Modelling Energy Storage for Demand Charge Mitigation in Commercial Buildings to Develop Standardized Design Guidelines

by

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DEDICATION PAGE

This is dedicated to Carole and Chanel. Thank you for your immense patience and for staying up late.

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ABSTRACT

In parallel to growing building electrification initiatives, the cost of lithium-ion batteries has fallen by over 85% since 2010. These factors have driven interest in using lithium-ion batteries to reduce demand charges in commercial and industrial buildings.

The research objective was to develop new models and control strategies for using batteries for demand charge management in Nova Scotia's commercial and industrial sector with basic monthly billing data for peak demand prediction. This research used four years of 15 minute electrical load data for 248 commercial buildings, across eight building categories, from Nova Scotia Power to explore the relationships between the peak demand, average load and monthly load factor of a building and the potential for demand savings, categories of buildings that are of interest, and the peak demand prediction accuracy with basic monthly billing data.

A new MATLAB battery model was developed to perform iterative demand reduction simulations across a range of battery capacities, inverter power rates, and demand reduction targets. New visualization methods were developed to sort results by both building size and load factor so trends between buildings load characteristics and demand savings results can be identified quickly.

Key findings of the research were that buildings with an average monthly load factor under 40% and an average load of less than 50 kW are the best candidates for using a battery in a demand charge management application. There were limited opportunities in the Hotel and Utility categories because of the high average loads and average monthly load factors. While in the Commercial, Retail, and Industrial there are strong opportunities for demand charge reduction, provided the buildings meet the average load and average monthly load factor guidelines above. Finally, there are diminishing returns for demand savings with larger battery pack sizes. Smaller battery packs offer the most demand savings per unit of battery capacity and the largest percentage of total demand reduction per unit of battery capacity.

LIST OF ABBREVIATIONS AND SYMBOLS USED

AAML	Actual Average Monthly Load
AC	Alternating Current
ACES	Advancing Contracting in Energy Storage
APMD	Actual Peak Monthly Demand
BESS	Battery Energy Storage System
BLAST	Battery Lifetime Analysis and Simulation Tool
BTM	Behind-the-Meter
C&I	Commercial, Institutional and Industrial
CaGBC	Canadian Green Building Council
CIESM	C&I Energy Storage Model
DC	Direct Current
DI	Demand Increment
DRF	Demand Reduction Factor
ESS	Energy Storage System
EV	Electric Vehicle
FAM	Fuel Adjustment Mechanism
GWh_{elc}	Gigawatt-Hour of Electrical Energy
h	Hour
IEA	International Energy Agency
IRP	Integrated Resource Plan
IRR	Internal Rate of Return
kVA_{elc}	Kilovolt-Ampere of Electrical Load
kVA_{inv}	Kilovolt-Ampere of Inverter Power
kW_{avg}	Average Kilowatt of Electrical Load
kW_{elc}	Kilowatt of Electrical Load
kW_{inv}	Kilowatt of Inverter Power
kW_{pd}	Kilowatt of Peak Demand
kWh_{cap}	Kilowatt-Hour of Battery Capacity
kWh_{elc}	Kilowatt-Hour of Electrical Energy
LCC	Life Cycle Cost

LF	Load Factor
LIB	Lithium Ion Battery
LRID	Load Research ID
min	Minute
MLF	Monthly Load Factor
mo	Month
MW_{pd}	Megawatt of Peak Demand
NA	Not Applicable
NEUD	National Energy Use Database
NDS	Normalized Demand Savings
NRCan	Natural Resources Canada
NREL	National Renewable Energy Laboratory
NSP	Nova Scotia Power
OEE	Office of Energy Efficiency
PAML	Predicted Average Monthly Load
PPMD	Predicted Peak Monthly Demand
PV	Photovoltaic
REopt	Renewable Energy Optimization Model
RESL	Renewable Energy Storage Laboratory
SAM	System Advisor Model
SOE	State of Energy
TD	Target Demand
TOU	Time-of-Use

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CHAPTER 1 INTRODUCTION

Despite interest in behind-the-meter (BTM) battery energy storage systems (BESS) to reduce electric utility bills, there has not been significant market uptake to date. There are still market barriers due to equipment cost and there are a lack of performance models and engineering consultants with capability and expertise to assess project sizing and economics quickly and accurately for BESS. The following thesis explores the opportunities of BESS for demand charge reduction in Nova Scotia, Canada for a variety of commercial, institutional, and industrial (C&I) customer types. New sizing methods and screening guidelines are developed that can be used for building owners, operators, and consultants in shortlisting candidate sites and sizing for BESS.

1.1 Background

According to the International Energy Agency (IEA) [1], buildings, and their construction, account for 40% of direct and indirect global emissions and more than 33% of final energy use. Buildings are the third highest emissions sector of the economy in Nova Scotia, representing 14% of all emissions [2]. Reducing the emissions impact of buildings is of increasing importance given rising concerns on the affects of climate change. Part of the emissions reduction effort will be focused on electrification for space heating, including outright bans on fossil fuels in some cities, electrification of buildings, and on-site charging infrastructure for electric vehicles [3] [4]. This move towards electrification is expected to drive increased demand for electrical energy which will put increased stress on the electrical grid [5].

The electricity grid produces and consumes electrical power in real time with virtually no energy storage. Utilities are required to have suitable generation, transmission, and distribution capacity available to always serve all customer loads. Electric utilities charge their customers for the cost to produce electrical energy as well as for the infrastructure required to deliver that energy to customers. Depending on the customer type, utility tariffs can be in a form of energy charges ($/kWh$_{elc}$) and or demand charges ($/kW$_{pd}$/mo or $/kVA$_{pd}$/mo).

Residential tariffs tend to blend energy and infrastructure costs into one energy charge ($/kWh$_{elc}$), while demand charges ($/kW$_{pd}$/mo) are typically applied to larger commercial, institutional, or industrial (C&I) customers to compensate utilities for their infrastructure investments required to deliver peak power. The relationship between these charges is distinct to a particular utility jurisdiction and each customer class, with some very large customers having custom tariffs.

Demand charges typically represent 30-70% of a C&I ratepayer's electric utility bill depending on the demand charge rate, energy rate, and load factor of a particular ratepayer [6]. This research focuses on Nova Scotia, and Nova Scotia Power (NSP) defines Load Factor (LF) as the total amount of electrical energy used by a customer in a billing period, divided by the customers peak demand in the billing period, multiplied by the number of hours in the billing period as shown in Equation (1) below. Load factor is unitless and expressed as a percentage that can range from 0% - 100%.

$$LF = \frac{Total\ Energy\ Consumption\ in\ Billing\ Period\ (kWh_{elc})}{Peak\ Demand\ in\ Billing\ Period\ \left(kW_{pd}\right)\ \times\ Hours\ in\ Billing\ Period\ (h)} \tag{1}$$

Demand charges allow utilities to recover the costs of infrastructure from those ratepayers who contribute to the need for infrastructure capacity. Building owners will be subject to increasing demand charges on their bill, even if peak demand charge rates ($/kW$_{pd}$/mo) remain constant, as building heating systems are electrified, and charging stations are added for electric vehicles (EVs). Research from the Rocky Mountain Institute indicates that most EV charging in commercial buildings takes place in the morning which could shift building peak loads or create a dual peak load profile, putting upward pressure on demand charges for buildings [7].

In contrast to billing for electrical energy consumption, utilities use an interval meter to determine the demand charge by measuring the maximum average rate of energy consumption over a defined time interval, for example 15 minutes (min) [8]. Since demand charges are based on the maximum average rate of electrical energy consumption within a given time interval, they are influenced by how a ratepayer consumes electrical energy and the shape of their load with respect to time.

In parallel to the growing demands for electrical energy, the cost of lithium ion batteries (LIBs) have declined significantly in recent years. Bloomberg has reported that LIB costs have fallen by over 85% since 2010 [9], dropping from approximately $1,160 USD per kWh of capacity ($/kWh$_{cap}$) in 2010 to $137/kWh$_{cap}$ in 2020. Shown below in Figure 1 is cost declines in LIB pack pricing from 2010 to 2020 using data from Bloomberg [10] [11] [12] . The Bloomberg pricing includes total pack prices over the 2010-2020 timeframe, and breakouts of the cell costs and balance of pack costs from 2013 to 2020.

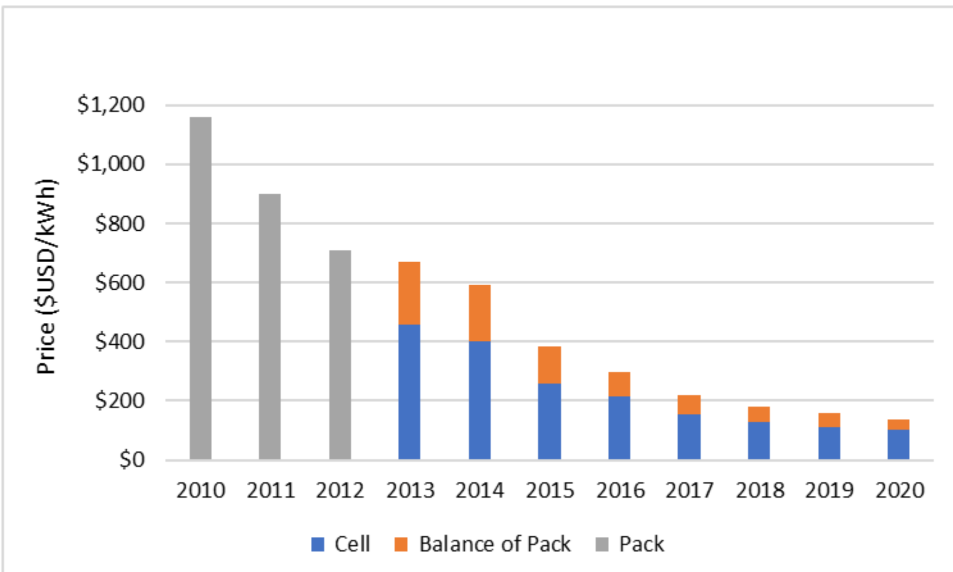


Figure 1: LIB Pack Pricing 2010-2019 [9]

LIB price declines to date have primarily been driven by increased production volumes and adoption of battery powered consumer electronics including cell phones and laptops. LIB costs have also been driven down by the rise of electric vehicles (EVs) and electricity grid scale energy storage. Bloomberg estimates that out to 2025, EVs will be the primary driver of new LIB battery capacity as shown in the demand forecast below in Figure 2 using Bloomberg data.

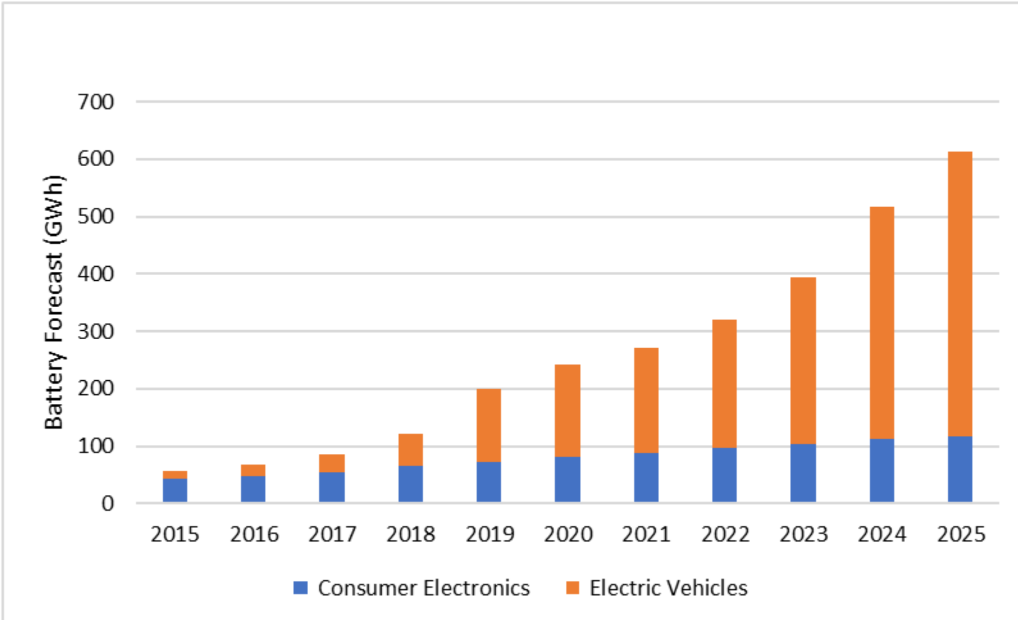


Figure 2: LIB Demand Forecast for Consumer Electronics and Electric Vehicles [13]

Bloomberg is projecting that by 2030 the price of an LIB battery pack will be $62/kWh$_{cap}$, in 2018 dollars, as shown below in Figure 3 using their data.

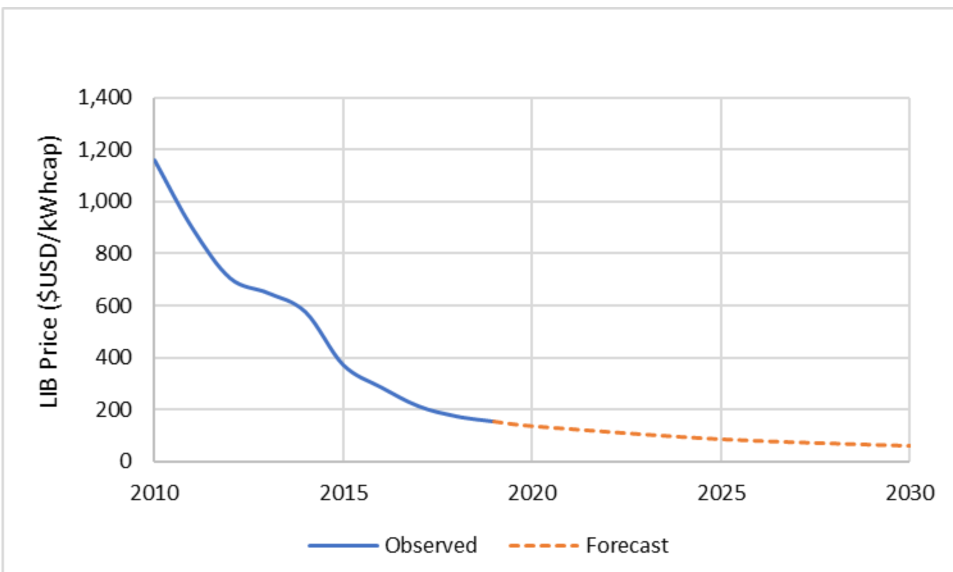


Figure 3: Bloomberg Price Forecast for LIBs to 2030 [12]

The cost reductions to date for LIBs, as well as projections of future price declines, have increased interest in BTM BESS to reduce demand charges in C&I buildings.

A BESS can reduce the demand charge of a C&I building by discharging during a peak demand period. The result of the battery discharging is a reduction of the net peak demand that that the building draws from the electrical grid. The net peak demand is measured by the interval meter on the building and is what the customer is billed for. It should be noted that the discharge strategy for demand charge management is different from energy arbitrage with Time-of-Use (TOU) rates. In contrast to using a battery to exploit a time-based differential in energy rates set by the utility, demand charge management is much more dependent on the building's pattern of electrical energy usage and must forecast upcoming demand peaks.

According to the National Renewable Energy Laboratory (NREL) [14], the economic viability of BTM energy storage for demand reduction is linked to the demand charge tariff in each utility jurisdiction and the amount of demand that can be reduced from the peak demand of a building. Research from NREL indicates that over 25% of commercial customers in the US are in jurisdictions where the demand charge tariffs are more than $15/kW$_{pd}$/mo which NREL suggest presents opportunities for BTM energy storage [8].

1.2 Commercial and Industrial Buildings in Canada

Electrical energy generation and consumption has been growing steadily in Canada for decades as shown below in Figure 4 using data from BP Statistical Review of World Energy [15]. The data from BP shows that economy wide electricity generation in Canada rose by nearly 43% from 1985 to 2019.

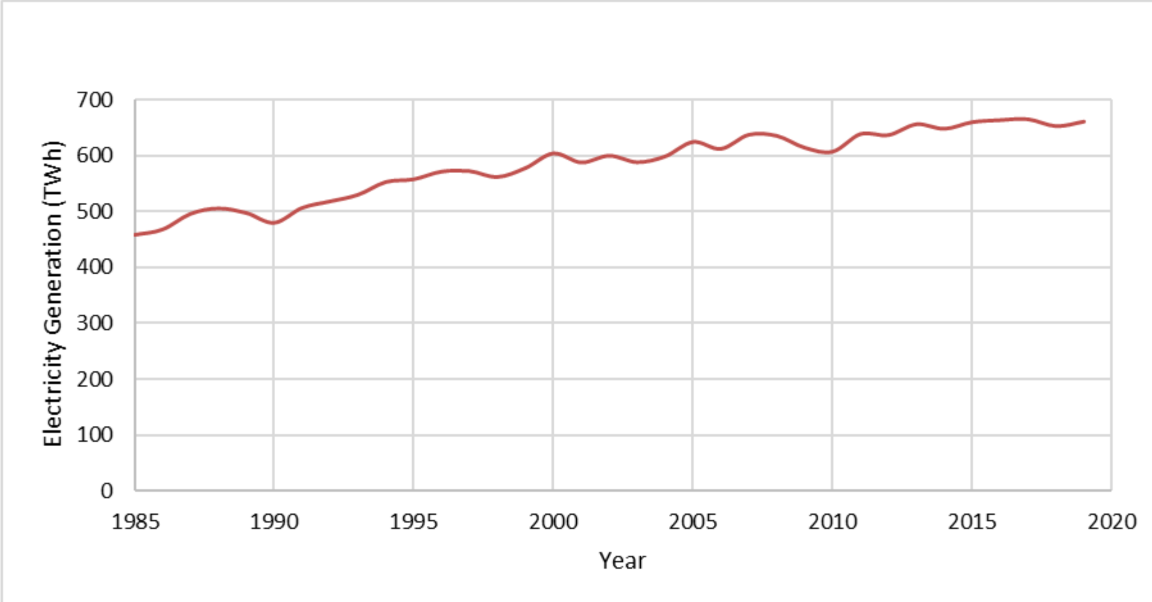


Figure 4: Gross Annual Electricity Generation in Canada

Increasing electrical usage for the C&I sector in Canada is reported in the Natural Resources Canada (NRCan) National Energy Use Database (NEUD) from the Office of Energy Efficiency (OEE). Data from NRCan [16] indicates that total electricity consumption has increased 43% from 1990 to 2018 as shown below in Figure 5. Specific electricity consumption, measured in energy use per meters squared of building space (kWh_{elc}/m^2), has declined 5% due to energy efficiency initiatives.

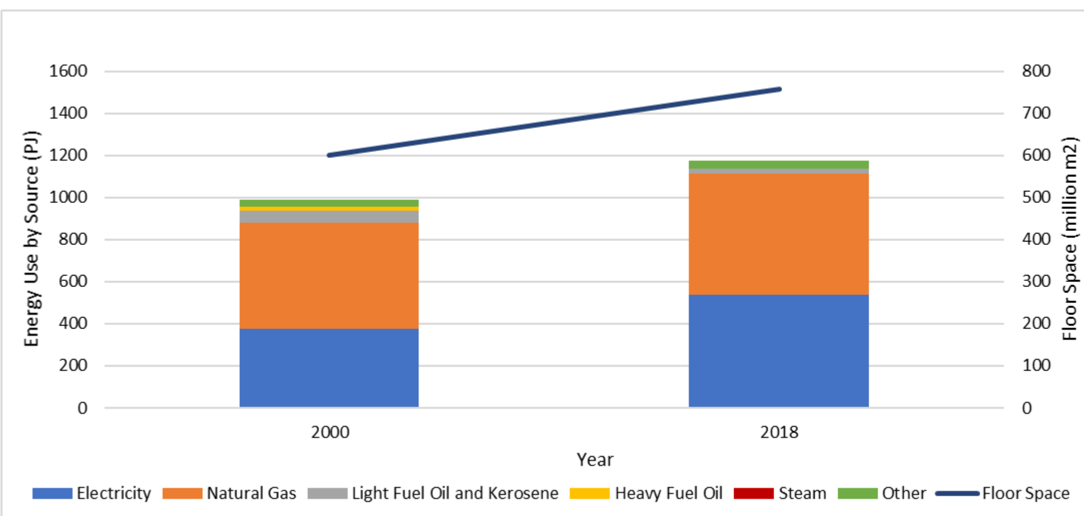


Figure 5: NRCan Commercial & Institutional Energy Use [16]

Overall energy usage in Canadian C&I buildings is changing as well. Auxiliary equipment (ex. computers) showed the largest increase from 1990 to 2018, increasing approximately 118%, due to an increased number of auxiliary devices per person and increased reliance on computers in the workspace as shown below in Figure 6 with data from NRCan.

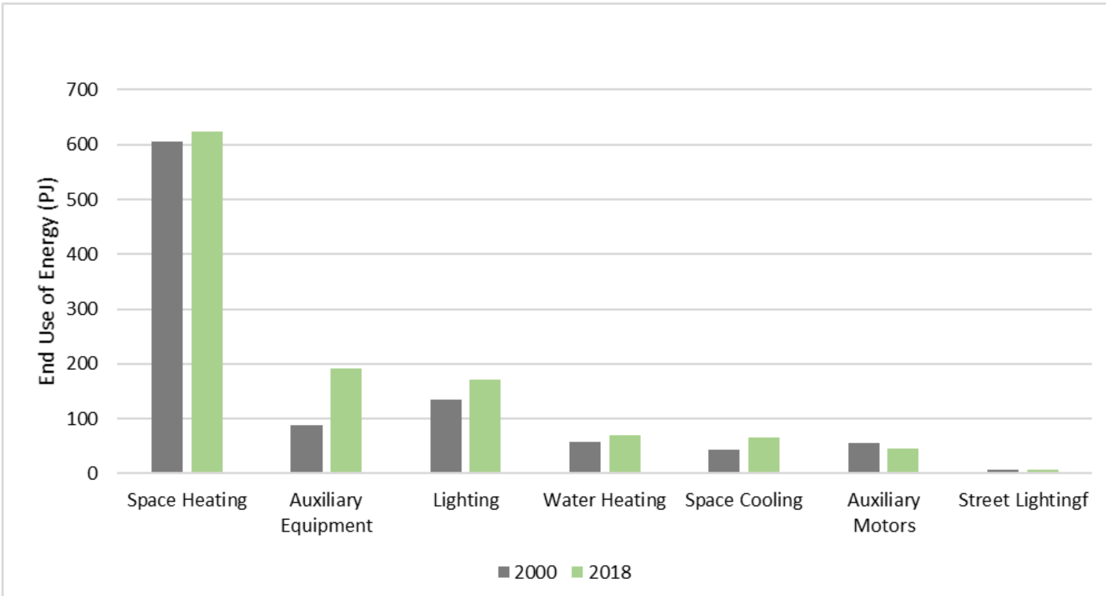


Figure 6: End Use of Energy in Canadian Commercial and Institutional Buildings

Natural gas remains the primary source of space and water heating in Canada. In 2000 it accounted for 51%, and 2018 in 49%, of C&I primary energy consumption while electricity consumption went from 38% to 46% over the same period. The proportion of heating energy delivered by natural gas is likely to continue to decline, and electricity consumption increase, over time due to emissions reduction efforts. The Canadian Green Building Council (CaGBC) [4] is recommending that 20% of all buildings over the age of 35-years fuel switch to electricity for low and medium emissions electric grids.

In their 2020 Integrated Resource Plan (IRP), NSP [17] found that increasing electrification for heating and transportation will put upward pressure on both total energy production and peak demand in future years. Under a high electrification scenario and low demand side management scenario, NSP estimates that total energy consumption could increase 9% from 11,531 GWh_{elc} in 2021 to as much as 12,572 GWh_{elc} in 2030 as shown in Figure 7. Under the same scenario NSP estimates that peak demand will increase 26% from 2,205 MW_{pd} in 2021 to 2,784 MW_{pd} in 2030, as shown in below in Figure 8.

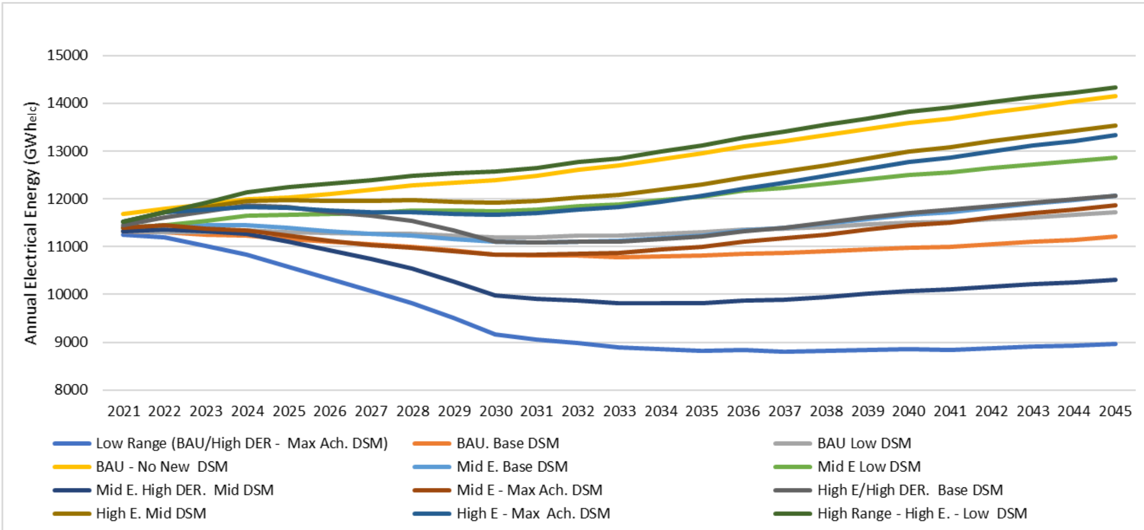


Figure 7: NSP Annual Energy Sales Forecast 2021-2045 [17]

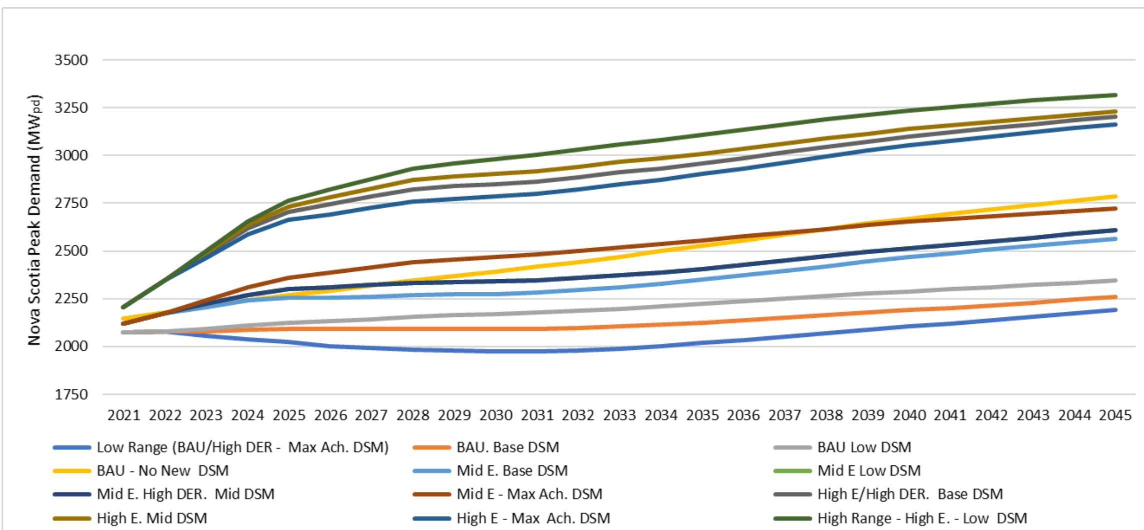


Figure 8: NSP Peak Demand Forecast 2021- 2045 [17]

Increases in the NSP peak demand may necessitate infrastructure investments that result in higher demand charges for C&I customers to compensate the utility for those infrastructure investments. Studying the opportunities to use a BESS for demand charge management is important given the moves towards electrification, the resultant upward pressure on utility infrastructure requirements, and the declining BESS costs.

1.3 Relevance, Objective and Hypothesis

According to McLaren et al. [18], approximately 20% of the costs for a commercial energy storage project are related to Engineering, Procurement, Construction, and Development/Soft Costs as shown in below in Figure 9 using data from McLaren et al.'s presentation: *Battery Energy Storage Market: Commercial Scale, Lithium-ion Projects in the U.S.* The total capital costs assumed in this scenario is \$883/$kWh_{cap.}$

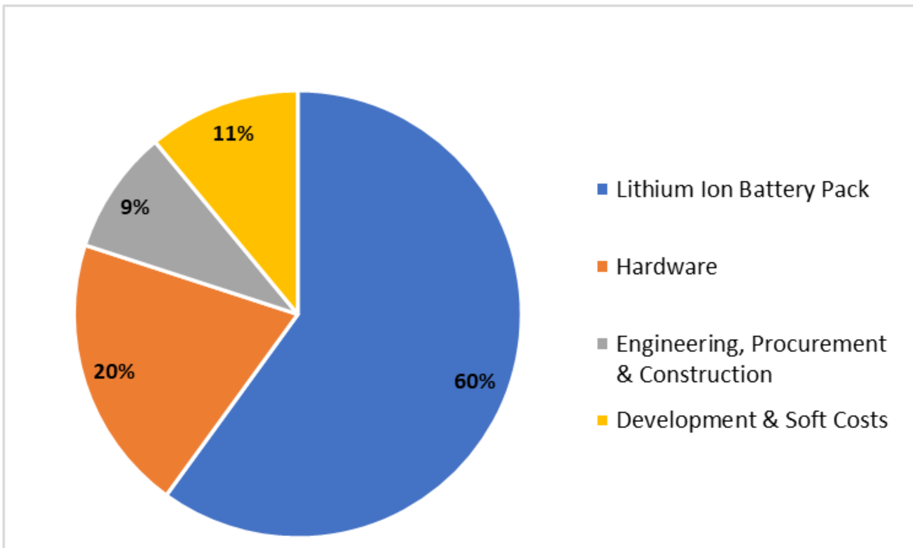


Figure 9: Breakdown of Costs for Commercial BESS

The questions that this research is aiming to address are as follows:

- What correlations exist between building monthly load characteristics (ex. peak demand, average load, load factor) and the demand reduction potential of a BESS at that site?
- Are there specific building categories (ex. hotel, educational, health care etc.) that are more conducive to energy storage due to their load characteristics?
- What level of prediction accuracy of peak demand can be obtained with basic interval meter billing information (ex. peak demand and total energy consumption)?
- Are there normalized recommended storage and inverter sizing that can be made on a per kW_{elc} basis based on the buildings average load or peak load during a

billing cycle?

- What level of demand savings could a commercial building owner expect to see with a BESS installed and how is this related to building load characteristics and categories?

The objective of this research is to develop new models and control strategies for BESS used for demand charge management in Nova Scotia's C&I sector using basic input data from a building owner or operator. The research will evaluate the technical performance of a range of BESS sizing and power characteristics and use the results to produce guidelines that can be used by building owners and project developers to quickly screen candidate buildings for BESS eligibility. The ability to quickly screen candidate buildings will assist in reducing the soft costs (e.g. engineering, customer acquisition and project development) and providing greater confidence and reduced sales cycles for project developers of BESS installations identified by McLaren et al. above.

Currently, building owners or operators that may be considering energy storage have limited tools or rules to determine the approximate size of the energy storage system and indicative peak demand charge savings in kilowatts (kW_{pd}). Additionally, building owners do not have a method to identify the approximate cycling use, or energy throughput, of the battery under a demand charge reduction control strategy. The cycling of the battery, or energy throughput, can be used as an indicator of lifespan using cell cycling curves from the original equipment manufacturer. The expected battery lifespan sets the technical upper bound on an acceptable simple payback period for the project.

A lack of guidelines in this space means that typically sub-metering projects and engineering studies need to be conducted to properly evaluate the potential for battery energy storage for a particular building. Site specific engineering is both time and cost intensive and will have a limiting impact on large scale adoption of BESS in buildings.

This research contributes new research results by concentrating on developing peak demand prediction methodologies and normalized battery sizing guidelines based on simple building load characteristics.

The hypothesis of the research is that the repeatability of the monthly load factor of the building and average load will be strong indicators of energy storage sizing and operation in a practical application for a given C&I building.

CHAPTER 2 LITERATURE REVIEW

The literature for grid-tied BESS focuses predominately on the residential market and specifically for applications with solar photovoltaics (PV). It is typical to analyze BESS under a TOU utility rate structure rather than a demand charge structure. The TOU use case focuses primarily on using the BESS for energy arbitrage between high and low energy rate ($\$/kWh_{elc}$) periods during a day while demand charge management focuses on reducing the peak demand during the billing period.

Most of the research that does look at demand charge reduction focuses on a limited building sample size or uses a representative building load profile from a synthesized dataset rather then actual building load data. Research that examines the relation between load factor and battery capacity utilizes load factor on an annual basis rather then examining it over the typical billing period of one or two months. This approach may lead to results that are skewed based on seasonal variation in building usage, for example an educational facility.

2.1 Demand Charges

MacLaren et al. [8] study and summarize utility tariffs throughout the United States to explore market opportunities for BESS. They find over 25% of the commercial customers in the US have access to utility tariffs with demand charges over $\$15/kW_{pd}/mo$. The research also found that approximately 15% of commercial customers are eligible for rates with demand charges more than $\$20/kW_{pd}/mo$. However, there can be significant variability in demand charge rates within a given state based on the different utilities that may operate in the state. As an example, one utility in New York has maximum demand charge over $\$50/kW_{pd}/mo$, but an average across all utilities in New York is less than $\$10/kW_{pd}/mo$. This study points to the markets that may have economic potential in the US for BESS, the scale of the market, and the regional variability of electricity tariffs. MacLaren et al. provides a list and a map of jurisdictions where for BESS may be economical for demand charge management due to the demand charge rates, but they do not present analysis based on building load profiles, any economic analysis, sizing tools or discharge strategies.

Long et al. [19] used a statistical analysis to explore the economics of BESS to reduce demand charges in commercial buildings using the US Department of Energy (DOE) Commercial Reference Buildings dataset. The DOE Commercial Reference Buildings are referenced several times in the literature and are available for public download from the DOE's Office of Energy Efficiency and Renewable Energy website [20]. The Commercial Reference Buildings were developed by NREL and detailed in research by Deru et al [21]. A regression analysis was performed to rank the importance of variables in determining the economics of a project. The variables included battery cost ($/kWh$_{cap}$), demand charge rate ($/kW$_{pd}$/mo), the average of the twelve months' peak demand over the year, among others. Long et al. [19] proposed the Load Profile Metric (LPM) characteristic to test the importance of the building's load shape on battery sizing and economic returns. First, the efficiency of a given BESS at reducing a buildings demand is defined as the difference between the old and new peak demand divided by the BESS power rating (kW$_{inv}$). Next, the Load Profile Metric was calculated by normalizing all the building load profiles by their annual energy consumption and assigning them equal annual energy consumption. The paper does not specify the annual energy consumption that was assigned to all buildings. Next, a series of demand reduction tests are run on the adjusted load profiles using battery sizes ranging from 0-30 kWh$_{cap}$ in steps of 2.5 kWh$_{cap}$. It is not stated in the paper if the model uses the known demand peak from the building load profile or a predicted peak. The demand reduction efficiency results of those trials are then averaged to produce a LPM value for that building category. Results show that demand charge rate ($/kW$_{pd}$) and battery storage cost ($/kWh$_{cap}$) are the two key indicators of project economic viability. Additionally, it was found that the LPM was not a strong indicator of project economic viability, but it was a strong indicator of battery sizing. This research concludes that the technical considerations that influence battery sizing are based on load shape, while the economics are primarily driven by the demand charge rate relative to the battery cost. Based *A Statistical Analysis of the Economic Drivers of Battery Energy Storage in Commercial Buildings* by Long et al. [19], opportunities exist to use actual building load data to explore additional indicators that may be better predictors of economic viability of BESS.

D'Aprile et al. [22] present results from a proprietary BESS dispatch model that considers real world load profiles, battery characteristics and electricity tariffs. Based on their findings, most North American C&I customers have breakeven cost for BESS at demand charge rates of $9/kW$_{pd}$/mo and BESS costs of approximately $400/kWh$_{cap}$. Although it is not specifically stated what time resolution the building load profiles were, the commentary notes that 15 min or lower resolution is needed to identify project opportunities. Additionally, the results indicated that increasing the charge and discharge rate of the BESS can improve its economic viability. How the charge and discharge rate affect the economics is not quantified in the paper but is an important consideration for project developers, particularly as BESS technology advances allow for higher rates. D'Aprile et al.'s research specifically references modelling and data collection as being key barriers to the identification and ranking of BESS opportunities which limits market adoption. D'Aprile et al. state that access to real world building load profile data will be important to determining which BESS projects will be economic due to the variability of how different buildings use energy during the day. They also conclude that the use of building load profile data will be critical to determining the viability of BESS for C&I customers.

Gagnon et al. [23] studied the affects of BESS combined with solar PV to reduce demand charges for commercial customers. Their research studied a variety of demand charge rate structures including seasonal variation in demand rates, billing frequency, time averaging interval, coincidence with system peak periods and tiered demand billing. The building load profiles used were the US DOE Commercial Reference Buildings. The paper notes that common averaging windows for demand charge calculation typically range between 15 min and 60 min. The smallest time step analyzed in the report was a 30 min demand charge window which is specifically identified as a limitation by the authors. No explanation is given to the selection of the 30 min minimum, but the load profile time step for the US DOE Commercial Reference Buildings is 1.0 hour (h) and the solar data used in the research is 30 min, which is likely why the minimum analysis period was 30 min. The authors note that savings tend to decrease with longer averaging periods, so the 15 min demand charge window would probably result in better savings then those presented in the paper. Ten solar system sizes and ten battery system sizes are analyzed. The solar system sizes are in 10% increments of the annual energy consumption, while the battery inverter system sizes are in 10% increments of the building lifetime peak demand. BESS capacity (kWh_{cap}) was designed for 3.0 h operation at the inverter rating. This approach means different battery and inverter sizes will be used on each building, with none of them likely to exactly correspond to commercially available products. The battery discharge strategy assumes perfect foresight of the peak demand in the billing period. Gagnon et al. show that that increasing storage size has diminishing returns as the peaks become wider which requires each subsequent kW_{pd} of demand savings to have more battery capacity (kWh_{cap}). The implication of this result is that small battery capacities tend to return better results from an optimization perspective, but there are practical limitations to this approach; for example, the minimum size and expansion increments are dictated by those commercially available by a supplier. The research found that demand charge savings tended to be lowest under basic demand charge tariffs that are unrelated to a defined system peak time (ex. 12:00 – 16:00). Gagnon et al. find that there is a high degree of variability in demand charge savings based on building type, location and solar and battery system size. Various project locations are also analyzed and some of the variation is attributable to the differences in solar resource available at the various cities used in the analysis.

Darghouth et al. [24] studied how utility rate design affected the economics of BESS. The study looks at how a BESS can provide utility bill savings for customers from both energy arbitrage and demand savings. No system level benefits are considered. The research describes how a variety of rate design characteristics affect the economics of BESS and the relative importance of those characteristics. Aspects related to demand charge that are studied are the price of the demand charge ($\$/kW_{pd}$), non-coincident and peak time pricing, peak duration, time averaging interval, seasonal variation in demand charge rates and ratchetting rates. In total they had access to one year (2012) of 5 min interval data from 100 commercial buildings using the EnerNOC database. The dataset, known as the EnerNOC GreenButton Data, is anonymous data for commercial and industrial buildings and is available for public download for non-commercial purposes [25]. Despite the high number of buildings in the database, the study selects only three representative load profiles to conduct the analysis: a shopping centre, a shopping centre with solar PV, and a manufacturing facility, which all display a different load profile shape. Except for the varying load profile shapes, no explanation is provided as to why the other 97 buildings were not utilized, and no results are shown for other facilities. This makes the results of the study hard to translate to other facilities as no general trends can be established when only three buildings are analyzed. The shopping centre without PV represents a consistent daytime load whereas the shopping centre with PV exhibits a morning and evening peak with a trough mid day due to the PV energy production. The manufacturing facility displays relatively constant load throughout the day. The storage is dispatched according to a HOMER model that uses perfect foresight. BESS inverter size was selected as 20% of the building peak annual load, and battery sizes of 1.0 h, 2.0 h and 4.0 h were tested. Darghouth et al. found that savings from a BESS was dependent on load shape and that buildings with peaky loads tended to have the most savings. In this study, “peaky” was the shopping centre with PV. The study found that storage was not effective in “flatter” load profiles since the BESS could not sustain the long durations required to effectively reduce the peak. “Flatter” and “peaky” were terms used by the authors to describe the load profile but were not quantified in the research. The study quantified and compared the normalized annual bill savings by BESS power rating ($/kW$_{inv}$) for the various demand charge rate design features discussed above. Darghouth et al. show that the demand charge rate ($/kW$_{pd}$) was the most significant factor on the economic outcome of the BESS. Peak time pricing and the averaging window also have a material affect on the savings, while the presence of seasonally adjusted demand charge rates and ratcheting demand charges had minimal affects. Demand charges that have specific time based “peak periods” (ex. 1200: - 16:00) tend to restrict the duration that the BESS must discharge over to reduce the billed demand charge, as the demand charge is only based on peak demand during the “peak period”. Restricting the discharge time window increases the opportunity for BESS to provide more significant demand reductions.

Neubauer et al. [26] use NREL’s Battery Lifetime Analysis and Simulation Tool (BLAST) to analyze how the energy and power characteristics of a BESS affect demand reduction project economics for commercial customers. The authors applied it to two categories: (1) BESS solely for demand charge management, and (2) BESS when combined with solar PV. One year of load data for 98 commercial buildings was taken from EnerNOC's online database and combined with solar generation data using historical solar irradiance data to create a net building load. The net building load was created with a 5 min time interval, prior to demand charge management by the BESS. Project economics for the were tested using a commercial rate structure from Southern California Edison that includes a regular time independent demand charge, but also includes additional seasonal and on-off peak demand charges. First a maximum battery size, E_{max}, is defined as the largest amount of energy required to completely flatten the daily load variability in the building over the course of the year. This value is calculated by identifying the average load for each day and summing the total energy above the daily average. The largest value identified over the course of the year is then defined as E_{max}. The BLAST model used a perfect 48.0 h forecast of building loads to show the maximum possible demand charge savings over a two day period to compare the value of demand charge savings to time shifting energy. The authors note that the two day forecast and analysis period is not representative of a typical commercial building's billing cycle, but is selected in this case to demonstrate the upper limit of potential demand reduction during the analysis period. Although this may be true in an academic sense, its not the practical case for C&I building owners, as they are typically billed on a monthly cycle. The way E_{max} is defined can lead to large values, in some cases E_{max} exceeds 10,000 kWh_{cap}. The result of this is that BESS energy capacities were set as relatively small percentages of E_{max}, in the analysis 0.5%, 1%, 2%, 3%, 5,%, 7%, and 10% of E_{max} were used. The power ratings used in the analysis were set by defining a power rate that resulted in constant full power discharge times of 0.5 h, 1.0 h, 2.0 h, and 4.0 h of BESS energy capacity.

Under the tariff structure, Neubauer et al. showed that demand charge reduction was a much more potent indicator of project economics then energy arbitrage with TOU rates. In some of the cases analyzed, demand charge reduction was as more than 10 times more affective at reducing the utility bill of a building than energy arbitrage with TOU. They also found that even the longest 4.0 h duration storage typically only reduced the building load by 85% of the inverter rating. Smaller BESS capacities have lower load reduction percentages as function of inverter rating and become more variable based on the building load shape. Project economics are assessed on a real dollar ($) basis as opposed to a normalized basis. Battery costs are assumed to be the sum of \$300/kWh_{cap} for energy storage component and \$300/kW_{inv} for the inverter component. The results indicate that the higher power 0.5 h BESS exhibited the fastest payback periods with results between 3-10 years depending on the energy capacity (% of E_{max}) used. The payback period for 0.5 h and 4.0 h power ratings displayed opposite behavior with respect to increasing energy capacity (% of E_{max}). The lower power systems exhibited shorter payback periods with larger battery capacities, while the higher power systems exhibited longer paybacks with larger battery capacities.

Next, Neubauer et al. looked at payback periods in terms of battery capacity (kWh_{cap}) and inverter rating (kW_{inv}) and found that systems with inverter ratings of <= 30.5 kW_{inv} and capacities of <=15.5 kWh_{cap} made up 75% of the systems with the lowest payback periods, despite the median building load being 569 kW_{elc}. This led Neubauer et al. to the conclusion that longer duration systems can achieve higher demand reductions as a fraction of their inverter rating, but they are less economic than smaller capacity systems that have lower demand reductions as a fraction of their inverter rating. They state that the reason for this is that there is a non-linear association between an incremental demand reduction (kW_{pd}) and the energy capacity (kWh_{cap}) required to complete it. Although the payback in years may be superior to a larger duration storage system, they note that the economic returns in monetary value for smaller systems may dissuade building owners from adopting them, moving more users into higher capacity systems that have longer paybacks but create larger monetary savings. This trend will also be influenced by the battery capacities that are available from the suppliers, as well as the fixed project development costs, such as engineering and customer acquisition. The non-normalized economics of this paper means that the reader can not quickly determine how the economics may change under conditions with different inverter or battery capacity pricing. Additionally, no guidance is provided as to which categories of buildings may be of interest for project developers.

Doluweera et al. [27] studied five different commercial building types to assess the economic opportunities for BESS to reduce C&I demand charges in Canada, given the rates in New Brunswick, Ontario, Saskatchewan, Alberta, and British Columbia. The OpenEI [28] building load datasets were used for analysis. The OpenEI dataset is published by the US DOE and available for public download. It includes representative hourly load profiles for commercial and residential buildings. The 16 commercial building included in the dataset are from the US DOE Commercial Reference Buildings research.

Since the dataset is based in the US, Doluweera et al. selected commercial buildings located in areas with similar climatic conditions to the provinces under consideration. Five building types were considered due to differing energy use patterns and various load factors. Doluweera et al. defined the average annual load factor of a building as the average annual load divided by the annual maximum peak demand. Defining the average annual load factor in this manner will not accurately represent the monthly load factor unless there is a relatively consistent ratio of average load to peak demand monthly. The average annual load factors for a strip mall, large office building, hospital, hotel, and secondary school were 30%, 40%, 70%, 60%, and 30% respectively. Next, an E_{max} value for each facility is calculated using the same formula as Neubauer et al.. Doluweera et al. follow the same methodology, BESS capacity selection and discharge duration power as Neubauer et al. [26]. They employ a setpoint based discharge strategy established on the fixed control method proposed by Chua et al. In this method, a maximum building load is set and the batteries will discharge the required power to bring the net building load back to the fixed value. This method does not consider the remaining energy in the battery prior to making a discharge decision, or adjust its output based on a failed discharge attempt during the billing cycle.

Doluweera et al. determine the optimum project economics by performing iterative economic analyses on a building's load profile using various BESS power and energy configurations and then plotting the internal rate of return (IRR) versus the power-to-energy ratios of the BESS configurations. Economic analysis is performed for the general commercial rate structures in New Brunswick, Ontario, Saskatchewan, Alberta, and British Columbia. The demand charge rates varied by province with all provinces but Alberta using a monthly billing cycle for measuring the demand charge. Monthly demand charge rates ranged between \$8.538/kW_{pd}/mo (Ontario) to \$14.28/kW_{pd}/mo (New Brunswick), while Alberta implements a daily demand charge rate of \$0.47769/kW_{pd}/day. Ontario also has a Global Adjustment rate that acts like a demand charge coincident to the overall system peak during the year. Alberta employs a daily demand charge that has separate rates based on the time of day in which the building peak occurs (on-peak versus off-peak). Although Doluweera et al. show some quantitative results graphically, most of the discussion is qualitative. The authors estimate the IRR if a BESS were installed in various years between 2018 and 2040 using BESS capital cost ranges and operation and maintenance (O&M) costs from Lazard for the five building types in the five provinces. Lazard is a research firm known for their annually published reports on the Levelized Cost of Energy (2020 was v. 14) and the Levelized Cost of Storage (2020 was v. 6). Their two reports are often cited in the clean technology industry as indicative of the competitiveness of intermittent renewables (solar and wind), and energy storage, versus conventional thermal (fossil fuel and nuclear) electricity generation. Lazard's [29] annual reports are available online for public download on their website. The installed cost range presented for 2020 are between \$201-\$447 CAD/kWh_{cap} and \$59-\$130 CAD/kWh_{cap} in 2040. The current 2020 costs appear low in comparison to the battery pack estimates by Bloomberg [10], and cost projections to 2040 are speculative. They find that BESS will have a positive IRR under most of the studied scenarios by 2025 and in all scenarios except strip malls and large office buildings in Ontario by 2030. The load shape and the rate structure are found to be the primary drivers of project economics and the authors conclude that BESS sizing will be site specific to a particular customer but do not specify what drives the BESS sizing. The conclusion that the important drivers of economics are load shape and tariffs. This indicates that buildings from different categories with similar load shapes and tariffs would have similar results. It is not clear in this paper if that is the case or not. Although the load shape discussion is not quantified, Doluweera et al. found that a "flat load profile" with minimal variation between the maximum and minimum loads in the month will reduce the economics of a BESS. Conclusions are not drawn on how this relates to the annual average load factor, but it would indicate that buildings with a higher monthly load factor would have poorer economics than those with a lower load factor. Doluweera et al. suggest that potential new research should include more advanced methods for battery sizing selection that consider battery degradation and integration of solar PV.

MacLaren et al. [30] evaluated the important elements that influence the economics of BESS and solar PV in commercial buildings using NREL's Renewable Energy Optimization Model (REopt). The functionality of the REopt program is discussed in detail in subsection 2.3 Control Strategy. Their study analyzed a variety of solar and storage sizes for 16 commercial building types using the US DOE Commercial Reference Buildings. A total of 17 cities across the United States and 73 electric utility tariffs from different jurisdictions were used in the analysis. In total, the study looked at over 24,000 different scenarios. MacLaren et al. studied project economics under combinations of seven rate structures including energy charges, tiered energy charges, TOU energy charges, fixed non-coincident demand charges, tiered demand charges, TOU demand charges and no demand charges. Four different costing models were used for the solar system, battery inverter, battery energy storage and equipment replacement costs. MacLaren et al. found that a BESS was economic for only one location (Boulder, CO) and one building type (Large Office) under the high-cost technology scenario ($1,332/kW$_{inv}$ for the inverter and $290/kWh$_{cap}$ for battery capacity), and only improving to two economic options for a BESS in the stretch technology cost scenario ($787/kW$_{inv}$ for the inverter and $106/kWh$_{cap}$ for battery capacity). The installed cost figure of $106/kWh$_{cap}$ for BESS capacity is particularly low, especially in reference to Bloomberg's 2024 LIB pack cost of $96/kWh$_{cap}$, leaving little room for the inverter, thermal management, other equipment, installation, and overhead. MacLaren et al. found the optimum system sizes increased with decreasing technology costs for both solar PV and BESS, and optimum BESS energy capacity was found to increase with annual building energy consumption. MacLaren et al. found cost savings opportunities for every building type analyzed for solar PV combined with BESS, significantly more than the economically viable opportunities for a BESS alone. The results showed that most of the utility bill reductions in solar plus BESS scenarios were attributable to energy savings from solar and not demand savings, but that the combination of solar and BESS significantly increases the demand savings versus a storage only scenario. Although this research does not explore why the savings are higher for the combination of solar and storage, this is like the results found by Gagnon et al. but in contrast to the results of Neubauer et al. [26]. Gagnon et al. [23] found that the production profile of solar could narrow the peak demand width of a commercial building in the morning and evening meaning less battery capacity was required to reduce the peak. Additionally, Gagnon et al. found that storage could effectively reduce mid-day peaks that may occur due to a sudden reduction in solar output, for example during cloud cover. Neubauer concludes that this may be due to the solar system providing some demand savings for the buildings, but this could be skewed because the analysis is being modelled in Los Angeles which has a very different solar resource to other parts of the country. Neubauer cautions that most buildings report minimal demand reduction from a solar installation and that the results could change significantly based on solar system size and other factors like incentives. Gagnon et al.'s findings conceptually align with the white paper released by NREL [31] discussing demand charge reductions from solar installations on commercial buildings where, depending on the building's load profile, solar can narrow morning and evening peaks which could then be more easily reduced with energy storage.

Wu et al. [32] propose an optimization formula to determine the trade offs between peak demand reduction and energy cost arbitrage in an office building using synthesized load profiles for the analysis. To quantify economic benefits, a fixed 200 kW_{inv} / 800 kWh_{cap} battery is selected, and one utility rate structure is provided for four test case jurisdictions. A typical office building is used in the analysis and a test is run in San Francisco, Chicago, Houston, and New York City to test the effects of different climatic conditions. The building load data is referenced as coming from ASHRAE research by Sun et al. [33]. Although the data timestep is not explicitly referenced, a load profile figure shows a 1.0 h timestep between readings. The reader is not provided any information on the peak or average load for the office building, or a description of its load shape. The results are all presented in dollar amounts, pre and post BESS installation. The same utility tariffs are applied in all four test cases including summer and winter on, off and mid peak pricing as well as a \$30/kW_{pd}/mo demand charge. MacLaren et al. [8] showed that 15% of US customers have access to demand charges above \$20/kW_{pd}/mo, but \$30/kW_{pd}/mo tends to be a high demand charge rate. Wu et al. find that demand charge mitigation is a stronger economic driver then energy shifting and that the demand reduction potential is based on a building's load shape. It is noted that demand savings tend to increase as load factor decreases, but not when load factor is calculated on an annual basis due to seasonal variations in building energy consumption. Like other work by Wu [34], this paper shows that battery sizes around the optimum have similar economic outcomes so sizing availability is important. The paper notes that work needs to be done to create guidelines for energy storage sizing. No results are shown in normalized fashion, so it is difficult to compare the findings between the different facilities with differing load sizes or profiles. As in [34], no results or discussion are presented for the full set of 68 buildings available to them which makes it challenging to see how the results can be transferred to a broader context (i.e. general sizing guidelines or rules of thumb).

Shown below in Table 1 is a summary of the literature discussed above. The following observations can be drawn:

- Much of the research uses the US DOE Commercial Reference Building dataset which has a 1.0 h time resolution, which is not well suited to capturing peak demand events that are billed on a 15 min interval.
- The number of distinct buildings in the analysis tends to be small, because of the use of the US DOE Commercial Reference Building dataset. Although the research may study a variety of climatic conditions to increase the number of cases analyzed, the load profile underpinning the modelling is the same except for variations due to heating and cooling loads. This “representative” building load profile approach may not be the most appropriate way to draw conclusions on the economics of BESS with much of the research indicating it is customer or site specific. More research should be done to assess if there is commonality between those site-specific scenarios that could be used in project guidelines.
- The demand charge rate is consistently a key driver of project economics.
- Load shape appears to be an indicator of battery size, but there is room for expanded research on this topic.
- Long term technology cost projections are speculative, so the use of normalization is helpful in avoiding assuming a specific technology cost for battery storage.

Table 1: Demand Charge Literature Review Summary

	Rate Structures Studied	Number and Type of Buildings Studied	Load Profile Data Source	Data Time Step	Load Shape	Demand Charge Rate	Battery Sizing	BESS Capital Cost	Normalization in Analysis
MacLaren et al.	Size of demand charges (\$/kW$_{pd}$/mo) in the US.	All US C&I buildings	NA	NA	NA	Referenced as \$15/kW$_{pd}$/mo when BESS is economic, but not studied here	NA	NA	NA
Long et al.	Regular non-coincident demand charge (\$/kW$_{pd}$/mo)	16 Building Types, 15 climate zones	US DOE Commercial Reference Buildings	1 h	Indicator of BESS sizing	Indicator of project economic viability	Linked to load shape	\$600-\$1500/kWh$_{cap}$ range, projects most likely to economic when costs are low	Load profiles normalized to determine Load Profile Metric
D'Aprile et al.	Regular non-coincident demand charge (\$/kW$_{pd}$/mo)	Not discussed	Identified as critical to assessing project economic viability, source not listed	Not discussed, but 15 min or less discussed as necessary to identify project opportunities	Not discussed	BESS economic with demand charges above \$9/kW$_{pd}$/mo	Not discussed	BESS economic with capital costs below \$400/kWh$_{cap}$	Project profitability normalized by battery capacity (\$/kWh$_{cap}$)
Gagnon et al.	Variety: energy, coincident and non-coincident demand charges, time of use, and averaging intervals	16 Building Types, 15 cities	US DOE Commercial Reference Buildings	1.0 h for load profile, 30 min for solar PV	Not discussed	Savings increase with shorter averaging periods	Smaller batteries tend to provide better return on investment	Not discussed - economic results normalized	Demand reduction shown as a percentage
Darghouth et al.	Regular non-coincident demand charge (\$/kW$_{pd}$/mo), and peak hours	Thee studied, representing three types: shopping centre, shopping centre with PV, and manufacturing	EnerNOC, 1 year	5 min	Qualitative - "peaky" load profiles have the most savings, "flat" load profiles have the least	Demand charge rate was the most significant indicator of project economic viability	Inverter set at 20% of annual peak demand, with 1.0 h, 2.0 h, and 4.0 h duration	Not discussed - economic results normalized	Annual bill savings normalized by BESS inverter power

	Rate Structures Studied	Number and Type of Buildings Studied	Load Profile Data Source	Data Time Step	Load Shape	Demand Charge Rate	Battery Sizing	BESS Capital Cost	Normalization in Analysis
Neubauer et al.	Regular non-coincident demand charge ($\$/kW_{pd}/mo$), seasonal on/off peak times	98	EnerNOC, 1 year	5 min	Not specifically discussed, but it would have a relation to Emax	More important to project economics then energy arbitrage	Based on %s of the energy required to flatten the load during the day. Fixed hour rate discharges	$\$300/kWh_{cap}$ for capacity and $\$300/kW_{inv}$ for the inverter, no other pricing tested	Not discussed
Doluweera et al.	Regular non-coincident demand charge ($\$/kW_{pd}/mo$), and non-coincident daily ($\$/kW_{pd}/day$)	5	US DOE Commercial Reference Buildings	1 h	Annual load factor studied, results discussed qualitatively, shape is a major driver of economics	Major driver of economics	Noted as site specific, no guidance or conclusions drawn	Range of prices tested from $\$447/kWh_{cap}$ in 2020 to $\$59/kWh_{cap}$ in 2040	Not discussed
MacLaren et al.	73 different utility tariff models across the US	16 Building types, 17 cities	US DOE Commercial Reference Buildings	1 h	More load variability (lower annual load factor) the higher the savings are	Higher demand charges result in the optimal battery size increasing	No relationship between load shape and optimal size, highly site specific	High, mid, and low technology costs studied	Total savings presented as percentages
Wu et al.	Four utility rates from different cities	1 Building type, 4 cities	ASHRAE	1 h	Economics improve as monthly load factor decreases	Demand charge rate is a primary driver of economics	Sizing linked to "load shape" and not "load factor". This is not quantified.	High, mid, and low technology costs studied just inverter ($\$/kW_{inv}$) and energy capacity ($\$/kWhc_{ap}$)	Not discussed

2.2 Evaluation Metrics

When studying the affects of both solar and storage on commercial demand charges, Gagnon et al. [23] define a Cooperation Ratio, shown below in Equation (2), as the ratio of the total demand reduction of a PV system combined with a BESS to the demand reduction of PV added to the demand reduction of a BESS when both are treated independently.

$$Cooperation\ Ratio = \frac{(Solar\ and\ BESS\ System\ Demand\ Reduction)}{(Solar\ Only\ Demand\ Reduction) + (BESS\ Only\ Demand\ Reduction)} \tag{2}$$

A Cooperation Ratio > 1 indicates that the combination of the two technologies reduces demand greater then then the sum of the two individual technologies. Their research found that cooperation ratios increased with increasing PV system size because the larger solar systems tended to create taller, thinner peaks in net load that the BESS could be effectively discharged to address.

Darghouth et al. [24] define Demand Charge Reduction Efficiency, shown below in Equation (3) as the monthly peak demand reduction divided by the BESS inverter power rating, both measured in kW.

$$Demand\ Charge\ Reduction\ Efficiency = \frac{Monthly\ Peak\ Demand\ Reduction\ (kWpd)}{BESS\ Inverter\ Size\ (kWinv)} \tag{3}$$

Demand charge reduction efficiency is then plotted for various battery system sizes (ex. 1.0 h, 2.0 h, and 4.0 h). The study found that longer duration storage could reduce demand charges over wider peaks, but that there are diminishing returns in the demand charge reduction efficiency with longer duration storage. The results are limited given that only three battery sizes were tested, especially in the context of the shopping centre having a repetitive 8.0 h load profile (8am – 4pm) throughout the year.

Fisher et al. [35] develop a metric called the Threshold Ratio to estimate the economics and optimal sizing of a BESS. Fisher et al. study the load shape of the building rather then the demand charge rate structure of a particular region. The Threshold Ratio measures the efficiency of a BESS at reducing demand and is based on the building's total energy consumption during the peak period relative to the battery size. No formula, or a specific threshold, is provided by Fisher et al. to define the Threshold Ratio, but an iterative step process is provided which is outlined below. Their research uses 665 C&I buildings from North and South Carolina that are published by EnerNOC, now Enel-X. The data used is 15 min interval data for one year (2013). The model assumes perfect foresight. First, a target threshold is defined as the peak building demand (kW_{pd}) over the time series, subtract the BESS inverter rating (kW_{inv}). Next, a Spike-to-Battery ratio is calculated as the ratio of the annual average of energy within the largest monthly peak demand relative to a target threshold, divided by the energy capacity of the BESS. The target threshold is based on an assumed maximum battery inverter discharge power, in this case 10 kW_{inv}. No justification is provided for how or why this value was selected. The average energy is used in the formula so that the Spike to Battery Ratio is unitless in relation to the BESS capacity. The formula for the Spike to Battery Ratio is shown below in Equation (4).

$$Spike\ to\ Battery\ Ratio = \frac{Average\ Energy\ in\ a\ Demand\ Spike\ above\ a\ specified\ threshold\ (kWh)}{BESS\ Capacity\ (kWhcap)} \tag{4}$$

In the case where a specific BESS capacity (kWh_{cap}) size is not large enough to reduce the average monthly peak demand event (i.e. Spike to Battery Ratio > 1) a lower discharge power then the maximum 10 kW_{inv} must be used to ensure the battery is not depleted. To determine the target threshold value, the Spike-to-Battery ratio is re-calculated for each month using a range of intermediate discharge powers. Next, the lowest monthly intermediate power value, where the Spike-to-Battery ratio is greater than or equal to one 1, is divided by the BESS inverter power rating in kW_{inv}.

The average of these ratios over the course of the year is the Threshold Ratio. Fisher et al. use a linear optimization with perfect foresight of the building load to select a battery size that minimizes the utility bills for the building owner. They cite research with error ranges of 5-10% for predictive models, drawing the conclusion that their results are transferrable to a load forecasted scenario. No details on how the optimization process works or what battery sizes are selected relative to building load or other metrics are presented. The results are shown as utility bill savings normalized by battery capacity ($/kWh$_{cap}$). The optimization was run for 665 buildings and a non-linear equation was used as a line of best fit to describe the relationship between Threshold Ratio and the normalized utility bill savings. This was tested for BESS inverters with various power capacities ranging from 15%-30% of a building maximum demand. The results showed that normalized revenue was consistent across all tested BESS inverter ratings, assuming a fixed discharge duration of 1.0 h. Using a fixed 1.0 h discharge duration means that the affect of discharge rate, or the ratio of BESS energy capacity to inverter rating, is not explored in the research. The fixed 1.0 h rate may not be an accurate representation of the types of BESS systems that are commercially available, and the model does not explore if there were solutions that provided better normalized savings by moving to a larger battery capacity relative to its inverter power rating (i.e. 2.0 h, 4.0 h, or 8.0 h BESS).

MacLaren et al. define load factor as the average load divided by the peak demand on an annual basis. This contrasts with the typical commercial billing period of one month. The study found that when defined this way, load factors varied between approximately 40% - 70%. This study evaluated the business case for a BESS as part of a combined solar PV plus BESS system. The results are presented as a percentage of total utility bill savings, for demand and energy. Most of the results are shown for both when both technologies are used together. While this approach is valuable for assessing hybrid installations, assessing the storage only results is difficult since research from Gagnon et al. shows that PV tends to narrow peak demand and improve BESS performance. Similar results are found by MacLaren et al. in the limited test case that shows the technologies separately and combined. The results show a trend towards greater savings as load factor decreases (more load variability), but the results are not presented to show how those savings are generated. For example, Gagnon et al. and Neubauer et al. show that combinations of solar and storage can decrease demand, but the demand savings presented in MacLaren et al.'s report are not prescribed to solar, storage, or the incremental value of the combined approach.

The study indicates that demand savings tend to be higher in projects with "more variability in load profile", but it is not clear if MacLaren et al. mean load factor, or if they are referring to some other measure of variability that is not defined. This reader assumes more variability means lower load factor since load factor is the independent variable shown on the abscissa axis of the analysis. The study showed no correlation between load variability and the optimum battery capacity and inverter size. Again, it is assumed that load variability in this case refers to load factor. This may be because load factor is being defined on an annual basis rather than the monthly billing cycle that demand savings would be calculated over which could mask affects of seasonal changes in usage for certain buildings. Whether load factor is being defined on an annual or monthly basis, this result is not intuitive and should be explored further as Long et al. found a strong relationship between their Load Profile Metric, which was representative of load shape, as a strong indicator of battery sizing. The results where the relationship between battery sizing and load factor are presented do not indicate if solar was being applied or not, but the title of the research, and other results, suggest PV would be included. This obscures the results from a BESS only case since the PV system tends to depress load during the day and shorten peak windows. Although PV tends to depress load, it is not necessarily reliable for demand charge management as shown in MacLaren et al.'s [30] analysis of utility bill savings for a PV only test case. MacLaren et al. found in some cases as much as 4 times the difference in the optimum normalized battery duration (kWh_{cap}/kW_{inv}) for buildings of the same type and with similar load factors. This result is not intuitive and should be explored further but is absent from their discussion.

Shown below in Table 2 is a summary of the literature discussed above. The following observations can be drawn:

- The evaluation metrics need to be intuitive and easy to implement if they are going to be used in guidelines to assist project developers and building owners quickly assess the viability of a BESS project.
- Metrics should be based on the demand charge billing cycle, not an annual basis. Limited focus on quantifying the monthly load shape and what role it may play in either battery sizing or economics.

Table 2: Evaluation Metrics Summary

	Evaluation Metric	Based On	Positive Indicator of	Ease of Implementation / Transferability	Draw Backs
Long et al.	Load Profile Metric	Normalized load profiles, set annual energy equal, average	Battery sizing	Annual load profiles required. Relatively straightforward to calculate	Based on averaging annual data when demand charges are billed monthly
Gagnon et al.	Cooperation Ratio	Assessing incremental increased demand savings when solar and storage are combined	Cases where hybrid projects will be economic	Easy to calculate, but still requires a method to determine the demand reductions	No use in storage only applications
Darghouth et al.	Demand Charge Reduction Efficiency	Monthly demand reduction relative to inverter size	Used to compare effectiveness of BESS with different capacities	Easy to calculate and intuitive	It is a metric for comparing results, does not help assess how to size or control the BESS
Fisher et al.	Threshold Ratio	Energy in a demand event, relative to a setpoint, in comparison to the BESS power and energy ratings	Non-linear equation used to fit Threshold ratio to normalized savings based on battery capacity ($\$/kWh_{cap}$)	Iterative calculations required, once spreadsheets were established it could be re-used	Not in any way intuitive or easy to understand for your average building owner or project developer
MacLaren et al.	Load Factor	Annual average load to annual peak demand	Generally lower load factor leads to greater savings	Very easy to calculate with annual electricity bills	Annual basis when demand charges are typically calculated monthly

2.3 Control Strategy

Chua et al. [36] develop and test three different control strategies for demand charge reduction on two commercial buildings at the Universiti Tunku Abdul Rahman (UTAR) in Malaysia. The thee control strategies presented and tested in the paper are a fixed, adaptive, and fuzzy logic based peak reduction strategies. A fixed size BESS with a 15 kW_{inv} inverter and 64 kWh_{cap} lead acid battery is used in the experiment. No justification is provided for the system sizing relative to the buildings loads. In the fixed control strategy, a maximum building load is set, and the batteries will discharge the required power to bring the net building load back to the fixed value. The adaptive threshold control strategy is like the fixed control, except that during discharge phase the upper power limit is adjusted if load remains above the setpoint for over a certain time. The length of time before the adjustment is made is not defined in the paper. The fuzzy logic control strategy uses the amount of available energy in the battery, and the current discharge time, to determine the battery’s power output. Chua et al. present a matrix that determines the output power based on the two input variables. The first two methods presented by Chua et al. do not consider the remaining energy in the battery and none consider the high load event previously seen in the month. The remaining energy in the battery is relevant for demand reduction as it will influence both the maximum rate of discharge in each time interval, and the duration that a given discharge power can be sustained for. The previous high demand point in the month may be the set point defined by Chua et al., or it may be some higher value if the set point was missed on a previous attempt. Failing to change the demand charge setpoint to the previously max in the billing period will result in the battery discharging at an unnecessarily high rate during a future demand event and again missing the peak.

Salis et al. [37] propose an adaptive discharge methodology for BESS to reduce demand charges in a commercial building. They claim that previously published discharge strategies focused on reducing building demand on a day-by-day basis without a need to potentially adjust the limit during the day. Salis et al.'s discharge strategy adjusts the demand reduction setpoint within the month based on the highest observed net demand while preforming demand charge management in that month. This method accounts for the case where a previous demand reduction target may have been missed due to depleted battery capacity and a new target needs to be set to account for the previously seen net peak during the billing period. Salis et al. utilize a historical record of building loads and the corresponding historical ambient temperatures, and a forecast of upcoming mean temperatures to predict the building load. The building load forecast is based on combining several forecast techniques. The first forecast technique, $Z\alpha$, utilizes the current building load, forecasted ambient temperature, the average building load for the same week one year previously, the average load for the same weekday, and the average load for the same time interval. The second method, Z_β, uses combinations of sub forecasts that all use the ambient temperature from a weather forecast, the average load over the previous five-time intervals, and the forecast error over previous time intervals. The Z_β combinations analyzed include the forecast with the lowest historical error over the entire analysis period, a weighting of the different forecasts, and whichever forecast has the lowest error over individual time intervals. Salis et al. define a "Ratchet Rule" which implements a discharge strategy based on the maximum net-building load observed previously within the month. Salis et al. analyze their technique using four buildings: two apartments, an office, and a university building by comparing the demand reduction using the forecast to the optimum demand reduction using perfect foresight. Without using the "Ratchet Rule", Salis et al.'s control strategy, using the Z_β forecast, results in demand reductions between 41%-66% of the ideal demand reduction depending on the building type. When the "Ratchet Rule" is implemented, and using the Z_β forecast, the results improve significantly to between 55%-90% of the ideal demand reduction based on the building type and the Z_β option used. What is not clear in this paper is over how many different demand set points do these improved results occur. If the demand setpoint was set too low, the "Ratchet Rule" would engage often and likely improve the results. Conversely, if the demand setpoint was not set low enough, the "Ratchet Rule" would rarely engage and not show an improvement.

NREL's System Advisor Model (SAM) has a tool that project developers or building owners could use for evaluating PV and BESS projects. DiOrio [38] describes the battery control methodology used in SAM. The battery model uses one of two methods, selectable by the user, for assessing the peak demand. The first is perfect foresight and the second assumes the coming day is identical to the previous day. In each case the daily load profile is scanned and the loads by time step are sorted from largest to smallest. Next a Target Power is selected by the user or can be calculated by SAM. When calculated by SAM, the Target Power is selected to ensure that the battery does not fully discharge either by perfect foresight or by assuming the following day is identical to the proceeding day. The BESS will discharge when the building load is above the Target Power and recharge when the building load is below the Target Power.

The Target Power is reset each 24.0 h period which does not match with how commercial customers are typically billed, except for some real-time pricing markets like Alberta.

Shown below in Table 3 is a summary of the literature discussed above. The following observations can be drawn:

- In all the control strategies reviewed, none assists the user in defining the demand charge setpoint based on characteristics of the building. This is a crucial missed opportunity as even a perfect control strategy will not provide optimal returns if the setpoints are too high and will have reduced effectiveness if they are set too low.

Table 3: Control Strategy Summary

	Strategy	**Based On**	**Positives**	**Draw Backs**
Chua et al.	Thee studied, fixed, adaptive and fuzzy logic	Demand thresholds set by the user	Simple and easy to implement	First two methods do not consider the energy in the battery, none consider a previously missed demand event
Salis et al.	Forecast building load and adapt demand reduction setpoint based on highest observed net demand within the month - "Ratchet Rule"	Demand thresholds set by the user	Utilizes a forecast rather than perfect foresight. Adapting "Ratchet Rule" significantly improved results	Does not help the user determine the demand reduction threshold
DiOrio	User selects perfect foresight or predicted method that assumes following day is identical to the previous day. Demand reduction is based on a 24.0 h period instead of a typical 1 mo billing period.	Target Power set by the user or calculated to ensure the battery does not fully discharge each day.	Simple forecast tool and easy to implement.	No reset of Target Power if the BESS fails to achieve objective.

2.4 Battery Sizing

NREL’s BLAST [39] is a model for assessing the lifespan of batteries in applications including BESS, EVs and grid services applications. There is a specific version of the model tailored to demand charge management called BLAST-BTM Lite that includes tools for sizing the BESS. Neubauer [40] describes the battery sizing methodology in the BLAST Documentation manual. BLAST-BTM Lite uses a similar methodology as Neubauer et al. described, and is detailed in subsection 2.1 Demand Charges, where users can input BESS energy capacities as percentages of E_{Max}, which is defined as the largest amount of energy required to completely flatten the daily load variability in the building over the course of the year. The default range in BLAST to select the BESS capacities (kWh_{cap}) for analysis are between 1% - 20% of E_{Max}. The user then selects discharge durations to test with defaults between 0.5 h and 4.0 h at full power as proxy for the inverter power rating. In this case the user is defining the boundaries of the BESS properties in terms of both power and energy that the model will test. The model then calculates and plots the IRR for each battery capacity (i.e. 1% - 20% of E_{Max}) as a function of power to energy ratio which is defined by the discharge durations (i.e. 0.5 h and 4.0 h at full power). The model will search along the plot of IRR as a function of power to energy ratio for each battery size to find the battery capacity and power to energy ratio with the maximum IRR. The searching function starts at the maximum power to energy ratio and moves to lower power to energy ratios (increasing storage capacity) to check if the IRR increases. The search function terminates when an IRR is returned that is less than the previously returned IRR. In a rare case there may be a dual peak and this methodology will always identify the first peak in IRR. Moving to larger storage systems may be the global peak but could also be a local peak under certain circumstances. Neubauer acknowledges that this could be the case but indicates that it has not been shown over any test cases explored by NREL. Although this model does suggest analysis ranges for both power and energy, the user is not provided any guidance as to how these may need to be adjusted based on the specifics of their building load profile.

Wu et al. [34] propose a sizing strategy for BESS for demand charge reduction based on a metric they call the "incremental levelized annual benefit". Wu et al. define the incremental benefit as the difference between the increased demand charge savings and increased cost of a larger battery bank for a given building. The research develops equations to evaluate demand charge savings and incremental battery cost based on the incremental demand reduction, and time associated with that reduction. Those equations are then solved to determine the maximum economic benefit. Wu et al. suggest increasing battery bank sizing until the point at which the incremental benefit, net of the incremental battery cost, is zero. One of the challenges of this approach is that it treats the battery and inverter sizes as small (ex. 1 kWh_{cap}, 1 kW_{inv}) discrete values that a building owner can incrementally purchase. In practice, the owner will be forced to purchase in significantly larger increments depending on what suppliers have available. While appropriate from a theoretical or mathematical optimization, this approach falls short when applied to practical purchasing decisions. Although Wu et al.

indicate they have load profile data for 68 buildings across six building categories and four climate zones, only one building is used as a case study for the economic results. The results in the paper show that the economic benefits do not vary considerable for battery capacities and inverter sizes around the optimum mark. This does benefit the model as it allows the user to select commercially available equipment close to the optimal value without expecting a significant decline in economic benefits. It is unclear, and not explored in the paper, if the common economic returns around the optimum value are common for all building categories, load shapes and climatic conditions, or if that is a specific result for the test case analyzed. No trends were shown on the full data set making it difficult for a reader to draw conclusions on how the findings could be applied to their building without going though the full optimization process proposed by Wu et al. The method proposed by Wu et al. uses perfect load foresight, as used by Gagnon et al. and Fisher et al., based on an individual load profile. Data from the US DOE Commercial Reference Buildings dataset is used in a sample analysis. Wu et al. suggest that the method can be applied to an individual day, representative of each month's daily load profile, to calculate the BESS sizing. The challenge with this approach is that demand charges are typically set based on the highest 15 min energy consumption within a month and building load profiles tend to vary day to day. A high load instance within a month can set the demand charge for the entire month, regardless of what the usual daily load profile looks like within the month. It is not clear from the paper how to select battery sizing based on the daily load variations common in commercial buildings.

Chua et al. [41] develop a battery sizing methodology for demand charge reduction in commercial buildings. The paper is based around a real-life test case with a lead acid BESS installed in a building at the Universiti Tunku Abdul Rahman (UTAR) in Malaysia, although it does not appear that the inverter rating (5 kVA_{inv}) or battery capacity (21.3 kWh_{cap}) were selected based on the results of the research. The annual load curve is not discussed in the paper, but a case study is shown for a specific weekday showing a nighttime load of approximately 20 kW_{elc} which rises rapidly from 07:30 onwards to a peak of 150 kW_{pd} at approximately 14:00, followed by a rapid decline to approximately 40 kW_{elc} at around 18:00 and then a gradual decline back down to 20 kW_{elc}. The representative daily load profile for the building is developed using two months worth of weekday data. Although due to university occupancy this may be a fair assumption for when the load peak will occur, this approach does not provide a comprehensive picture of what happens during the weekends and will have limited transferability to building types that have less variation in occupancy, or ones that experience peaks during the weekends (ex. bars or restaurants). A single variable quadratic equation relationship between inverter rating and battery capacity is developed by analyzing the size and shape of the generic weekday load profile. It should be noted that the equation presented is only relevant to the building analyzed and requires knowledge of the load profile size and shape to generate the formula. Chua et al. then preform an iterative calculation to determine the battery capacity based on the peak demand in the generic load profile and the relationship developed previously between inverter rating battery capacity. The methodology used in this work can be applied to buildings when the load profile is known, but it does not present any guidelines when limited building load data is known.

Shown below in Table 4 is a summary of the literature discussed above. The following observations can be drawn:

- Battery sizing strategies need to utilize easily accessible building data to effectively reduce BESS project soft costs for project developers and building owners. All the strategies below rely on knowing the complete building load profile, which does not account for the cases where only basic billing information is available.

Table 4: Battery Sizing Summary

	Strategy	Based On	Positives	Draw Backs
NREL BLAST - Neubauer	User selectable % of Emax	Largest daily amount of energy required to completed flatten the daily load profile over the course of the year	Easy to understand and relatively simple to implement	Full load profile data needs to be known. Still fully user selectable, is not guided based on building load characteristics
Wu et al.	Bring the incremental benefits of added demand charge savings subtract added battery cost to zero	Perfect load foresight and defining all terms as math variables and solving for the maximum benefit	Allows for very precise results	Too complicated for most building owners or project developers. BESS sold in discreet sizes
Chua et al.	Develop a relationship between BESS inverter and BESS energy capacity	Quadratic equation based on load size and shape of a generic weekday	Allows user to capture both the energy and power ratings of the BESS	Full load profile data needs to be known. Some buildings (ex. restaurants) peak on weekends.

2.5 Energy Storage Implementation Guidelines

The US DOE's Better Buildings Initiative published a report called *On-Site Energy Storage Decision Guide* in April 2017 by Mitchell et al. The report is purported to be a decision guide for energy storage; however, there are no guidelines, sizing tools or strategies presented to assess a commercial energy storage project. The report is an introduction to BESS for commercial building(s). Common energy storage technologies including lead acid batteries, capacitors, flow batteries, ice storage and LIB are introduced with a summary of the technology characteristics and applications. Applications considered include energy arbitrage, demand charge management, power factor correction, reliability, and renewables integration. The report identifies the potential benefits from BESS to building owners, and demand charge management is identified as one of the key benefits. The report notes that demand charge management is more effective for buildings with "peaky" rather than "flat" load profiles but does not provide any quantification or guidelines around those two terms. The report does not offer the reader any suggestions on how to determine if their building is "peaky" or "flat" or how to quantify potential benefits of a BESS. The report does not discuss the billing cycle for demand charges and its influence on battery discharge strategy and project economic viability. The approach taken in this report is helpful for readers that are not familiar with the energy storage technology, or technical considerations and need a basic primer before deciding to go further with their project. The report presents clear graphical examples of “flat” and “peaky” load profiles that a reader can understand the function and value of a BESS for demand charge management, but it can not be used to help a building owner or project developer in the sizing or economic analysis of a potential project.

Kintner-Meyer et al.’s [42] research was published in 2010 as joint report between Pacific Northwest National Laboratory (PNNL), National Renewable energy Laboratory (NREL), and Argonne National Laboratory (ANL). The purpose of the report is to outline the various applications and associated value streams in commercial buildings for thermal and electrochemical energy storage. Given the changes in the energy storage market over the last decade, some of the material presented is out of date. For example, thermal storage for air conditioning loads is discussed in relation to demand charge management and renewables integration, while the cost and custom design complexity are identified as barriers for BESS for load shifting. The analysis section of the report has a strong focus on the interaction between BESS and the overall power grid through large scale BESS deployment for demand response. For example, demand response activity by building operators is modelled in response to real time grid energy rate ($\$/kWh_{elc}$) price signals, in contrast to conventional rate structures that have fixed, or time blocked, defined rates for energy and demand. The focus on overall power grid benefits is unhelpful for a project developer trying to assess the impact of a BESS on a particular building.

Baxter et al. [43] published the *Energy Storage Best Practice Guide* by the Advancing Contracting in Energy Storage (ACES) Working Group. The ACES Working Group is a US based consortium including private companies, trade associations and national research labs to develop guidelines for energy storage project implementation. The document provides guidelines for project development, engineering, economics, long term performance, operation, risk management, and standards. It is written in a general format to introduce the reader to the basic considerations of developing and contracting an energy storage project. It is not written specifically for commercial buildings, but for energy storage project implementation more generally. The topics discussed are not particular to BESS and would be applicable to most clean energy project development including permitting, engineering due diligence, debt financing, maintenance and warranty considerations. It is noted that an independent engineer should assess the BESS capacity and inverter rating to ensure that it is suitable for the project application, but no guidance is provided on how to either size a BESS or evaluate the merits of a BESS size for a particular application. A subsection within the engineering chapter that focuses on challenges specifically references that cycling related to the control strategy will be important to project investors because of the affect on battery life and maintenance. The economic model is discussed as important, but no guidance on how to construct or evaluate an economic model is provided. The economics section of the report outlines the major categories of services that a BESS can provide and lists demand charge reduction as part of the retail category. The economics section starts with an introduction to utility rate design. High demand charges referenced here as +$20/kW$_{pd}$/mo, TOU rates and coincident demand charges are listed as favourable forms of rate design for BESS project economics. Low demand charges are referenced as <$10/kW$_{pd}$/mo. Annual demand ratchets and flat energy charges were listed as rate structures unfavourable to BESS project economics. This observation for the unfavorability of annual demand ratches matches the conclusions of Darghouth et al. [24]. The relative importance of these rate structures is not discussed, and no further clarity is provided in terms of enabling rates other then to define the high and low demand charges above. The report is comprehensive and informative from a project owner's perspective when planning how to contract a BESS project but is written too broadly to apply as a technical or economical guideline for developing BESS projects for commercial buildings.

Torrie et al.'s [44] report focuses on BESS for commercial buildings in Massachusetts. The report provides a brief introduction to BESS in the US and cites demand charges of $15/kW$_{pd}$/mo as a common indication of an economic opportunities for a BESS to deliver savings. The report is written for a non-technical audience and dedicates sections to defining power and energy and how they relate to BESS projects as well as the difference between the behind the meter and in front of the meter. It is noted that a BESS can provide the most demand savings for buildings with high peak demand relative to average load, meaning a low load factor. This is not quantified or shown though experimentation or case studies in the report. Several BESS use cases are summarized including demand charge management, energy arbitrage, backup power, uninterruptible power supply, renewables firming and power quality improvement. Next, several energy storage technologies are compared in terms of use cases, cost, lifetime, and pros and cons. The energy storage technologies considered include lead acid batteries, LIBs, flow batteries and thermal storage. Financing and funding, including Massachusetts specific programs, and are discussed as enablers for these projects. Finally, the report summarizes supportive policy alternatives and market hurdles for BESS in Massachusetts, although issues like capital cost are applicable broadly. The report is an energy storage primer, specifically tailored for the Massachusetts market. There is not any technical analysis included or guidelines on how to size or operate a BESS for demand charge management, or any of the other services outlined in the report.

Freed et al. [45] published an energy storage guideline on behalf of the New South Whale's Office of Environment and Heritage in Australia. The guide is aimed specifically at commercial building owners who are interested in learning the basics of energy storage and how the technology could be applied to their facility. Its specifically noted in the report that it is not meant as a replacement for an engineering review and does not provide any detailed economic feasibility or technical assessment. Economic opportunities derived from changing how or when a building uses energy from the grid is listed as the main reason to install a BESS. The report starts with definitions of basic energy storage terminology including charge, discharge, energy and power, depth of discharge, state of charge and cycle life. Time of use rates, demand charges, and PV integration are discussed as the business cases in New South Whales that allow BESS to save money for commercial buildings. Several bar charts are used to illustrate how a BESS can interact with a building load profile and energy output of a solar system. When discussing demand charge management, the report sites data of past consumption patterns as crucial to a successful implementation. The report notes that demand charge management is most effective when the duration of the peak is short, but this is described qualitatively rather then quantitative. Other applications including off-grid systems and backup power are also described. Next, the report provides guidelines for purchasing decisions. First, the report prompts owners to answer questions about their current, and future energy and power usage. Next, a flow diagram is shown to assist owners in identifying the BESS application (ex. backup, demand charges, PV integration etc.) that best suits their needs. The flow chart is based on qualitative yes/no questions rather then specific building technical characteristics. Building owners are asked to consider how their building uses energy and to quantify variation on a daily, weekly, and seasonal basis. The report then provides a table that readers can fill in for energy and demand charges for each month of the year, although no directions are given as to how these values should be used to assess the opportunity for a BESS. Examples of how to calculate savings for a BESS applying either TOU rates or demand charge management are shown. The economic analysis is basic as a peak demand threshold is arbitrarily selected and the demand savings multiplied by the demand charge rate to calculate the dollar savings. No guidance is provided as to how the user should select that threshold value based on building load characteristics. Finally, a questions checklist for BESS buyers to ask vendors is presented which covers things like battery chemistry, warranty, degradation, operating temperature and power and energy capacities.

Mullendore et al.'s [46] report is a guide to behind the meter PV and storage for commercial buildings. The paper starts with the basics of behind the meter PV and then provides descriptions for both DC and AC coupled behind the meter PV and storage systems. Four case studies are presented for PV and BESS with a primary focus on resiliency and the comparison to a conventional diesel generator. The case study for the Scripps Ranch Community Recreation Center in San Diego California notes that although the system was installed for emergency power purposes, it also savings the facility money though demand charge management. The system size for this project is listed as 30 kW_{inv} of PV and a 100 kW_{inv} / 100 kWh_{cap} BESS. The combination of the two systems saves the facility approximately $2,000 a month in utility bills, but no information is provided on the makeup of energy and demand savings. Finally, a checklist is provided for building owners prior to considering a PV and BESS project. Topics included are: understanding the utility bill, identifying interconnection guidelines, identifying critical loads, physical constraints for the PV system, BESS technology selection and financial implications. The remarks in the checklist are broad and do not provide the reader with any quantitative tools to assess the merits of a project.

Shown below in Table 5 is a summary of the literature discussed above. The following observations can be drawn:

- None of the guidelines provide quantitative analysis for BESS sizing or economics.
- Most guidelines are written for those first learning about energy storage, so they start with the basics of how the technology works and some example applications.
- Demand charge management is consistently discussed as one of the key savings opportunities for a behind the meter energy storage system.
- PV integration or renewables smoothing are commonly discussed.

Table 5: Energy Storage Implementation Guidelines Summary

	Guideline Focus Area	Technologies Considered	Use Cases Considered	Demand Charge Management Commentary	Highlights	Draw Backs
Mitchell et al.	Commercial buildings	Lead acid, LIBs, capacitors, flow batteries, ice storage	Energy arbitrage, demand charge management, power factor correction, reliability, and renewables integration	Demand charge management is more effective for "peaky" rather than "flat" load profiles	Good introduction to energy storage basics	No quantitative analysis for BESS sizing or project economics
Kintner-Meyer et al.	Commercial buildings	Thermal storage, battery energy storage, phase change materials	Opportunities to provide services behind the meter and to the grid, wind smoothing	Demand charge management is primarily discussed in relation to thermal storage for reducing peaks associated with HVAC	Early analysis on how behind the meter storage can provide benefits to the grid	Dated commentary. No technical or economic guidelines provided.
Baxter et al.	Contacting energy storage, not specifically for buildings	NA - written generically	NA - written generically	NA - written generically	Informative for project developers and potential owners on project considerations from a contracting, permitting and financing perspective	No quantitative analysis for BESS sizing or project economics
Torrie et al.	Commercial buildings in Massachusetts	LIBs	Demand charge management, energy arbitrage, backup power, uninterruptible power supply, renewables firming and power quality improvement.	Buildings with demand charge rates above $15/kWpd/mo identified as opportunities for BESS	Summary for available programs and incentives as well as policy opportunities for BESS	No quantitative analysis for BESS sizing or project economics
Freed et al.	Commercial buildings in New South Whales, Australia	Lead acid, LIBs, and salt	Time of use rates, demand charges, solar integration	Detailed knowledge of past load profiles is identified as critical	Bar charts that demonstrate how the BESS interacts with the building load profile are intuitive	No quantitative analysis for BESS sizing or project economics, although tables to outline the important considerations are provided
Mullendore et al.	Resilience with solar and storage for commercial buildings	LIBs and PV. Both DC and AC coupled	Focus is on backup power, although demand charge management is discussed in the case studies	Discussed in case studies with a project example provided. Short on details other than system sizing and overall utility bill savings	Flow diagrams of DC and AC coupled systems are easy to understand and not discussed in any of the other guidelines	No quantitative analysis for BESS sizing or project economics

METHODOLOGY

3.1 Overview

The development of battery sizing guidelines was based on the following building input data:

- One-to-two years of electrical utility bills that are typically available to any commercial operation seeking invest in a BESS. Bills include the following data:
  - Energy consumption (kWh_{elc})
  - Peak demand (kW_{elc} or kVA_{elc})
  - Utility rate code (tariff)
- Building category as defined by the utility (ex. healthcare, hotel, retail, educational, etc.)

Using interval-type electricity meter data for many commercial buildings, of various categories, in Nova Scotia will demonstrate relationships between the utility bill metrics described above and battery sizing and demand reduction potential. The relationships are determined by running simulations of different battery sizes and demand charge reduction targets on each building and then analyzing the results for patterns.

Four years of building load interval meter electricity data at 15 min timesteps was provided by NSP. The data is discussed in detail in Chapter 4. The data set includes 248 buildings across eight categories defined by NSP. All the data was in either spreadsheet (.xls) or comma-separated values (.csv) format.

Shown below in Table 6 are the quantities of buildings by category and examples of the use cases for the building category.

Table 6: Building Categories and Quantities

Building Type	Number of Buildings	Building Type Examples
Commercial	24	Office space
Community	5	Municipal facilities (ex. ice rinks, community centres, libraires)
Education	28	Schools
Health Care	11	Clinics, hospitals
Hotel	3	Hotels
Industrial	83	Manufacturing
Retail	27	Stores and restaurants
Utility	7	Pumping stations and telecommunications

MATLAB software was chosen as the tool for the analysis because of the large number of simulations. A total of 297,600 simulations were conducted across 248 buildings, four years of data, five demand reduction increments, six battery capacities, five discharge rates, and two monthly peak demand values. The results of those simulations are analyzed to determine what conclusions can be drawn as to relationships between building load data, category, battery discharge strategy, and sizing.

A MATLAB model was built to use a common demand reduction strategy to analyze various battery storage sizes and peak reduction increments for each building. The battery sizes in the model were discrete values based on commercially available LIB pack sizing. The battery sizes tested in the model were 25, 50, 100, 250, 500, and 1,000 kWh_{cap}. Five inverter maximum power ratings are used in the tests. The power ratings range from 15 min to 12.0 h. The 15 min discharge time is used to examine what improvements in demand reduction results are possible as technology battery improves. The 2.0 h discharge time reflects commercially available products and the 4.0 h to 12.0 h rates are used to test if slower rates improve demand reduction results in certain categories. Although the battery sizing and inverter power ratings tested are not exhaustive, it has sufficient resolution and range to reflect commercially available products and typical purchasing increments available for a project. The battery sizes and inverter power ratings used in the test are shown below in Table 7.

Table 7: Battery Capacity and Inverter Power

Battery Capacity (kWh_{cap})	**15 min Rate Inverter Power (kW_{inv})**	**2.0 h Rate Inverter Power (kW_{inv})**	**4.0 h Rate Inverter Power (kW_{inv})**	**8.0 h Rate Inverter Power (kW_{inv})**	**12.0 h Rate Inverter Power (kW_{inv})**
25	100	12.5	6.3	3.1	2.1
50	200	25	12.5	6.3	4.2
100	400	50	25.0	12.5	8.3
250	1000	125	62.5	31.3	20.8
500	2000	250	125.0	62.5	41.7
1,000	4000	500	250.0	125.0	83.3

Comparing the results between the 15 min, 2.0 h, and slower rate scenarios will be informative for understanding if significant improvements in results for demand charge management applications can be expected as new BESS technology is developed that will allow high rates of charge and discharge versus commercially available BESS products (130 kW_{inv} / 2.0 h Tesla Powerpack) [47].

The demand reduction model uses the Monthly Load Factor (*MLF*) from the same month in the previous year to determine the Target Demand (*TD*). This allows the discharge strategy to raise the *TD* for months with a historically high *MLF* and to lower the *TD* for months with a historically low *MLF*. The *MLF* was treated as one of the independent variables that was expected to influence the sizing and demand reduction potential of a BESS for a commercial building.

The model used the first year of data (2016) to represent one year of historical utility bills that a building owner or project developer would typically have access to. The following years (2017-2019) were tested for demand reduction results using perfect foresight and predicted peak demand based on the 2016 bill data. . The model is not a learning or training model as it assumes the building owner or project developer only has access to utility bill data. The results between the perfect foresight and predicted peak demand were compared, as were the demand reduction savings using the various rate scenarios. The results are presented with normalized demand reduction savings by building average load (kW_{pd} / kW_{avg}).

The model is based on the alternating current (AC) loads seen in the building rather then the direct current (DC) ratings on the battery. An AC model was selected because AC electrical system in the building is the point of common coupling for metering. The building owner is billed in AC, and commercially available BESS systems, like the Tesla Powerpack, market their BESS products with energy capacity rated in AC kWh_{cap} and inverter power ratings in AC kW_{inv}.

Fixed AC-DC efficiency conversions of 86% and 100% are used on charge and discharge, respectively. Since the model is based on AC loads, it was decided to capture the full round-trip energy efficiency while charging so that any energy stored within the battery could be considered usable AC capacity. This method is helpful for owners and designers as the battery capacity represents the total amount of useful energy that can be accessed for demand reduction or other applications. Energy efficiency of 86% was selected to align with published material including analysis by Lazard (80%-94%) [29], Pacific Northwest National Laboratory (86%) [42], and Tesla (88-89.5%) [47].

The battery capacities, efficiency, and rate are representative of LIB storage technology, which is the primary battery storage technology being deployed at commercial scale. These parameters could be adjusted to reflect other types of energy storage technology, but this research focuses on LIB BESS.

3.2 C&I Energy Storage Model Development

A C&I Energy Storage Model (CIESM) was developed for analyzing various buildings, battery sizes and demand reduction targets on buildings in Nova Scotia.

First, an array of building load profiles, for all building categories, is loaded into the CIESM. The model can iteratively simulate all the buildings in the array, a category of buildings, or a single building.

For the first year the model scans the entirety of the building load timeseries to find the peak demand in each calendar month, and to calculate the monthly average demand. It is assumed that the calendar months and billing months are the same in the analysis. The *MLF* is calculated from the peak monthly demand and average monthly demand as shown below in Equation (5).

$$MLF = \frac{\text{Average Monthly Demand } (\text{kW}_{avg})}{\text{Peak Monthly Demand } \left(\text{kW}_{pd}\right)} \tag{5}$$

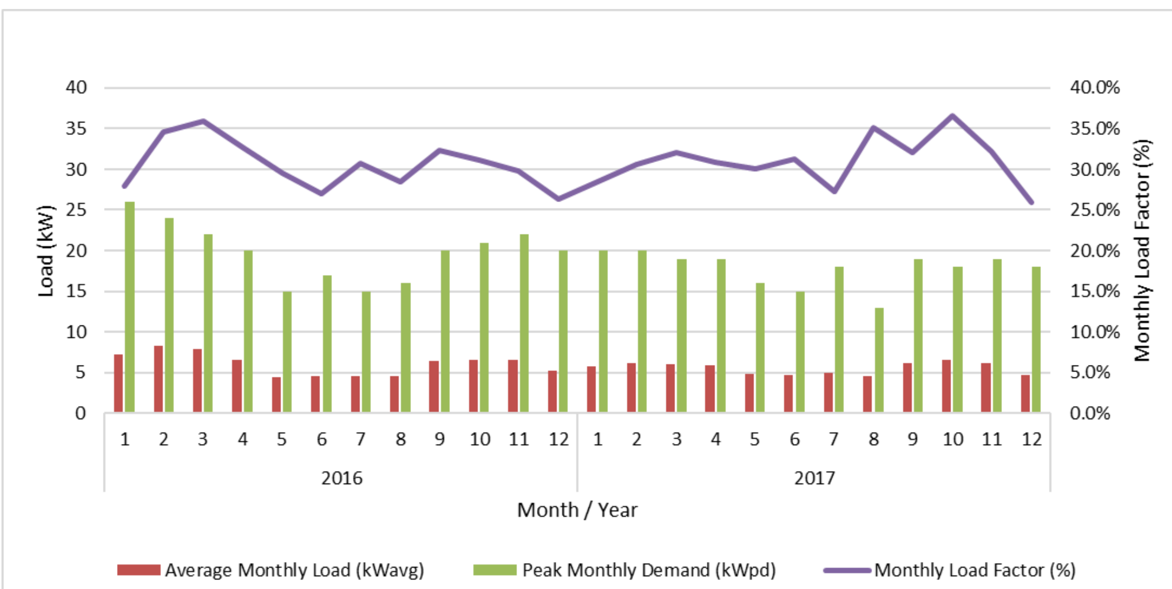
Two examples of the calculation of the MLF are shown below in Table 8 to illustrate buildings with a low and high MLF. The first building shown in the table with Load Research ID (LRID) 314110 is an Education facility with rate code 11 (general commercial tariff). The second building is LRID 354710 is a Hotel with rate code 11.

Table 8: Examples of Monthly Load Factor Calculation

Year	**Month**	**Education - 314110**			**Hotel - 354710**		
		Avg. Mon. Load (kW_{avg})	**Peak Mon. Demand (kW_{pd})**	**Monthly Load Factor (%)**	**Avg. Mon. Load (kW_{avg})**	**Peak Mon. Demand (kW_{pd})**	**Monthly Load Factor (%)**
2016	**1**	7.3	26	27.9%	480.5	761	63.1%
	2	8.3	24	34.6%	419.5	842	49.8%
	3	7.9	22	35.9%	412.6	723	57.1%
	4	6.5	20	32.7%	337.5	619	54.5%
	5	4.4	15	29.5%	249.4	417	59.8%
	6	4.6	17	27.0%	235.9	426	55.4%
	7	4.6	15	30.7%	293.7	504	58.3%
	8	4.6	16	28.5%	307.1	499	61.5%
	9	6.5	20	32.4%	283.2	524	54.0%
	10	6.5	21	31.2%	270.2	447	60.4%
	11	6.6	22	29.9%	311.8	520	60.0%
	12	5.3	20	26.3%	438.5	791	55.4%

Year	Month	Education - 314110			Hotel - 354710		
		Avg. Mon. Load (kW_{avg})	Peak Mon. Demand (kW_{pd})	Monthly Load Factor (%)	Avg. Mon. Load (kW_{avg})	Peak Mon. Demand (kW_{pd})	Monthly Load Factor (%)
2017	**1**	5.7	20	28.4%	450.8	721	62.5%
	2	6.1	20	30.5%	455.5	693	65.7%
	3	6.1	19	32.0%	463.7	736	63.0%
	4	5.9	19	30.9%	317.9	533	59.6%
	5	4.8	16	30.1%	314.7	446	70.6%
	6	4.7	15	31.2%	271.0	518	52.3%
	7	4.9	18	27.2%	287.7	542	53.1%
	8	4.6	13	35.1%	311.2	488	63.8%
	9	6.1	19	32.1%	301.7	516	58.5%
	10	6.6	18	36.6%	292.0	418	69.8%
	11	6.1	19	32.1%	375.3	608	61.7%
	12	4.7	18	26.0%	495.5	807	61.4%

The values from Table 8 are plotted in Figure 10. Seasonal variations in average load and peak demand are apparent for both buildings with higher electrical consumption in the winter months and lower consumption in the spring and summer months. No seasonal trends are apparent for the *MLF*.



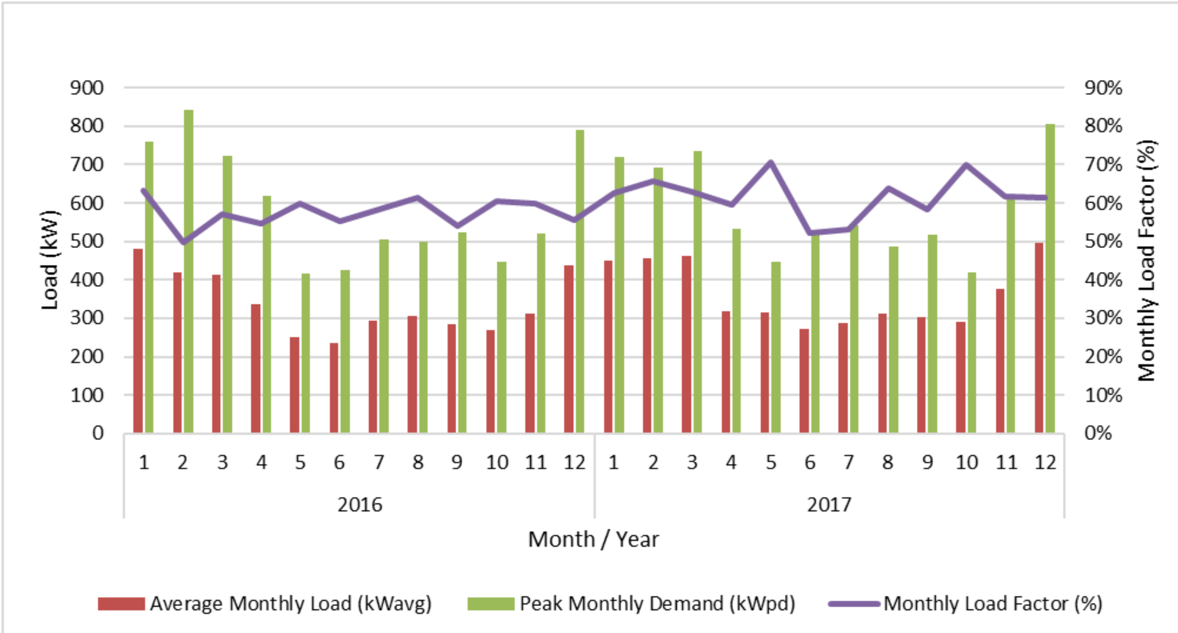


Figure 10: Average and Peak Monthly Load with Monthly Load Factor for Education 314110 (top) and Hotel 354710 (bottom)

The control strategy is based on using iteration to determine the optimum battery storage size and peak demand reduction potential for a given building. The model iteratively simulates incremental demand charge reduction scenarios, down to the average demand, by calculating a Target Demand (*TD*) to use in the analysis.

This approach uses five Demand Increments (*DI*) of the *MLF* ranging from 20%, which reduces only the highest peaks, to 100% where the building load profile would appear as a flat demand at the monthly average. The first step in calculating the *TD* is calculating a Demand Reduction Factor (*DRF*) that is based on the *DI* and the *MLF*. The formula for the *DRF* is shown in Equation (6).

$$DRF = (1 - MLF) \times DI\ (\%) \tag{6}$$

The relationship between *DRF*, *MLF* for various *DI*s is plotted below in Figure 11. The resultant *DRF*s for a given *MLF* narrow as the *MLF* meaning that the largest spread of demand savings results between various *DI* scenarios would be expected for buildings with a lower *MLF*s and to narrow for buildings with a higher *MLF*. This conclusion is intuitive when considering that a BESS can not reduce the peak demand in the billing period below the average demand load.

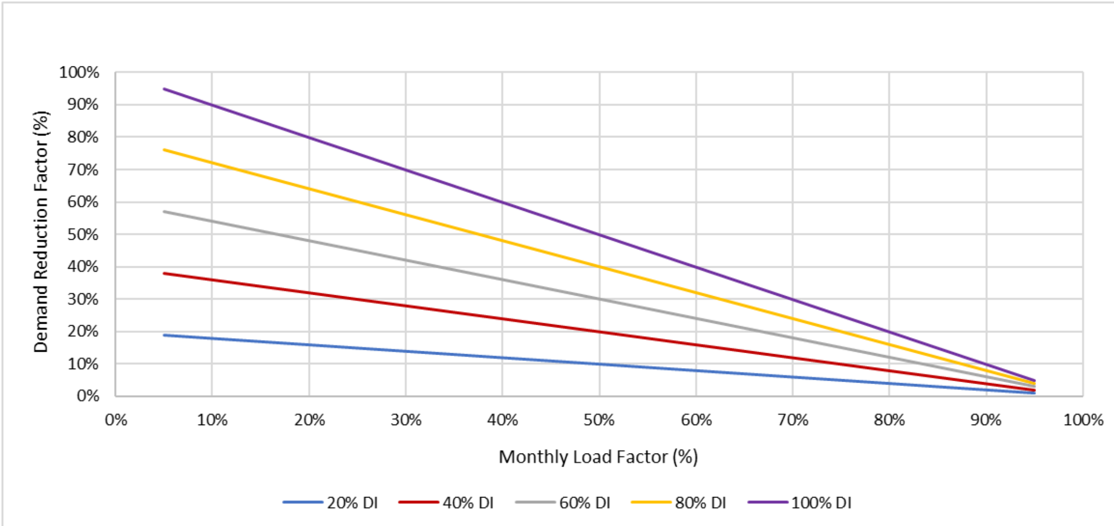


Figure 11: Demand Reduction Factor vs Monthly Load Factor for Various Demand Increments

This method allows the *DRF* and, resultant *TD*, to vary monthly in absolute terms, and as a relative percentage of peak demand, to optimize the use of the battery. The *DRF* is then multiplied by the Peak Monthly Demand (*PMD*) to determine the *TD* as shown in Equation (7).

$$TD = DRF \times PMD \tag{7}$$

Examples of calculating the five different *DRF*s and *TD*s for May 2017 in buildings Education – 314110 and Hotel – 354710 are shown in shown below in Table 9 and

Table 10 respectively.

Table 9: Education – 314110 Example Calculations of Demand Reduction Factor and Monthly Target Building Demand

Education - 314110					
DI (%)	**MLF (%)**	**DRF (%)**	**Peak Monthly Demand (kW_{pd})**	**TD (kW_{pd})**	**PMD - MTBD (kW_{pd})**
20.0%	30.1%	14.0%	16	13.8	2.2
40.0%		28.0%		11.5	4.5
60.0%		41.9%		9.3	6.7
80.0%		55.9%		7.1	8.9
100.0%		69.9%		4.8	11.2

Table 10: Hotel – 354710 Example Calculations of Demand Reduction Factor and Monthly Target

Building Demand

Hotel - 354710					
DI (%)	**MLF (%)**	**DRF (%)**	**Peak Monthly Demand (kW_{pd})**	**TD (kW_{pd})**	**PMD - MTBD (kW_{pd})**
20.0%		5.9%		419.7	26.3
40.0%		11.8%		393.5	52.5
60.0%	70.6%	17.7%	446	367.2	78.8
80.0%		23.6%		341.0	105.0
100.0%		29.4%		314.7	131.3

As shown above, the highest *DI* (100%) brings the peak monthly demand inline with the average monthly demand, while the lowest *DI* (20%) targets modest reduction in peak demand. The demand reduction increments are dependent on the variability in the building load because the *DRF* is based on the *MLF.* A higher load variability (i.e. low *MLF*) will result in larger step changes than a scenario with a low load variability (i.e. high *MLF*).This is illustrated in Figure 12 and Figure 13 where equivalent *DI*s of 60% result in significantly different *DRF*s because of the difference in *MLF* for the two buildings. The low *MLF* (~30%) in Education 314110 means the resultant *DRF*, for the same *DI*, results in more than twice the relative demand reduction (41.9% vs 17.7%) in comparison to Hotel 354710 with a higher *MLF* (~70%). The result is the model will attempt to reduce the peak demand more dramatically in buildings with a low *MLF* than a building with a high *MLF*.

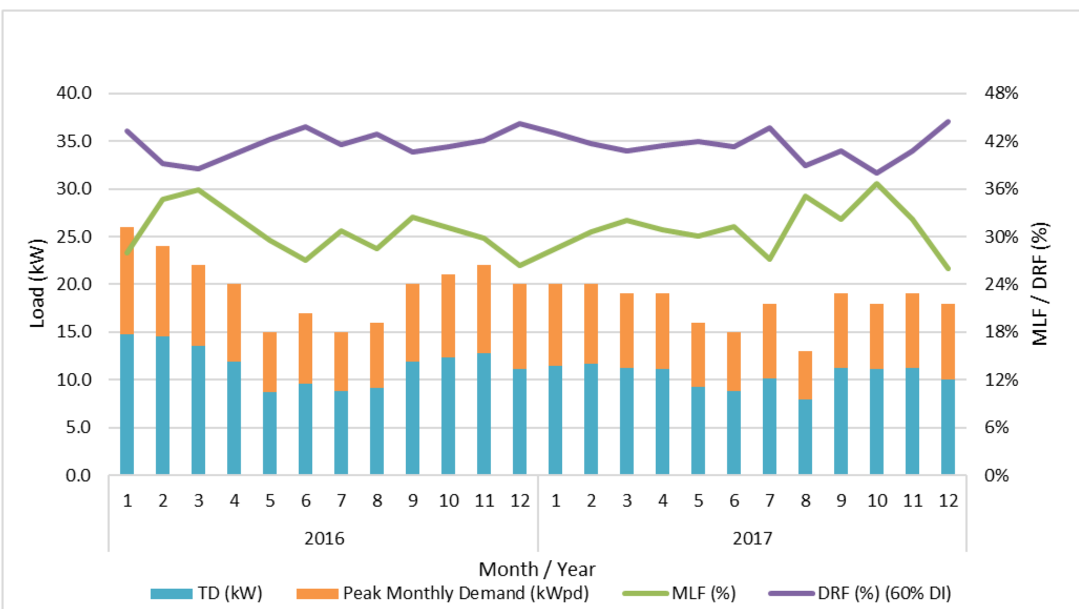


Figure 12: Education 314110 - MBTD for DRF with 60% DI

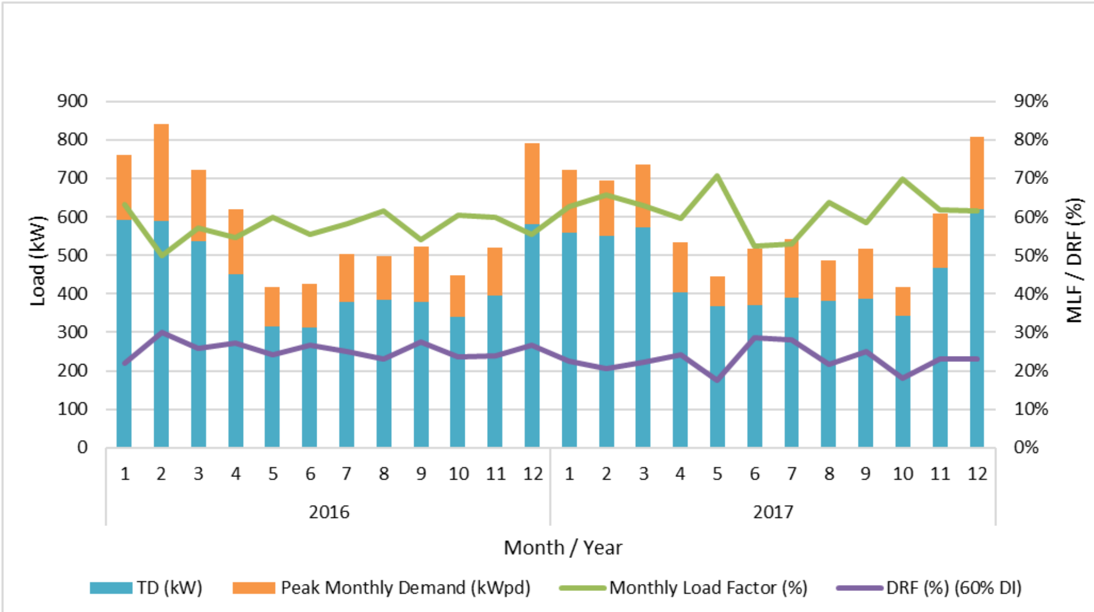


Figure 13: Hotel 354710 - MBTD for DRF with 60% DI

Once the *TD* has been established, a timestep analysis is performed for the battery and building load profile. The maximum battery charge and discharge rates are determined by checking the remaining energy in the battery, the time step, and the maximum allowable charge and discharge rates (i.e. 15 min or 2.0 h).

Next, the model checks if the building load in the time step, *t*, is below the *TD*. If the building load is below the *TD* in the timestep, then the battery charges at a rate, inclusive of charging efficiency, which is the minimum of:

- the maximum defined inverter power rating;
- the maximum rate defined by the energy remaining in the battery;
- or a rate which will keep the building load, inclusive of battery charging, under the *TD*.

If the battery is fully charged during the timestep, *t*, or during a previous timestep, *t-1*, then it remains in standby and cannot accept any additional energy. When the building load exceeds the *TD*, then the battery will exit standby by discharging energy to bring the net building load down to the *TD*.

If the building load is greater then the *TD* in timestep *t*, then the battery discharges at the minimum a rate defined by:

- the maximum inverter discharge rate;
- the maximum rate defined by the energy remaining in the battery;
- or the minimum rate required to reduce the building demand to the *TD*.

If the battery runs out of energy in timestep *t* then the battery stops discharging and remains in standby until the building load falls below the *TD*, at which stage the battery can recharge.

Next, the remaining battery energy, state of charge (SOC), and net building demand is calculated for the time step, *t*. During a given timestep, *t*, the battery may not be able to reduce the building demand to the *TD* because the battery becomes fully discharged, or the discharge power is insufficient due to the amount of energy remaining in the battery or maximum inverter rate. The net building demand could exceed the *TD* in these scenarios. In this case, the *TD* is reset to be the net building demand in timestep *t*. If, in timestep *t*, the net building demand exceeds the *TD*, then the *TD* is reset prior to *t+1*, to give a new objective demand value for the battery to meet. Resetting the *TD* to the highest observed net building load in the billing period ensures that the battery is not discharging in situations that would not produce a reduction in net building demand.

A flow chart of the C&I Energy Storage Model is shown below in Figure 14.

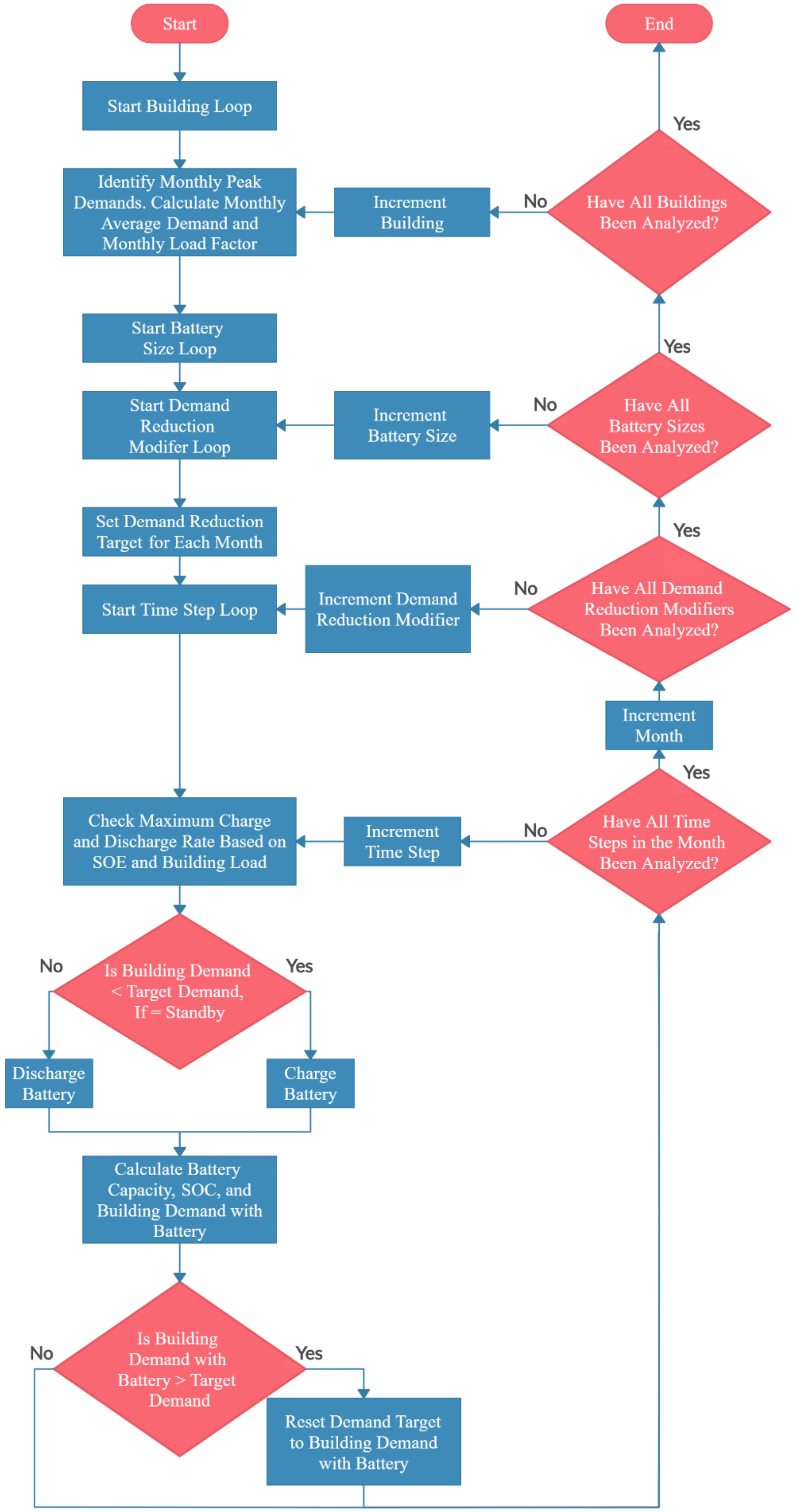


Figure 14: Control Strategy Flow Chart

3.3 Predicting the Peak Monthly Demand

In the first year of analysis, the *TD* was determined using perfect foresight to identify the peak monthly demand in each billing period. While perfect foresight is helpful for setting the base case scenario for demand savings, it is not practical from a project implementation perspective since a building owner does not have perfect foresight of the peak demand. Four simple methods were developed for predicting the peak monthly demand. It was assumed that the project developer, or building owner, had access to a minimum 12 months of utility bills that contain at least the peak monthly demand and total monthly energy consumption. Relying on historical data means the methods can be slow to react to large changes in load due to sudden growth (ex. heating system electrification or EVs being introduced) or decline in consumption (ex. COVID-19). This is a potential drawback of the assessment approach taken, but this decision was made to simplify the analysis. Weather data was not used to assess correlations between outside ambient temperature and either the monthly peak demand or average load for the building. Future work could incorporate historical weather data and a weather forecast to improve the peak demand prediction accuracy.

Method 1 uses the Actual Peak Monthly Demand (*APMD*) from the same month in the preceding year as the Predicted Peak Monthly Demand (*PPMD*) for the current year and is shown below in Equation (8).

$$PPMD_{Yi,Mj} = APMD_{Yi-1,Mj} \tag{8}$$

Method 2 uses the *APMD* from the same month in the preceding year and is error adjusted based on the average error between the *PPMD* and the *APMD* in the current year as shown below in Equation (9).

$$PPMD_{Yi,Mj} = APMD_{Yi-1,Mj} \times \frac{\frac{1}{j}\sum_{1}^{j-1} APMD_{Yi,Mj}}{\frac{1}{j}\sum_{1}^{j-1} PPMD_{Yi,Mj}} \tag{9}$$

Method 3 uses the *APMD* from the same month in the preceding year but is adjusted based on average error between the Actual Average Monthly Load (*AAML*) and the Predicted Average Monthly Load *(PAML)*. The *PAML* is calculated as the *AAML* from the same month in the previous year and is adjusted based on the *AAML* and *PAML* for the previous months in the year, as shown below in Equation (10).

$$PAML_{Yi,Mj} = AAML_{Yi-1,Mj} \times \frac{\frac{1}{j}\sum_{1}^{j-1} AAML_{Yi,Mj}}{\frac{1}{j}\sum_{1}^{j-1} PAML_{Yi,Mj}} \tag{10}$$

The formula for the *PPMD* using Method 3 is shown below in Equation (11).

$$PPMD_{Yi,Mj} = APMD_{Yi-1,Mj} \times \frac{\frac{1}{j}\sum_{1}^{j-1} AAML_{Yi,Mj}}{\frac{1}{j}\sum_{1}^{j-1} PAML_{Yi,Mj}} \tag{11}$$

Method 4 uses the *MLF* from the same month in the previous year, the *PAML*, and an average error correction based on the *PPMD* and *APMD* to calculate the *PPMD* as shown below in Equation (12).

$$PPMD_{Yi,Mj} = \frac{PAML_{Yi,Mj}}{MLF_{Yi-1,Mj}} \times \frac{\sum_{1}^{j} APMD_{Yi,Mj-1}}{\sum_{1}^{j} PPMD_{Yi,Mj-1}} \tag{12}$$

Methods 2-4 use a similar average error ratio concept. In each case, for the first month being analyzed beyond the initial year, the *PPMD* or *PAML* is assumed to be equal to the peak demand or average load in the same month of the previous year since no offset ratio can be used.

An example of Method 4 calculations for the *PAML* and *PPMD* for 2017-2019 using 2016 utility billing data is shown below for Education – 314110 and Hotel – 354710 in Table 11 and Table 12 respectively.

Table 11: Education – 314110 Predicted Average Monthly Demand and Predicted Peak Monthly Demand

Year	Month	Actual Average Monthly Load (kW_{elc})	Actual Peak Monthly Demand (kW_{pd})	Monthly Load Factor (%)	Predicted Average Monthly Load (kW_{elc})	PAML Cumulative Average Error Offset (%)	Predicted Peak Monthly Demand (kW_{pd})	PPMD Cumulative Average Error Offset (%)	PPMD Monthly Error (%)
2016	**1**	7.3	26	28%	-	-	-	-	-
	2	8.3	24	35%	-	-	-	-	-
	3	7.9	22	36%	-	-	-	-	-
	4	6.5	20	33%	-	-	-	-	-
	5	4.4	15	30%	-	-	-	-	-
	6	4.6	17	27%	-	-	-	-	-
	7	4.6	15	31%	-	-	-	-	-
	8	4.6	16	28%	-	-	-	-	-
	9	6.5	20	32%	-	-	-	-	-
	10	6.5	21	31%	-	-	-	-	-
	11	6.6	22	30%	-	-	-	-	-
	12	5.3	20	26%	-	-	-	-	-
2017	**1**	5.7	20	28%	7.3	28%	26	30%	30%
	2	6.1	20	31%	6.0	13%	12	-5%	-39%
	3	6.1	19	32%	6.9	13%	20	-1%	6%
	4	5.9	19	31%	5.7	9%	18	-3%	-7%
	5	4.8	16	30%	4.0	5%	14	-4%	-12%
	6	4.7	15	31%	4.4	3%	17	-2%	13%
	7	4.9	18	27%	4.5	2%	15	-4%	-18%
	8	4.6	13	35%	4.5	1%	16	-1%	26%
	9	6.1	19	32%	6.4	2%	20	-1%	5%
	10	6.6	18	37%	6.4	1%	21	1%	15%
	11	6.1	19	32%	6.5	2%	22	2%	13%
	12	4.7	18	26%	5.2	2%	19	3%	7%
2018	**1**	5.5	20	28%	5.6	0%	19	-5%	-5%
	2	6.2	19	33%	6.1	-1%	21	2%	10%
	3	6.3	20	31%	6.1	-1%	19	-1%	-7%
	4	5.6	19	30%	5.9	0%	19	0%	2%
	5	4.3	17	26%	4.8	2%	16	-1%	-6%
	6	4.7	17	28%	4.6	1%	15	-3%	-12%
	7	4.4	16	28%	4.8	2%	18	-1%	14%
	8	4.1	15	27%	4.5	3%	13	-2%	-15%
	9	5.9	21	28%	5.9	3%	19	-3%	-10%
	10	7.0	20	35%	6.4	1%	18	-4%	-10%
	11	7.5	22	34%	6.0	-1%	19	-5%	-11%
	12	5.2	18	29%	4.7	-2%	19	-4%	6%

Year	Month	Actual Average Monthly Load (kW_{elc})	Actual Peak Monthly Demand (kW_{pd})	Monthly Load Factor (%)	Predicted Average Monthly Load (kW_{elc})	PAML Cumulative Average Error Offset (%)	Predicted Peak Monthly Demand (kW_{pd})	PPMD Cumulative Average Error Offset (%)	PPMD Monthly Error (%)
2019	1	6.7	21	32%	5.6	-16%	21	1%	1%
	2	7.2	21	34%	7.2	-8%	22	2%	4%
	3	6.9	22	31%	6.8	-6%	21	0%	-4%
	4	6.2	20	31%	6.0	-5%	20	0%	1%
	5	4.9	16	31%	4.6	-6%	18	2%	12%
	6	4.8	21	23%	5.0	-5%	18	-1%	-16%
	7	4.5	16	28%	4.6	-4%	17	0%	6%
	8	4.2	16	26%	4.2	-3%	16	-1%	-2%
	9	6.4	20	32%	6.1	-3%	22	1%	9%
	10	6.5	20	33%	7.2	-2%	21	1%	3%
	11	6.8	26	26%	7.6	0%	22	-1%	-15%
	12	5.2	20	26%	5.3	0%	18	-2%	-9%

Table 12; Hotel – 354710 Predicted Average Monthly Demand and Predicted Peak Monthly Demand

Year	Month	Actual Average Monthly Load (kW_{elc})	Actual Peak Monthly Demand (kW_{pd})	Monthly Load Factor (%)	Predicted Average Monthly Load (kW_{elc})	PAML Cumulative Average Error Offset (%)	Predicted Peak Monthly Demand (kW_{pd})	PPMD Cumulative Average Error Offset (%)	PPMD Monthly Error (%)
2016	**1**	481	761	63%	-		-	-	-
	2	420	842	50%	-		-	-	-
	3	413	723	57%	-		-	-	-
	4	338	619	55%	-		-	-	-
	5	249	417	60%	-		-	-	-
	6	236	426	55%	-		-	-	-
	7	294	504	58%	-		-	-	-
	8	307	499	62%	-		-	-	-
	9	283	524	54%	-		-	-	-
	10	270	447	60%	-		-	-	-
	11	312	520	60%	-		-	-	-
	12	438	791	55%	-		-	-	-
2017	**1**	451	721	63%	480.5	7%	761	6%	6%
	2	455	693	66%	391.9	-4%	743	6%	7%
	3	464	736	63%	428.0	-5%	702	3%	-5%
	4	318	533	60%	354.6	-2%	633	6%	19%
	5	315	446	71%	254.3	-5%	400	4%	-10%
	6	271	518	52%	246.9	-5%	430	1%	-17%
	7	288	542	53%	308.8	-4%	527	0%	-3%
	8	311	488	64%	318.6	-3%	517	1%	6%
	9	302	516	58%	291.9	-3%	536	1%	4%
	10	292	418	70%	278.6	-3%	456	2%	9%

Year	Month	Actual Average Monthly Load (kW_{elc})	Actual Peak Monthly Demand (kW_{pd})	Monthly Load Factor (%)	Predicted Average Monthly Load (kW_{elc})	PAML Cumulative Average Error Offset (%)	Predicted Peak Monthly Demand (kW_{pd})	PPMD Cumulative Average Error Offset (%)	PPMD Monthly Error (%)
	11	375	608	62%	321.9	-4%	528	0%	-13%
	12	496	807	61%	457.3	-5%	823	0%	2%
2018	**1**	538	930	58%	471.9	-12%	752	-19%	-19%
	2	456	748	61%	511.7	-1%	928	0%	24%
	3	419	642	65%	468.6	3%	743	4%	16%
	4	361	579	62%	309.2	-1%	496	1%	-14%
	5	273	392	70%	317.1	1%	446	2%	14%
	6	286	490	58%	267.0	0%	499	2%	2%
	7	335	535	63%	286.3	-1%	528	2%	-1%
	8	365	596	61%	315.6	-3%	486	-1%	-18%
	9	296	475	62%	310.3	-2%	534	0%	13%
	10	311	517	60%	298.3	-2%	425	-1%	-18%
	11	435	771	56%	384.0	-3%	629	-3%	-18%
	12	526	742	71%	512.1	-3%	860	-1%	16%
2019	**1**	567	775	73%	555.9	-2%	972	25%	25%
	2	542	760	71%	464.5	-8%	568	0%	-25%
	3	399	668	60%	452.9	-2%	691	1%	3%
	4	323	492	66%	369.8	1%	585	4%	19%
	5	273	371	73%	271.6	1%	372	4%	0%
	6	265	404	66%	284.4	1%	468	5%	16%
	7	328	564	58%	331.1	1%	500	3%	-11%
	8	310	479	65%	360.0	3%	571	5%	19%
	9	259	411	63%	288.0	3%	440	5%	7%
	10	278	404	69%	300.3	4%	475	6%	17%
	11	355	600	59%	418.4	5%	698	7%	16%
	12	465	693	67%	499.1	5%	655	6%	-5%

Using 2016 as the reference utility billing data, the *APMD*, *PPMD* and the monthly and cumulative average error for 2017-2019 using Method 4, are shown graphically below for Education – 314110 and Hotel – 354710 in Figure 15 and Figure 16 respectively.

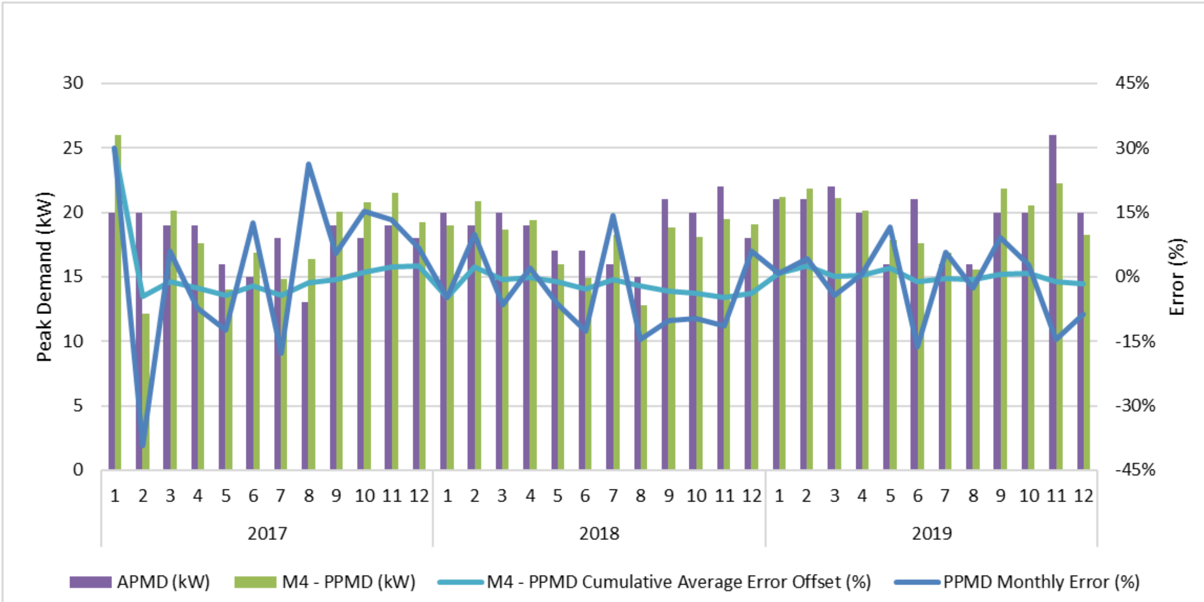


Figure 15: Method 4 - Actual and Predicted Peak Monthly Demand 2017-2019 - Education 314110

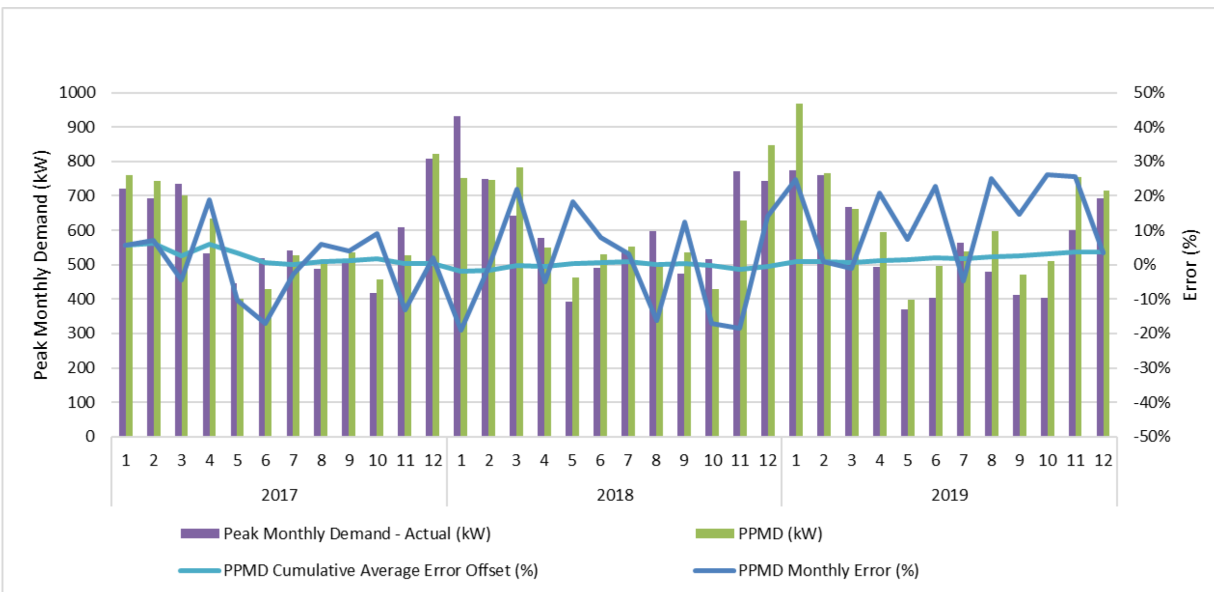


Figure 16: Method 4 - Actual and Predicted Peak Monthly Demand 2017-2019 - Hotel 354710

A sample comparison of the Methods 1-4 for 2017 are shown below for Education – 314110 and Hotel – 354710 in Figure 17 and Figure 18 and respectively. The *APMD* for each month is 2016 is shown as reference as well.

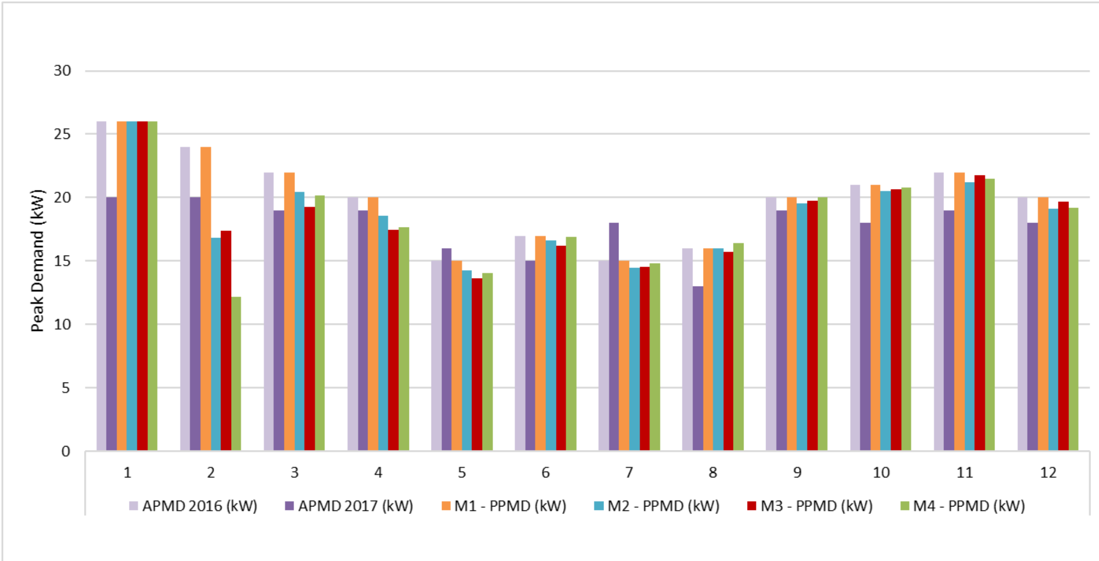


Figure 17: Peak Monthly Demand Prediction Method Comparison - 2017 - Education 314110

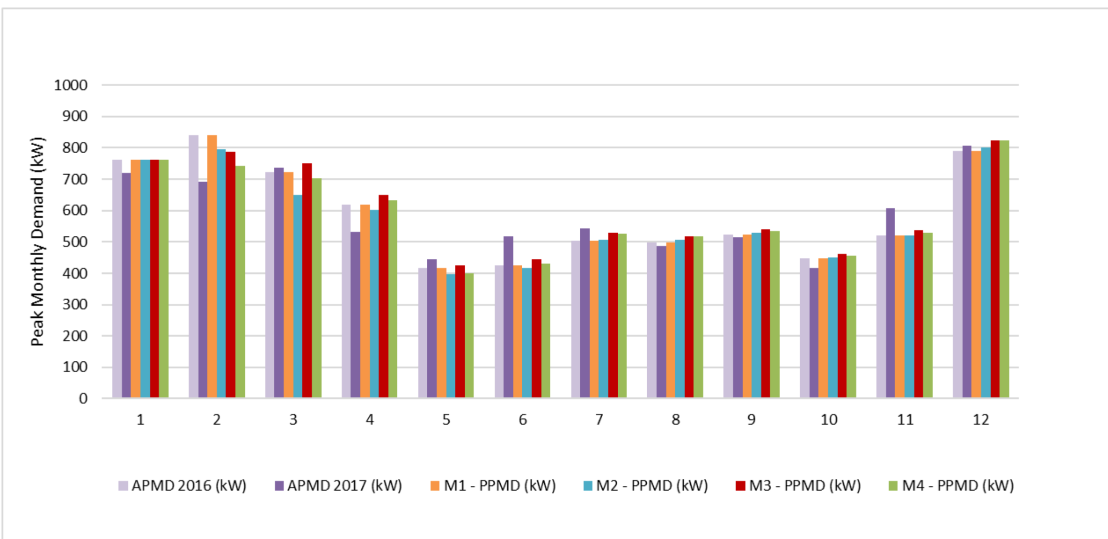


Figure 18: Peak Monthly Demand Prediction Method Comparison - 2017 - Hotel 354710

Both building examples demonstrate that the *PPMD* calculated by Methods 1-4 tracks the *APMD* well for months in which the *APMD* is close to the previous year. In instances where the *APMD* varies significantly from year to year there are prediction errors. A detailed comparison of the prediction Methods by building category and load are presented in Chapter 5.

In Methods 3-4 the error adjustment is made on the ratio of actual to predicted results rather than the error between the actual and predicted results. Using the actual and predicted results rather than the error introduces a seasonal bias to the adjustment depending on if the annual peak demand for the building is in the summertime or wintertime.

After data from the first year is collected, the *PPMD* is used to calculate the *TD* rather than using perfect foresight as in the base case scenario. The demand savings results from the predicted peak demand scenarios can be compared to the perfect foresight case to determine the effect of predicting the peak demand on potential demand savings for a building owner.

The sign of the error reported for the *PPMD* has different implications for how the battery will interact with the building. In the case of a positive error, the *PPMD* is higher than the *APMD*, and as a result a higher *DRF* will be required to achieve the same demand savings and ensure that the battery does not remain inactive during peak demand events. In contrast, a negative error means that at the *PPMD* is below the *APMD*. In this case, in the absence of a lower *DRF*, the battery will discharge more frequently to reduce building demand further than the *APMD*.

Depending on the degree of underestimating or overestimating the *APMD*, and the *DRF* that is applied, there could be asymmetrical effects on demand savings for the building owner. A scenario that underestimates the *APMD* could cause the battery to discharge prematurely, run out of energy and result in no demand savings for the month. Conversely, overestimating the *APMD* may result in reduced demand savings versus the optimal scenario. The nature of the demand savings results when the *APMD* is overestimated or underestimated is explored in Chapter 5.

CHAPTER 4 DATA

4.1 Electric Utility Tariffs in Nova Scotia

NSP is a regulated electrical utility that provides electricity generation, transmission, and distribution services in the province of Nova Scotia. NSP is the primary electrical utility in the province, supplying 95% of these services to over 500,000 customers [48].

In Nova Scotia, different customer classes have differing rate structures that are used to bill for electrical services. These rates can include energy charges ($\$/kWh_{elc}$), demand charges ($\$/kW_{pd}$ or $\$/kVA_{pd}$), fixed monthly charges ($/mon), or a combination. The value of the different rate components is dependent on the customer class [49]. The two usage-based rates are the energy charge and demand charge. Shown below in Table 13 are the energy and demand charges for the various customer classes. The prices shown below are net of the Fuel Adjustment Mechanism (FAM) credits and or chargers, pre-tax, excludes initial billing blocks, and fixed monthly charges are ignored as they are typically in the range of $10-20 per month so are small relative to the consumption-based portions of the bill.

Table 13: Nova Scotia Power Rates by Customer Class

Customer Class	**NSP Rate Code**	**Energy Charge ($\$/kWh_{elc}$)**	**Demand Charge ($\$/kW_{pd}$, $\$/kVA_{pd}$)**
Residential	02, 03, 04	$ 0.16008	$ -
Small Commercial	10	$ 0.14602	$ -
General Commercial	11	$ 0.09266	$ 10.497 / **kW_{pd}**
Large Commercial	12	$ 0.09526	$ 13.345 / **kVA_{pd}**
Small Industrial	21	$ 0.09044	$ 7.714 / **kVA_{pd}**
Medium Industrial	22	$ 0.08672	$ 12.501 / **kVA_{pd}**
Large Industrial	23	$ 0.08987	$ 11.995 / **kVA_{pd}**

The economic analysis presented in Section 5.6 utilizes the General Commercial (Rate Code 11) tariffs for all the buildings. This approach was selected to focus the analysis on the impact of the building load characteristics rather than the differences in demand charge rates and energy rates.

The average or effective billing rate ($\$/kWh_{elc}$) that any given customer class pays is dependent on the characteristics of its load profile in the billing month and the energy and demand charges that correspond with that customer's rate class.

$$LF = \frac{Total\ Energy\ Consumption\ in\ Billing\ Period\ (kWh_{elc})}{Peak\ Demand\ in\ Billing\ Period\ \left(kW_{pd}\right) \times\ Hours\ in\ Billing\ Period\ (h)}$$

For customers with a demand charge, the effective billing rate is dependent on their LF. In this thesis effective billing rate is defined as the total pre-tax electrical utility charges ($) in the billing period divided by the total electrical energy (kWh_{elc}) usage in the billing period. Shown below in Figure 19 is the effective billing rate for different rate classes depending on the customer's load factor during that month. For simplicity, flat billing period charges and blocked energy charges have been ignored as have fixed monthly charges. As shown below, customers with a demand charge and a lower load factor have a higher effective billing rate than customers with a higher load factor. A low load factor indicates a low average load relative to the peak load in the billing period, while a high load factor indicates an average load that is closer to the peak load in the billing period.

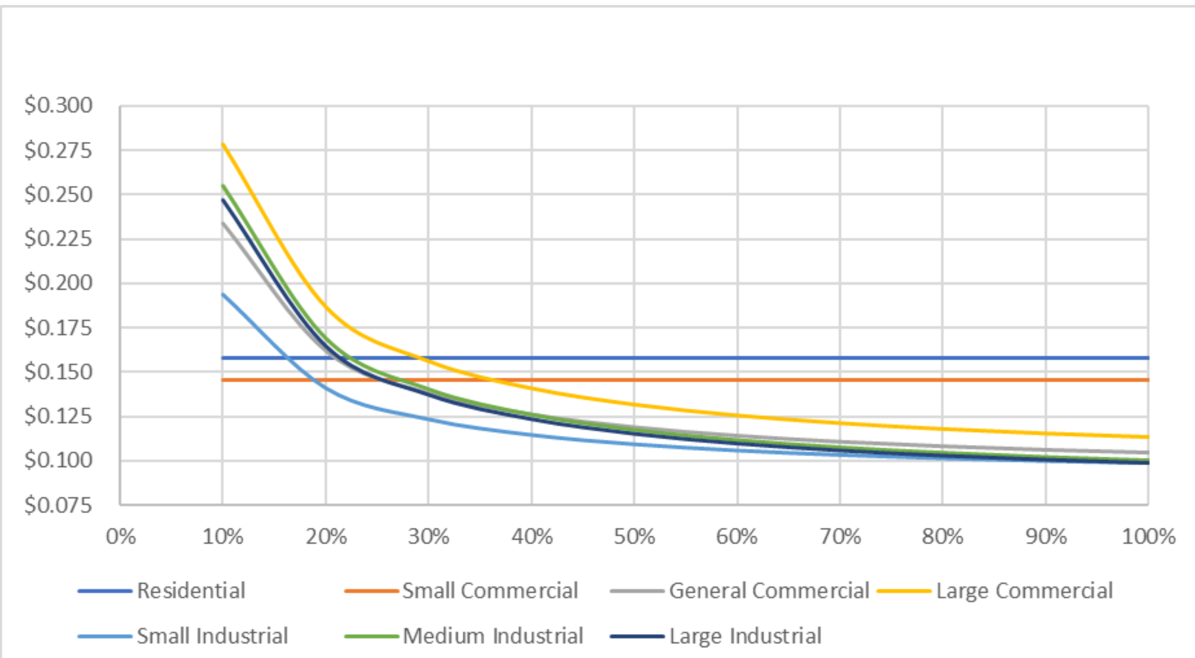


Figure 19: Effective Billing Rate versus Load Factor

A low load factor results in a larger fraction of the customer's bill comprised of the demand charge relative to the energy charge. Shown below in Figure 20 is the percentage of the customer's electric utility bill that is represented by the demand charge based on the customer's load factor.

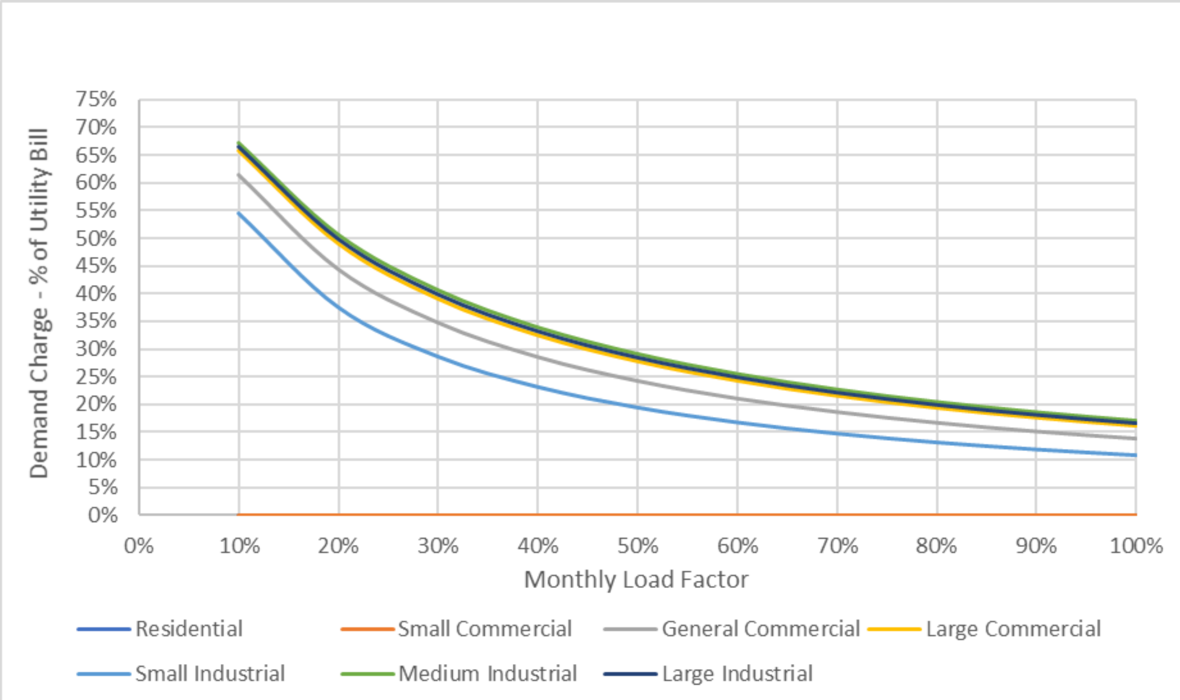


Figure 20: Demand Charge Percentage of Bill versus Load Factor

The rate analysis above shows that Large Commercial, Medium Industrial and Large Industrial customer classes will have a higher economic incentive to adopt energy storage because of a higher percentage of their utility bill represented by the demand charge across all load factors. This is driven by the relative demand and energy rate components in comparison to Small Industrial and General Commercial. Project developers and building owners need to consider not only the percentage of the bill the demand charge represents, but also the absolute value of the demand charge reduction, as that will be directly proportional to the monetary savings the battery system can generate. The demand charge of a commercial building can never be reduced to zero, even if the building has a perfectly flat load profile and consumes the same amount of power at all points during the month. As shown above in Figure 20, even a building with a LF of 100% (Average Load = Peak Demand) will have a demand charge that represents 10-15% of the total bill depending on the customer class and corresponding demand charge.

The NSP customer classes are listed below in order of percentage of the utility bill represented by the demand charge for a load factor of 20%, along with their demand charge rate for reference:

1. Medium Industrial (51% @ 20% LF, \$12.501/kVA_{pd})
2. Large Industrial (50% @ 20% LF, \$11.995/kVA_{pd})
3. Large Commercial (49% @ 20% LF, \$13.345/kW_{pd})
4. General Commercial (44% @ 20% LF, \$10.497/kW_{pd})
5. Small Industrial (38% @ 20% LF, \$7.714/kVA_{pd})
6. Small Commercial (no demand charge)
7. Residential (no demand charge)

Figure 20 also demonstrates that the opportunity for a BESS to provide monetary demand charge savings for buildings with a load factor above 50% is reduced due to the declining fraction of the utility bill that the demand charge represents.

4.2 Nova Scotia Power Data Set

NSP provided Dalhousie University Renewable Energy Storage Laboratory (RESL) with commercial and industrial customer interval meter data to explore BESS applications. The research benefits from a dataset that includes 248 buildings across eight (8) NSP defined building types and three (3) NSP rate class as shown in Table 14. The dataset covers the four years of 2016-2019 inclusively with 15 min building load data. All three rate classes have a demand charge. No Large Commercial or Large Industrial customers were represented due to privacy concerns because of the small number of those customers in Nova Scotia.

Table 14: Number of Buildings by Rate Class and Nova Scotia Power Classification

Building Type	**Total Buildings in Type**	**Rate Class**		
		General Commercial (Rate Code 11)	**Small Industrial (Rate Code 21)**	**Medium Industrial (Rate Code 22)**
Commercial	39	39	-	-
Community	9	9	-	-
Education	34	34	-	-
Health Care	18	18	-	-
Hotel	7	7	-	-
Industrial	86	1	41	44
Retail	48	48	-	-
Utility	7	4	1	2

The availability conditions for the three rate classes included in the data set are shown below in Table 15.

Table 15: NSPI Rate Code Availability Conditions for Buildings in the Dataset

General Commercial (Rate Code 11)	**Small Industrial (Rate Code 21)**	**Medium Industrial (Rate Code 22)**
Annual energy consumption => 32,000 kWh_{elc}	Regular billing demand is < 250 kVA_{pd} or < 225 kW_{pd}	Regular billing demand is => 250 kVA_{pd} or => 225 kW_{pd}

The data was provided to RESL in Excel (.xlms) and comma separated value (.csv) formats. A sample of the data is shown below in Table 16.

Table 16: NSP Data Sample

RECORDER ID	**DATE**	**HOUR**	**IN**	**UN**	**KW**	**KVAR**	**KVAR**	
A02410	160101	15	15	KW	203	103	0	0
A02410	160101	30	15	KW	197	98	0	0
A02410	160101	45	15	KW	198	102	0	0
A02410	160101	100	15	KW	195	101	0	0
A02410	160101	115	15	KW	199	102	0	0
A02410	160101	130	15	KW	198	106	0	0
A02410	160101	145	15	KW	197	99	0	0
A02410	160101	200	15	KW	202	95	0	0
A02410	160101	215	15	KW	206	97	0	0
A02410	160101	230	15	KW	210	100	0	0
A02410	160101	245	15	KW	207	99	0	0

The data in the columns is organized as follows:

1) Recorder ID: Unique meter identification number for the customer
2) Date: Date in the format YYMMDD
3) Hour: Time in the format HHMM
4) IN: Measurement interval of 15 min
5) UN: Unit of power in kilowatt (kW)
6) KW: Average power reading, in kilowatts, during that 15-minute interval
7) KVAR: Lagging reactive power
8) KVAR: Leading reactive power
9) "": placeholder column unless the customer has a net-metered account. In the event of a net-metered account this column represents the average exported power reading during that 15-minute interval

4.3 Building Load Characteristics in the Dataset

The buildings in the data set vary considerably in terms of average load, peak demand and *MLF*. Figure 21 below illustrates the difference between average load and peak demand. The building load is plotted as a function of time for a commercial building in Nova Scotia during January 2017. There is a cyclical nature to the load with the daily peak occurring during the day and valley at night. The global peak demand in January was set at 61 kW_{pd} for this customer, noted with the red circle. The average load over the billing period was 40 kW_{elc}, noted with the green line.

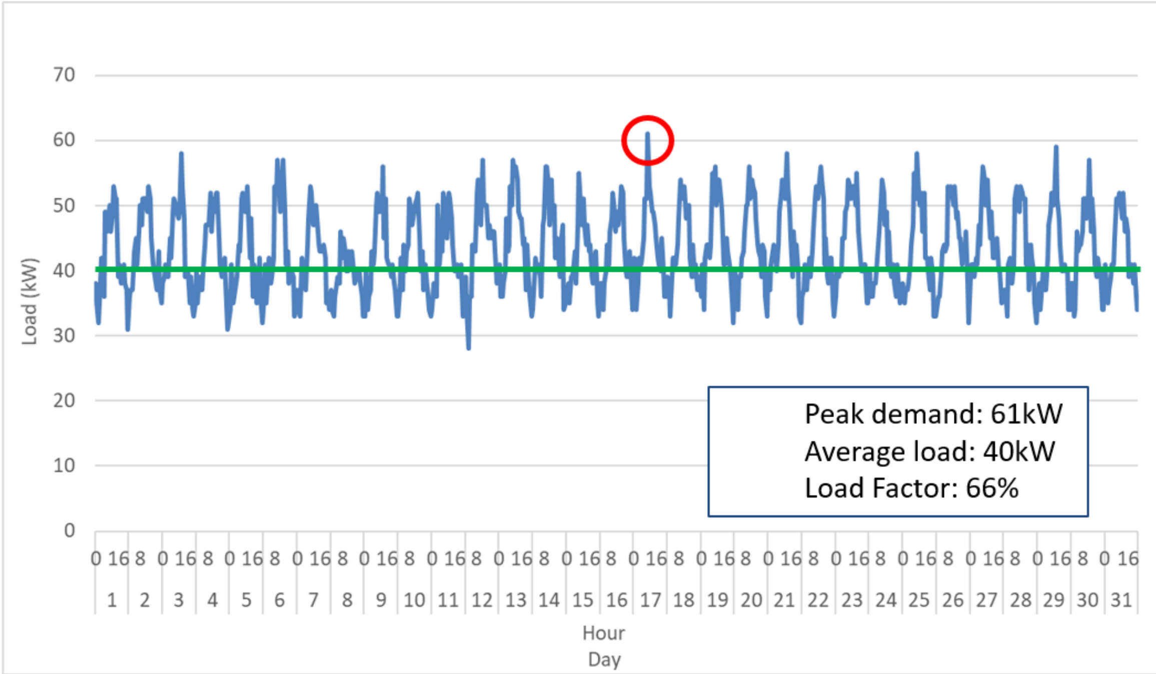


Figure 21: Example Monthly Load Profile for a Commercial Building

Shown below in Figure 22 is the annual average load distribution by category for 2017. The labelled bars on the x-axis represent average load bars of $x_{i-1} < x <= x_i$. The bins of average load range from 0 $kW_{avg} < x <= 100$ kW_{avg} to 2400 $kW_{avg} < x <= 2500$ kW_{avg}. Nearly half of all the buildings in the dataset have an average annual load of less than 100 kW_{avg} and there are very few buildings with an average annual load more than 1000 kW_{avg}.

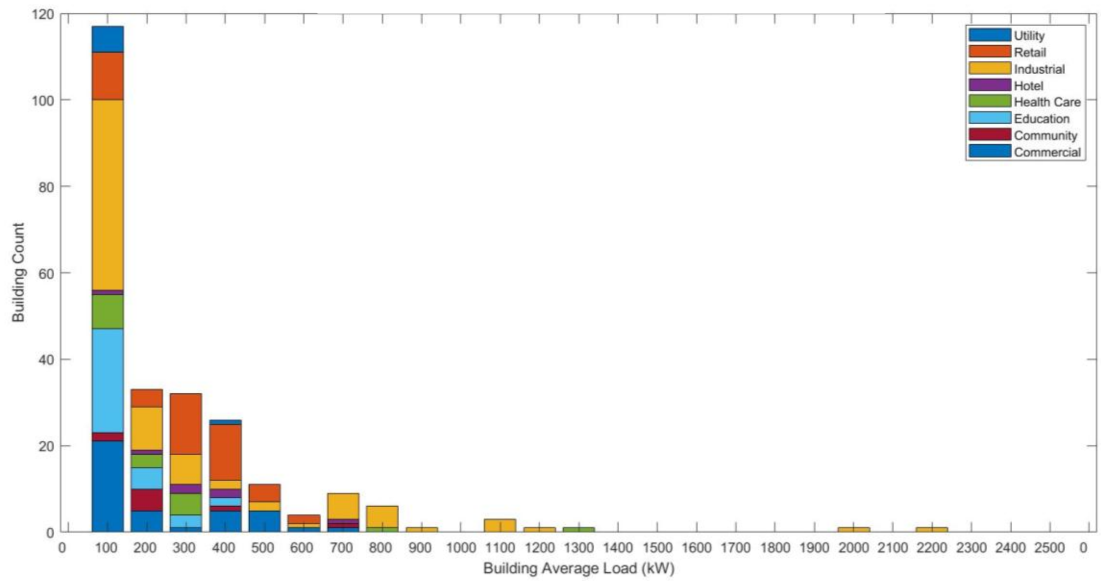


Figure 22: Annual Average Load Distribution by Category – 2017

Shown below in Figure 23 is the annual average load distribution by category for 2017 only for the buildings with an average annual load of less than or equal to 100 kW_{avg}. The bins of average load range from 0 kW_{avg} < x <= 10 kW_{avg} to 90 kW_{avg} < x <= 100 kW_{avg}. Nearly a third of the total number of buildings with an annual load of less than or equal to 100 kW_{avg} have an annual load of less than or equal to 20 kW_{avg}. Of these buildings, Industrial represents the largest category.

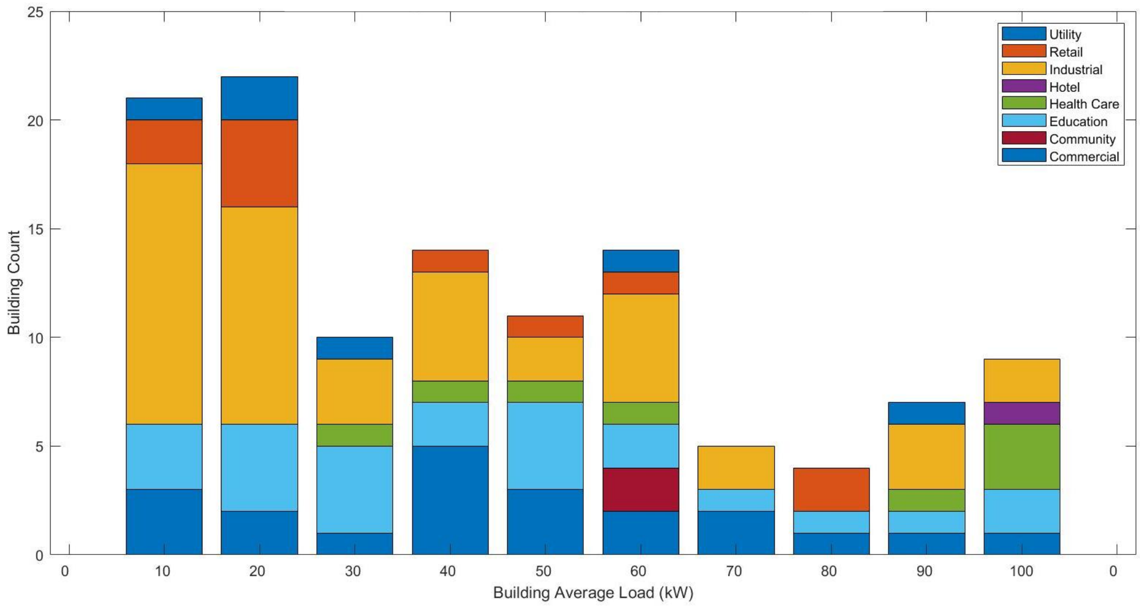


Figure 23: Annual Average Load Distribution by Category, <= 100 kW – 2017

Shown below Figure 24 *MLF* distribution by category for 2017. The *MLF* bins range from 0 % < x <= 5% to 95% < x <= 100%. Most of the buildings and months in the dataset have monthly load factors between 20-80%, with few buildings and months on the bottom and top 20% extremities. This plot provides some insight into which categories will be strong candidates for demand charge reduction and which will not. For example, both Industrial and Education have significant data points below a 50% *MLF*, while the Health Care and Hotel categories have most of their data points above a 50% *MLF*.

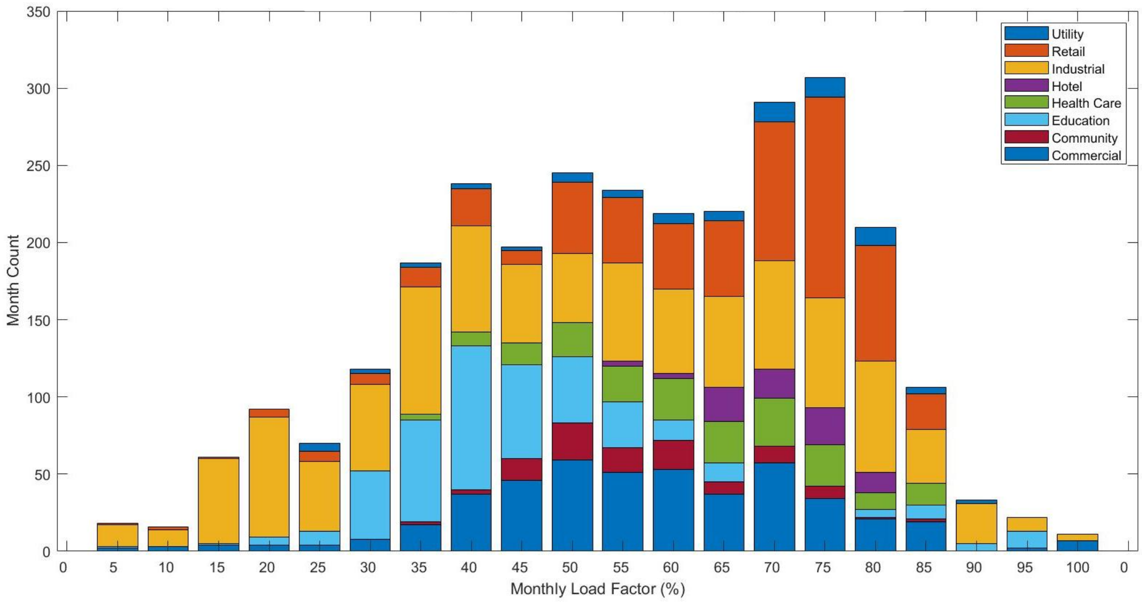


Figure 24: Monthly Load Factor Distribution by Category - 2017

The following sections examine the load characteristics of the buildings in each of the categories.

4.3.1 Commercial Buildings

Shown below in Figure 25 is the average load distribution for the 39 commercial buildings in the data set for 2016-2019. The labelled bars on the x-axis represent load bars of $x_{i-1} < x <= x_i$. The bins of average loads for the commercial buildings range from 0 $kW_{avg} < x <= 35$ kW_{avg} to 630 $kW_{avg} < x <= 665$ kW_{avg}.

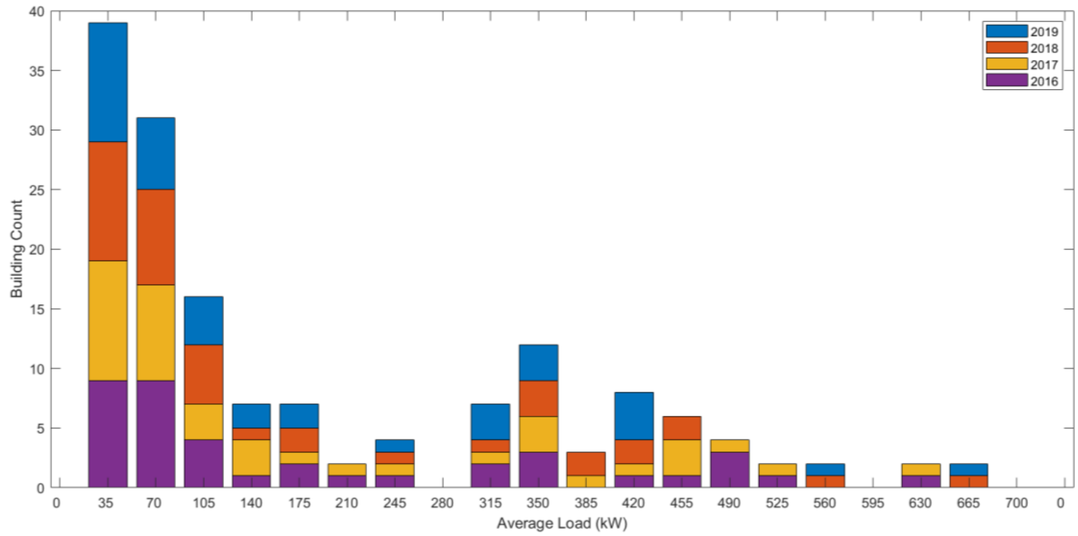


Figure 25: Commercial Building Average Load Distribution by Year

Figure 26 shows the average annual load, annual peak demand, and average monthly load factor for each building in the commercial category from 2016-2019. The buildings are sorted by average annual load in 2017. Most buildings show consistency year to year for maximum demand, average load, and average load factor. Presenting the data in this manner is useful for identifying buildings where energy storage could be effective by comparing the peak demand and load factor for buildings with similar average loads.

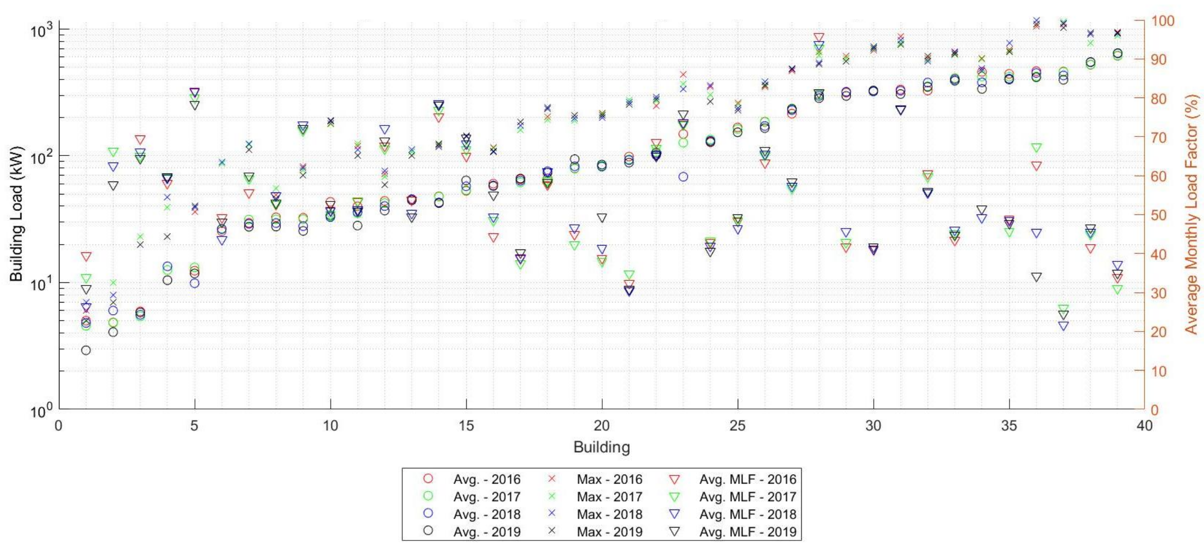


Figure 26: Commercial – Annual Average Load, Peak Demand and Average - Sorted by 2017 Average Load

Shown below in Figure 27 is *MLF* for each commercial building from 2016-2019 sorted by average *MLF* in 2017. There is a wide range in the *MLF*s observed in the commercial buildings with lows of less than 20% and highs above 80%, although values outside of those bounds are rare. Additionally, there is a range of *MLF* distributions depending on the building. Some buildings exhibit significant variations in *MLF* from month-to-month, while others are very tightly grouped. This shows the value of examining load factor on a monthly rather than annual basis because depending on the building, the annual load factor may or may not reflect what happens on the customers monthly billing basis.

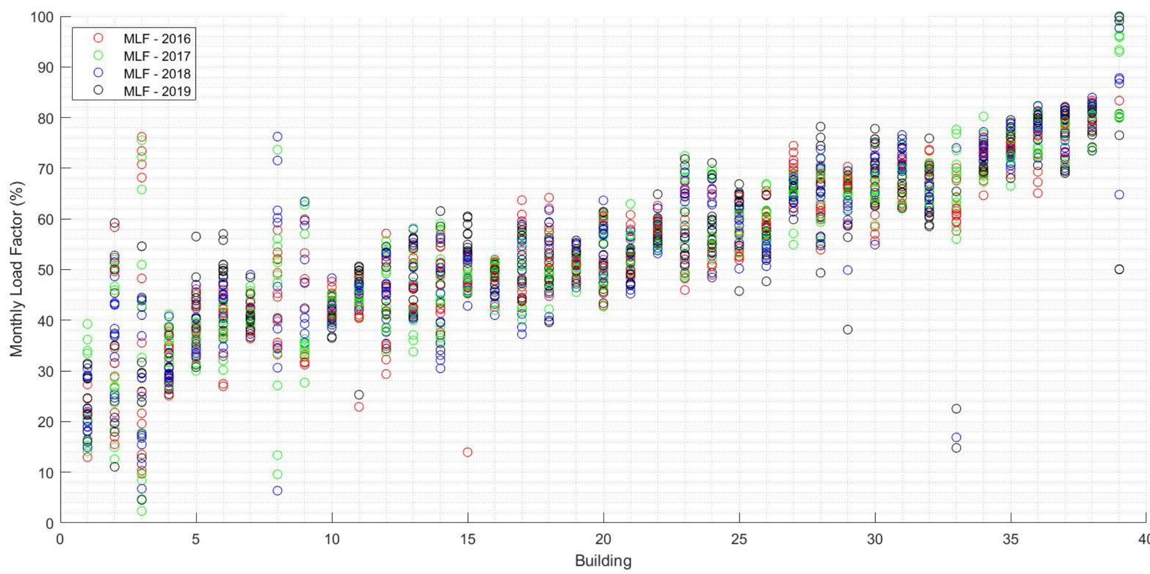


Figure 27: Commercial - Monthly Load Factor by Year - Sorted by 2017 Average Monthly Load Factor

4.3.2 Community Buildings

Shown below in Figure 28 is the average load distribution for the nine (9) community buildings in the data set for 2016-2019. The average loads for the community facilities range from 35 $kW_{avg} < x <= 70$ kW_{avg} to 665 $kW_{avg} < x <= 700$ kW_{avg}.

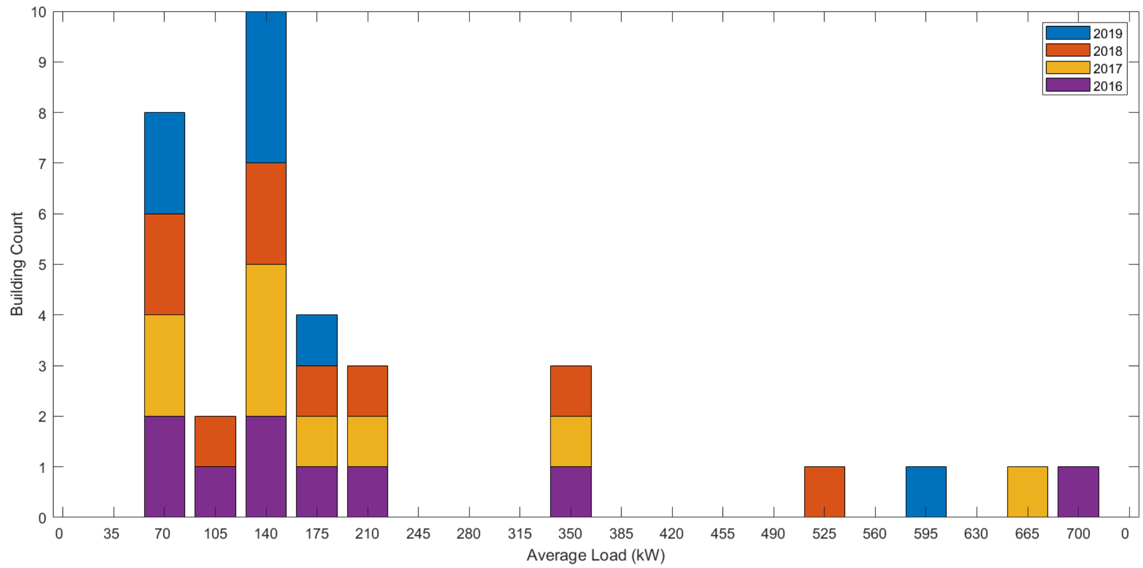


Figure 28: Community Buildings Average Load Distribution

Shown below in Figure 29 is the average and max load for each building in the community category from 2016-2019 sorted by the average annual observed load in 2016 along with the average *MLF* in each year. As with the commercial buildings, the data shows reasonable consistency year to year for both max and average load for a given building, but there appears to be greater consistency on average load than max load.

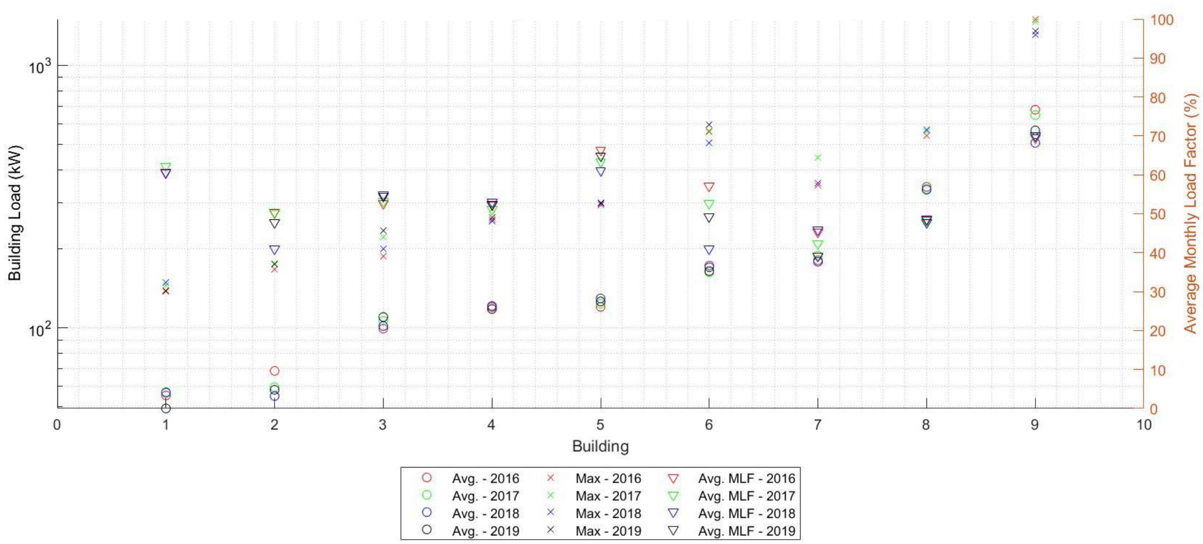


Figure 29: Community – Annual Average Load, Peak Demand and Average - Sorted by 2017 Average Load

Figure 30 shows the *MLF* for each community building from 2016-2019 arrange by average *MLF* in 2017. There is a smaller range of *MLFs* in the community building than observed in the commercial buildings, with most data points falling between 30% and 70%, but the building sample size is considerably smaller. As with the commercial category, there is a range month-to-month *MLF*s with some buildings being more tightly distributed than others.

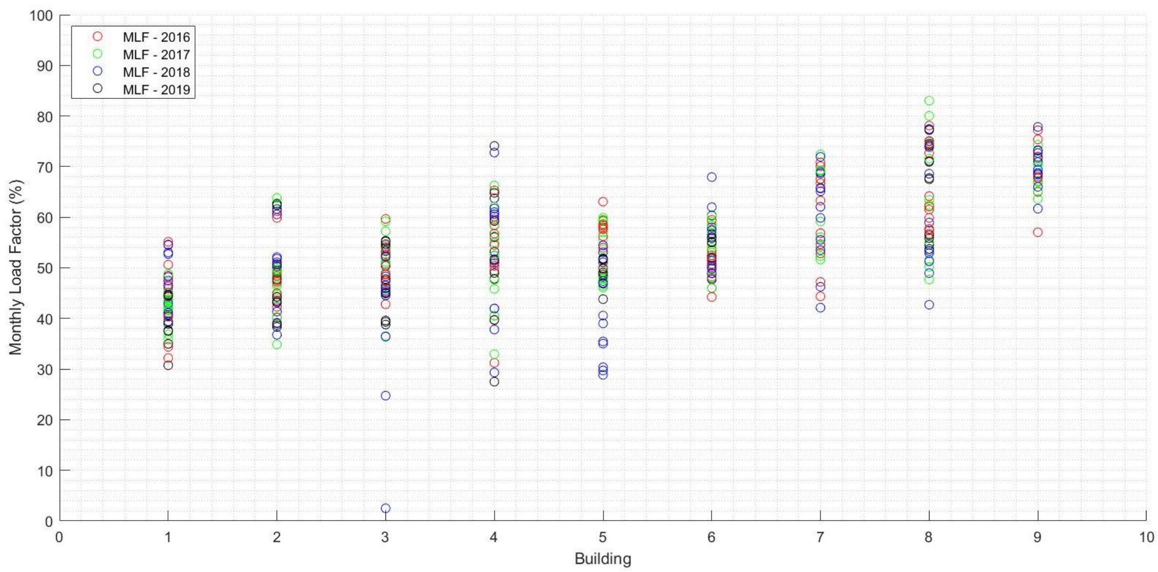


Figure 30: Community - Monthly Load Factor by Year - Sorted by 2017 Average Monthly Load Factor

4.3.3 Education Buildings

Shown below in Figure 31 is the average load distribution for the 34 education buildings in the data set for 2016-2019. The average loads for the education buildings range from 0 kW_{avg} < x <= 20 kW_{avg} to 360 kW_{avg} < x <= 380 kW_{avg}.

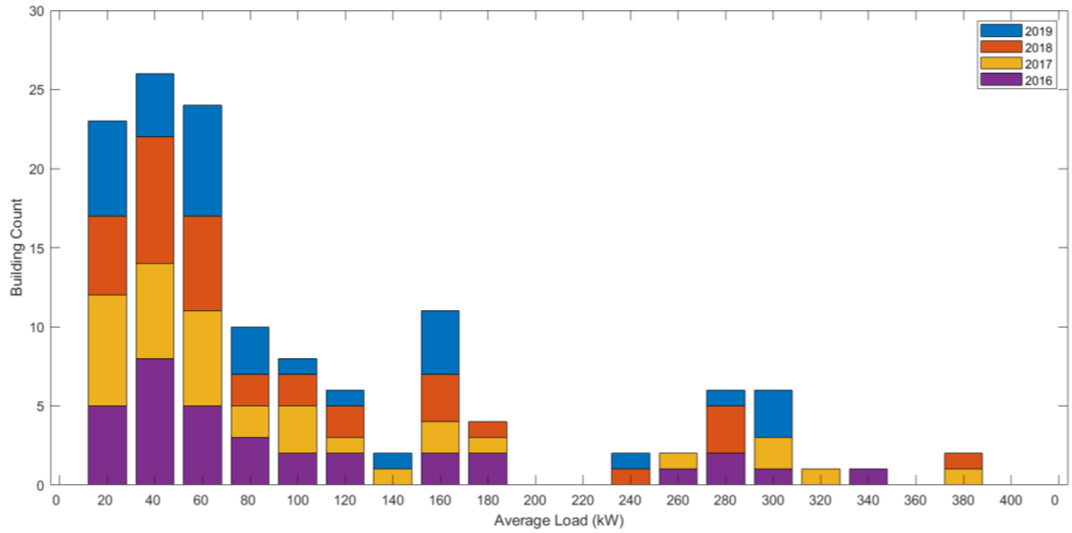


Figure 31: Education Buildings Average Load Distribution by Year

Shown below in Figure 32 is the average load and max demand, and average *MLF* for each building in the education category from 2016-2019 sorted by the average annual observed load in 2017. As with the other categories there is consistency in the data from year to year for most buildings. There is a trend in this category to lower average *MLF*s for buildings with a larger average load, although this does not apply to all buildings in this category.

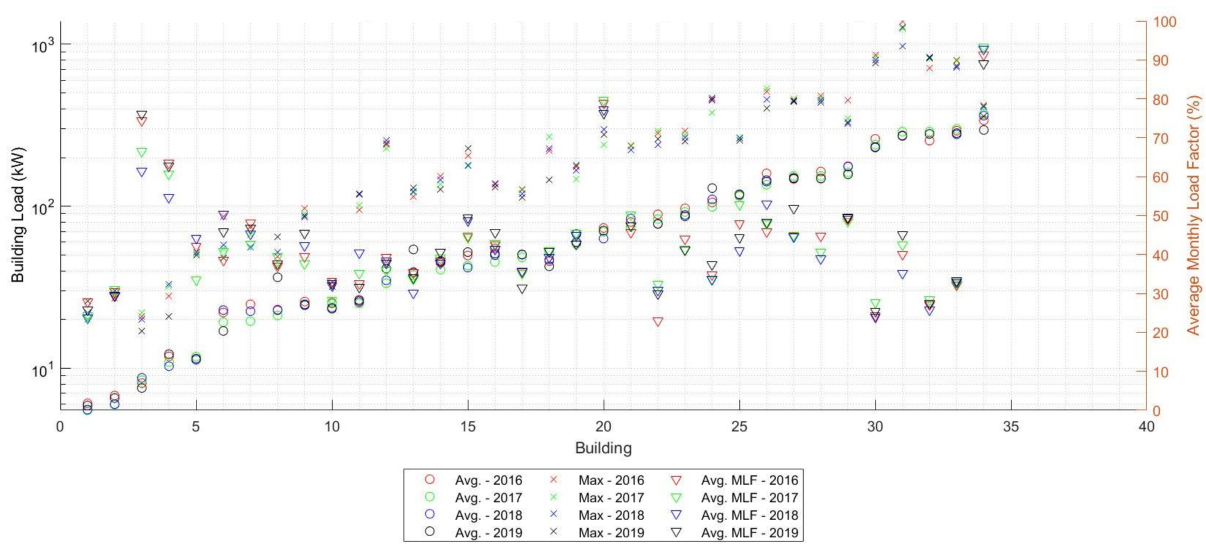


Figure 32: Education – Annual Average Load, Peak Demand and Average - Sorted by 2017 Average Load

Shown below in Figure 33 is the *MLF* by year for each of the education buildings. The education buildings tend to have a lower monthly load factor than the other building categories, with a significant number of the monthly load factor instances below 50%. There are also buildings that display tight groupings of *MLF*s consistently below 40% which indicates a strong opportunity for demand savings in these buildings.

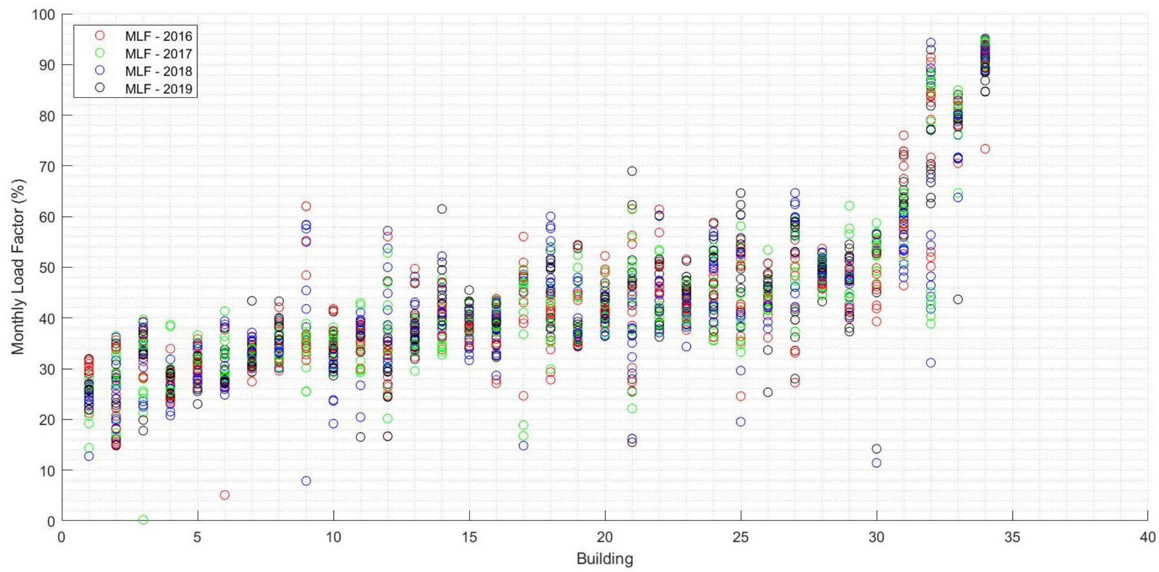


Figure 33: Education - Monthly Load Factor by Year - Sorted by 2017 Average Monthly Load Factor

4.3.4 Health Care Buildings

Shown below in Figure 34 is the average load distribution for the 18 health care buildings in the data set for 2016-2019. The average loads for the health care buildings range from 0 kW_{avg} < x <= 65 kW_{avg} to 1170 kW_{avg} < x <= 1235 kW_{avg}.

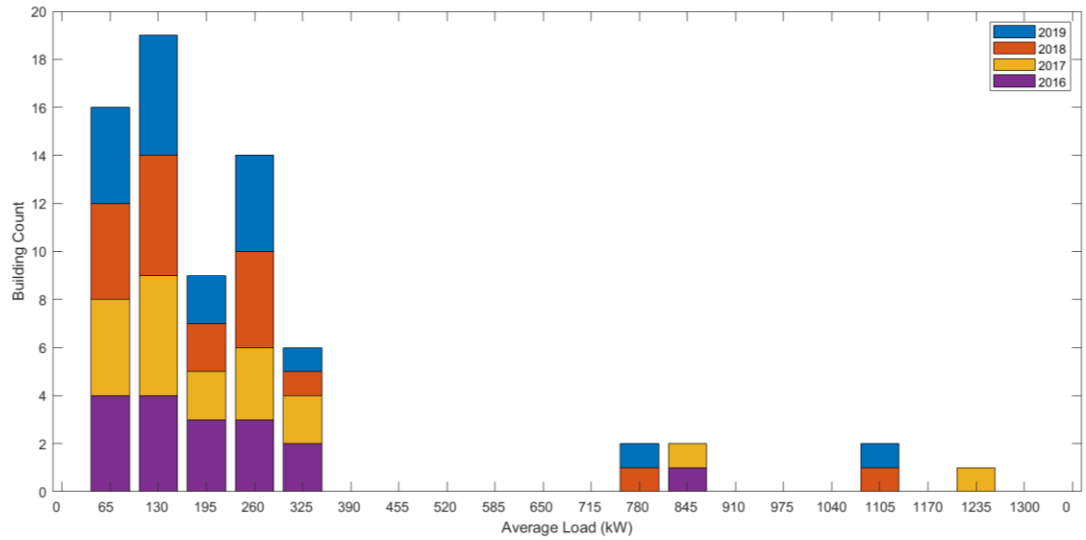


Figure 34: Health Care Buildings Average Load Distribution by Year

Figure 35 shows the average load, max demand and average *MLF* for each building in the health care category from 2016-2019 sorted by the average annual load in 2017.

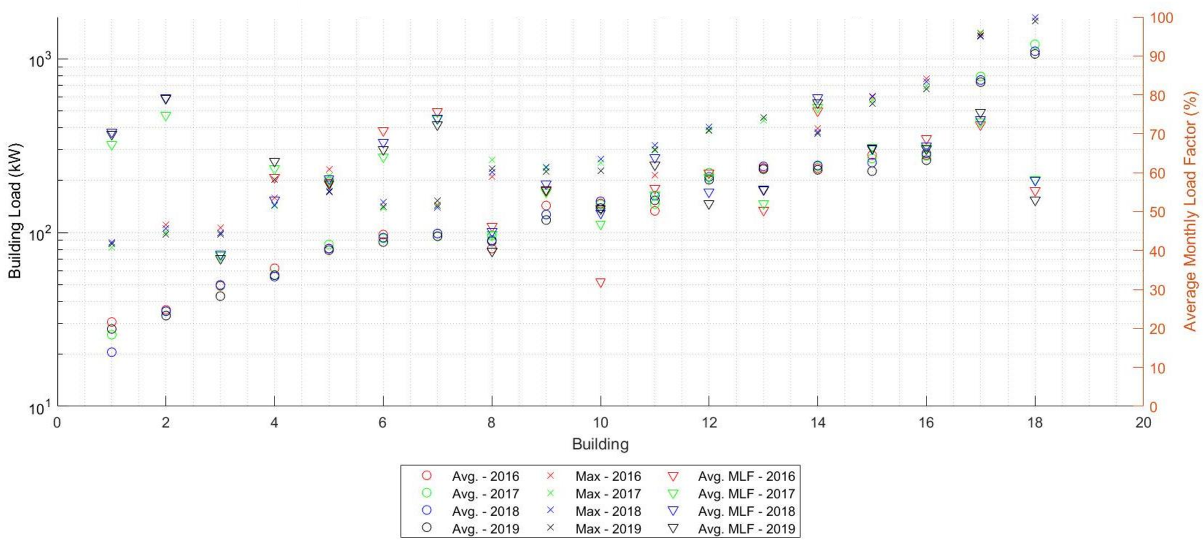


Figure 35: Health Care – Annual Average Load, Peak Demand and Average - Sorted by 2017 Average Load

Shown below in Figure 36 is the *MLF* for the health care buildings. In this sample of health care buildings there is rarely an observance of a monthly load factor below 30% and the month-to-month distributions tend to be tighter than the other building categories.

A tighter distribution of high *MLF*s means there will be reduced opportunities for demand savings in this category.

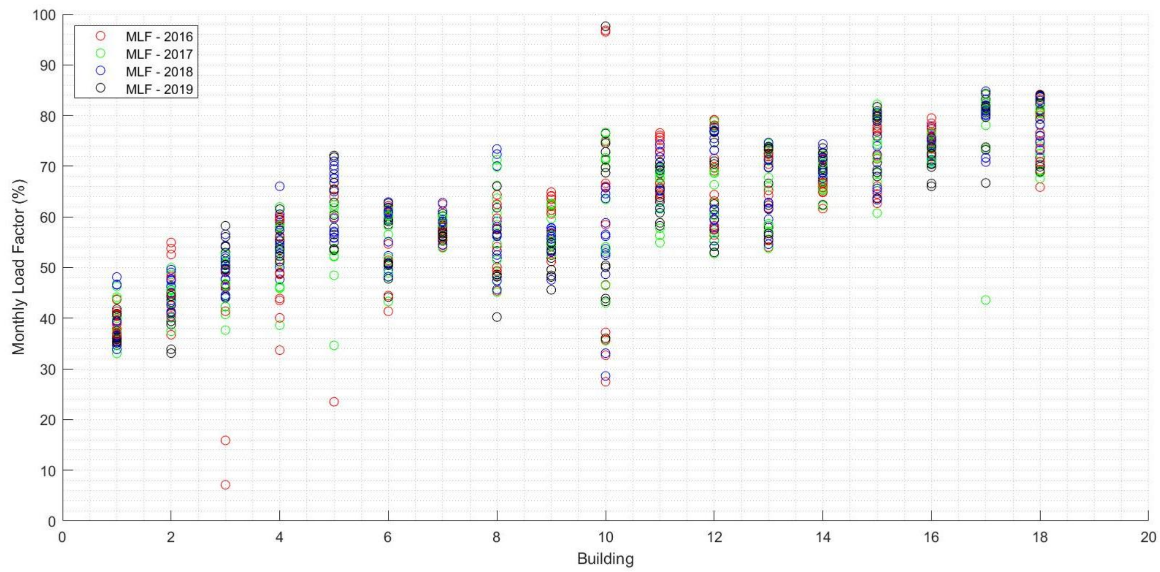


Figure 36: Health Care - Monthly Load Factor by Year - Sorted by 2017 Average Monthly Load Factor

4.3.5 Hotel Buildings

Figure 37 shows the average load distribution for the 18 buildings in the health care category from 2016-2019. The average loads for the hotels range from 70 kW_{avg} < x <= 105 kW_{avg} to 665 kW_{avg} < x <= 700 kW_{avg}.

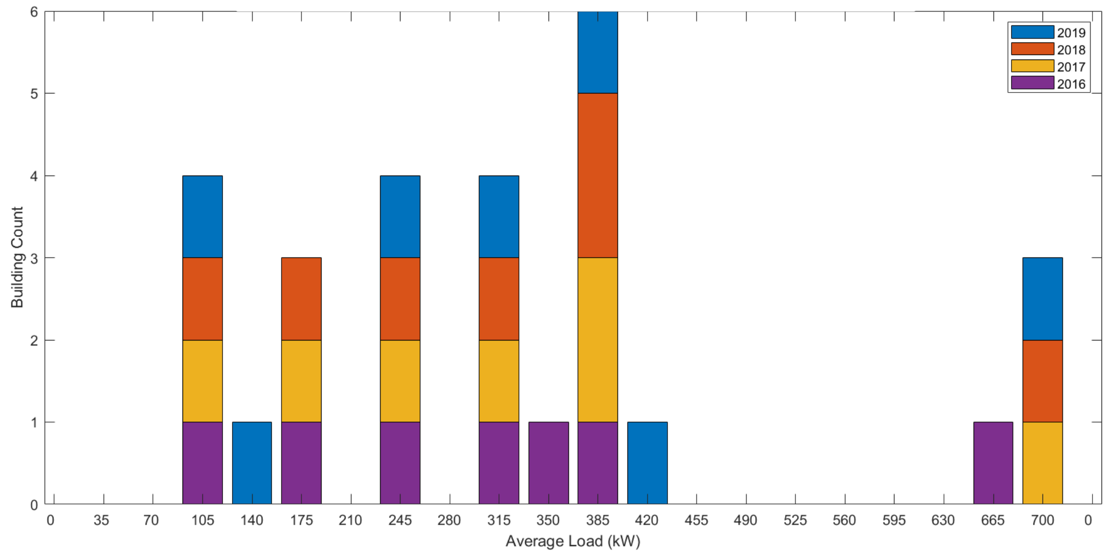


Figure 37: Hotel Buildings Average Load Distribution by Year

Figure 35 shows the average load, max demand and *MLF* for each building in the category from 2016-2019 sorted by the average annual load in 2017. It is evident that this category exhibit high average *MLF*s in comparison to the other categories.

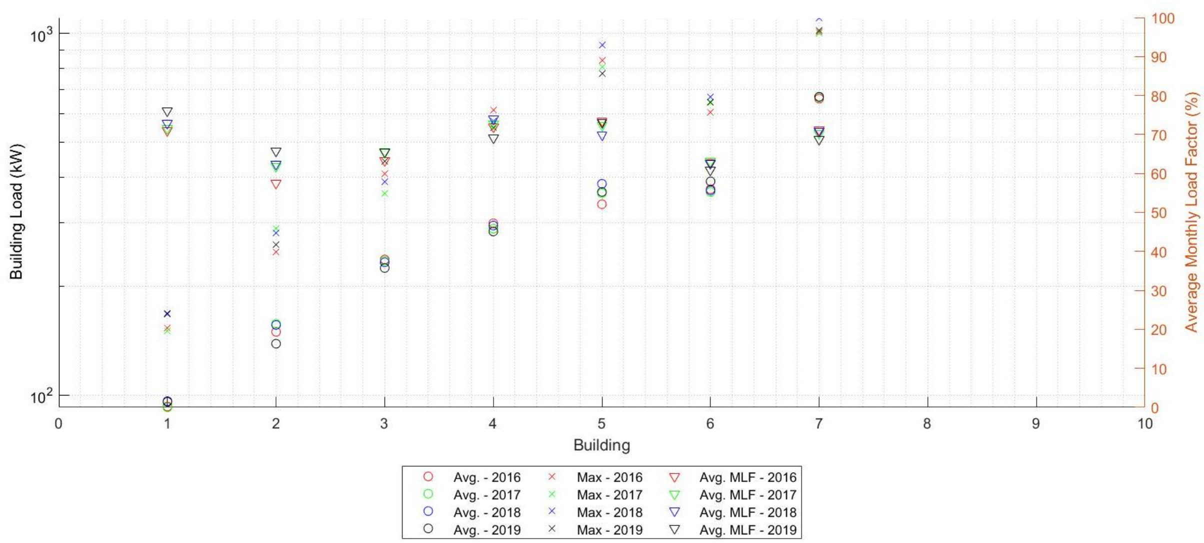


Figure 38: Hotel – Annual Average Load, Peak Demand and Average - Sorted by 2017 Average Load

Figure 39 shows the *MLF* or for the hotel category from 2016-2019. Although the sample size is small, this category of buildings has consistently high load factors and relatively tight *MLF* distributions in comparison to other categories. This indicates that like the health care category, there will be reduced opportunities for demand reduction.

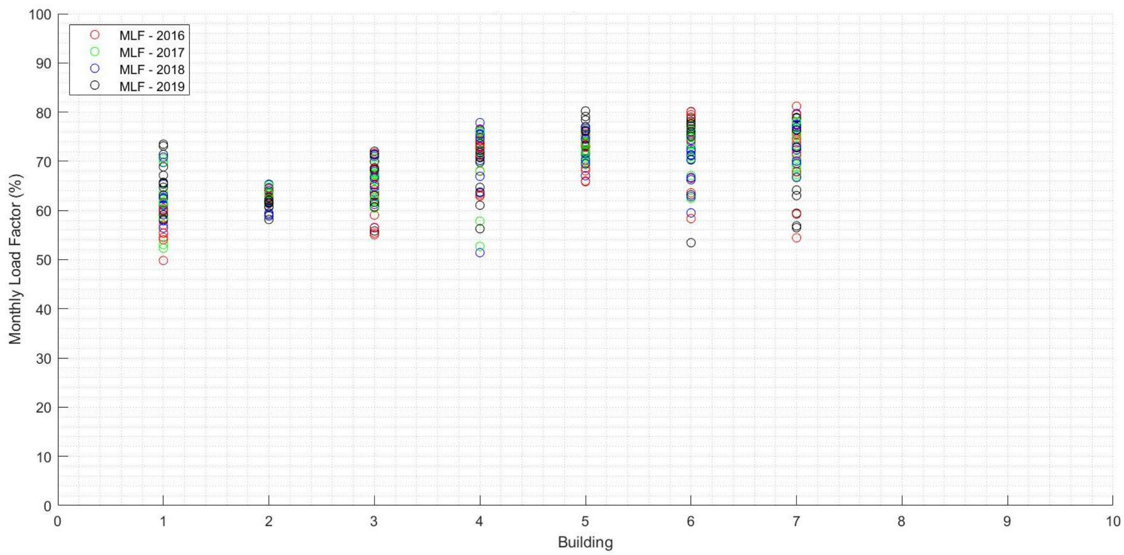


Figure 39: Hotel - Monthly Load Factor by Year - Sorted by 2017 Average Monthly Load Factor

4.3.6 Industrial Buildings

Figure 40 shows the average load distribution for the 86 industrial buildings in the data set for 2016-2019. The average loads for the industrial facilities range from 0 kW_{avg} < x <= 140 kW_{avg} to 2660 kW_{avg} < x <= 2800 kW_{avg} with approximately 50% of the buildings in the first category.

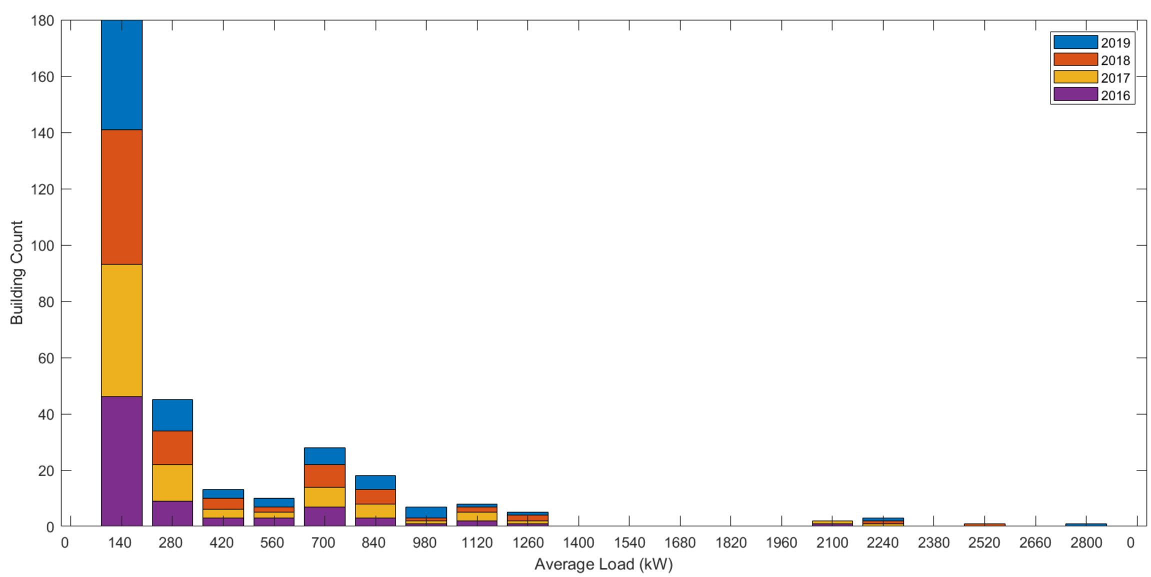


Figure 40: Industrial Buildings Average Load Distribution by Year

Figure 41 shows the average load, max demand and average *MLF* for each building in the industrial category from 2016-2019, sorted by the average annual load in 2017. As with the other categories, there is reasonable consistency year to year for both max demand and average load for a given building.

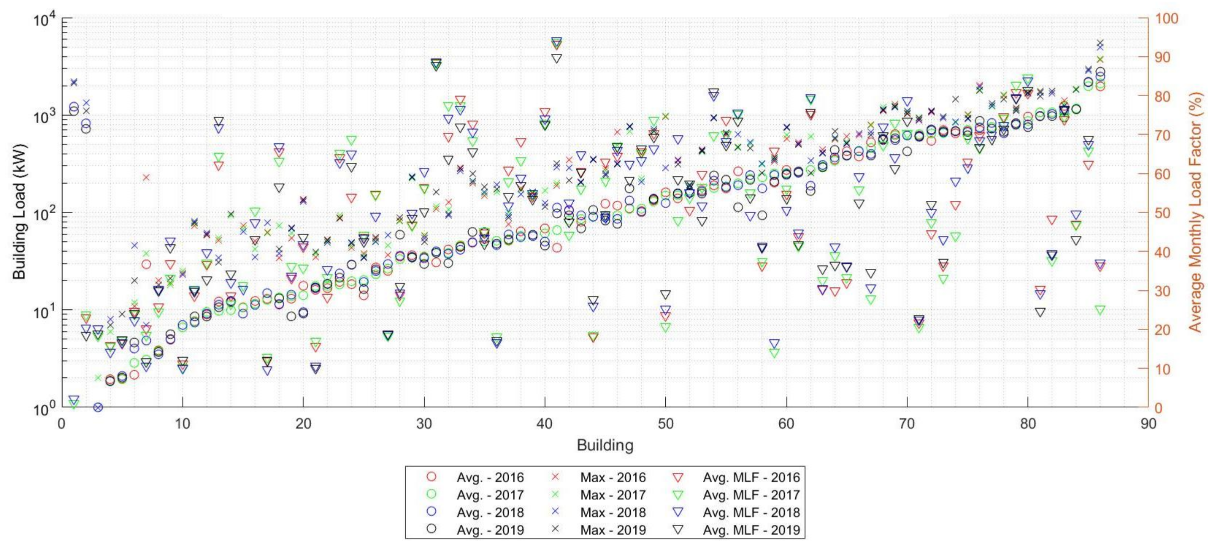


Figure 41: Industrial – Annual Average Load, Peak Demand and Average - Sorted by 2017 Average Load

Figure 42 shows the *MLF* by year for the industrial buildings. The industrial category exhibits both the largest range in monthly load factors and the largest distributions month-to-month.

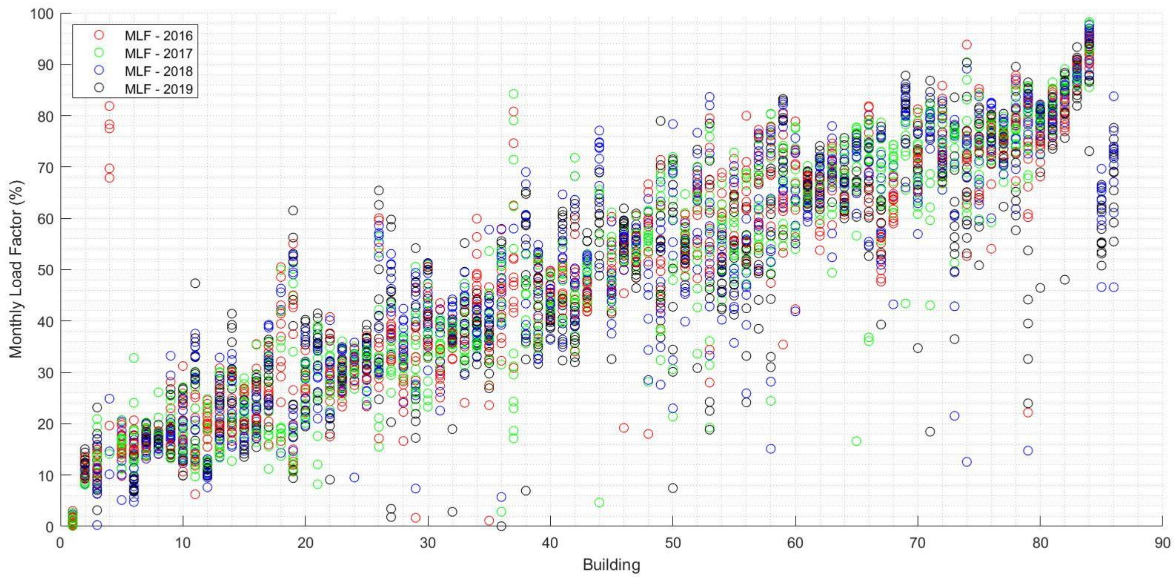


Figure 42: Industrial - Monthly Load Factor by Year - Sorted by 2017 Average Monthly Load Factor

4.3.7 Retail Buildings

Figure 43 shows the average load distribution for the 48 retail buildings in the data set for 2016-2019. The average load bins for this category range from 0 $kW_{avg} < x <= 30$ kW_{avg} to 540 $kW_{avg} < x <= 570$ kW_{avg} with a broader distribution along the load range than most of the other categories.

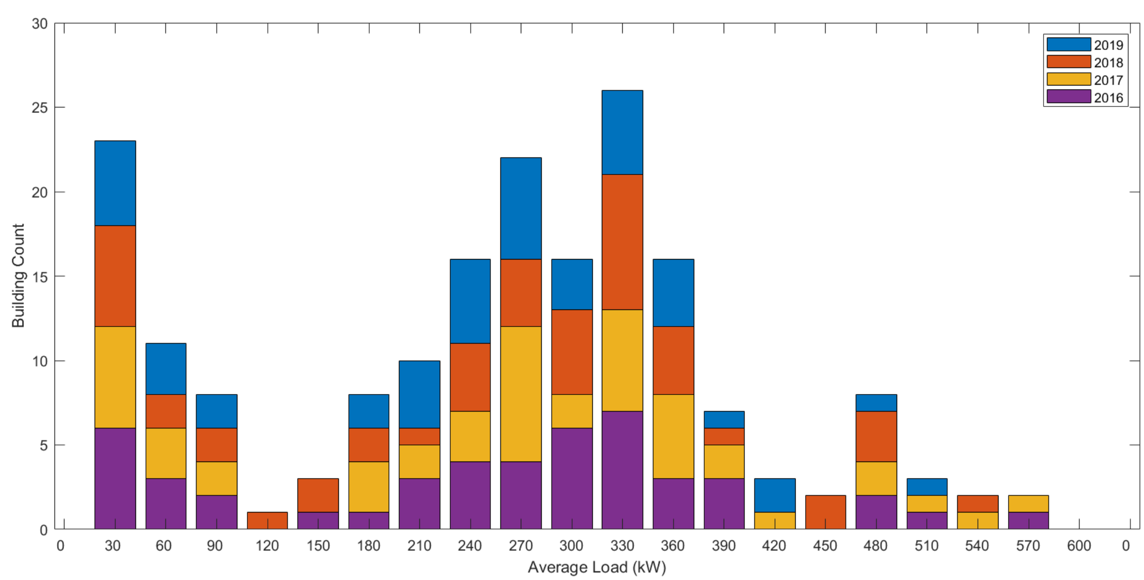


Figure 43: Retail Buildings Average Load Distribution by Year

Figure 44 shows the average load, max demand and average *MLF* for each building in the retail category from 2016-2019 sorted by the average annual load in 2017. This category shows a trend towards higher a higher average *MLF* with increasing building average load which was not always the case with categories like industrial.

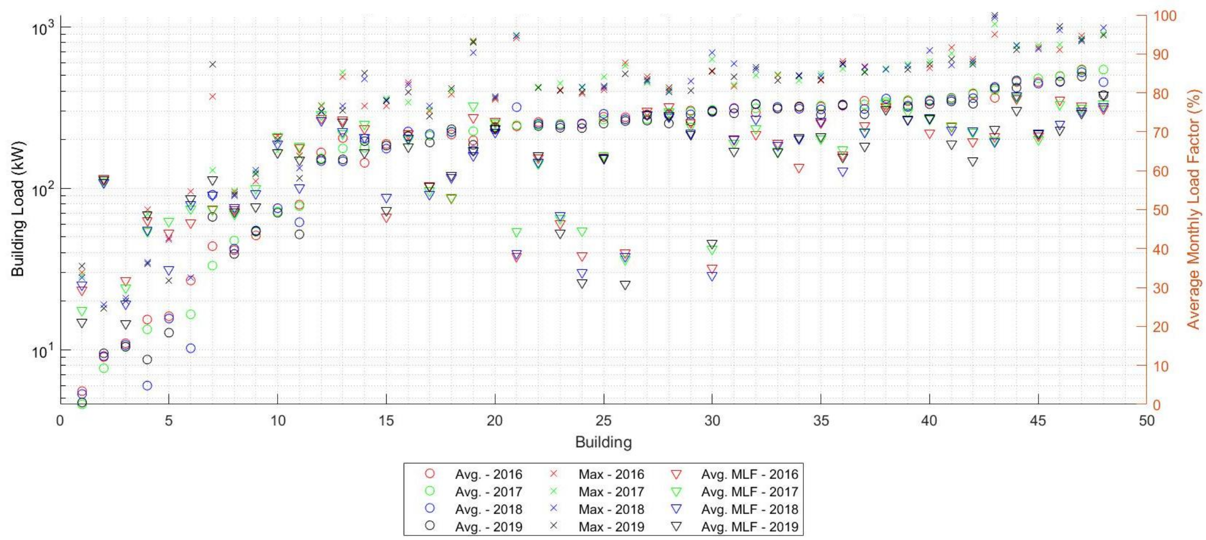


Figure 44: Retail – Annual Average Load, Peak Demand and Average - Sorted by 2017 Average Load

Figure 45 shows the *MLF* by year for the retail buildings. The retail category tends to have higher monthly load factors than other categories with most of buildings having *MLF*s above 50%. Although these buildings will have a reduced opportunity for demand savings, there are several buildings with *MLF*s under 40% that will have good opportunities for demand reduction.

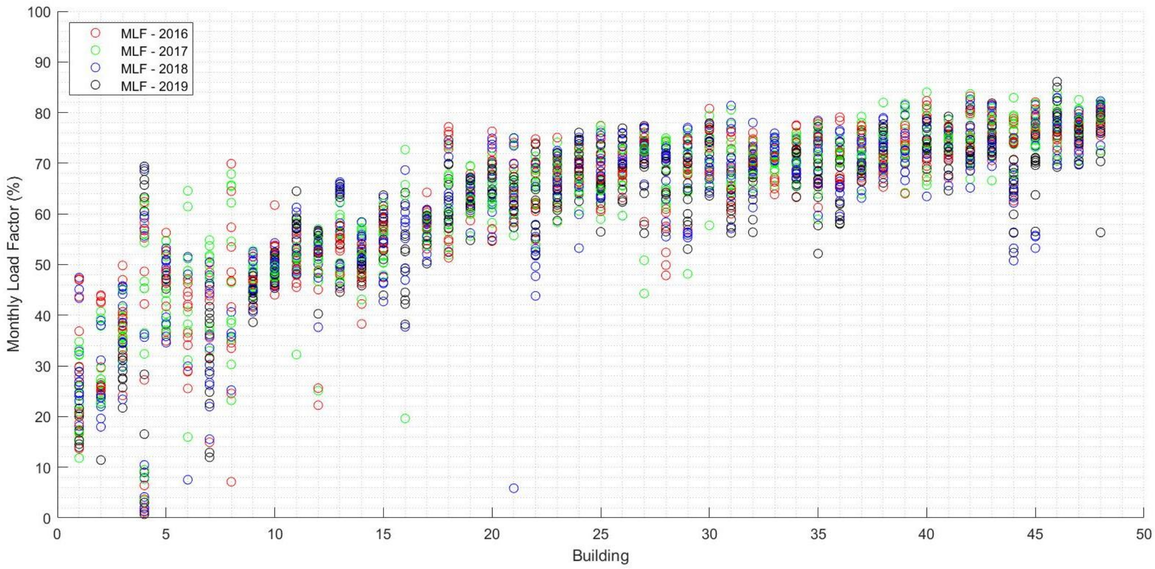


Figure 45: Retail - Monthly Load Factor by Year - Sorted by 2017 Average Monthly Load Factor

4.3.8 Utility Buildings

Figure 46 shows the average load distribution for the seven (7) utility buildings in the data set for 2016-2019. The average loads for the utility buildings range from 0 kW_{avg} < x <= 20 kW_{avg} to 380 kW_{avg} < x <= 400 kW_{avg}. Except for one building, all others in the category had an average load of less than or equal to 100 kW_{avg}.

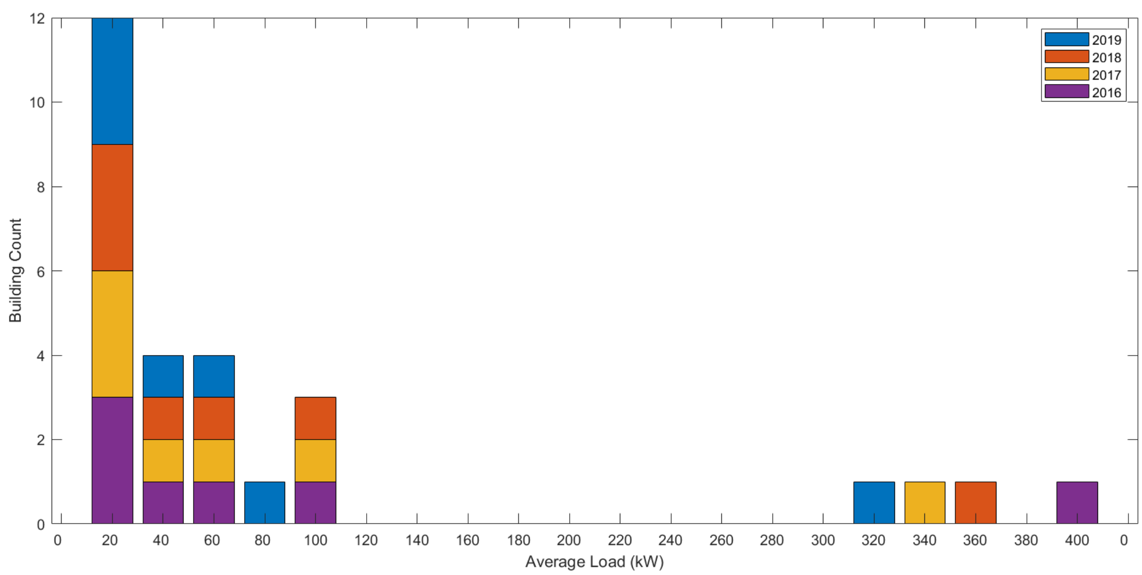


Figure 46: Utility Buildings Average Load Distribution by Year

Figure 47 shows the average load, max demand and *MLF* for each building in the utility category from 2016-2019 sorted by the average annual load in 2017. The small sample size makes it difficult to identify any trends with respect to *MLF* and building load, particularly that there is only a single building with an average load of greater than 100 kW_{avg}.

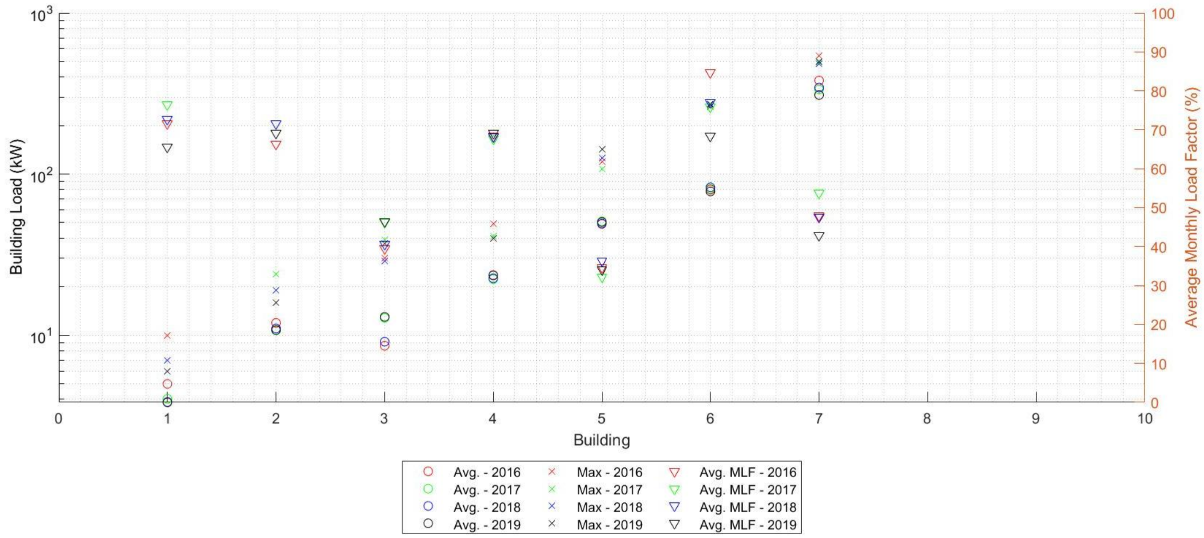


Figure 47: Utility – Annual Average Load, Peak Demand and Average - Sorted by 2017 Average Load

Figure 48 shows the *MLF*s by year for the utility category. Despite the small sample size, this category does have buildings with a range of *MLF*s, and *MLF* distributions.

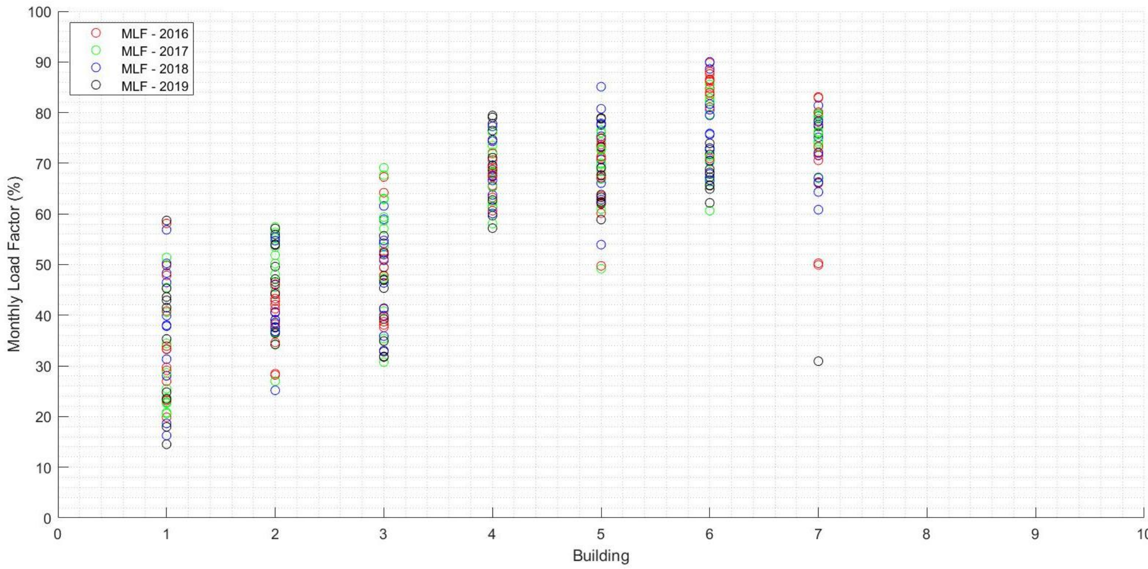


Figure 48: Utility - Monthly Load Factor by Year - Sorted by 2017 Average Monthly Load Factor

4.4 Data Filtering

The data supplied by NSP was modified to be used in the MATLAB model. The data was imported from Excel (.xls) and CSV (.csv) files into a MATLAB array. The following steps are taken to process the data:

- The date and time are imported and then split into year, month, day, hour, and minute values.
- An additional time array is created using the start and end dates of the dataset to allow interpolation of the data.
- Duplicate timesteps due to the change from daylight savings time to standard time in the fall are removed.
- A linear interpolation is used to fill gaps in power and time due to the change from standard time to daylight savings time in the spring.
- The building load in each timestep is saved in the new MATLAB array.

Several of the buildings have missing data values that could be due to measurement errors, power outages, or temporary disconnection of service at the facility. The missing data for these buildings is left unchanged and registers as zero (0) kW_{elc} or power and zero (0) kVA_{elc} of reactive power. This approach will result in the battery charging more than it may otherwise, due to the building load of zero kW_{elc} being below the monthly peak demand target. Depending on when the data is missing relative to the regular electrical usage, there is a possibility that this approach introduces errors in the demand reduction savings for a building. It was decided not to synthesize data for these missing periods because one of the key differentiators of this research is the use of real building datasets rather than synthesized or representative load profiles. Additionally, the objective of the research is to develop guidelines to assist project developers and building owners in assessing the potential for battery storage at a site. Missing data will be a realty of some site assessments and project developers and building owners may not have the tools at their disposal to create representative load profiles to patch missing data.

The dataset includes reactive power (Q) for each building. Although the reactive power is saved in the MATLAB array, it is not used in the model, which only utilizes real power. The decision to utilize only the real power was made to align the research with literature that typically discusses demand on a real power (kW_{pd}) versus apparent power (kVA_{pd}) basis. The economics analysis presented used General Commercial (Rate Code 11) tariffs for all the buildings to remove the differences in demand and energy rates from the results. The General Commercial tariffs are based on real power (kW_{pd}) which was an additional consideration for this approach. Future research could incorporate reactive power to explore the relationship between power factor and opportunities for demand charge reduction. Incorporating reactive power would cause the billing peaks to increase for the buildings in the Small Industrial and Medium Industrial rate classes to increase, but billing peaks for buildings in General Commercial would remain the same. The opportunity for peak demand reduction would increase when reactive power is considered meaning the results in the research are conservative. The degree to which the peak demand reduction results would improve would depend on how the inverter was modelled with respect to its ability to provide reactive power support. Incorporating various inverter P-Q curves into the model and including the reactive power data is an opportunity for future research.

4.5 MATLAB Data Format

The building data is loaded into MATLAB in an 11 field structure array so that both numeric and text values can be stored. The format for the structure array is shown below in Table 17.

Table 17: MATLAB Data Format

Building Category	METERID	Rate Code	P16	Q16	P17	Q17	P18	Q18	P19	Q19
'Utility'	'232110'	'11M'	1x35137 double	1x35137 double	1x35041 double	1x35041 double	1x35041 double	1x35041 double	1x35041 double	1x35041 double
'Utility'	'312510'	'11M'	1x35137 double	1x35137 double	1x35041 double	1x35041 double	1x35041 double	1x35041 double	1x35041 double	1x35041 double
'Utility'	'313610'	'11M'	1x35137 double	1x35137 double	1x35041 double	1x35041 double	1x35041 double	1x35041 double	1x35041 double	1x35041 double
'Utility'	'431610'	'21M'	1x35137 double	1x35137 double	1x35041 double	1x35041 double	1x35041 double	1x35041 double	1x35041 double	1x35041 double
'Utility'	'511710'	'22M'	1x35137 double	1x35137 double	1x35041 double	1x35041 double	1x35041 double	1x35041 double	1x35041 double	1x35041 double
'Utility'	'534510'	'22M'	1x35137 double	1x35137 double	1x35041 double	1x35041 double	1x35041 double	1x35041 double	1x35041 double	1x35041 double
'Utility'	'804010'	'11M'	1x35137 double	1x35137 double	1x35041 double	1x35041 double	1x35041 double	1x35041 double	1x35041 double	1x35041 double

The data in the columns of the structure array are organized as follows:

1) BuildingCategory: NSP defined building category
2) METERID: NSP defined meter identification number for the customer
3) RateCode: NSP rate code tag
4) P16: Array of real power values for 2016 in fifteen-minute increments
5) Q16: Array of reactive power values for 2016 in fifteen-minute increments
6) P17: Array of real power values for 2017 in fifteen-minute increments
7) Q17: Array of reactive power values for 2017 in fifteen-minute increments
8) P18: Array of real power values for 2018 in fifteen-minute increments
9) Q18: Array of reactive power values for 2018 in fifteen-minute increments
10) P19: Array of real power values for 2019 in fifteen-minute increments
11) Q19: Array of reactive power values for 2019 in fifteen-minute increments

CHAPTER 5 RESULTS

The results are presented in four subsections followed by a summary of the major findings. First, the predicted peak monthly demand is compared to the actual peak monthly demand. Next, sample peak demand reduction scenarios are shown, followed by a battery sizing examination. Finally demand reduction results are compared by buildings category and the major findings are summarized.

5.1 Predicted Peak Monthly Demand

Four separate methods were trialed, for all building classes and years, to predict the peak monthly demand based on the following building characteristics:

i. Method 1: Based on previous years' peak monthly demand with no error adjustment as shown in Equation (8) on page 56.
ii. Method 2: Previous year peak monthly demand with error adjustment based on cumulative error in the current year of predicted peak monthly demand in comparison to actual peak monthly demand as shown in Equation (9) on page 56.
iii. Method 3: Previous year peak monthly demand with error adjustment based on cumulative error of predicted average monthly demand in comparison to actual average monthly demand as shown in Equation (11) on page 57.
iv. Method 4: Predicted peak monthly demand based on predicted average monthly load, and monthly load factor from the previous year, with error adjustment based on cumulative error of predicted peak monthly demand in comparison to actual peak monthly demand as shown in Equation (12) on page 57.

Figure 49 and Figure 50 show the prediction accuracy of Method 1 and Method 2 for all categories, buildings, and all months from 2017-2019 in linear and log graphs, respectively. Figure 51 and Figure 52 show the same analysis for Method 3 and Method 4. In all for plots the data is shown in blue and the line of best fit is shown in black. The line of best fit is not used to predict the peak demand, it is used to define the results of Methods 1-4 above. The log plots show an additional 1:1 reference line to better compare the results that fall below the Y-axis intercept of the line of best fit.

All four Methods show a linear fit greater than 0.95 and a coefficient of determination (R^2) greater than 0.90 between the Predicted Peak Monthly Demand (*PPMD)* and Actual Peak Monthly Demand (*APMD)*. A perfect coefficient of determination would be 1.00, meaning that all variation is perfectly captured by the model. A minimum acceptable coefficient of determination of 0.85 was selected to ensure that at least 85% of the variation in actual peak demands was captured by the prediction method.

Although the error corrections introduced in Methods 2-4 do improve the linear fit results to greater than or equal to 0.975, the R^2 in Methods 3 and 4 (R^2 = 0.942 and R^2 = 0.922 respectively) is lower than the control scenario of using the peak demand of the same month in the previous year (R^2 = 0.963). Both Method 3 and Method 4 both use the Average Monthly Demand in their calculation. Based on these results, future work on refining the prediction methods should focus on calculations using the *APMD* rather than introducing the *AAMD*.

The results show that, provided the project developers or building owners have access to at least one year of historical data and that the building equipment and or operation has not changed significantly, they do not need to implement complex prediction methodologies to estimate monthly peak demands with a high degree of certainty.

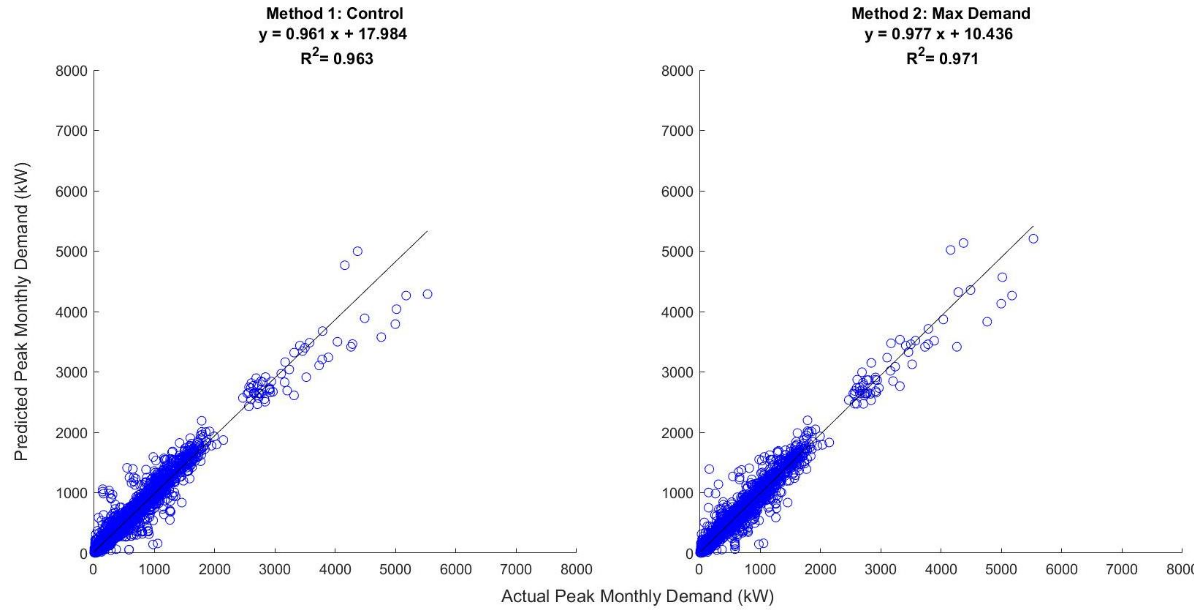


Figure 49: Predicted Peak Monthly Demand for Method 1 and Method 2 – Linear

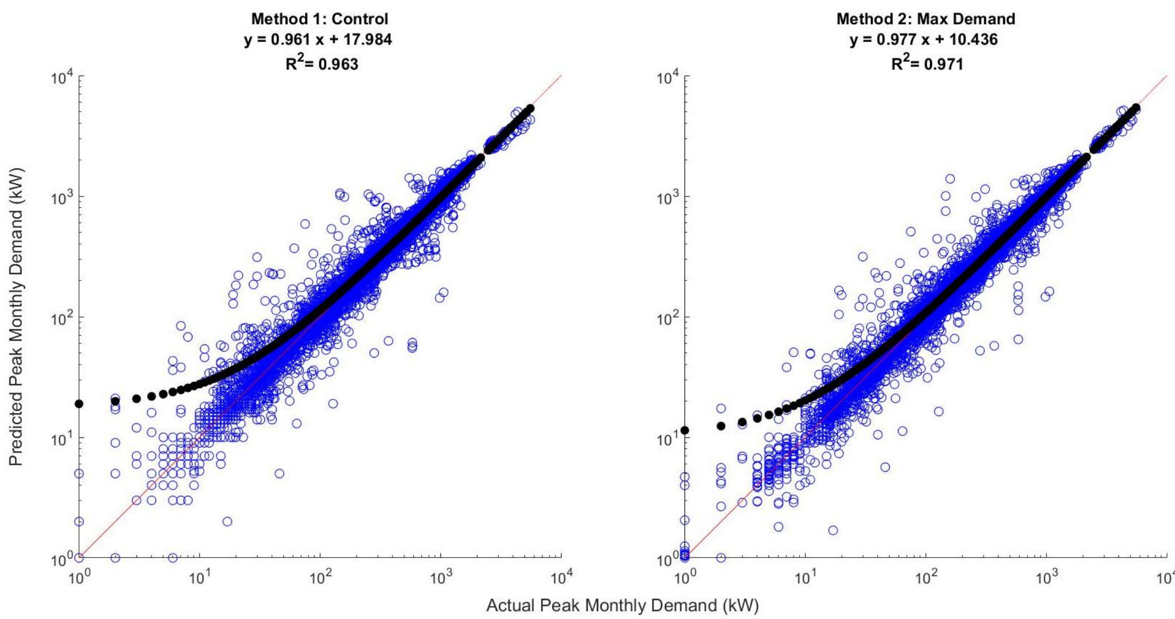


Figure 50: Predicted Peak Monthly Demand for Method 1 and Method 2 - Log

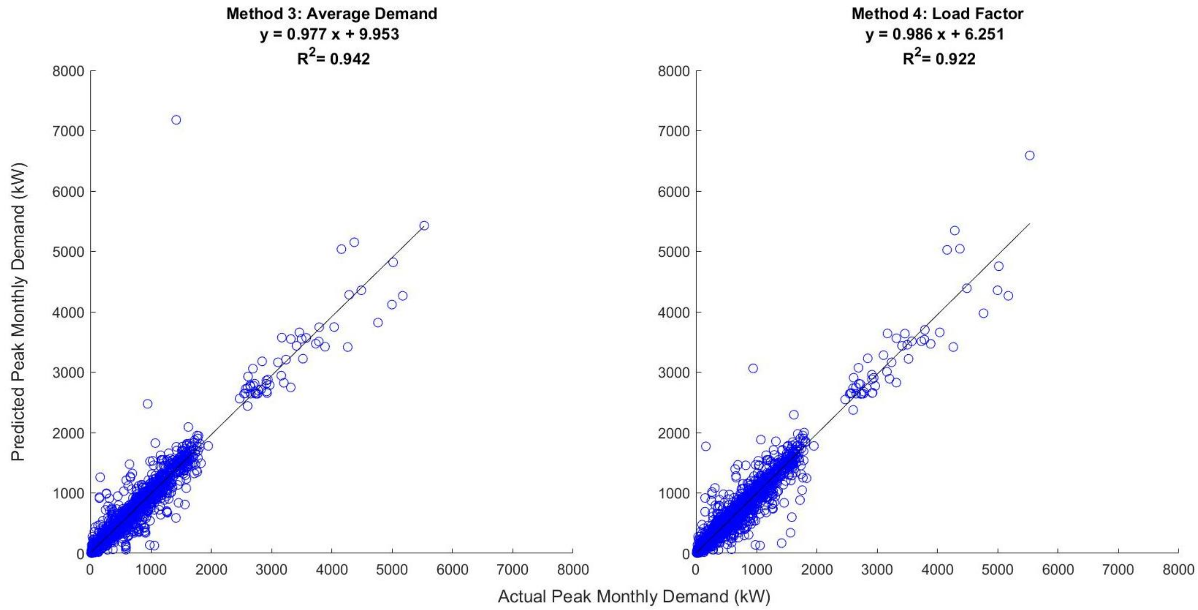


Figure 51: Predicted Peak Monthly Demand for Method 3 and Method 4 – Linear

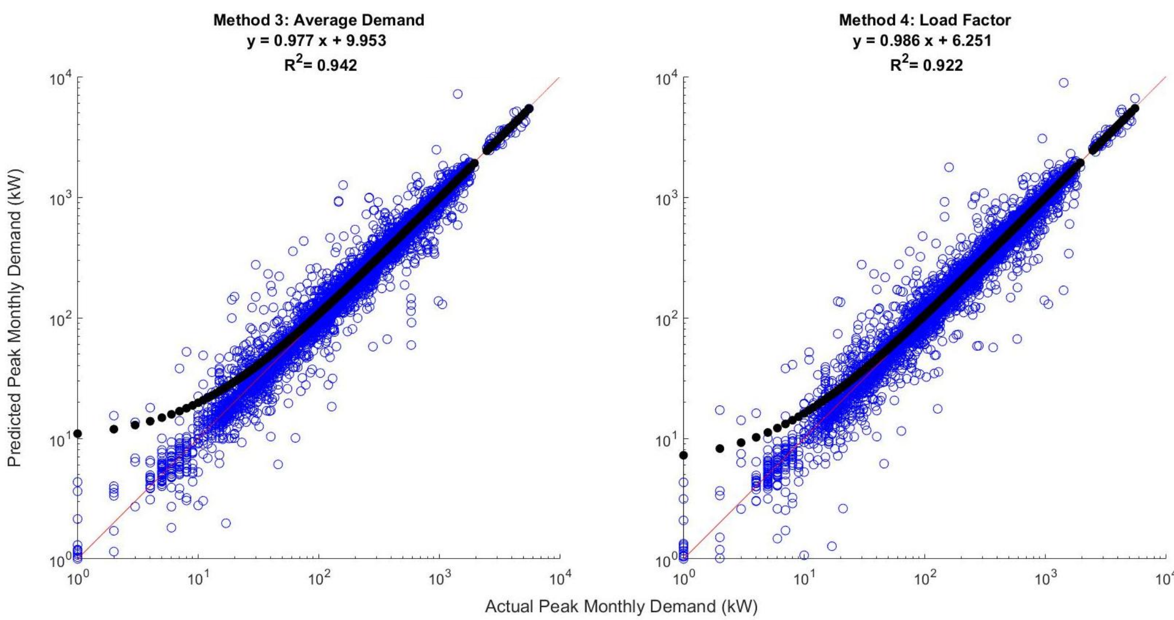


Figure 52: Predicted Peak Monthly Demand for Method 3 and Method 4 - Log

The log plots show that the Y-axis intercept of the line of best fit (black) causes the line to not track well for buildings with peak demands under approximately 50 kW_{pd}, even if the actual predictions below 50 kW_{pd} still track well as shown by the 1:1 reference line.

Method 2 was selected and used in further analysis because it had the highest the highest R^2 value of 0.971 and a strong linear fit of 0.977 in comparison to the other Methods tested. Additionally, as Method 2 is an error corrected version of the monthly peak demand from the previous year, it is the simplest form of error corrected peak load prediction explored which fits with the intent of the research.

Method 2 was plotted for individual building categories to check if there are differences in the fit by category as shown below in Figure 53.

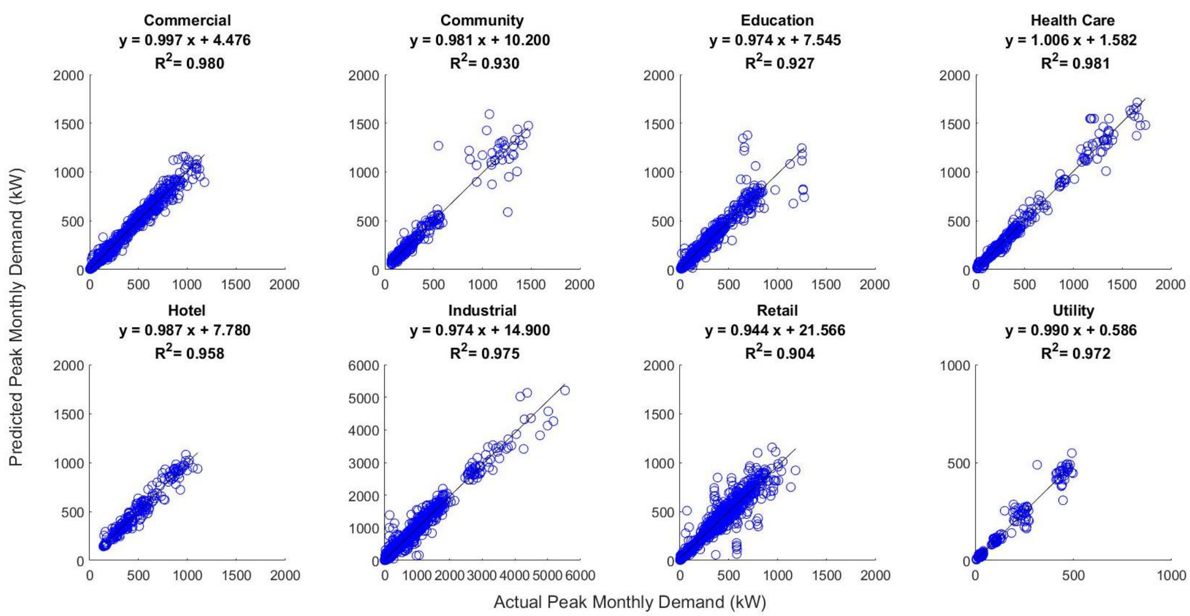


Figure 53: Predicted Peak Monthly Demand for Method 2 by Category

All categories have a strong linear fit above 0.90, with Retail having the lowest linear fit of 0.904 and Commercial having the closest linear fit of 0.997. The Retail, Education and Community categories have the lowest R^2 values of 0.904, 0.927 and 0.930 respectively while the Health Care category has the highest R^2 value of 0.981.

Above 750 kW_{pd} there are fewer data points, but there is a noticeable dispersion relative to the line of best fit, particularly in Community and Educational, which is explored further in Figure 54.

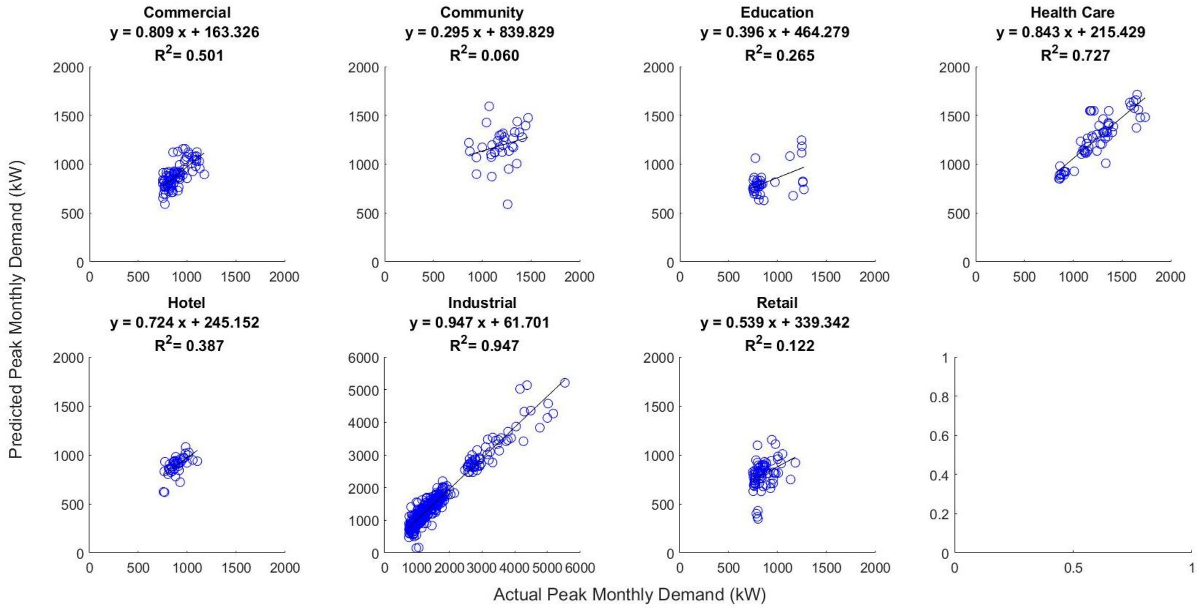


Figure 54: Predicted Peak Monthly Demand for Method 2 by Category – Actual Demand > 750 kW

All categories exhibit a worse linear fit and R^2 when only the actual demand values above 750 kW_{pd} are considered. The Community, Education and Retail categories exhibit particularly poor results with linear fits of 0.295, 0.396, 0.539 respectively and R^2 values of 0.060, 0.265, and 0.122 respectively. No changes to the prediction methods were incorporated since all the categories met the minimum coefficient of determination of 0.85 when all the buildings in each category were considered. Although no changes were made, these results show do show there are opportunities for improvement in the prediction methodology for buildings with peak loads greater than 750 kW_{pd}.

A perfect repetition of monthly peak demand from year to year would result in a linear fit of 1:1 and R^2 of 1.00.To test if the poor results above 750 kW_{pd} were due to variability in demand from year to year for the same month, the peak demand in a given month and given year was plotted against the peak demand for the same month in the previous year as shown below in Figure 55. Plotting the monthly peak demand in this manner shows that the Community, Education and Retail categories have significant peak demand variability because of the linear fit of 0.135, 0.288 and 0.486 respectively and R^2 values of 0.011, 0.127 and 0.086 respectively.

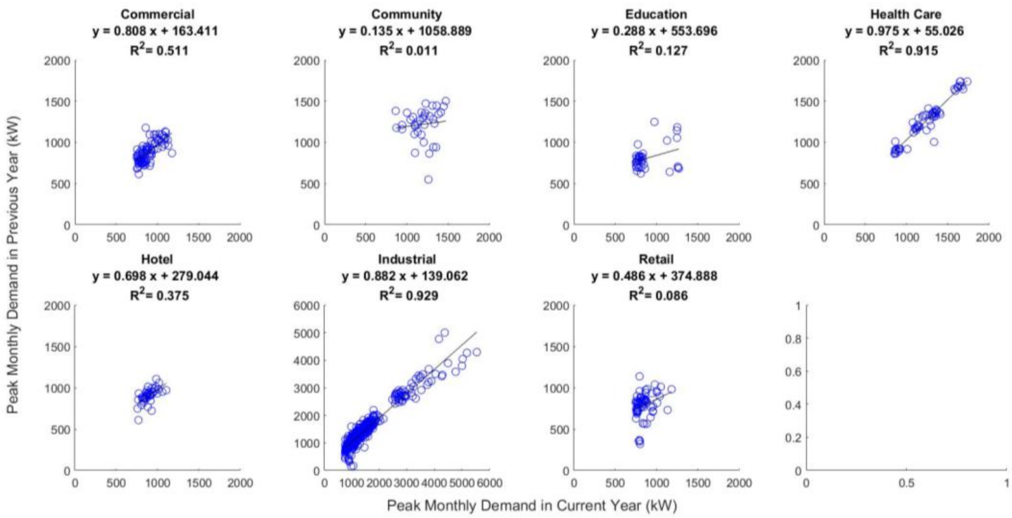


Figure 55: Demand Variability for the Same Month Year to Year – Demand > 750 kW

Figure 54 and Figure 55 also demonstrates the shortcomings of the prediction methods trialed. The results are very similar between the two figures because the performance of the prediction method is largely driven by the variability, or lack thereof, in peak demand. Since all the methods tested are based on the demand characteristics of the same month in the previous year, none of the methods adapt well to large swings in a given month from year to year.

Buildings that demonstrate minimal peak demand variability for a given month from year to year will be better candidates for a BESS if simple demand prediction methods like those trialed are used. Conversely, if buildings have a history of significant demand variability, project developers or buildings owners will need to consider more complex peak demand prediction methods to maximize demand savings. Future work could explore new prediction methods to improve the forecast accuracy for buildings that demonstrate significant demand variability year to year.

This research has focused on developing prediction methods that could be used with simple billing data. If the building owner had access to detailed historical load profiles more complex prediction methods could be developed that consider other load characteristics such as daily frequency, rate of change, width, and shape. Electrification of transportation and space heating will also change the load profile of buildings, and potentially prediction accuracy, going forward. Future work could incorporate load growth modelling to explore the effects of EVs and space heating electrification on the load profiles of commercial buildings, prediction accuracy, and the corresponding demand charges and implications for BESS use.

5.2 Sample Peak Demand Reductions

Shown below in Figure 56 is an example of the battery providing peak shaving. Two battery packs (100 kWh_{cap} and 250 kWh_{cap}) are shown in the simulation, both using the same *DI* of 20%, meaning that the battery will aim for a *TD* that reduces the predicted peak demand 20% in relative terms towards the average demand (i.e. 100% *DI* would reduce the peak demand to the average demand not 0 kW_{elc}). Both battery packs are run with the maximum charge and discharge rate limited to 2.0 h.

Although the *TD* for the two battery packs would have been the same at the start of the month, by 2017-09-26 they are different due to the results of previous demand reduction discharges earlier in the month. Figure 56 demonstrates one of several ways in which a new *TD* can be set within a month. There is a rapid increase in building demand of approximately 100 kW_{elc} above the *TD* that occurs around 13:00. Due to the 2.0 h rate limit of 50 kW_{inv}, the 100 kWh_{cap} battery can only mitigate approximately 50% of this demand increase, while it can be mitigated by the 250 kWh_{cap} battery.

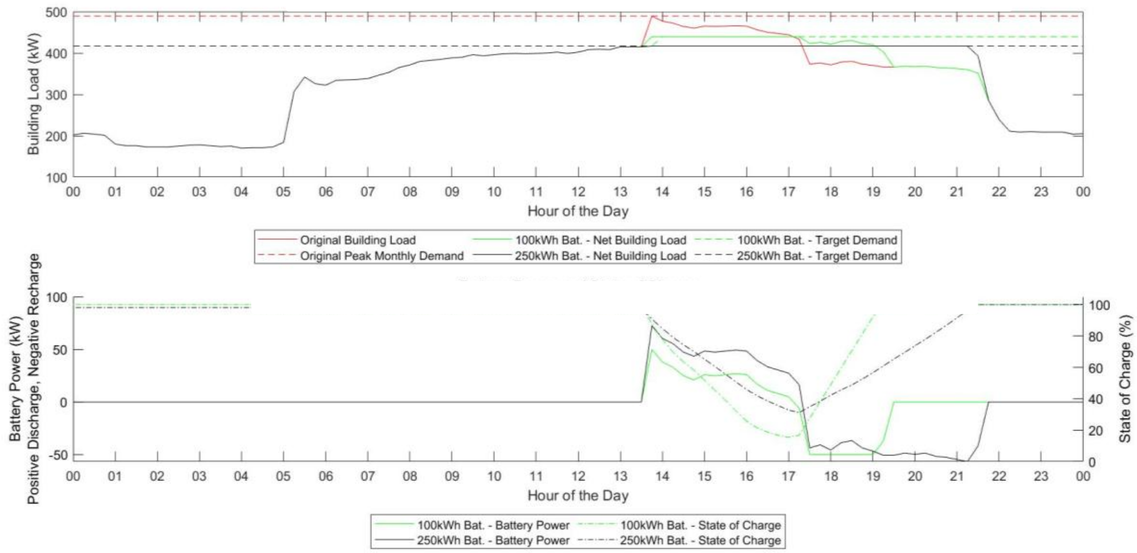


Figure 56: Sample Day Peak Demand Reduction with 100 kWh and 250 kWh Battery Packs, Meter ID 341410, 2017-09-26.

The full month of 2017-09 is shown below in Figure 57 plotted with building demand and battery power.

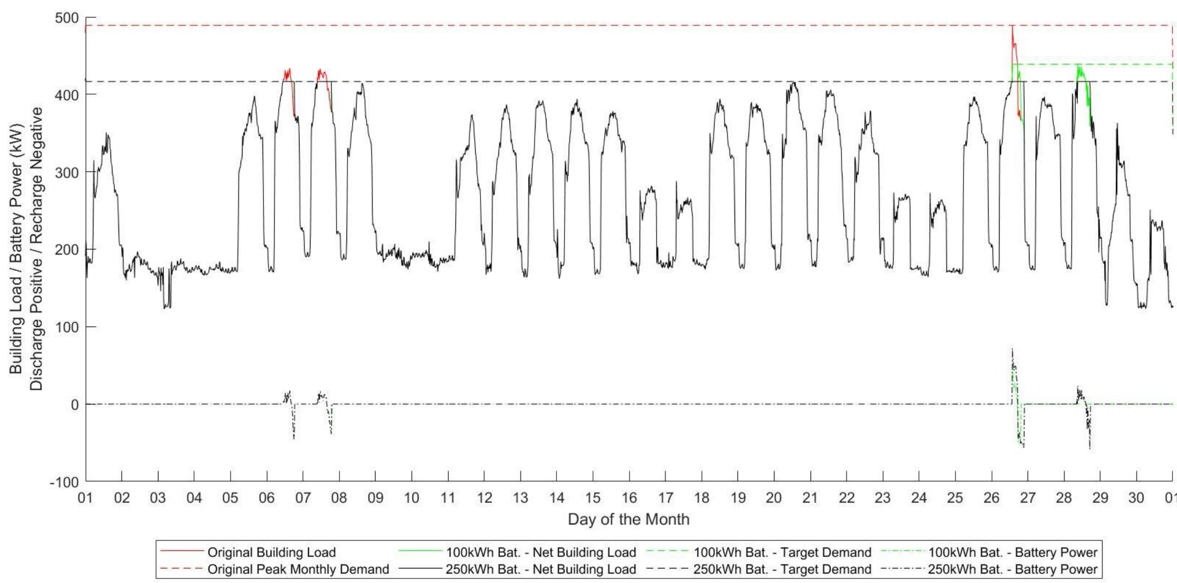


Figure 57: Sample Month Peak Demand Reduction with 100 kWh and 250 kWh Battery Packs

In this example, the 250 kWh_{cap} battery can maintain the *TD* throughout the month, while the 100 kWh_{cap} battery has the *TD* reset twice. The battery power plot demonstrates that the battery is only "active" on six days in the month, consequently, the remaining days it is in standby waiting to discharge.

While the discharge frequency of the BESS is dependent on the building load and Target Demand, low battery utilization behaviour is characteristic of a demand reduction application. The low utilization rate of a battery pack under this scenario presents opportunities for alternate revenue streams that could utilize the battery when not required for demand reduction, provided the appropriate utility tariffs or service agreements where in place to monetize the activity. Examples of additional revenue streams include, but are not limited to, frequency regulation, secure power supply, and reactive power support. Future work could explore if there is time coincidence, or not, between when a utility typically needs these services and when a commercial building could expect a demand peak to test which of these services could be practically stacked with demand charge reduction.

The demand reduction results for the same building are shown for the full year of 2017 in Figure 58. The original monthly peak demands are shown in the broken red line, along with the corresponding *TD* for the 100 kWh_{cap} battery pack in green and the 250 kWh_{cap} battery pack in black.

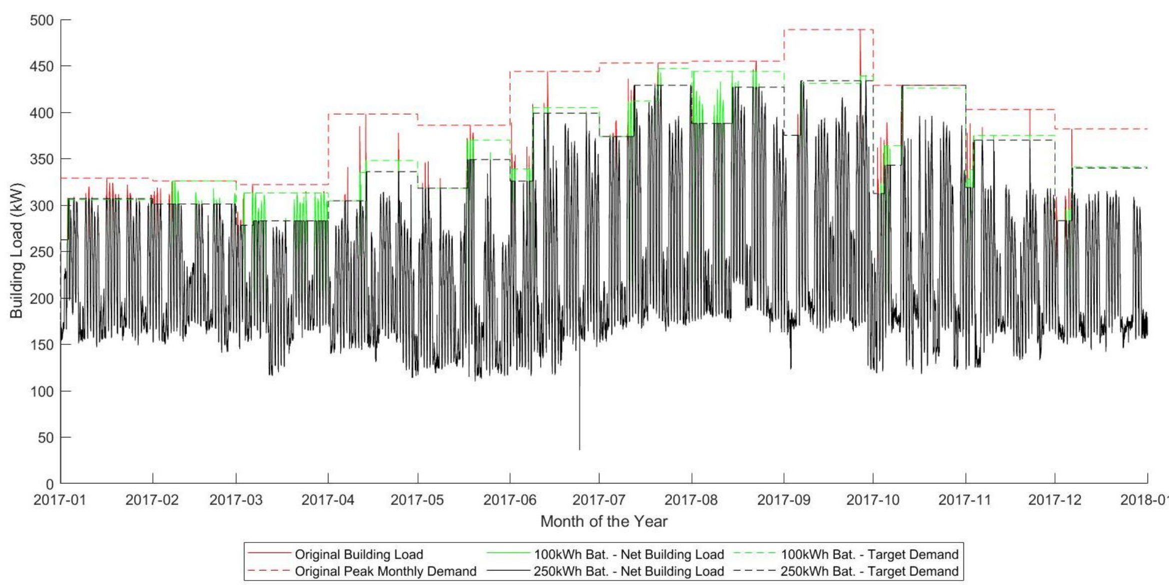


Figure 58: Sample Year Peak Demand Reduction with 100 kWh and 250 kWh Battery Packs

The *TD* is reset in every month for both battery packs which is shown numerically in Table 18 below. In most months the 250 kWh_{cap} battery out preforms the 100 kWh_{cap} in terms of demand savings, resulting in a total demand reduction over the year of 412 kW_{pd} versus 276 kW_{pd} for the 100 kWh_{cap} battery. The total demand savings each year is the sum of the differences between the original monthly peak demand and the highest recorded *TD* in each month.

Table 18: Peak Demand Comparison for 100 and 250 kWh Battery 2017-09

Month	Original Peak Demand (kW_{pd})	Target Demand (kW_{pd}) 40% DI	Final Target Demand (kW_{pd}) 100 kWh_{cap}	Demand Savings (kW_{pd}) 100 kWh_{cap}	Final Target Demand (kW_{pd}) 250 kWh_{cap}	Demand Savings (kW_{pd}) 250 kWh_{cap}	250 kWh_{cap} - Demand Savings (kW_{pd}) Relative to 100 kWh_{cap}	250 kWh_{cap} - Demand Savings (%) Relative to 100 kWh_{cap}
January	329	263	306	23	307	22	-1	-4%
February	326	301	326	0	301	25	25	-
March	322	278	313	9	283	39	30	333%
April	398	305	348	50	336	62	12	24%
May	386	318	370	16	349	37	21	131%
June	444	326	405	39	399	45	6	15%
July	453	374	447	6	429	24	18	300%
August	455	388	444	11	427	28	17	155%
September	489	375	439	50	434	55	5	10%
October	429	313	426	3	429	0	-3	-100%
November	403	319	375	28	370	33	5	18%
December	382	283	341	41	340	42	1	2%
Annual Totals	**4816**	**3843**	**4540**	**276**	**4404**	**412**	**136**	**49%**

In both of the months (January and October) when the 100 kWh_{cap} battery outperformed the 250 kWh_{cap} battery it occurred in situations where both battery sizes reset the *TD* during a particular day, but at different points in the day as shown below in Figure 59 and Figure 60. This shows that both the building load profile and control strategy contribute to situations where a smaller battery can outperform a larger battery even with the same peak demand forecasting and original *TD*.

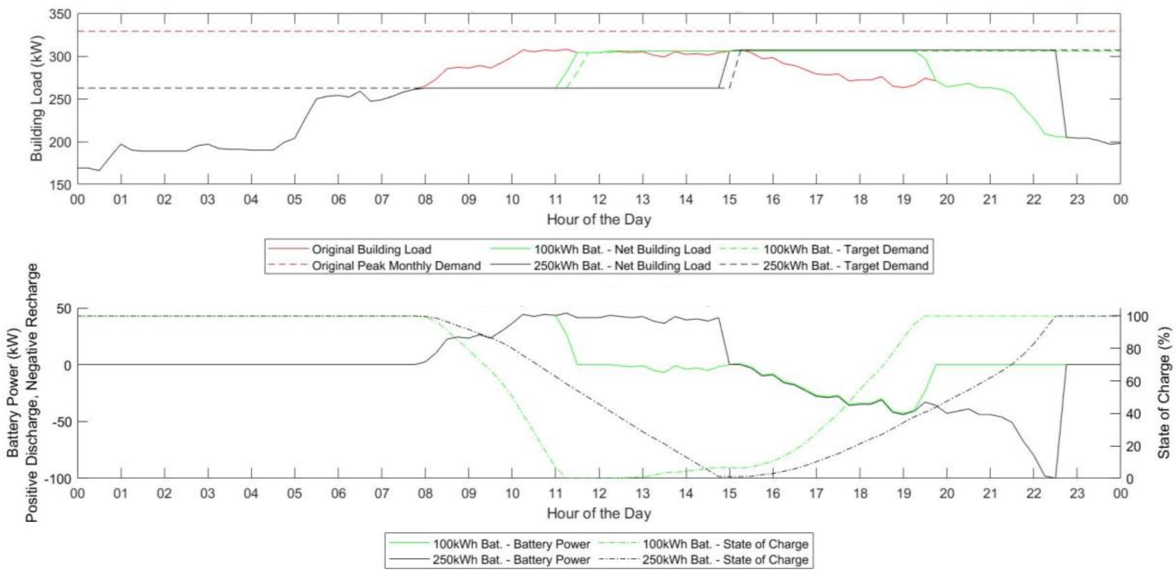


Figure 59: 100 kWh Outperforming 250 kWh Battery Pack, Meter ID 341410, 2017-01-03.

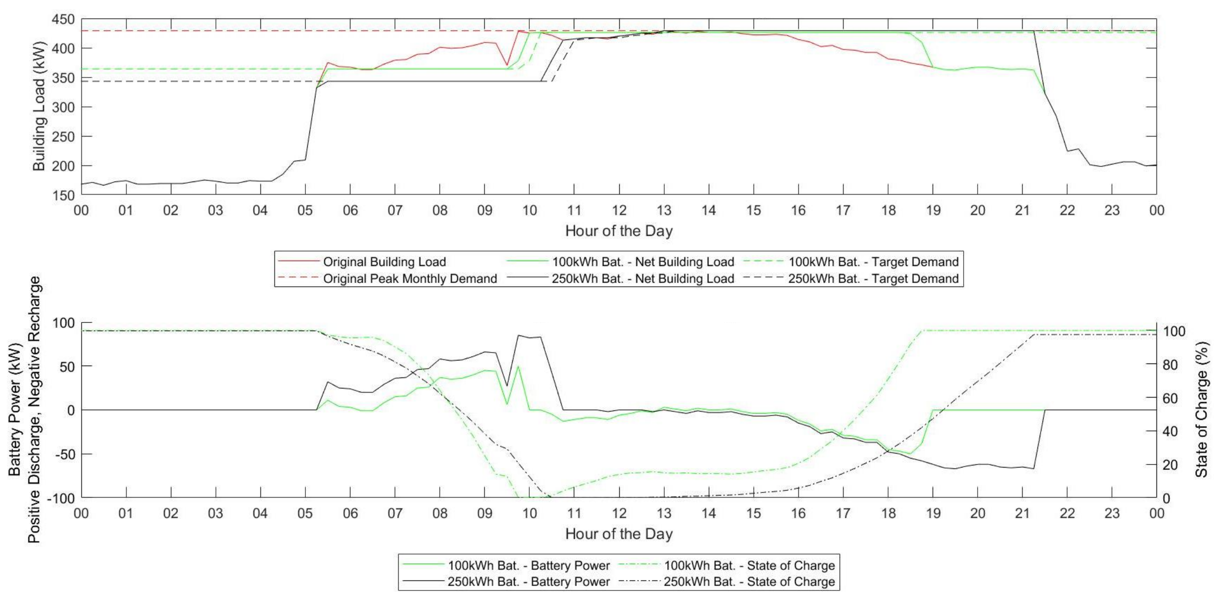


Figure 60: 100 kWh Outperforming 250 kWh Battery Pack, Meter ID 341410, 2017-01-03.

Figure 61 compares demand reduction scenarios for both a 20% and 40% *DI*. The same building is used as in the previous analysis, with the date period changed to 2017-09-05 to 2017-09-06. Only one battery pack (100 kWh_{cap}) is shown in the simulation, but two separate *DIs,* to demonstrate the scenario where a battery runs out energy while trying to hold a given *TD*. *TD*s representing a 20% and 40% relative reduction in predicted peak monthly demand were selected. On 2017-09-05 the building demand does not exceed the *TD* for the 20% *DI,* so the battery does not discharge. The battery does discharge for the 40% *DI* scenario and is successful in mitigating the peak demand on 2017-09-05. On the following day, 2017-09-06, the building demand exceeds the *TD* associated with both the 20% and 40% *DI*s. The 100 kWh_{cap} battery has enough energy capacity to mitigate the 20% *DI* peak but runs out of energy shortly after 12:00 in the 40% *DI* scenario. When the battery runs out of energy, the 40% *DI* *TD* is reset due to the building demand returning to its original profile momentarily. At this point, the battery charges and discharges based on the new *TD*.

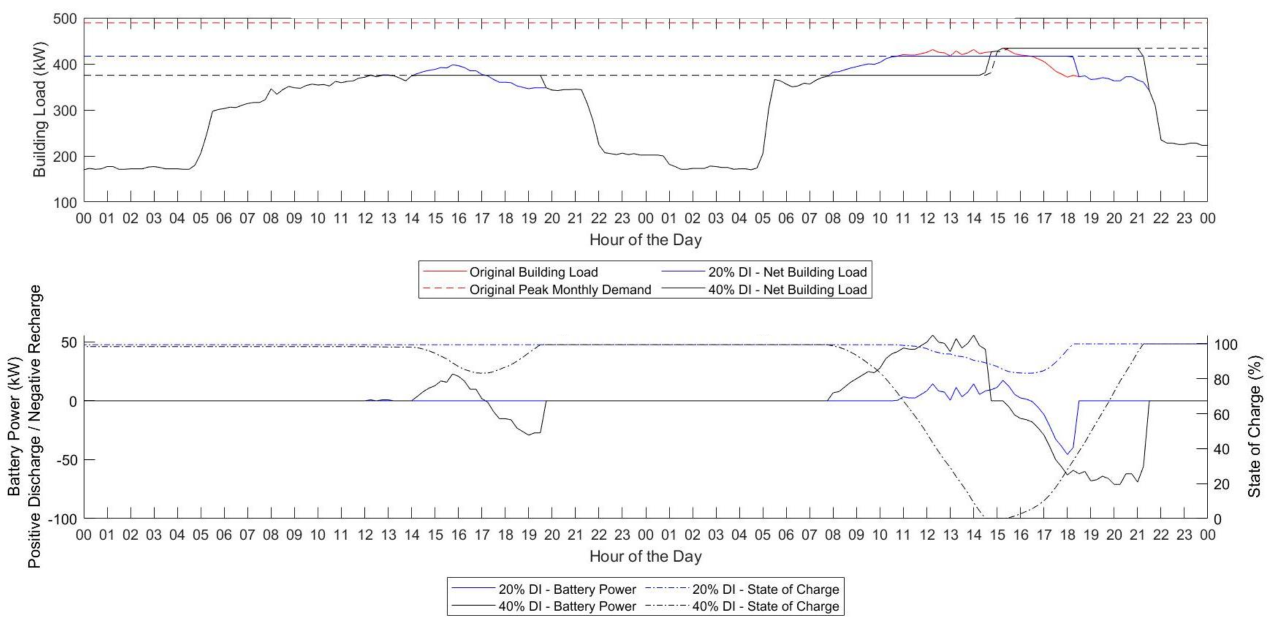


Figure 61: Day Peak Demand Reduction with 20% and 40% Demand Increment

5.3 Demand Savings Results Comparisons

The total demand savings for each building class and *DI* is summed and shown below in Table 19 to assess the benefits of perfect foresight in comparison to using the predicted peak demand. The analysis was done using a 250 kWh_{cap} battery and load data from 2017.

The results in Table 19 highlight the difference between perfect foresight of peak demand and a perfect discharge strategy based on perfect foresight. This research did not investigate the perfect discharge strategy based on perfect foresight of the peak demand. The perfect foresight peak demand was used with the same *DI* and *DRF* formulas to calculate a *TD* based on the known peak demand. So even with perfect foresight of the peak demand, the control strategy and *TD* will still impact the total demand savings. This can result in some scenarios where the total savings for the predicted peak demand can be superior to those realized with perfect foresight because of the influence of the control strategy (i.e. *DI* and resultant *TD*).

Table 19: Predicted Peak and Perfect Foresight – Total Demand Savings by Building Category and Demand Increment – 250kWh Battery - 2017

		Commercial	Community	Education	Health Care	Hotel	Industrial	Retail	Utility	Total
	Total Peak Demand Across All Buildings (kW_{pd})	134566	40059	89124	57950	37813	382103	203970	10359	955944
20% DI	**Perfect Foresight Total Demand Savings (kW_{pd})**	10570	2979	9766	4412	2461	27034	13907	533	71661
	Predicted Peak Total Demand Savings (kW_{pd})	8593	2551	7891	4111	2181	21718	13764	502	61309
	Percent of Perfect Foresight Savings with Predicted Peak (%)	**81.3%**	**85.6%**	**80.8%**	**93.2%**	**88.6%**	**80.3%**	**99.0%**	**94.1%**	**85.6%**
40% DI	**Perfect Foresight Total Demand Savings (kW_{pd})**	13779	4202	12057	6571	3325	33378	22396	825	96533
	Predicted Peak Total Demand Savings (kW_{pd})	12020	4020	10880	5989	3291	30584	20134	617	87534
	Percent of Perfect Foresight Savings with Predicted Peak (%)	**87.2%**	**95.7%**	**90.2%**	**91.1%**	**99.0%**	**91.6%**	**89.9%**	**74.7%**	**90.7%**
60% DI	**Perfect Foresight Total Demand Savings (kW_{pd})**	13978	4500	12623	7178	3165	34802	24395	852	101493
	Predicted Peak Total Demand Savings (kW_{pd})	13931	3963	12292	6914	3039	32587	23239	769	96735
	Percent of Perfect Foresight Savings with Predicted Peak (%)	**99.7%**	**88.1%**	**97.4%**	**96.3%**	**96.0%**	**93.6%**	**95.3%**	**90.3%**	**95.3%**
80% DI	**Perfect Foresight Total Demand Savings (kW_{pd})**	13159	3948	11796	6827	3114	33117	23367	756	96084
	Predicted Peak Total Demand Savings (kW_{pd})	13769	3977	11643	6573	3145	32848	22904	832	95691
	Percent of Perfect Foresight Savings with Predicted Peak (%)	**104.6%**	**100.7%**	**98.7%**	**96.3%**	**101.0%**	**99.2%**	**98.0%**	**110.0%**	**99.6%**
100% DI	**Perfect Foresight Total Demand Savings (kW_{pd})**	12920	4176	11061	6410	2997	31916	22662	810	92950
	Predicted Peak Total Demand Savings (kW_{pd})	12987	4085	11201	6395	3029	31874	22609	778	92958
	Percent of Perfect Foresight Savings with Predicted Peak (%)	**100.5%**	**97.8%**	**101.3%**	**99.8%**	**101.1%**	**99.9%**	**100.2%**	**104.0%**	**100.0%**

Table 19 shows that demand savings increase for all building categories above a 20% *DI*, but savings typically start to decline between 80% and 100% *DI* as plotted below in Figure 62. The results show that over any given category of buildings the operator will be better served by using a higher *DI* to set a lower *TD*, with the best demand savings results realized when a *TD* is set using a 40% - 80% *DI*.

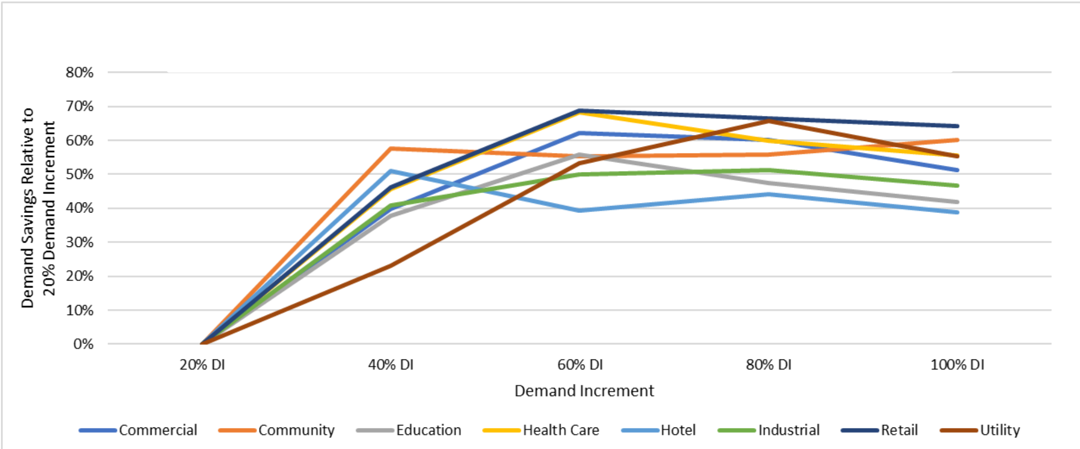


Figure 62: Relative Total Demand Savings by Building Category - Predicted Peak

Table 19 shows the predicted peak demand savings relative to perfect foresight increase with *DI*, meaning that the lower the *TD* is set, relative to a predicted peak, the greater confidence a project developer or building owner can have that the BESS project is delivering demand savings close to the optimal results if the peak demand had been known with perfect foresight.

Shown below in Figure 63 is the total demand savings, as a percentage of total peak demand, for all buildings in 2017 utilizing a 250 kWh_{cap} BESS. The results are sorted by 20% *MLF* brackets and for the five (5) *DI*s tested. The results show that across a large cross section of C&I building stock a lower *MLF* leads to higher demand savings. Sorting the results by *DI* reinforces the conclusion from Figure 62 that the higher *DI*s produce more demand savings but with diminishing returns. The *MLF* brackets in Figure 63 show higher *DI*s result in strong improvements in demand savings when *MLF* <= 40% but improvements diminish significantly for when the *MLF* is > 40%. This means that for buildings with a low *MLF* (<= 40%), the default control strategy should set lower *TD*s to maximize savings, but for buildings with a higher *MLF* this is less important as the change in total savings with increasing *DI* is minimal.

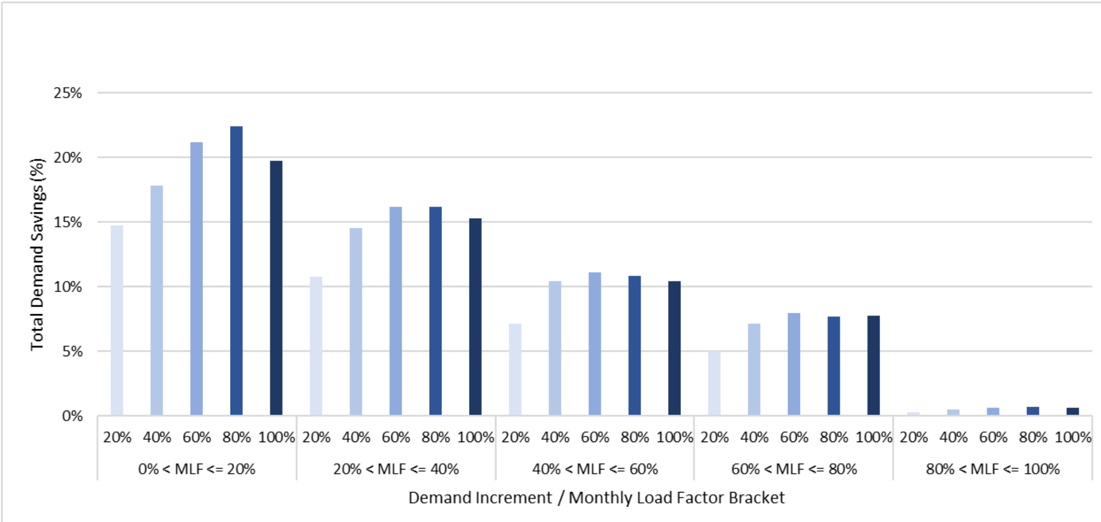


Figure 63: Total 2017 Demand Savings by Monthly Load Factor and Demand Increment, 250 kWh BESS

Demand savings when the peak demand is overestimated or underestimated has the potential to be asymmetric. When the peak demand is overestimated the battery could still deliver demand savings depending on the *DI* and resulting *TD*. Alternatively, if the peak demand was overestimated and the *TD* was not set low enough the battery may be inactive for the entire billing period. In contrast, in scenarios where the peak demand is underestimated, the battery can run out of energy, resulting in a peak demand event. Table 20 compares the scenarios where the peak demand is over and underestimated to determine if the results are asymmetric, and if so in which direction.

Table 20: Comparison of Demand Savings for Overpredicted and Underpredicted Peak Demands

		Commercial	Community	Education	Health Care	Hotel	Industrial	Retail	Utility	Total
	Total Peak Demand Across All Buildings (kW_{pd})	134566	40059	89124	57950	37813	382103	203970	10359	955944
20% DI	**Predicted Peak < Actual Peak - Total Demand Savings (kW_{pd})**	6209	1876	5597	3209	1703	16251	11000	397	46243
	Predicted Peak => Actual Peak - Total Demand Savings (kW_{pd})	2384	675	2295	901	478	5466	2763	105	15066
	Savings Difference When Predicted Peak is Underestimated (%)	**160%**	**178%**	**144%**	**256%**	**256%**	**197%**	**298%**	**280%**	**207%**
40% DI	**Predicted Peak < Actual Peak - Total Demand Savings (kW_{pd})**	6537	2334	5975	3795	1854	17564	12756	472	51286
	Predicted Peak => Actual Peak - Total Demand Savings (kW_{pd})	5483	1686	4905	2194	1437	13020	7378	145	36248
	Savings Difference When Predicted Peak is Underestimated (%)	**19.2%**	**38.4%**	**21.8%**	**73.0%**	**29.0%**	**34.9%**	**72.9%**	**224.8%**	**41.5%**
60% DI	**Predicted Peak < Actual Peak - Total Demand Savings (kW_{pd})**	6805	1830	5988	3952	1490	17080	12704	519	50368
	Predicted Peak => Actual Peak - Total Demand Savings (kW_{pd})	7126	2133	6304	2962	1550	15508	10535	251	46367
	Savings Difference When Predicted Peak is Underestimated (%)	**-4.5%**	**-14.2%**	**-5.0%**	**33.4%**	**-3.8%**	**10.1%**	**20.6%**	**106.9%**	**8.6%**
80% DI	**Predicted Peak < Actual Peak - Total Demand Savings (kW_{pd})**	6608	1846	5638	3600	1627	16719	12032	523	48592
	Predicted Peak => Actual Peak - Total Demand Savings (kW_{pd})	7161	2131	6005	2974	1519	16130	10871	309	47099
	Savings Difference When Predicted Peak is Underestimated (%)	**-7.7%**	**-13.4%**	**-6.1%**	**21.0%**	**7.1%**	**3.7%**	**10.7%**	**69.4%**	**3.2%**
100% DI	**Predicted Peak < Actual Peak - Total Demand Savings (kW_{pd})**	6189	1786	5435	3599	1465	16292	12162	488	47415
	Predicted Peak => Actual Peak - Total Demand Savings (kW_{pd})	6798	2299	5766	2796	1564	15582	10447	290	45543
	Savings Difference When Predicted Peak is Underestimated (%)	**-9.0%**	**-22.3%**	**-5.8%**	**28.7%**	**-6.3%**	**4.6%**	**16.4%**	**68.4%**	**4.1%**

The results are asymmetric for the 20% and 40% *DI* scenarios where the predicted peak demand was below the actual peak demand. Across all the buildings tested there was more than a 200% increase at the 20% *DI* and more than a 40% increase at the 40% *DI*. This shows that if a building owner were to install a BESS system, and the predicted peaks were historically higher than the actual demand, the operator should not run a mild demand reduction strategy (i.e. 20% - 40% DI) or there will be significant potential demand savings unrealized. Results change by category as the *DI*s increases beyond 40% and when summed across all buildings and categories there is less than a 10% difference in savings between the overestimation and underestimation scenarios for *DI*s above 40%.

In Table 21 demand savings are summed by category and *DI* to determine if there is a material change in performance based on inverter power rate. Based on the previous results only *DI*s between 40% and 80% were examined. The results in the table utilize a 250 kWh_{cap} battery and charge/discharge rates ranging from 15 min (1000 kW_{inv} inverter) to 12.0 h (20.8 kW_{inv} inverter). Although a 15 min rate is not representative of commercially available technology for this application, it was analyzed to check the sensitivity of the results to the inverter size relative to the battery capacity to check if significantly improved results could be expected were battery and inverter technology to advance to allow much higher rates of charge and discharge than are commercially available.

This model did not adjust the discharge rate of the battery as the SOC changed. Future work could explore if a variable discharge rate based on SOC could improve demand savings results, and what relation this may have with the base discharge rate (ex. 2.0 h, 4.0 h etc.). A basic version of this modified control strategy could limit the discharge power proportionally to SOC. For example, a 100 kWh_{cap} BESS with a 2.0 h rate (50 kW_{inv} power) would have a maximum discharge rate of 50 kW_{inv}, 37.5 kW_{inv}, 25 kW_{inv}, and 12.5 kW_{inv} at a SOC of 100%, 75%, 50%, and 25% respectively.

Table 21: Comparison of Demand Savings by Inverter Power Rate

		Commercial	Community	Education	Health Care	Hotel	Industrial	Retail	Utility	Total	% Of 15 min Savings
	Total Peak Demand - All Buildings (kW_{pd})	134566	40059	89124	57950	37813	382103	203970	10359	955944	
40% DI	**15 min Rate - Total Demand Savings (kW_{pd})**	11714	3921	10869	5896	3259	30335	20240	617	86850	100%
	2 hr Rate - Total Demand Savings (kW_{pd})	12020	4020	10880	5989	3291	30584	20134	617	87534	101%
	4 hr Rate - Total Demand Savings (kW_{pd})	12537	3885	10904	5863	2922	25376	18452	655	80595	93%
	8 hr Rate - Total Demand Savings (kW_{pd})	9777	2662	8023	4611	2268	17244	13131	622	58338	67%
	12 hr Rate - Total Demand Savings (kW_{pd})	5871	1453	4786	2707	1239	10038	7322	554	33970	39%
60% DI	**15 min Rate - Total Demand Savings (kW_{pd})**	13724	3740	12490	6663	3119	32463	23233	762	96195	100%
	2 hr Rate - Total Demand Savings (kW_{pd})	13931	3963	12292	6914	3039	32587	23239	769	96735	101%
	4 hr Rate - Total Demand Savings (kW_{pd})	14274	4046	12506	6820	2963	28390	20606	794	90399	94%
	8 hr Rate - Total Demand Savings (kW_{pd})	11327	2942	9336	5136	2557	19241	14832	703	66075	69%
	12 hr Rate - Total Demand Savings (kW_{pd})	6412	1588	5334	2907	1306	11000	8041	657	37246	39%
80% DI	**15 min Rate - Total Demand Savings (kW_{pd})**	13468	3811	11633	6499	3049	32253	23260	832	94805	100%
	2 hr Rate - Total Demand Savings (kW_{pd})	13769	3977	11643	6573	3145	32848	22904	832	95691	101%
	4 hr Rate - Total Demand Savings (kW_{pd})	14050	4130	12409	6782	3069	28830	20785	800	90854	96%
	8 hr Rate - Total Demand Savings (kW_{pd})	11721	3037	9925	5287	2600	20193	15061	732	68557	72%
	12 hr Rate - Total Demand Savings (kW_{pd})	6569	1660	5610	2996	1313	11552	8223	667	38590	41%

When the demand savings results are summed across all categories the results between the 15 min and 2.0 h rate have less than a 2% difference depending on the *DI*. When individual categories are examined, there is less than a 10% difference. Although there may be individual buildings that benefit from the faster 15 min rate, interestingly in many categories the slower 2.0 h rate delivers better overall savings results. This is likely due to diurnal nature of building load profiles. Since buildings do not typically have narrow 15 min load spikes the slower 2.0 h rate allows the BESS to manage broader morning, evening, or daily peaks. The comparison of results between the 15 min and 2.0 h rates shows that advances in BESS technology that allow for higher rates will not unlock significantly more demand charge management opportunities when considering a broad section of C&I building stock. The 4.0 h rate delivers reduced, but similar results to the 2.0 h rate scenario, but the results drop for 8.0 h and 12.0 h rates. This trend holds across all building categories, but the results with 8.0 h and 12.0 h rates do not drop off as quick for high *MLF* categories like Hotel and Health Care category. This shows that a commercially available BESS with a 2.0 h or 4.0 h rate will work well for demand charge reduction applications, but longer duration systems, or control strategies that limit the BESS charge and discharge power, are not well suited to this application and should be avoided.

5.4 Demand Savings Analysis by Category

The relationship between the average monthly load factor of a building and demand savings is explored in Figure 64 though Figure 76.

The Normalized Demand Savings (*NDS*) demand savings is plotted against average monthly load factor for all building categories, using a common battery pack size of 250 kWh_{cap} in Figure 64.The *NDS* for different buildings categories was calculated by totalling the demand savings in a given year and dividing the total demand savings by the average annual demand of the building as shown in Equation (13) below.

$$NDS_{Yi,Mj} = \frac{\sum (Original\ Peak\ Monthly\ Demand_{Yi,Mj} - Modified\ Peak\ Monthly\ Demand_{Yi,Mj})}{\sum Original\ Peak\ Monthly\ Demand_{Yi,Mj}} \quad (13)$$

A common ordinate axis, scaled to the maximum normalized savings in any given category, was used to display the results to allow for simplified comparison between building categories. Results are shown for the five Demand Increment scenarios analyzed, as per the legend in Figure 64.

The following subsections will discuss the building categories individually. The commercial category will be introduced first with detailed discussion followed by the other categories with notable differences in the individual categories discussed.

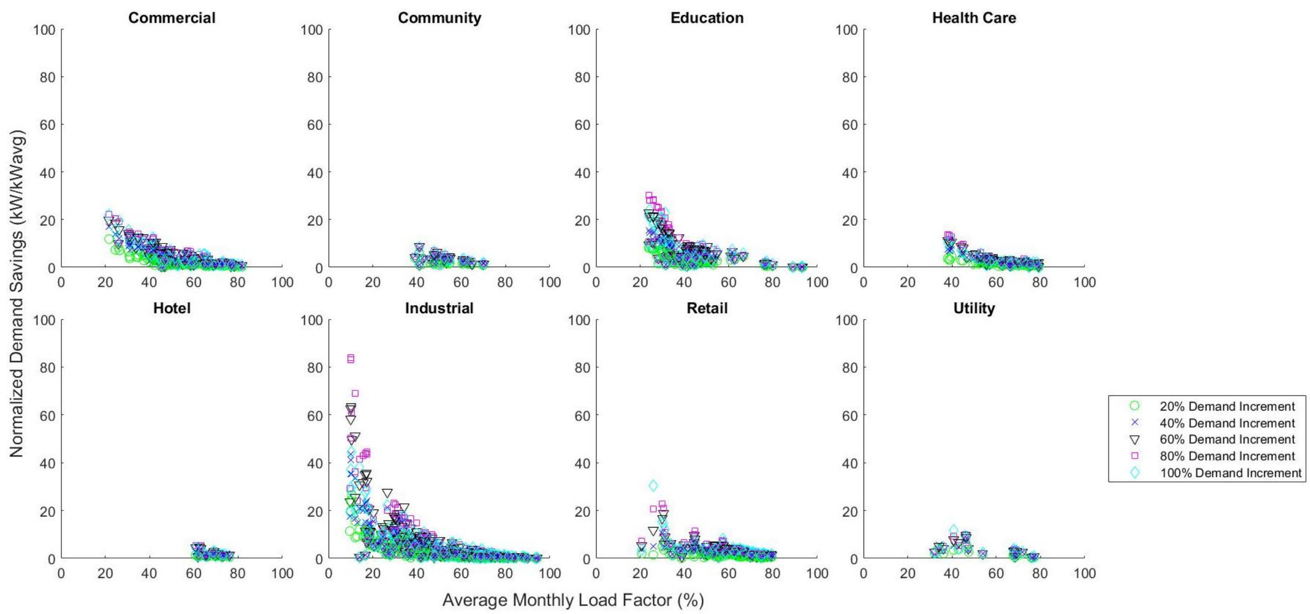


Figure 64: Normalized Demand Savings vs Average Monthly Load by Category – 250 kWh Battery

5.4.1 Commercial Buildings

Shown below Figure 65 is the same graph for the Commercial category only, with the Y-axis scale adjusted appropriately, to examine the trends within the results more closely.

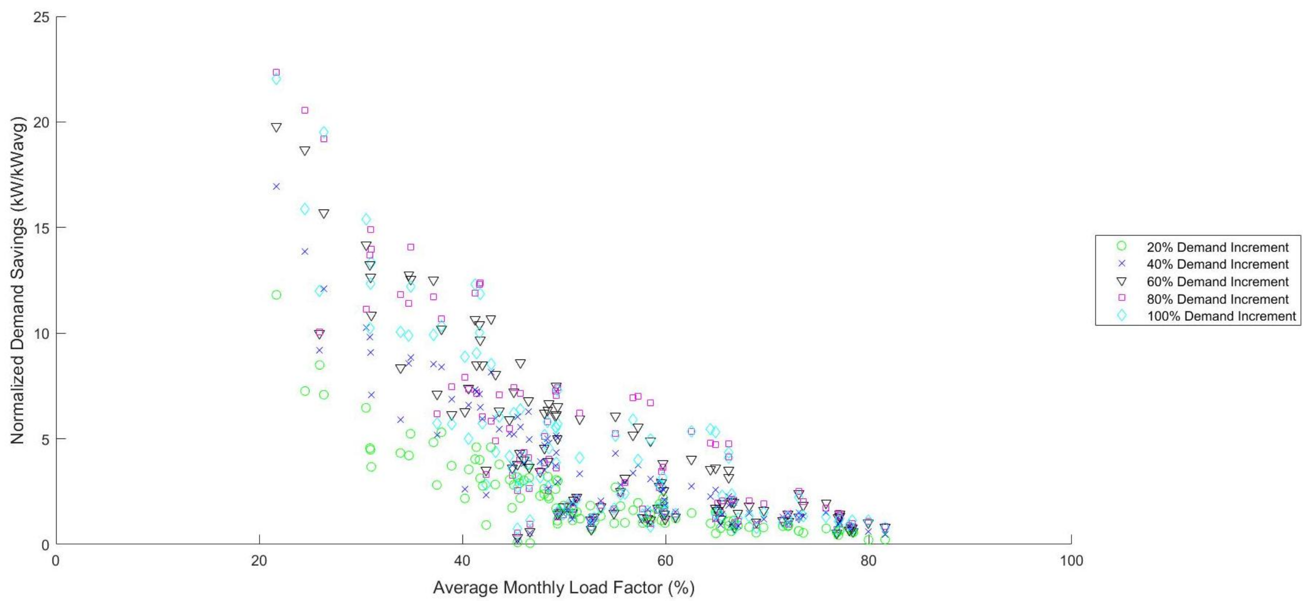


Figure 65: Normalized Demand Savings vs Average Monthly Load – Commercial Category with 250 kWh Battery

As shown above, buildings with a lower average monthly load factor correspond with greater potential savings. Additionally, as the average monthly load factor decreases, the range of *NDS* increases with a greater spread and stratification of results between different *DI*s. This trend shows that as the average monthly load factor for a building decreases, the *TD* should be set lower (higher *DI*) which tends to result in better demand reduction savings. Conversely, for buildings with a higher average monthly load factor, there is limited benefit in discharging the BESS more aggressively because there is little to be gained in terms of savings, but potentially higher cycling degradation on the battery.

Next, the normalized demand savings were examined in the same way over the six battery sizes. As expected, larger battery sizes result in larger demand savings, but the trend towards diminishing returns identified previously is also evident on these plots, particularly for the three largest battery sizes considered.

There was evidence of stratification of results based on Demand Increment in Figure 65 with the 250 kWh_{cap} battery, and it is more pronounced for larger batteries when all the battery pack sizes are examined below in Figure 66.

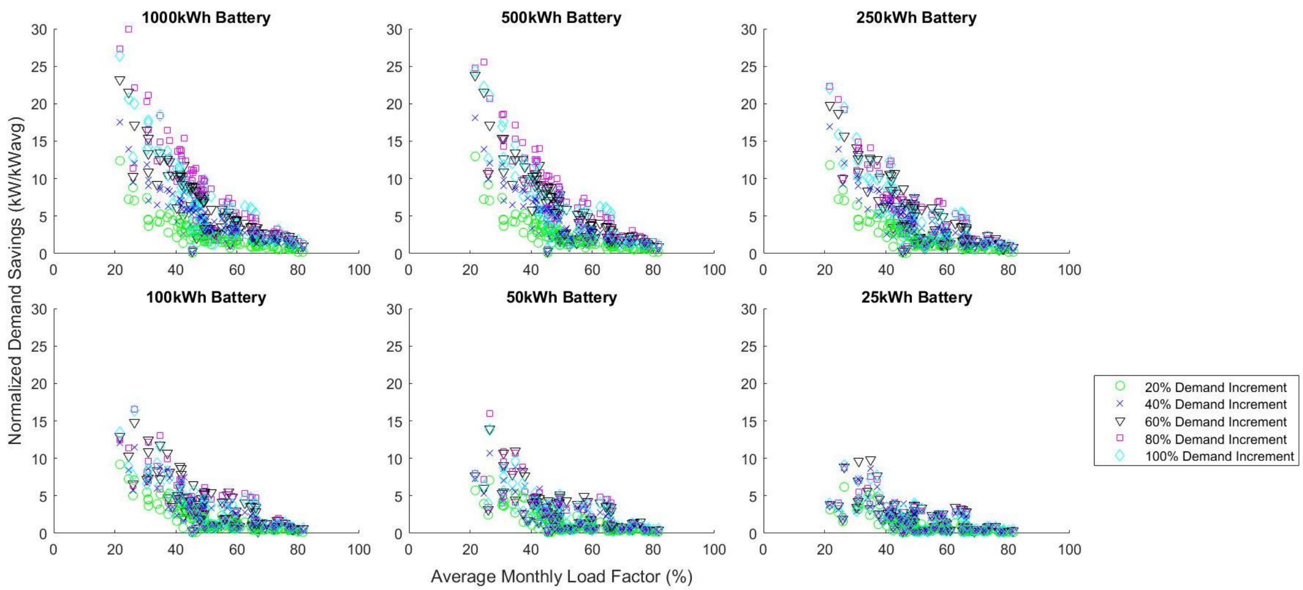


Figure 66: Normalized Demand Savings vs Average Monthly Load by Battery Size - Commercial

The stratification of *NDS* as *DI*s increase means that larger battery sizes allow a lower *TD* to be set (higher *DI*) resulting in increased savings versus the smaller battery pack sizes.

Lower average monthly load factors provide a better opportunity for demand savings. In the case of the Commercial category, an average *MLF* of less than 40% indicates a good opportunity for demand savings across all *DI*s. Additionally, the trend is non-linear, meaning the buildings with average monthly load factors in the 20-30% range generate significantly better results.

As expected, the 20% and 40% *DI* tend to result in lower demand savings than the 60%, 80% and 100% *DI*s. Across all battery sizes there does not appear to be increased demand savings associated with the 100% *DI* versus the 80% *DI*. This means that there is limited value in trying to reduce the predicted peak demand to the predicted average (100% Demand Increment) as it does not result in more savings. Future research could explore if a higher *DI* has any correlation with either a higher frequency of charge and discharge and or a higher throughput of battery energy. Either of these scenarios could introduce additional operations and maintenance costs on the BESS.

5.4.2 Community Buildings

Shown below in Figure 67, are the results for the Normalized Demand Savings versus Average Monthly Load Factor for the Community category. The same trend of a lower Average Monthly Load Factor resulting in an increased opportunity for demand savings is also observable. The buildings under consideration in this category have limited samples with an Average Monthly Load Factor of less than 40% so the opportunities for demand savings are reduced. Although the scale as been changed, the demand reduction results for Community and Commercial facilities are similar for buildings of a similar load factor.

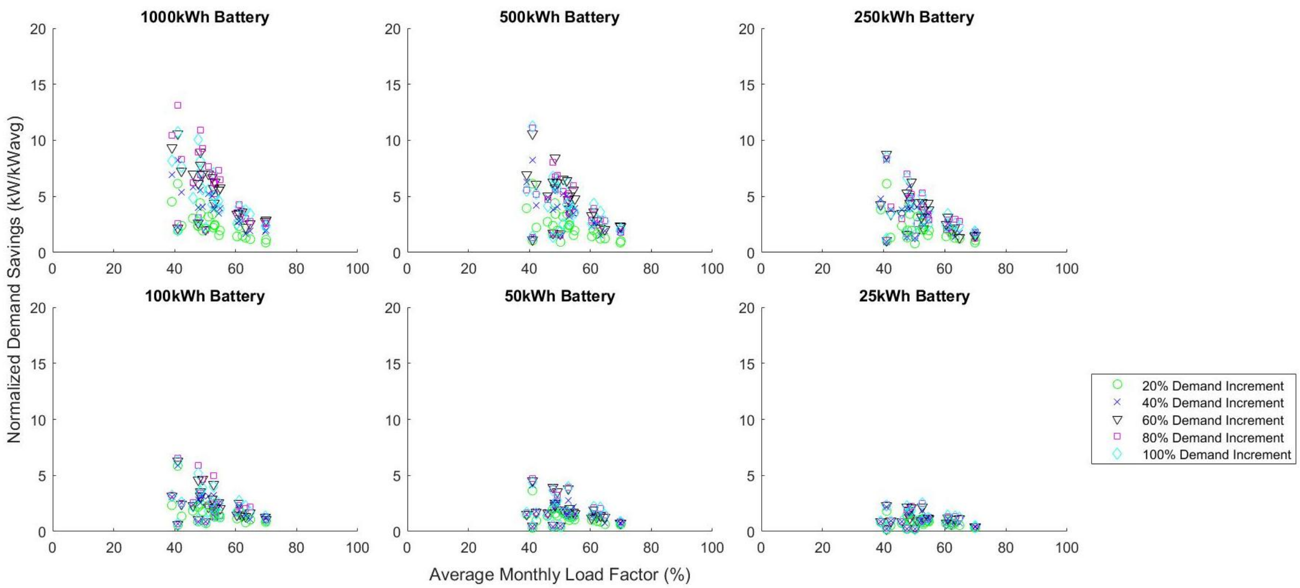


Figure 67: Normalized Demand Savings vs Average Monthly Load by Battery Size - Community

5.4.3 Education Buildings

Shown below in Figure 68, are the results for the Education category. The same trends of a non-linear improvement in results at lower load factor is observable for this category. Interestingly, the Education category appears to have some promising buildings even with the smallest battery size tested, with Normalized Demand Savings in the range of 10-20 kW_{pd} / kW_{avg}. In contrast, the Commercial category did not realize savings in this range until the larger (250 kWh_{cap}+) batteries were used. Figure 79 in Section 5.5 on page 125 explores the relationship between building average load, *MLF* and demand savings. The results show that small buildings (average load of <=

50 kW_{avg}) with a low *MLF* produce the best demand savings results. In 2017 the Education category had a total of 128 building-months for building with an annual average load of <= 50 kW_{avg} and a *MLF* of less than 40%. In contrast, the Commercial category had 61 buildings-months with the same load characteristics. The higher number of buildings-months that fit these load characteristics is why the Education category can outperform the Commercial category for demand reduction savings that are normalized by building average load.

There are also a greater number of poor demand savings results for buildings with a *MLF*s of less than 40%. This is because the Education category has a high number of buildings with an average load of > 100 kW_{avg} and a *MLF* of less than 40%. The Education category has 45 building-months with these load characteristics in comparison to only seven (7) for the commercial category.

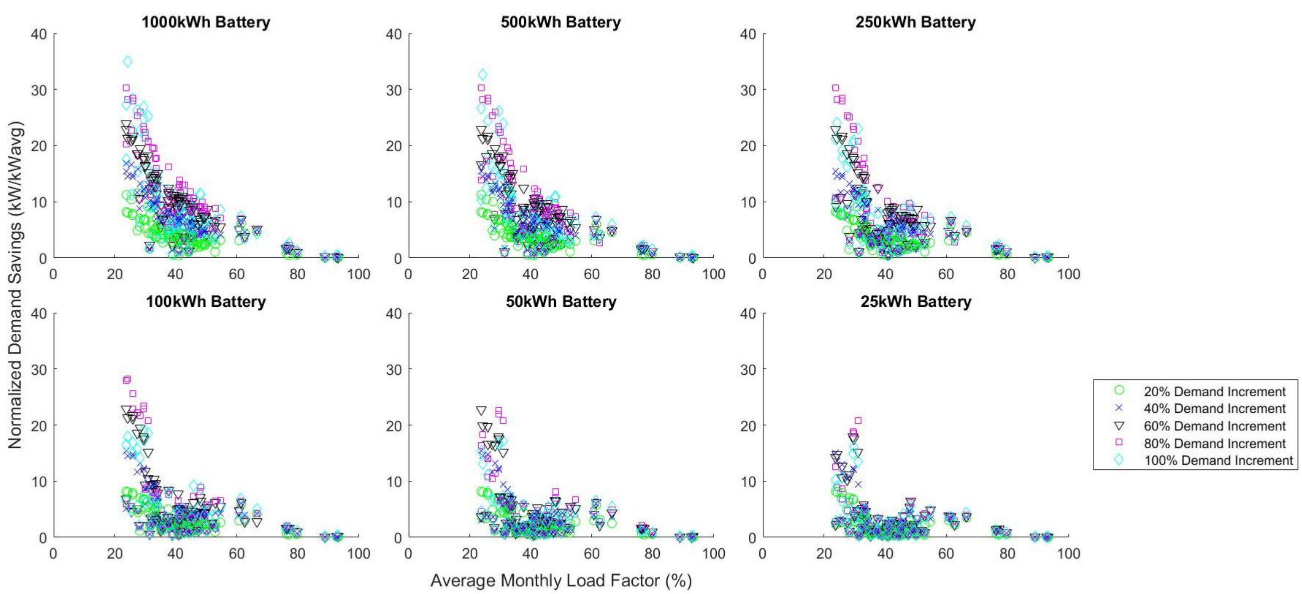


Figure 68: Normalized Demand Savings vs Average Monthly Load by Battery Size - Education

To examine if the poor results are a result of prediction accuracy or building load characteristics, the monthly *NDS* was plotted versus the monthly predicted peak demand relative to the monthly actual peak demand as shown below in Figure 69 and Figure 70 for *DI* of 20% and 60% respectively. The *MLF* of the buildings is color coded and the annual average building load is denoted by marker size.

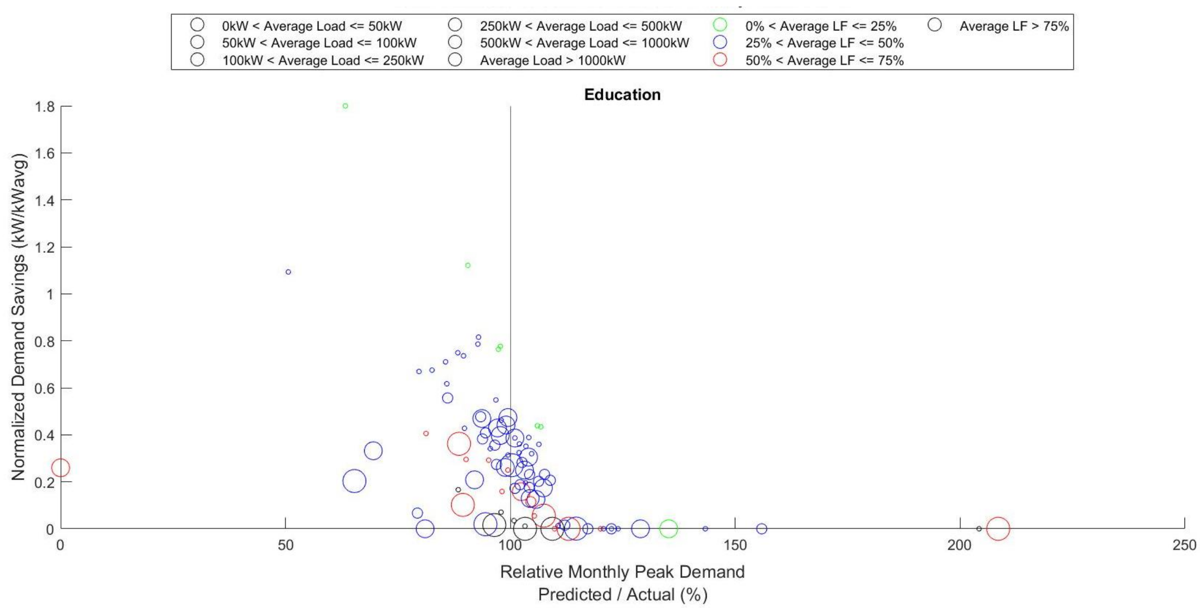


Figure 69: Normalized Demand Savings vs Relative Monthly Peak Demand, Education, 250 kWh Battery, 20% DI

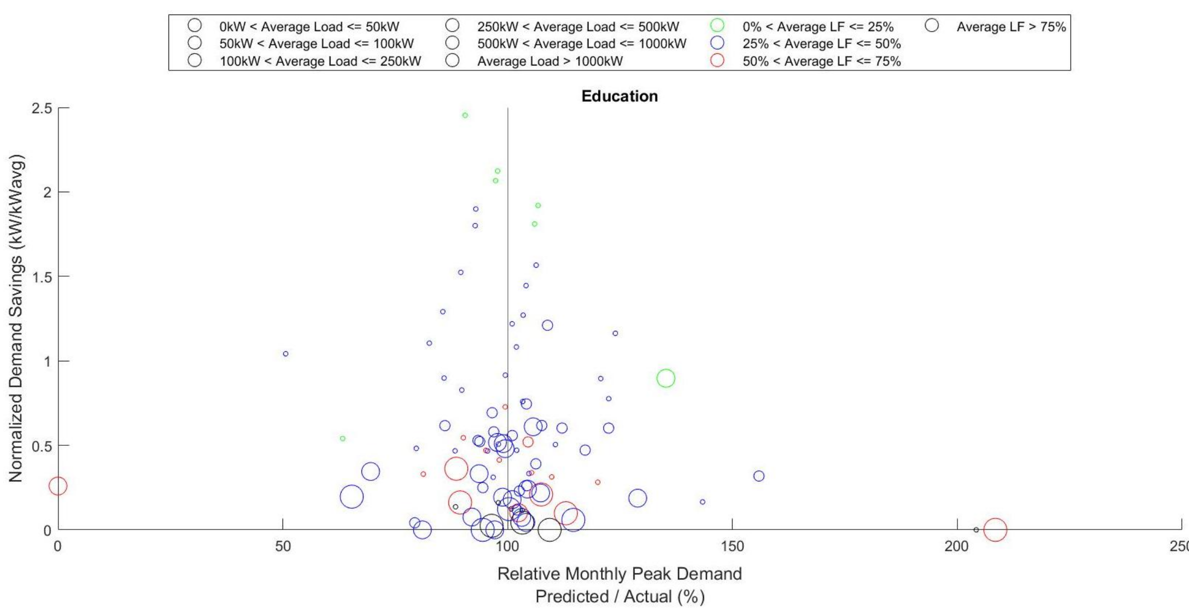


Figure 70: Normalized Demand Savings vs Relative Monthly Peak Demand, Education, 250 kWh Battery, 60% DI

The results above show that for scenarios where a low *DI* was used the best demand savings tended to be in scenarios where the predicted demand was low relative to the actual peak demand. This confirms that even with perfect foresight of the monthly peak demand, if the *TD* for the battery is not set low enough there will be demand reduction potential, and economic benefits, left uncaptured.

The highest demand reduction results are grouped around scenarios where the *PPMD* is close to the *APMD* which makes sense intuitively. Taken together the results from the two figures show that better prediction accuracy results in better demand savings, provided the battery is being run aggressively enough. These results mean that building operators or project developers will be best suited by selecting higher demand reduction targets rather than lightly operating the battery (ex. DI < 20%).

These results continue to show the same trends identified earlier, where large buildings (ex. average load > 100 kW_{avg}) with higher monthly load factors (ex. *MLF* >50%) are poor candidates for demand reduction from a BESS. These trends persist even in scenarios where the predicted peak monthly demand very closely matched the actual peak monthly demand. This means that even in scenarios with high forecast accuracy, the average load and monthly load factor of the building are key determining factors for demand reduction potential.

5.4.4 Health Care Buildings

Shown below in Figure 71 are the results for the Health Care category. The Heath Care category exhibits similar characteristic to the previous categories in terms of lower average *MLF*s having a better opportunity for demand savings and diminishing returns for larger battery sizes.

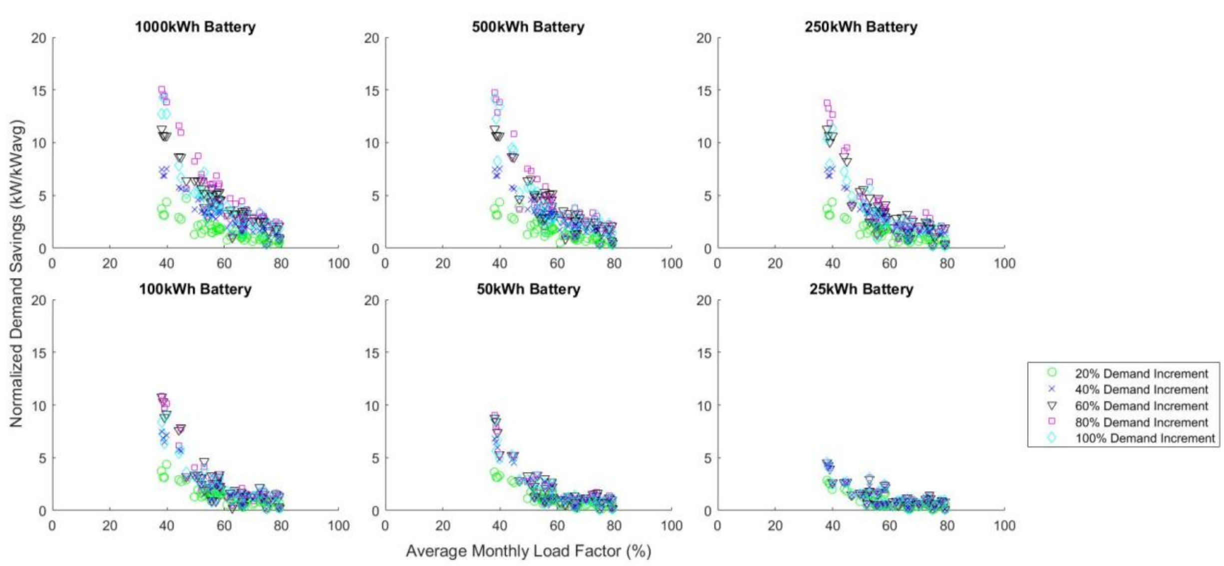


Figure 71: Normalized Demand Savings vs Average Monthly Load by Battery Size – Health Care

5.4.5 Hotel Buildings

Shown below in Figure 72 are the results for the Hotel category. Although the sample size for the Hotel category is small, the results are grouped closely. The Hotel category in particular exhibits poor opportunities for demand reduction because of the combination of high average loads and high *MLF*s. Uniquely, the Hotel category does not have a single building-month with a *MLF* of less than 50%. Additionally, this category has the highest minimum average load, with only a single building with an average load below 100 kW_{avg}. Across all categories when buildings have average monthly load factors above 60% the *NDS* are typically less than 5 kW_{pd}/kW_{avg} except for the largest battery sizes.

As shown in Table 21, the Hotel category retains higher total demand charge savings with slower discharge rates (ex. 8.0 h) relative to other categories. Buildings in other categories with the same load characteristics of the Hotel category (i.e. high average load and MLF), may benefit from a slower charge and discharge rate to attempt to offset the broader load profiles. This means that as new low cost, long duration storage technology becomes available buildings with these load characteristics should be revisited.

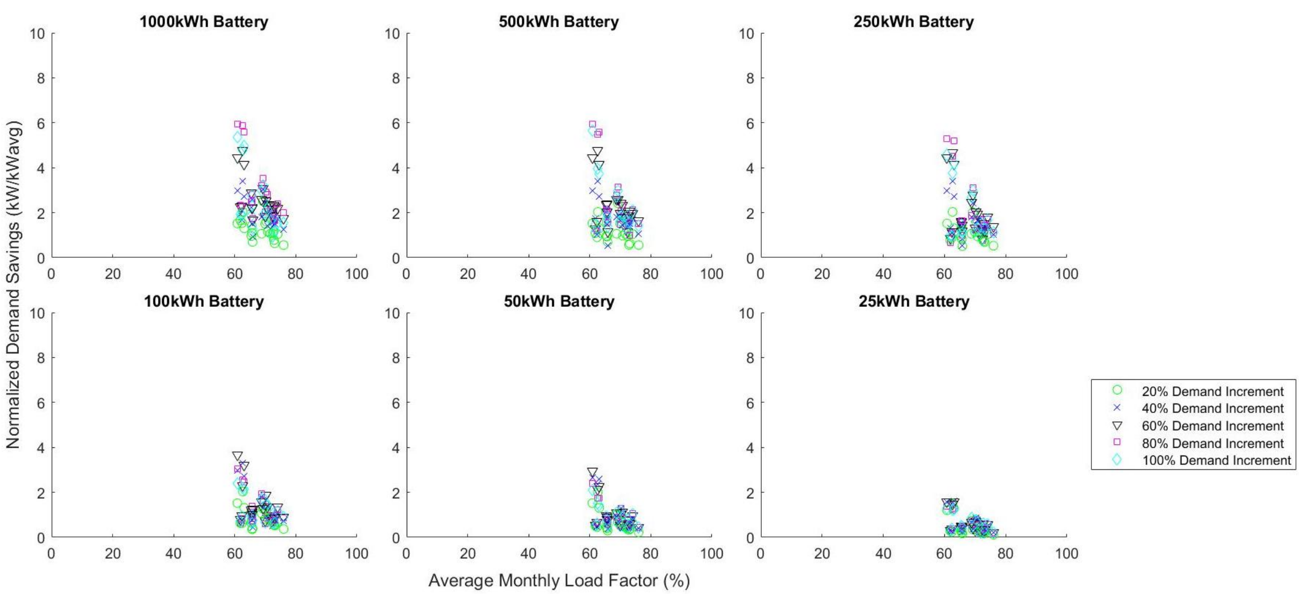


Figure 72: Normalized Demand Savings vs Average Monthly Load by Battery Size – Hotel

5.4.6 Industrial Buildings

Shown below in Figure 73 are the results for the Industrial category.

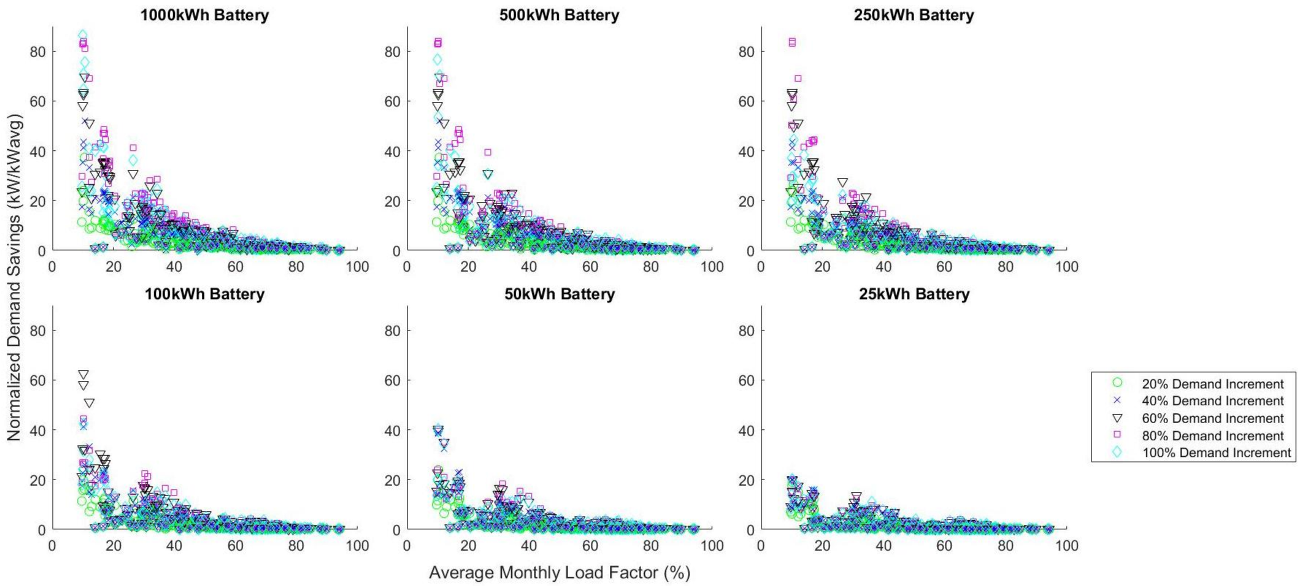


Figure 73: Normalized Demand Savings vs Average Monthly Load by Battery Size – Industrial

The non-linear nature of the results is particularly evident in this category because of the buildings with an average monthly load factor below 20%. The Industrial category also has examples of buildings with average monthly load factors less than 40% that exhibit particularly poor results for normalized demand savings. Figure 41 showed that the Industrial category had large buildings (average loads >500 kW_{avg}) that had average monthly load factors below 40%. To confirm if the buildings with high average loads are the ones with poor demand reduction results, the monthly *NDS* is plotted against the relative monthly peak demand and buildings with a monthly load factor above 40% are screened out. The marker sizes in correspond to the building average load and the are color coded to the monthly load factor.

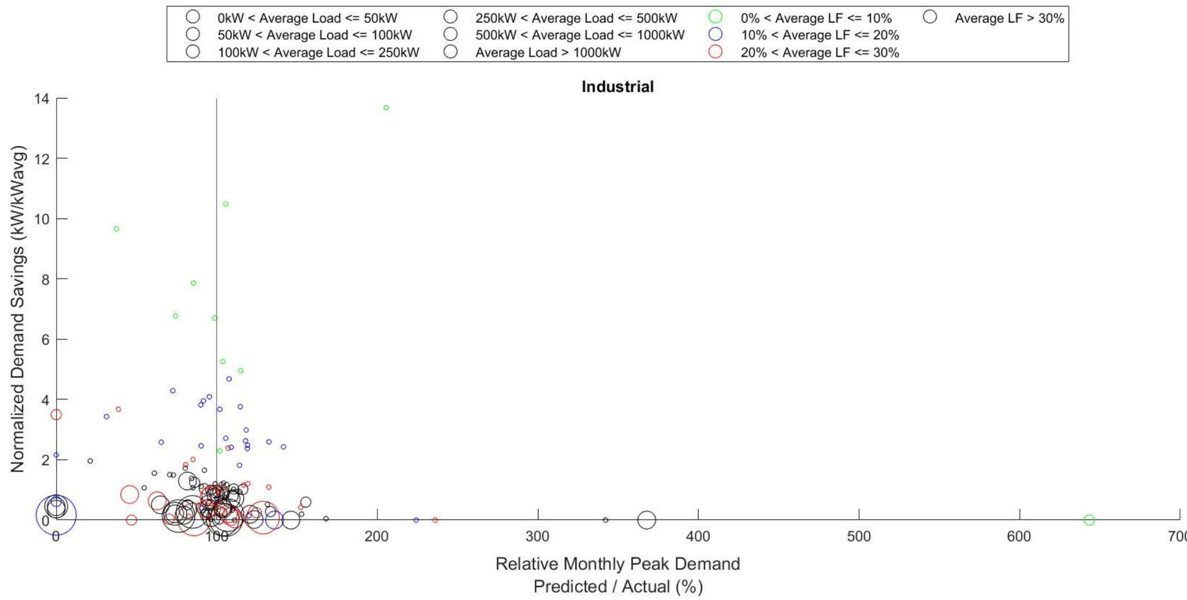


Figure 74: Normalized Demand Savings vs Relative Monthly Peak Demand, Industrial, 250 kWh Battery, 60% DI

The results above confirm that the buildings with poor performance below a 40% monthly load factor tend to have a high average load and tend to have a higher load factor even in the 0% - 40% monthly load factor bracket. These results reinforce the importance of both a low monthly load factor and a low building load as indicators of an opportunity for peak demand reduction with a BESS.

5.4.7 Retail Buildings

Shown below in Figure 75 are the results for the Retail category which exhibits similar characteristics to the buildings discussed above.

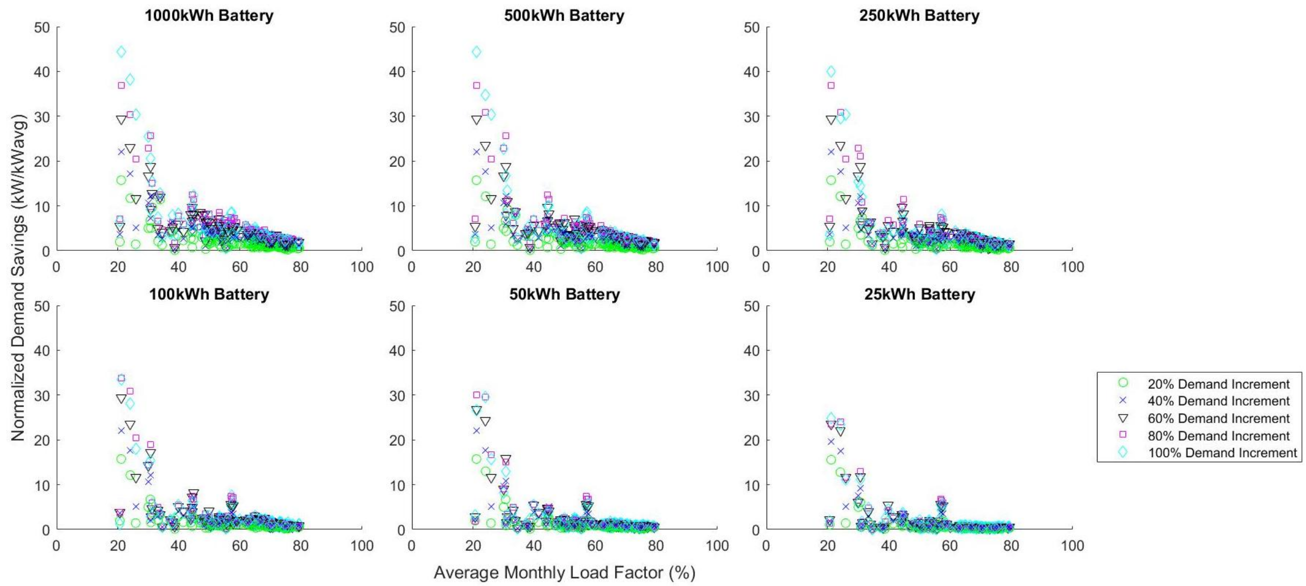


Figure 75: Retail Buildings – Normalized Demand Savings vs Average Monthly Load by Battery Size

5.4.8 Utility Buildings

Shown below in Figure 76 are the results for the Utility category. There are only seven buildings in this category, but a range of average monthly loads and building sizes.

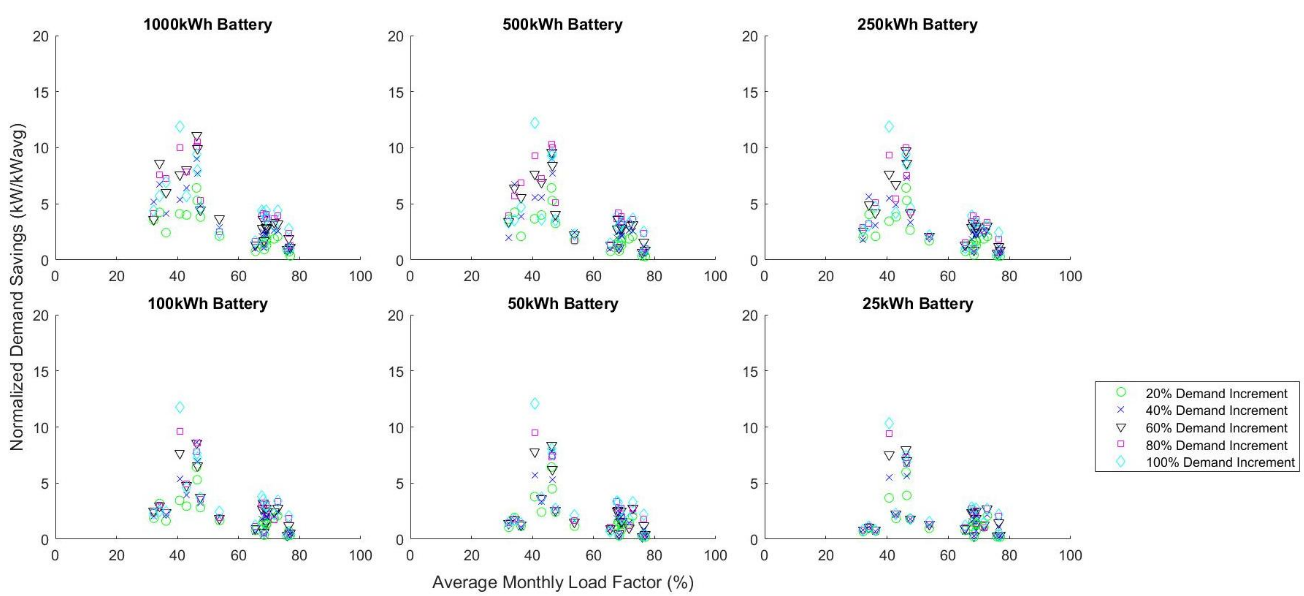


Figure 76: Utility Buildings - Normalized Demand Savings vs Average Monthly Load by Battery Size

The Utility category is unique in that the most promising buildings from a demand reduction perspective have average monthly load factors in the 40-60% range in comparison to other categories. This is because the utility category has more building-months with an average load below 50 kW_{avg} and an average load factor below 50% than building-months with both a low average load and load factor as shown in Figure 77.

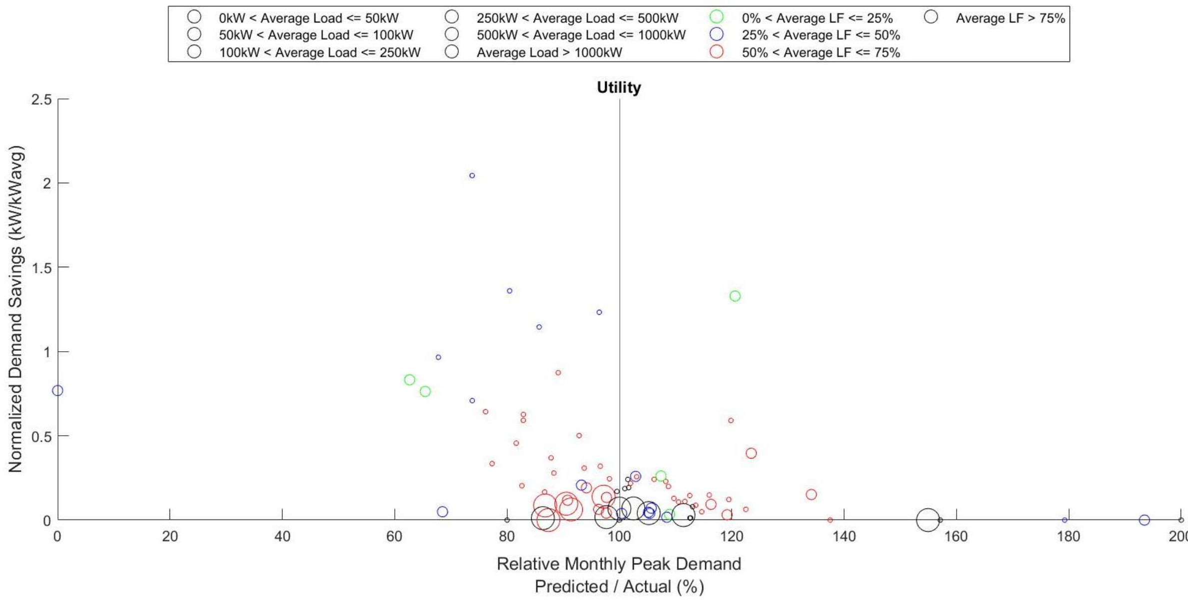


Figure 77: Normalized Demand Savings vs Relative Monthly Peak Demand, Industrial, 250 kWh Battery, 60% DI

5.5 Battery Sizing

Battery pack sizes of 25, 50, 100, 250, 500, and 1000 kWh_{cap} were used in the model. This distribution is representative of battery pack sizes that are commercially available on the market.

Figure 79 shows the optimum predicted demand savings for each building, sorted by category, for all the battery pack sizes. The optimum predicted demand savings is based on the predicted peak building demand and the best demand reduction results on a monthly basis when all the *DI* scenarios are considered. Across all categories and battery sizes it is evident that there are technical diminishing returns for larger battery sizes because the rate of change for the demand savings is decreasing with larger battery sizes. Fixed costs such as engineering, installation, and customer acquisition would favour larger battery pack sizes. There are also clear differences in the effectiveness of battery packs to reduce peak building demand by building category.

Although data for 2018 and 2019 is not shown here, the results for both years are like 2017.

The results of the Commercial and Education building categories show that there are significant opportunities for demand reductions in the range of 10-20% even with the smallest two battery pack sizes (25 kWh_{cap} and 50 kWh_{cap}). The results show that the Industrial category has particularly strong opportunities for demand reductions with relatively small battery pack sizes due to the high number of buildings in the category that have both a low average load and a low *MLF*.

As identified previously, the poor demand reduction results for the Hotel category are due to the combination of high average load and high *MLF*. As with the other categories, there is diminishing returns with the larger battery pack sizes.

To determine if there were common characteristics between the buildings that are the most promising from a demand reduction perspective the demand savings for each battery size was plotted with color coding for average *MLF* and marker size for average building load as shown in Figure 79.

In Figure 80 the specific demand savings relative to the battery pack size (kW_{pd}/kWh_{cap}) are compared per battery size. This confirms that there are diminishing returns in both relative (%) and absolute (kW_{pd}) demand savings as the battery pack sizes increases.

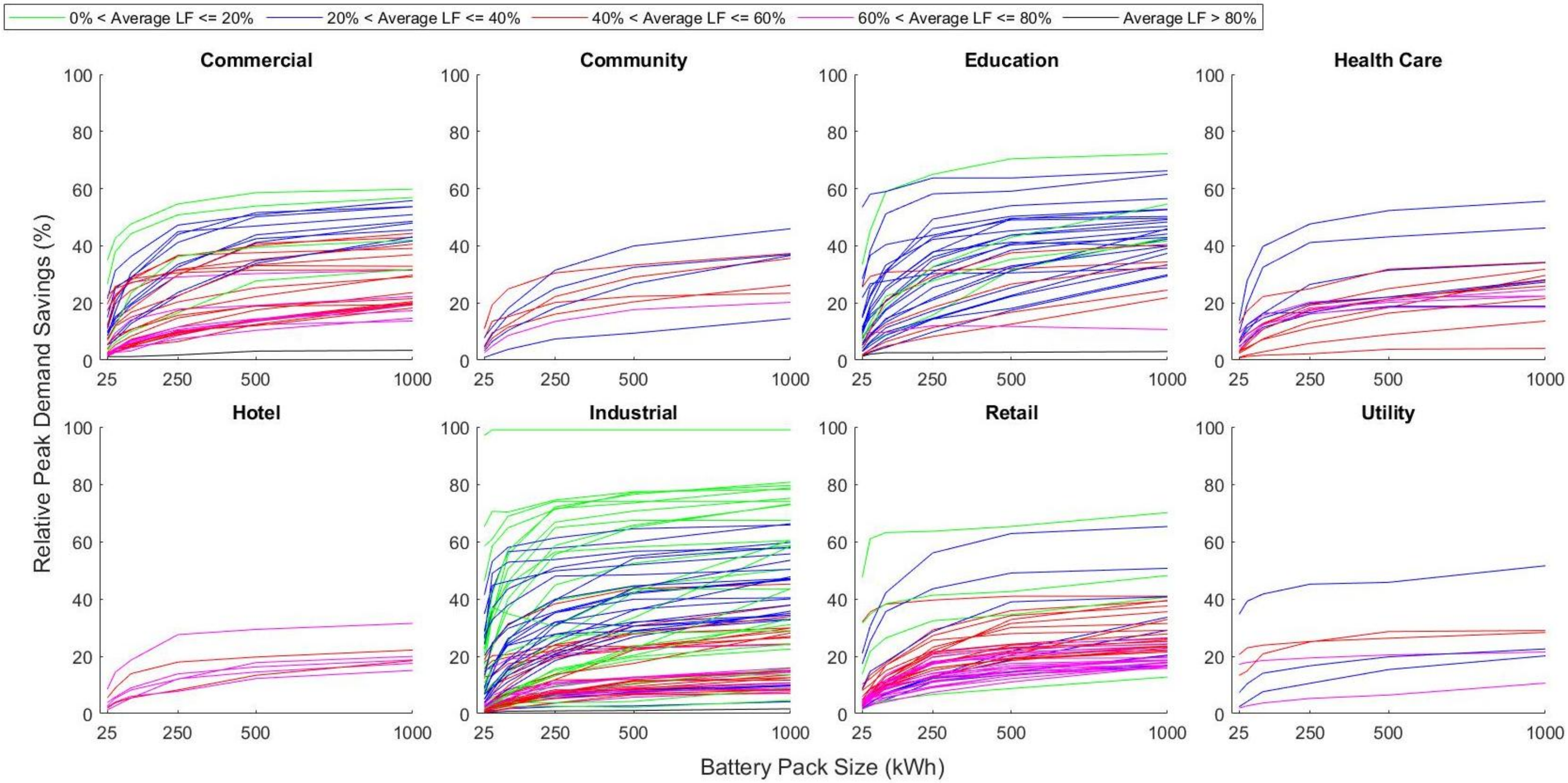


Figure 78: Relative Demand Savings Versus Battery Pack Size - 2017

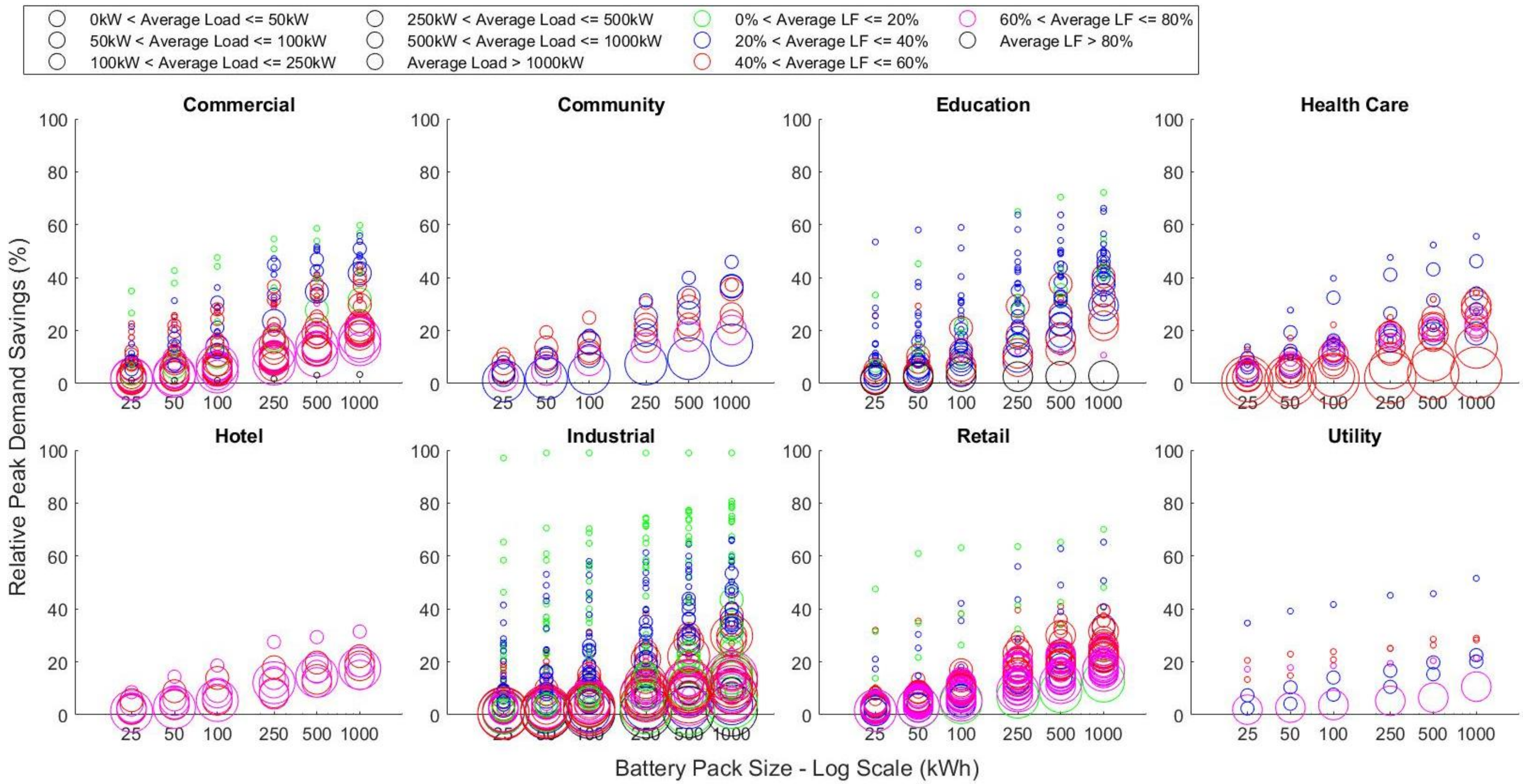


Figure 79: Demand Savings Percentage by Category and Battery Pack Size - 2017

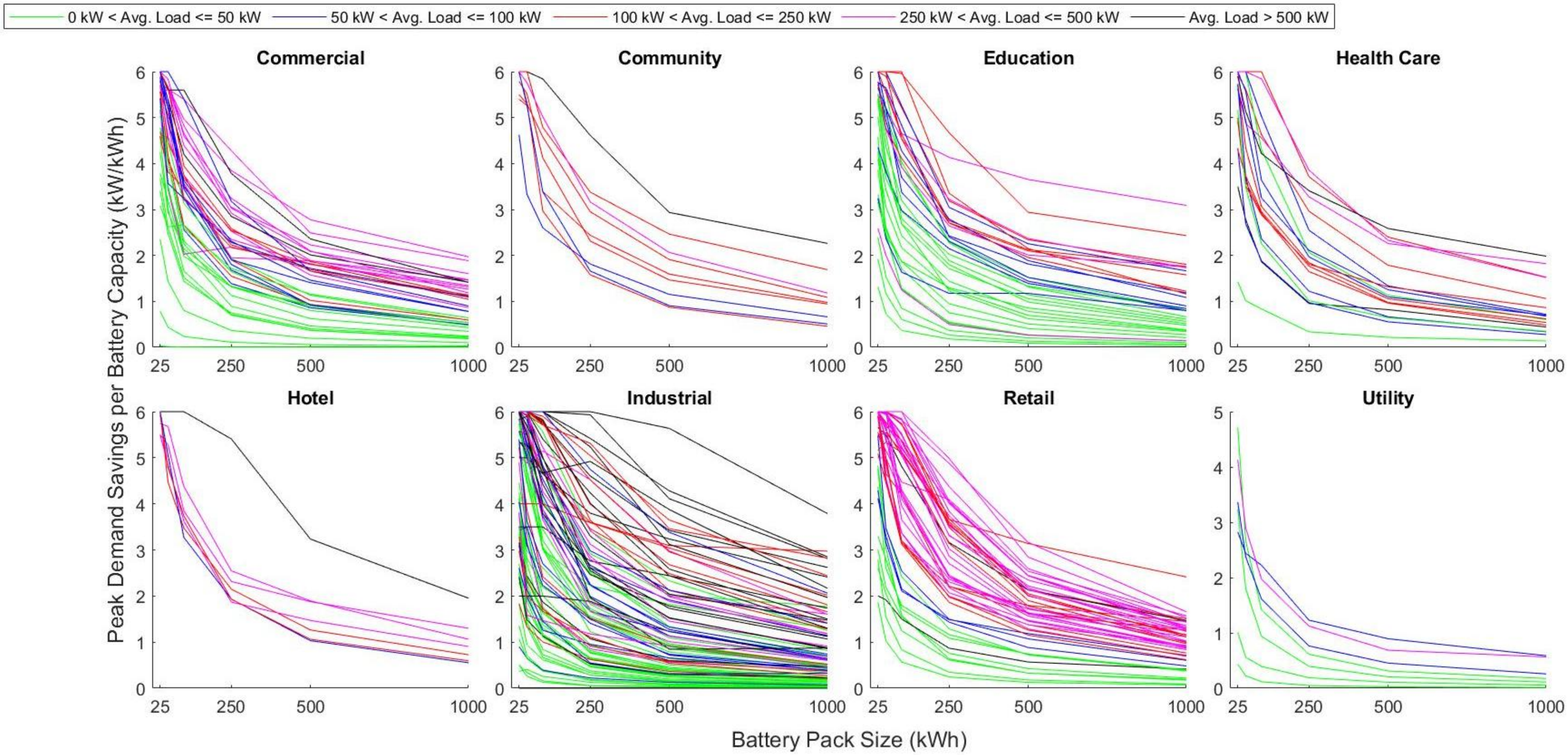


Figure 80: Specific Demand Savings (kW/kWh) Versus Battery Pack Size - 2017

Across all buildings in all categories there are two clear trends that are evident when the results are plotted in this manner:

- It is difficult to deliver large demand reductions, in relation to a buildings load or original demand, in buildings that have a large average load. Some of this may be explained by the tendency of these buildings towards a higher average monthly load factor. Consistently buildings with an average load of less than 50 kW_{avg} offer the best opportunities to reduce the demand of buildings relative to the original demand.
- A BESS in buildings with an average load above 100 kW_{avg} can deliver the highest demand reductions in kW_{pd} relative to BESS capacity in kWh_{cap}, but these demand reductions will not be meaningful in relation to the original demand of the building.
- Buildings with an average monthly load factor of less than 40% tend to offer the best opportunities for demand reductions.
- Based on these two trends, building categories with the best opportunities for batteries to provide demand savings are Commercial, Education, Industrial and, to a lesser extent, Retail buildings because they have buildings that match the load characteristics identified above.

The tendency for the best demand reduction results coming from buildings with average loads of under 50 kW_{avg} and monthly average load factor of less than 40% was consistent across building categories with a strong fit between actual and predicted peak demand (ex. Commercial) and categories with a poor fit between actual and predicted peak demand (ex. Retail). For example, the Retail, Education and Community categories had the lowest R^2 values of 0.904, 0.927 and 0.930 respectively, but there are still strong opportunities for demand reduction, provided the buildings meet the average load and average load factor criteria above. Since the buildings with a smaller load tend to offer the best opportunities for the demand reduction, prediction accuracy for those small buildings is more important than for larger buildings where the likelihood of savings tends to be smaller, even in the categories with a relatively strong fit for the predicted peak demand.

5.6 Economic Analysis

The specific demand savings (kW_{pd}/kWh_{cap}) introduced in Figure 80 is a useful metric for evaluating the economics of a BESS project in isolation from the total utility bills since demand charges are based on a per kW_{pd} basis and BESS pricing is typically listed specifically on an energy basis ($\$/kWh_{cap}$).

Figure 80 shows that for a 2.0 h rate limit and a 250 kWh_{cap} BESS, most buildings have specific demand savings between 1-5 kW_{pd}/kWh_{cap} on an annual basis. Shown below in Figure 81 is the simple payback, ignoring operations and maintenance costs, of BESS projects calculated across a range of net battery costs ($\$/kWh_{cap}$) and specific demand savings (kW_{pd}/kWh_{cap}). The calculations are shown for three demand charge rates of $\$5/kW_{pd}$, $\$10/kW_{pd,}$ and $\$15/kW_{pd}$. The center chart with the $\$10/kW_{pd}$ is close to the demand charge NSP uses in the General Commercial rate code of $\$10.497/kW_{pd}$.

$5 / kW Demand Charge — Specific Demand Savings (kW / kWh)

Net Battery Cost ($/kWh)	1	2	3	4	5	6
$ 100	20	10	7	5	4	3
$ 200	40	20	13	10	8	7
$ 300	60	30	20	15	12	10
$ 400	80	40	27	20	16	13
$ 500	100	50	33	25	20	17
$ 600	120	60	40	30	24	20
$ 700	140	70	47	35	28	23
$ 800	160	80	53	40	32	27
$ 900	180	90	60	45	36	30
$1,000	200	100	67	50	40	33

$10 / kW Demand Charge — Specific Demand Savings (kW / kWh)

Net Battery Cost ($/kWh)	1	2	3	4	5	6
$ 100	10	5	3	3	2	2
$ 200	20	10	7	5	4	3
$ 300	30	15	10	8	6	5
$ 400	40	20	13	10	8	7
$ 500	50	25	17	13	10	8
$ 600	60	30	20	15	12	10
$ 700	70	35	23	18	14	12
$ 800	80	40	27	20	16	13
$ 900	90	45	30	23	18	15
$1,000	100	50	33	25	20	17

$15 / kW Demand Charge — Specific Demand Savings (kW / kWh)

Net Battery Cost ($/kWh)	1	2	3	4	5	6
$ 100	7	3	2	2	1	1
$ 200	13	7	4	3	3	2
$ 300	20	10	7	5	4	3
$ 400	27	13	9	7	5	4
$ 500	33	17	11	8	7	6
$ 600	40	20	13	10	8	7
$ 700	47	23	16	12	9	8
$ 800	53	27	18	13	11	9
$ 900	60	30	20	15	12	10
$1,000	67	33	22	17	13	11

Figure 81: Simple Payback for a Range of Specific Demand Savings and Battery Costs

A line has been drawn for simple paybacks of less than 10 years. Simple paybacks beyond 10 years would be outside the warranty period for commercially available BESS systems. Given the demand charge rates in Nova Scotia, and assuming a \$400-$\$500/kWh_{cap}$ capital cost of commercially available BESS, there are a limited number of buildings with a simple payback of less than 10 years in 2021.

Analyzing Figure 79 and Figure 80 together shows that buildings with an average load of less than 50 kW_{avg} have the best demand reduction opportunities as a percentage of original load, but a BESS in these buildings will not deliver the highest absolute demand savings relative to the capacity of the battery. Conversely, buildings with an average load above 100 kW_{avg} have the highest absolute demand reductions relative to BESS capacity, but those savings represent a smaller impact on the total annual demand of a building. Shown below in Figure 82 is the percentage of utility bill savings that can be realized for individual buildings in each category by installing a 250 kWh_{cap} battery. The analysis assumes all buildings utilize the General Commercial (Rate Code 11) tariffs. This approach was selected so the results reflect the differences in building load characteristics rather than the differences in demand charge rates and energy rates.

The smaller buildings with average loads of less than 50 kW_{avg} and *MLF*s below 40% consistently have the best results in terms of bill savings. This trend holds true across the six BESS capacities tested. Although only the 250 kWh_{cap} results are shown here, the results for the 1000 kWh_{cap} BESS were plotted and the diminishing returns noted in Figure 79 were apparent in the utility bill savings plot as well. This highlights that although some large buildings may have a load profile that allows a BESS to achieve a high specific demand savings (kW_{pd}/kWh_{cap}) relative to a smaller building, the resulting economics of the project will not be material to the building owner, relative to the utility bill, making a BESS project unlikely to proceed.

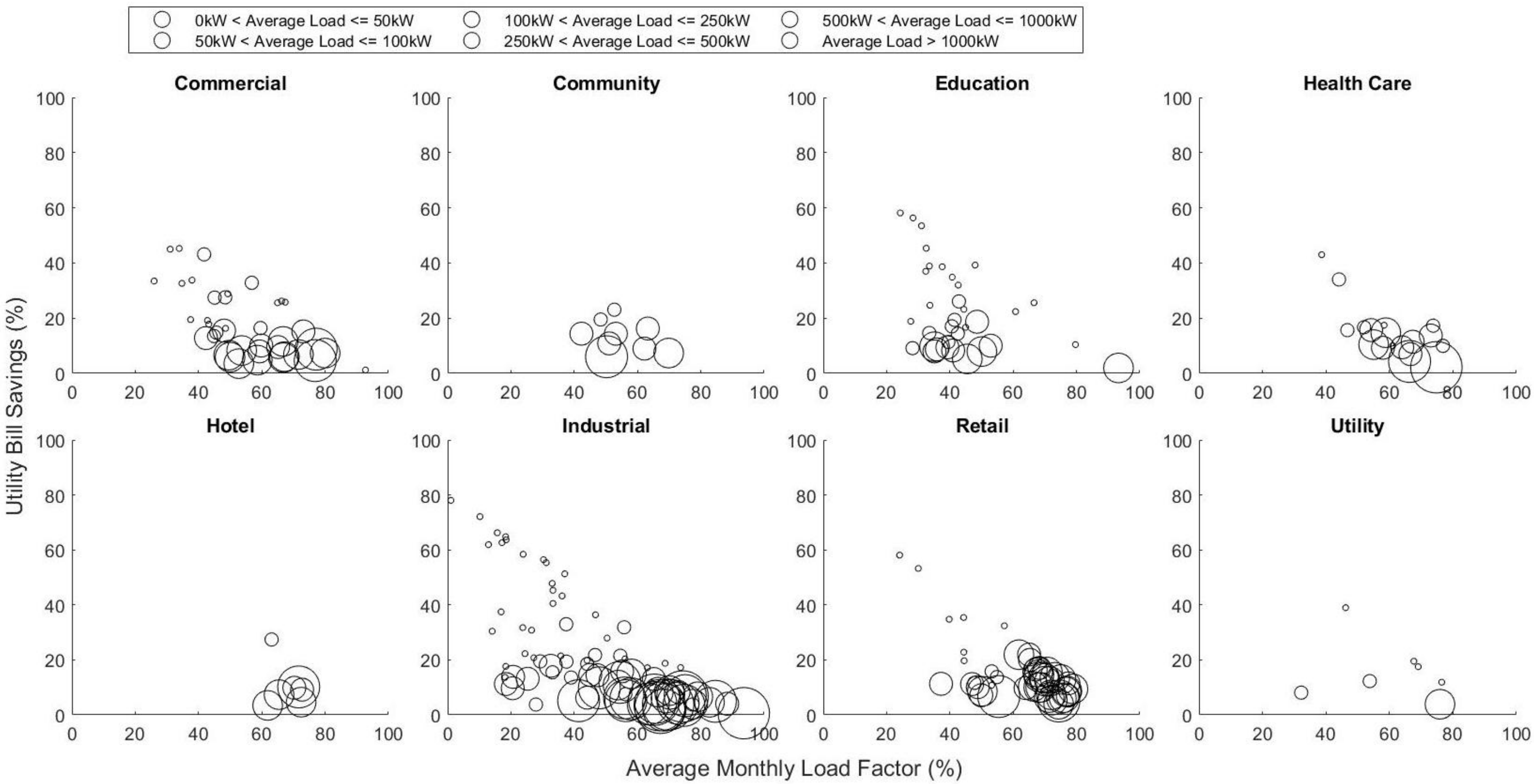


Figure 82: Utility Bill Savings with a 250 kWh BESS vs Average Monthly Load Factor - 2017

5.7 Summary of Results

This chapter details the results of modelling a range of battery sizes and demand reduction scenarios for the commercial buildings. Key findings are listed below:

- Simply using the peak demand from the same month in the previous year yields a reasonably strong (>0.95 linear fit, >0.90 R^2) agreement between predicted and actual peak demand so complex prediction methodologies are not required. Introducing an error adjustment improves (>0.975 linear fit, >0.95 R^2) the prediction results, although this varies by category.
- Buildings with average *MLF* under 40% and average loads of less than 50 kW_{avg} consistently produce the highest demand savings, relative to building load and original peak demand, across all battery sizes and *DI*s.
- Buildings with a lower load factor present better opportunities for demand savings, and the trend is non-linear so buildings with average monthly load factors in the 20-30% range generate significantly better results.
- There are limited opportunities in the Hotel and Utility categories because of the high average loads and high average *MLF*s. Categories with a higher *MLF* retain total demand savings with slower discharge rates (ex. 4.0 h, 8.0 h and 12.0 h) better than categories with lower *MLF*s. This meaning the high *MLF* categories are better candidates for long duration storage.
- The Commercial, Education, Retail, and Industrial categories all show strong opportunities for demand charge reduction, provided the buildings meet the average load and average month load factor guidelines above.
- Since buildings do not typically have narrow 15 min load spikes the slower 2.0 h rate allows the BESS to manage broader morning, evening, or daily peaks. This means for demand charge reduction applications, advances in BESS technology that allow for higher rates will not significantly improve demand savings results versus the commercially available 2.0 h when considering a broad section of C&I building stock. Conversely, a BESS with a duration above 4.0 h, or control strategies that limit the BESS charge and discharge power beyond 4.0 h, will result in reduced savings so are not well suited to demand charge management applications and should be avoided.

- Across all categories of buildings, and nearly all individual buildings, there are technical diminishing returns in terms of demand savings for larger battery pack sizes. This means smaller battery packs tend to deliver the most demand savings (kW_{pd}) per unit of battery capacity (kWh_{cap}). Although battery capacity is a major driver of cost, high fixed project costs such as engineering, installation, and customer acquisition will favor larger battery pack sizes. If fixed costs are low, smaller battery packs will tend to offer a better return on investment. Although this may be the case in modelling, in practice building owners and project developers may be constrained by product availability to larger battery packs that do not reflect the ideal or optimized modelling scenario.
- The building load profile and control strategy can contribute to situations where a smaller battery can outperform a larger battery even when the same peak demand forecasting and original *TD* are used.
- Low battery utilization behavior is emblematic of a demand reduction scenario. This presents opportunities for alternate revenue when the battery is not required for peak demand management. Examples include, but are not limited to, frequency regulation, secure power supply, and reactive power support.
- Across a broad cross section of buildings, the best demand savings results were realized when a *TD* is set using a 60% - 80% *DI*. The predicted peak demand savings relative to perfect foresight increase with *DI*, meaning that the lower the *TD* is set, relative to a predicted peak, the greater confidence a project developer or building owner can have that the BESS project is delivering demand savings close to the optimal results if the peak demand had been known with perfect foresight.
- If a building owner were to install a BESS system, and the predicted peaks were historically higher than the actual peak demand, the operator should not run a mild demand reduction strategy (i.e. 20% - 40% DI) or there will be significant potential demand savings unrealized.

CHAPTER 6 CONCLUSIONS AND RECOMMENDATIONS

6.1 Conclusions and Recommendations

Buildings account for 40% of global emissions and over 33% of final energy use. Given the concerns of addressing climate change, electrification of buildings will be key to reducing long term emissions impacts. Electrification of space heating and transportation sectors will increase demand for electrical energy which will require utilities to recoup the costs of their corresponding infrastructure investments.

Utilities use demand charges to recover infrastructure costs from ratepayers who contribute to the need for grid capacity. Presently demand charges represent 30-70% of a C&I ratepayer’s electric utility bill. As building heating systems are electrified, and charging stations are added for EVs, building owners will have increasing demand charges in monetary terms, even if demand charge rates remain constant.

In parallel to growing electrification initiatives, the pack cost of LIBs has fallen by over 85% since 2010. These cost declines have driven interest in using batteries to reduce demand charges in C&I buildings. Despite the growing interest, using a BESS to mitigate demand charges in exceeding rare when the stock of C&I buildings is considered.

This research explored the following issues relevant to advancing the use of BESS in demand charge management applications in Nova Scotia:

- Correlations between building load characteristics that can be found on, or calculated from, a typically utility bill (ex. peak demand, average load, load factor) and the potential for demand savings as well as the peak demand prediction accuracy using the same billing data.
- The demand savings that a C&I building owner could expect based on building load characteristics and category.
- An analysis of which building categories are more conducive to demand savings with a BESS and why.

To address these topics a literature review was undertaken. Several important gaps were identified in the existing literature that informed the research:

- The literature relies heavily on the US DOE Commercial Reference Building dataset. This dataset has a 1.0 h time resolution which is not aligned with the 15 min billing period used in Nova Scotia.
- Evaluation metrics proposed in the literature are not easy enough to be used as guidelines to allow for rapid screening candidate BESS applications.
- A significant portion of the literature focus on building load characteristics on an annual basis when demand charges are typically billed monthly.
- The control strategies reviewed did not help the user to define demand reduction targets based on the load characteristics of the building. This is missed opportunity as the effectiveness of the control strategy will be reduced if the demand reduction targets are either too high or too low.
- Existing BESS guidelines are written for those first learning about energy storage and provide quantitative analysis to help building owners or project developers screen project opportunities.

To study BESS applications in Nova Scotia, NSP provided RESL with C&I interval meter data from 248 buildings across eight (8) NSP defined building types. The dataset covers the four years of 2016-2019 inclusively with 15 min building load data and includes a range of building sizes from average loads of < 10 kW_{avg} to > 2000 kW_{avg}.

The research contributions of this work are:

- A new MATLAB battery model was developed to perform iterative demand reduction simulations across a range of battery capacities, inverter power rates, and demand reduction targets.
- New methods were developed to accurately predict the monthly peak demand of a building without needing the full load profile, only one year of basic utility billing data.
- New visualization methods to sort results by both building size and load factor so trends between buildings load characteristics and demand savings results can

be identified quickly.

- New guidelines for project developers and building owners to screen candidate buildings for demand charge reduction applications based on building average load, monthly load factor and building category.

To address the guidelines aspect of the research objectives, listed below are practical recommendations that can be used by building owners, project developers, and other industry participants when considering a BESS project for C&I buildings:

- Buildings with average *MLF* under 40% and average loads of less than 50 kW_{avg} consistently produce the highest demand savings across all battery sizes and *DI*s. Use monthly billing data to screen candidate buildings by both average load (<= 50 kW) and monthly load factor (<= 40%). Buildings that meet both criteria should be pursued for BESS projects.
- With commercially available technology, do not pursue BESS projects in Utility and Hotel building categories because the high average load and high monthly load factors typical of these buildings limit the effectiveness of a BESS for demand charge reduction. As new low cost long duration storage becomes available these categories should be revisited.
- The Commercial, Retail, and Industrial categories all show strong opportunities for demand charge reduction, provided the buildings meet the average load and average month load factor guidelines above.
- Historical billing data can be used to accurately predict the peak monthly demand of C&I buildings without complicated methodologies, provided the buildings have a peak demand of less than 750 kW_{pd}.
- Across all categories of buildings, and all building sizes, there are diminishing returns for demand savings with larger battery pack sizes. Smaller battery packs offer the most demand savings per unit of battery capacity and the largest percentage of total demand reduction per unit of battery capacity. Provided fixed costs like engineering, installation, and customer acquisition can be minimized, building owners will find that smaller battery packs provide the best return on investment.
- When developing BESS projects, the demand reduction targets should be set

to at least a 60% reduction relative to the average load to achieve optimum demand savings.

- A BESS used in a demand charge management application has low utilization. Consider what other value, or revenue, streams may be available to improve project returns. Examples of additional revenue streams could include, but are not limited to, frequency regulation, energy rate arbitrage, reactive power support, and backup power.
- Maintenance on a BESS system used for demand charge management should be conducted in the evenings or on weekends to minimize the possibility that a peak demand event corresponds with the downtime for maintenance.

6.2 Research Recommendations

Listed below are recommendations for future research:

- New peak demand prediction methods could be explored to improve the forecast accuracy for buildings that demonstrate significant demand variability year to year and for buildings with peak demands greater than 750 kW_{pd}. This research could incorporate historical weather data and a future weather forecast, ambient temperature, humidity, load shape, change in load rate (ramp rate), and daily load amplitude and frequency among others. A starting point for this research could be a literature and best practices review on how electric utilities conduct day ahead and system peak demand forecasting.
- Study if lower demand targets have any correlation with either a higher frequency of charge and discharge and or a higher throughput of battery energy to determine if there could be different operations and maintenance considerations for a BESS based on control strategy decisions.
- Explore if a variable discharge rate based on SOC could improve demand savings results, and what relation this may have with the base discharge rate (ex. 2.0 h, 4.0 h etc.). This new methodology could include a timer based on how long the battery has been discharging to estimate the remaining duration of the peak demand event and adjust the discharge rate accordingly.
- Research could be conducted on a broad range of existing rate codes and potential future rate codes in Nova Scotia (ex. TOU) or other jurisdictions (ex.

seasonally varying demand charges, ratcheted demand charges etc.).

- Incorporate reactive power into the model to study the relationship between the power factor of a building and opportunities to use a BESS for demand charge reduction, particularly for the rate codes that base the demand charge on kVA_{pd}. Future research on this topic should also include various P-Q inverter curves to explore how the reactive power characteristics of the inverter may help or hinder addressing peak demand.
- Electrification of space heating and the addition of EV chargers will change the load profile of commercial buildings because of the distinctly different use case. Electric load growth modelling for EVs and space heating could be incorporated to explore the effects on the load profile, peak demand, the corresponding demand charges and implications for BESS use.
- Explore what improvement in demand charge reduction results can be achieved by adding both a solar PV and BESS system to the building. In Nova Scotia the addition of solar energy is only likely to improve the demand charge management results for buildings that have an afternoon summertime peak due to cooling loads. In contrast, electrically heated buildings with a winter morning peak will see limited improvements in demand reduction, if any, from a solar PV system.

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