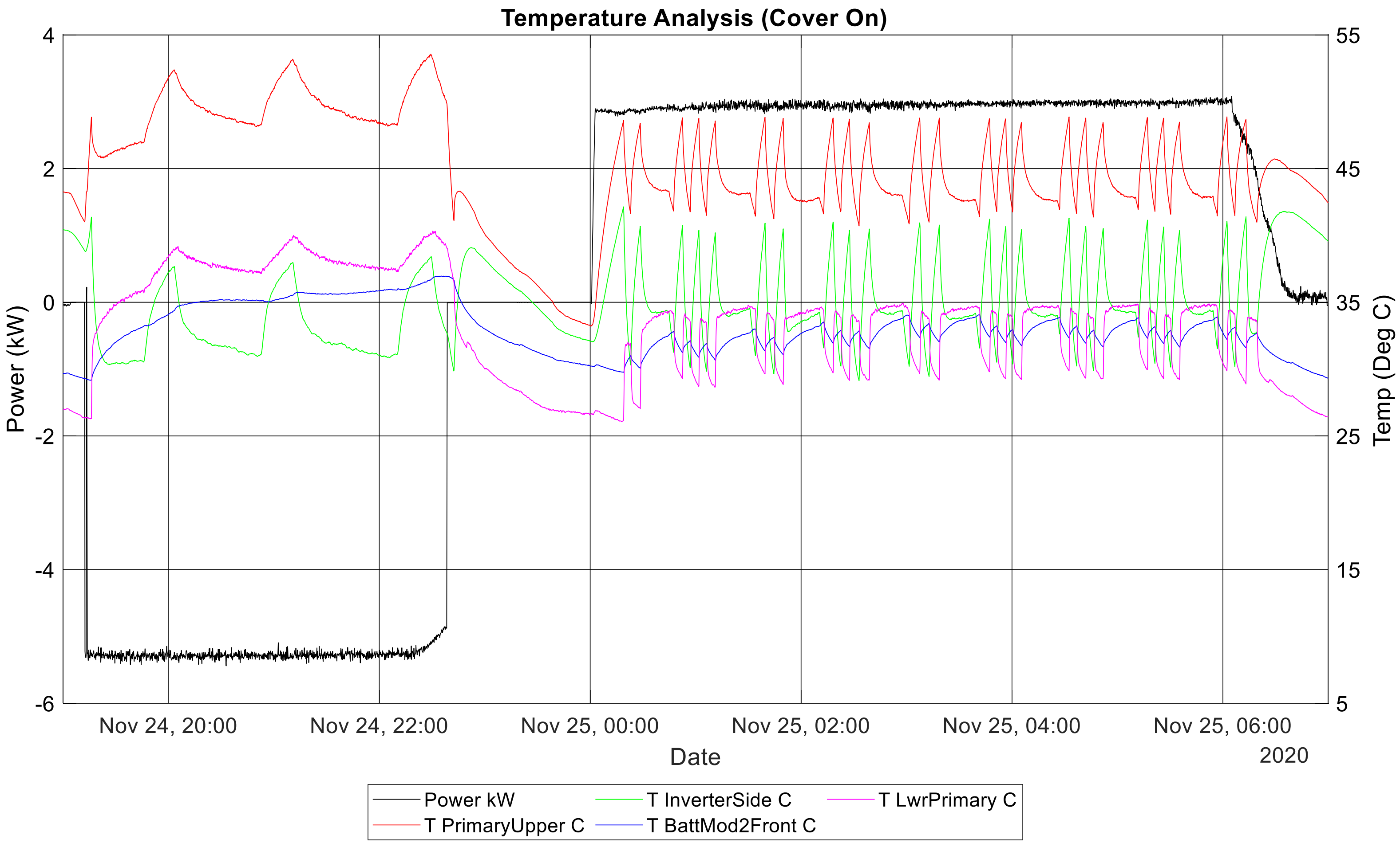
System process energy and efficiency

- Arrows indicate process flow (note this starts from charge for clarity)
- Process efficiencies are appropriate for converter and LFP battery
- Reduced fan use should increase converter efficiencies to 90%
- Coulombic efficiency is 100% as expected for lithium ion battery
- Round trip efficiency is 74.8%
- DC Energy Capacity of 19.64 kWh, usable DC capacity 18.72 kWh, usable AC capacity 16.76 kWh

	Input	Output	Process Efficiency
Converter AC to DC Conversion	22.34 kWh AC	19.64 kWh DC	87.9%
Battery Storage DC to DC	19.64 kWh DC	18.72 kWh DC	95.3%
	372.3 Ah	372.5 Ah	100.1%
Converter DC to AC Conversion	18.71 kWh DC	16.76 kWh AC	89.6%
Round-trip AC to AC	22.34 kWh AC	16.72 kWh AC	74.8%

Temperature

- Discharge
  - Less fan cycles likely because higher power produces more heat so longer runtime
  - Inverter side is cool (25-35 C) by inverter fans heat upper cabinet substantially (50+ C)
  - Batteries operate at 35 C. This is acceptable.
- Charge
  - Fans cycle on and off frequently
  - Battery temperature does show fluctuation, this is because we are measuring the side of the module (metal) not the cell side.
- StorTera notes that new fan control regime will alter these results



Experimental vs Simulated Battery Cycle

- Experimental system capacity and efficiency values fed into MATLAB model
- Simulated power results compared to experimental results

Model vs Actual

- Energy Arbitrage Test Case

- DC Energy Capacity set to match hardware testing

Capacity	19.64 kW

- Efficiencies set to match hardware testing

Charge	87 %
Discharge	89 %
Battery	95 %

- Converter Capacities (AC side) set to match hardware testing

Discharge power	4.7 kW
Charge power	3.3 kW

- Strong agreement between Simulated and experimental cycle