Managing load aggregations and distributed generation resources for peak shaving

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ABSTRACT

Power consumption variation during the day may lead to imbalances in energy supply and demand. To maintain the balance, utilities need to generate more anergy, typically at a higher cost. Demand side management is an effective solution that has been used by utilities to avoid utilizing more expensive, or fossil generation when higher demand is expected.

The use of direct load control (DLC) with aggregation of high number of small loads has been successfully used to reduce electricity costs for energy companies. Virtual power plants (VPPs) are effective methods to strategically coordinate the use of multiple aggregators and small renewable resources.

This study aims to find a method to reduce the electricity peak demand by VPPs optimally managing a fleet of aggregators, diesel generators, solar energy, and battery systems. In this thesis, a simple but effective threshold mechanism is used for peak load shaving. Diversity factors and genetic algorithms are used for identifying optimal scheduling and management of the load aggregations and resources.

As a real example, the available capacity for peak shaving at Saint John Energy Company (SJE) is used. This capacity includes several load aggregators: electric water heaters (EWHs), heat pumps (HPs), baseboard heaters (BBHs), and electric thermal storage systems (ETSs); as well as other energy resources such as a utility battery (UB), diesel generators (DGs), and residential batteries (RBs). Two optimization scenarios are simulated with MatLab® taking into consideration common utility's constraints and disregarding them to identify possible improvements in demand reduction.

DEDICATION

I dedicate my dissertation to my family for the support, patience, and understanding with which they instilled in me the value of perseverance and diligence.

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It's been difficult in a variety of ways to start a research project for the first time. For my part, I've grown into an intellectually and emotionally stronger person because of this steep learning curve. In order to complete my voyage, I needed the aid of folks I encountered along the way.

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In appreciation for the opportunity to work with Prof. Castillo and Dr. Cardenas as my mentors, I write this letter of thanks. Throughout this time, your tolerance, encouragement, effort, and continual feedback kept me going. In fact, I feel like I've gained a lot of knowledge from you. I appreciate all you've done for me, and please know that I don't take it for granted.

Table of Contents

List of Tables

List of Figures

List of Symbols, Nomenclature or Abbreviations

BSS	Battery Storage System
DER	Distributed Energy Resource
DLC	Direct Load Control
DR	Demand Response
DSM	Demand side management
DSM	Demand Side Management
EBH	Electric Baseboard Heater
EER	Embedded energy resources
ETS	Electric Thermal Storage System
EWH	Electric water heaters
GHG	Greenhouse gas
HP	Heat pump
HVAC	Heating Ventilation and Air Conditioning
ILC	Indirect Load Control
LDN	Local Distribution Network
MBC	Model-Based Controller
MC	Monte Carlo
RB	Residential battery
SJE	Saint John Energy
TCL	Thermostatically Controlled Load
TOU	Time of Use
VPP	Virtual Power Plant

Chapter 1

1.1 Introduction

The main goal of a power system is to deliver electricity to their customers reliably. The reliability of the power system is threatened during periods of high demand forcing utilities to use more expensive generation resources. The use of renewable energy sources during high-demand periods is not always possible due to the stochastic nature of the energy that they transform. A virtual power plant (VPP) is a software-based power delivery solution that can manage aggregations of distributed energy resources (DERs) to balance stochastic power fluctuations and help match load demand [1-2]. DERs can substitute the energy provided by non-distributed generation and they can also modify their own energy capacity under the management of a VPP [3]. VPPs can help provide system-wide ancillary services such as frequency control, system restoration, congestion management, loss optimization, and reserve management. VPPs may schedule DERs to supply energy during high-demand hours. This use has proven to have advantages, but it also bears some challenges, particularly when DERs are stochastic in nature [4].

Embedded energy resources (EERs) consist of a collection of some kinds of loads with storage capacity that provide the flexibility required for load-generation balancing and ancillary service (AS). Such EERs are able to store energy that can be charged and discharged when needed. They mainly include thermostatically controlled loads (TCLs), non-thermostatically controlled loads (Non-TCLs) and residential batteries (RBs).

EER consumption patterns can be altered directly by the utility using control signals sent to the devices. This method is known as Direct Load Control (DLC) [5]. DLC is commonly used to reduce the load demand during peak periods with high price of electricity by creating ON/OFF signals or changing TCL temperature setpoints when Demand Side Management (DSM) is implemented. DSM is generally implemented to bring economic benefits to the utilities and consumers.

DSM often relies on the aggregation of loads to alter the load profile of the network. Aggregators facilitate the deployment of control measures without impacting the quality of the service or the user's comfort [6]. Energy resources that are completely responsive to AS are created by aggregating TCLs' stored capacity. TCLs make excellent variable energy resources because they can be directly controlled without affecting end-user comfort.

1.2 Problem definition & Challenges

This thesis was written at UNB as part of a collaboration project between the Emera and NB Power Smart Grid Center and Saint John Energy (SJE) to implement a DSM mechanism for peak shaving. The mechanism contains two levels of control: load-level (aggregators) [7] and high-level control (VPP). This thesis investigates a novel method to deal with the high-level control. A major challenge at this level is to determine the optimum approach to regulate and manage existing EERs so that maximum shaving performance may be achieved while still ensuring end-user comfort. This is addressed in this investigation by simulating a local distribution network with real data from SJE network to create an optimized control mechanism for peak shaving and assess the economic benefits of such actions for the utility, customers, and the environment.

The optimization of network resources has two main challenges that increase the complexity of the task. The first challenge lies on addressing the variability of load demand and peak shaving capacity of aggregators when DERs are stochastic in nature. The second challenge is the selection of what resources to use for peak shaving based on their cost and usage during the billing cycle. Both challenges are addressed in this research by scheduling, controlling and optimizing of ERRs.

1.3 Research Objectives and Contributions

1.3.1 Thesis Objectives

This thesis focuses on the optimization of DERs and aggregations of customer appliances at the VPP level in order to shift the electricity consumption from peak-demand to off-peak-demand hours (peak shaving). The main objective is to provide solutions for reducing electricity supply costs during peak demand times. This can be accomplished by reducing load demand and maximizing the resource utilization during peak demand hours when electricity prices are significantly higher than off-peak hours. An important second objective of the research is to conduct economic analyses of the peak shaving mechanism implemented by our industry partner, Saint John Energy (SJE), during their monthly billing cycle. Simulations are conducted to schedule and control the EERs in order to leverage the price difference between peak demand costs and off-peak energy costs. The customer loads used in this research include aggregators built with domestic electric water heaters (DEWH), Heat Pumps (HP), baseboard heaters (BBH) and electric thermal storage (ETS) units. Other resources considered as part of the fleet of available DERs at SJE network are utility-scale batteries, residential batteries, conservation voltage reduction (CVR) mechanisms, photovoltaic generation (PV) and aggregation of small-scale fossil-fuel-based (diesel) generators.

1.3.2 Research Contribution

The contributions of this research are the following:

- Determined the best optimization method based on peak cost component to reduce the peak-electricity demand on local distribution companies (LDC) and tailored a method specifically for SJE network.
- Showed the economic benefits of optimizing the dispatch capacity of DERs and load aggregations for peak shaving relying on real characteristic of the billing mechanisms used in LDCs.

1.4 Thesis Structure

This thesis is structured as follows: Chapter 2 provides a literature review on the use of aggregations of distributed generation and customers' controllable loads to support efficient electricity delivery as well as existing optimization and control techniques used for peak shaving. Chapter 3 describes the materials and the energy resources that are available to SJE to shift the demand from peak hours to non-peak hours. Also, the SJE billing model, costs and system constraints are presented. A methodology has been applied in order to attain optimum performance and peak shaving. Chapter 4 provides the results of applying the proposed optimization method to shave peak demands of a local utility. The optimization solution is applied to scenarios with different constraints to demonstrate the effectiveness of the method. Finally, Chapter 5 provides the conclusions of the study and suggest directions for future research.

Chapter 2 Literature review

This chapter will discuss about homogeneous aggregations of load and resources to help reduce the electricity demand during peak hours. Also, it is presented regarding the control techniques for peak shaving using VPP, which are cited in the references.

2.1 Homogeneous Aggregators

This research studies the use of homogeneous load aggregations of residential loads to help reduce the electricity demand of a local distribution network. The loads used include DEWH, HP, baseboard heaters, and ETS units. A homogeneous aggregation groups multiple devices of a single type. It is seen as a single, larger DER, and is more manageable by a VPP [7]. Other network resources aggregations like small-scale fossil-fuel-based (diesel) generators, utility-scale batteries, and Photovoltaic (PV) are also part of the fleet of EERs available for peak shaving in this study. This section shows the effectiveness of these aggregations for providing ancillary services to power utilities, with emphasis on their utilization for peak shaving.

2.1.1 Aggregations of Domestic Electric Water Heaters

VPPs and DERMSs have used aggregations of DEWHs. This aggregation has been used to control the collective demands by the DEWHs and to allow DEWHs to participate in power system operations [8-12]. DEWHs contain significant mass of hot water storing the energy that facilitates shifting the time of consumption of individual units without affecting the quality of service to end-users, even if their operation is interrupted for some time. In a pilot project of a local distribution company in Atlantic Canada, an aggregation of 96 3kW DEWHs was able to shift up to 288kW for up to 30 minutes without affecting end-user comfort using direct load control [8]. It was possible to identify thermodynamic characteristics and predict water use patterns by measuring the power consumption of DEWHs in this project. The temperature of the water in the tank was kept constant in the single-zone model provided by Shad et al. This model is valid either when the EWH tank is full or empty of water (all hot or all cold). A first-order differential equation of the heat transmission was used as the foundation for the development of the model [8]. Another study revealed that the aggregation of DEWH loads may be manipulated to help shift the system's peak load [9]. Water heater emulations were linked to a central energy resource manager through an IoT (internet-of-things) network. There was a 10% decrease of peak power demand due to the use of 69 emulated EWHs. The process has been taken place over 24 hours within a range of 0 to 90 kWh utilizing the general dispatch plan and IoT network. The study argues that managing the aggregations can potentially improve grid resilience and save money for utilities and consumers alike without losing end-users' comfort [9].

Changing the thermostat to provide load-balancing services allows researchers [10] to examine the open-loop response of EWH to a centralized control signal. There are 147 homes represented as EWHs in a distribution feeder on a simulation platform that can run electromechanical simulations. EWHs may use up to 30% of a home's peak load and substantially contribute to the peak load. The energy storage capacity of water heaters enables them to be turned off for up to six hours the maximum power reduction is 384 kW [10]. Historically, passive control mechanisms (such as timer or ripple control) were used to fine-tune EWHs performance [11]. Using this mechanism, the control system may be optimized, which in effect boosts the power grid's efficiency. The suggested technique can decrease load fluctuation throughout the optimization phase, taking the base load into consideration. This technique reduced the loads of 100,000 households, including 30,000 EWHs, by 10 to 20 MW. Reference [12] proposes a control method for water heaters that guarantees hot water for customers at all times while minimizing the pick-up demand that occurs when heating components are reactivated after a load-shifting phase. The research relies on a water heater simulation model that was verified experimentally and accounts for the varying hot water withdrawal profiles that exist in the population. The simulation model was given the data of 8,167 actual water withdrawal profiles collected from a variety of customers so that it could assess the performance of water heaters under a variety of different circumstances of operation. Peak reduction potential in [12] is roughly 595 MW when reactivation is phased over a two-hour period, compared to 225 MW when reactivation is uncontrolled.

2.1.2 Aggregations of Domestic Heat Pumps

Heat pumps transfer thermal energy between two places, often an enclosed interior and the outside. Aggregations of HPs have been used to increase the resiliency of the power system [13-16]. A recent study demonstrated the use of centralized and decentralized Model Predictive Control (MPC) to manage Heating, Ventilation and Air Conditioning (HVAC) systems for compensating the variations solar power generation for residential consumption [13]. A compensation of up to 2 MW was achieved using a large aggregation of 10,000 residential HVAC. The aggregated demand response of a population of ACs to changes in thermostat setpoints under fluctuating ambient temperatures is modeled using a second-order linear time-varying model in the receding horizon control (RHC), also known as model predictive control (MPC) suggested in [13]. Another investigation reported in [14] describes an optimal scheduling solution for aggregations of electric heat pumps that reduce power peak demand without compromising user thermal comfort. The method uses a mixed-integer linear programming optimization method with data collected from 20 HPs. The results indicate that the implementation of the optimization process leads to significantly better results, with a load factor up to 90%. The authors of [15] looked into an aggregated control system that would include HPs and wind power in order to balance electricity consumption and user comfort. A forecaster (for wind power generation) and an ON/OFF controller were utilized to save costs and improve efficiency. The authors of this research devised a successful control method that prioritizes the control of the appliances based on their status and users' setpoints according to on room temperature measurements and the information of the status of the available HPs. They achieved the generation-consumption balance using the suggested control algorithm in a simulation of 10,000 HPs with rate of 1 to 10 kW without disrupting temperature settings of the rooms. The study has been able to reduce the demand by 6 MW. The outside temperature was changed from 5 to 15 ^{o}C in a time span of 24 hours with sinusoidal signal pattern.

2.1.3 Aggregations of Domestic Baseboard Heaters

The heat produced by electric baseboard heating systems is distributed without the need for heating ducts, vents, or blowers. The baseboard heaters have the potential to considerably increase power consumption during peak load hours since multiple users may heat several rooms concurrently with multiple baseboard heaters per household [17]. There are few articles discussing the aggregation of baseboard heaters from the perspective of homogeneous aggregation [18]. They were able to postpone peak consumption by storing the power as usable thermal energy before the peak time using a smart thermostat and a setpoint controller. Power was turned off during peak hours to lower the overall load demand while keeping people comfortable. The thermostat temperature increases by 10 ºC during preheating periods and decreases by 10 degrees Celsius during peak times. As predicted, the total demand increases during off-peak hours and decreases during peak hour. Average daily energy savings of 6.8% were obtained, with morning and afternoon peaks decreasing by 36.2 and 24.6%, respectively. Reference [18] also shows that up to 8 kW, out of 12.05 kW can be reduced from a BBH participating in a demand response program, showing the potential of their aggregation for peak shaving. Reference [53] shows the effects of the strategy on the aggregation assuming peak time from 7 to 9 am also randomness of some parameters including outdoor temperature on offer capacity for 200 BBHs. The simulation was run under the assumption that at least one and no more than two walls in each room are open to the ambient air temperature outside. The ambient temperature is assumed to be the starting point for the temperature control algorithm, as stated in [53]. The initial on/off states of the EBHs are similarly randomized in a consistent manner, with fifty percent of them being on.

Using 1200 BBHs with four methods (DTFC controller, SBC controller, OFF-controller, and Setpoint controller), and taking into account the controller's ability to maximize the requested capacity and the impact of outside temperature on the control of the aggregated power, Reference [7] was able to reduce 401, 397, 400, and 401 kWh in peak duration per day as offered capacity.

2.1.4 Aggregations of Domestic Electric Thermal Storage units

The electric thermal storage (ETS) is an electric residential heating device that utilizes efficient storage media to store energy during periods when electricity costs are lower and deliver the stored energy when costs are higher. ETSs have become popular in the North American market since they provide a cost-effective heating option for both, customers, and power providers. Good et al. [19], employed an aggregation of electro-thermal storage to provide an optimization solution for day-ahead market. The solution minimizes retailer costs, which are represented by import/export and gas expenses, as well as projected real-time balancing costs. They use two tests of a portfolio of 50 residential flats to quantify user discomfort a "price of discomfort test" (total expected costs 468 $) over the "deadband test" (costs and disbenefits of 7924 $) and a "deadband test" leading to results showing 94 percent reduction in total costs without impacting end-user comfort [19].

To the best of our knowledge, there are not many papers reporting the use of aggregations of ETSs to provide ancillary services [20-23]. The authors of [20] examined a strategy for integrating renewable energy sources like as wind power (maximum capacity of 20MW) and 550-units ETSs into medium-sized systems. ETS was modeled as a thermal battery with a minimal standby loss and a tunable discharge rate. Based on time-of-use and dynamic techniques, the authors analyzed two distinct control strategies (ON/OFF controller) for charging and discharging ETSs. Time-of-use is a control technique based on pricing signals, while individual ETS units may be dynamically regulated. They found that utilizing ETSs with time-of-use management might cut power consumption further, but dynamic ETS control (at big quantities) becomes important to prevent new peaks and energy loss. A conclusion stated that ETSs and wind resources might serve complementary roles and work in tandem to economically satisfy energy balancing requirements. Average generation savings of ETSs per ETS unit is between 700 to 900 $ (total 385 to 500 k$) per year.

2.1.5 Aggregation of Diesel Generators

Dispatchable generation, like diesel generators, are commonly used in distribution networks to help maintain the load demand balance. Some researchers have recommended to combine the management and scheduling of local diesel generators with energy storage system, and Conservation Voltage Reduction (CVR) to address issues associated with production and consumption imbalances during peak periods [24]. The power is split between the diesel generator and the energy storage system during peak demand. The DG model described in [24] consists of a governor and the engine itself, with the governor being a combination of a speed regulator and an actuator. The diesel generator's participation in this kind of solution [24] reduced the power flowing through the connecting line from 1550 kW to 1100 kW. Diesel generators have been extensively used by utilities to support peak shaving when a focalized injection of power is needed at specific times [25]. There are three tariffs in [25]: demand ($/kW), consumption ($/kWh), and excess of demand ($/kW). The energy compensation during the peak time of the day in [25] according to the consumer's tariff structure. The economic feasibility of the proposed peak shaving system is determined by comparing the value of kWh generated by the diesel generator set to the value of kWh acquired from the utility [25]. The contribution of the diesel generator in [24] decreased the power flow from 2500 kW to 2000 kW. A stochastic cooperative energy management technique for linked microgrids to optimize cost of microgrids using an independent performance indicator is provided in reference [26]. Loads that are able to respond market price are eligible for DR programs. An iterative process of scenario development and reduction is used as a decision-making strategy to describe the uncertainty associated with renewable power as stochastic [26]. The rated power of two DGs in [26] are 300 and 400 kW, respectively. According to the price signal, diesel generators contributed 270 kWh during peak time. Khalid et al. [27] examined off-grid communities to find out how to size and place grid-owned DG rather than an isolated micro-grid. The authors of the study [27] took a step further by including the ideal site selection into the optimum design of DG and BESS size. Loss-voltage-factor (LVF) was created to guarantee fewer losses and higher voltage quality when determining the optimal placement of distributed generating units. The nominal power of the diesel generator in [27] is 4 MW, but in the optimal state, a maximum of 1.5 MW has been used during the peak time.

2.1.6 Photovoltaic Generation

A photovoltaic (PV) system is made up of solar panels to generate the appropriate voltage and current. Mohammad et al. [28] established a transactive market-clearing model based on mixed-integer linear programming (MILP) and optimal power flow (OPF) for managing the aggregation of large-scale solar photovoltaic (PV) farms and demand response (DR) capable loads. This study uses reinforcement learning to optimize the scheduling an ESS. The benefit of using the aggregator calculated in [28] is $1270 in a day at assumed power rates (the capacity of the ESSs is between 0.7 to 1.5 MW), which is precisely the difference between the operational cost without DR and the DR compensation cost passed on to end-user consumers. The research [29] examines the development of domestic power consumption patterns resulting from the widespread deployment of solar PV systems and battery storage. The penetration rate of PV-only and PV with storage systems, as well as the kind and functioning of battery energy storage systems, are explored under the scenarios. The impact of solar PV penetration on residential demand on an average clear-sky (sunny) summer day is between 200 kW and 800 kW.

2.2 Control techniques for peak shaving with VPP

The control techniques for peak shaving in VPP reviewed in different references [30–34]. A recent review [35] identifies some relevant research papers [36–45] that study the optimization and coordination in the virtual aggregation of energy, as well as their limitations. Kasaei et al. [36] employed an imperialist competitive algorithm for optimum energy management. The variability in the outputs of wind turbines, solar panels, and thermal and electrical loads was considered to pursuit maximum power from a VPP in [36]. Kasaei et al. created a day-ahead scheduling model that used a 2m-point estimation technique to handle uncertainty in order to lower VPP costs. Using algorithm for optimum energy management and also according to the low rated power rate used in this study, an average profit of $100 to $150 per day, at assumed power rates, has been obtained. Baringo [37] offered a technique for the strategy of a day ahead and real-time energy market in VPP, this VPP functions as a entity and optimizes its own resources. A hybrid optimization technique was reported by Baringo [37] where wind power production uncertainties were modelled using robust optimization and market price uncertainties were modelled using stochastic optimization. This problem is described as a mixed-integer linear programming (MILP) problem based on Karush–Kuhn–Tucker (K-K-T) optimality requirements and strong duality theory [37]. The average daily profit, at assumed power rate, achieved by the VPP across all strategies is $48861.

Optimization at virtual power plants is the subject of more recent research papers [38]. This study focuses on the categorization and in-depth examination of current research proposing VPP models with interactions with various forms of energy markets. Each resource's penalties for not responding as planned to the day-ahead schedule are discussed in [39]. Using a set of renewable energy resources, the proposed model creates a reliable, cost-effective, and environmentally friendly distribution system. VPP decision-makers identify the most cost-effective alternative for feature power production depending on their individual project budget. This essay provided the most practical approach for enhancing DGs, ESSs, and microgrid integration using the Monte Carlo method and the symbiotic organisms search algorithm (SOSA) also the stud krill herd algorithm (SKHA). The findings indicated that the proportion of renewable production to total generation is 43%. In this research, just two diesel generators supplied power to the loads, while grid purchases accounted for around 35 % of total production. The electricity cost for the first year at assumed power rate is decreased to $600,000. Probabilistic models for optimum day-ahead scheduling of electrical and thermal energy resources in a VPP were investigated by Zamani et al. [40]. They developed an optimization technique based on a two-stage Point Estimate Method for a virtual power plant (VPP) in Canada. They aimed at optimizing the profitability of the plants by bidding planned combined heat and power (CHP) power to the day-ahead market and the VPP's available reserve capacity to the rotating reserve markets. The VPP included a wind turbine, solar photovoltaic (PV) units, (CHP) units, electric boiler, demand response resources (controlled load), electrical storage, and thermal storage. Without part-load efficiency modeling, the CHP efficiency is assumed to be constant, resulting in considerable outcome uncertainty. The average daily profit of the VPP at assumed power rate in [40] is $763.

VPP portfolio optimization using multi-criteria optimization heuristics is researched in [41] to concurrently supply cross-sector integrated services for enhanced flexibility provisioning and to create a visible, verifiable, and trustworthy management framework. VPP in [41] takes three optimization aims into account: reducing operational reserve needs, reducing carbon dioxide emissions, and increasing power plant adaptability. Three metaheuristics from the computational intelligence area of evolutionary computation algorithms—simulated annealing (SA), particle swarm optimization (PSO), and ant colony optimization (ACO)—were utilized to effectively construct this control approach

[41]. The power consumption by VPP in this study has decreased between 5 and 10 %. Day-ahead scheduling algorithms have also been extensively explored [42-45] due to their applicability to the time scales used by VPP scheduling, which typically uses 1 to 24 hours as scheduling periods and intervals, respectively.

Authors of [30] reported a detailed strategy for examining the viability of utilizing a VPP to benefit both the plant side and demand side. They used historic data from a Japanese smart community, known as Higashida District, to examine the energy-saving potential of a VPP consisting of a PV and an energy storage system. The VPP's economic evaluation was done using analyses of payback periods and a life cycle cost. Also, cooperative game theory was used to investigate the possibilities for collaboration in view of the profit imbalance between the demand and plant sides. This research considered the impact of government subsidy programs on both the plant and demand sides. Authors identified profits on the demand and plant side of 130 thousand and 21 million US dollars at assumed power rate in a period of 30 years.

The costs and benefits of building a realistic virtual power plant (VPP) in Western Australia, consisting of 67 houses, are calculated in depth in [31]. The VPP is intended to combine and coordinate rooftop photovoltaic (PV) systems, vanadium redox flow batteries (VRFBs), heat pump, and demand control methods. The usage of a heat pump offers households a unique ability to conserve energy and lower the overall cost of power, in addition to controlling demand for this type of appliance. The research conducted in [31] demonstrates that customers may save up to 24% of their energy costs when VPP optimization is conducted. Additionally, implementing the VPP generates an annual rate of return of, at least, 11% with a payback time of less than nine years.

Reference [32] considers a VPP that trades in day-ahead and reserve energy markets. The main research objective of [32] is to determine the VPP's optimal strategy in these two markets to maximize the anticipated profit. Confidence bounds and intervals (85%) are used to simulate the uncertainty of the available wind power production and reserve deployment demands, also scenarios are used to model the uncertainty of the market pricing. Consequently, the resulting model is formulated as a stochastic adaptive robust optimization problem, which is addressed using a column-and-constraint generation approach. The energy market's trading range is between 80 MW and 110 MW, whereas the participation in each reserve market is limited to 70 MW.

The implementation of a load shifting strategy based on charging and discharging a battery energy storage system (BESS) is presented in [33]. Using dynamic programming, the BESS develops an ideal operating strategy to reduce power consumption as much as possible while still meeting the limits imposed by the battery. This research was conducted with the goal of finding the cheapest possible BESS for meeting a customer's minimum power consumption while yet providing enough savings to the consumer. The research shows that an annual saving on the energy bills of 4% (power demand decreased by 8%) could be achieved when compared to a similar scenario without BESS. The research also demonstrated lack of significant peak shaving benefits when the discharge time (peak-demand widths) was longer than one hour.

Reference [34] presents a self-developed model for simulating virtual power plants as DR agents in grids with decentralized energy resources. The main goal of the research is to maximize the final VPP profit by optimizing the management and scheduling of various generation facilities, storage systems, and energy consumption. The objective function reduces expenses by taking bids for energy and reserve items from suppliers, generators, and DR into account. Quadratic cost functions are used in every bid. The research includes a case study of a 32-bus distribution network with 66 generating units, 218 consumers, and five suppliers. Researchers concluded that the VPP operating expenses are dependent on the quantity of the reserve resources needed and the utilization of the power reserve. They reduced the network power consumption by about 750 kW while considering the objective function of minimizing the VPP costs.

Homogeneous aggregators and control techniques for peak shaving with VPP cites a number of references that showed the need for aggregators and techniques to shorten peak profiles and duration, reduce losses, and have less of an impact on the environment while also increasing the resulting profit and efficiency.

Chapter 3 Materials and Research Methodology

This chapter describes a methodology that has been applied in order to attain optimum performance and peak shaving. This methodology, the control algorithm and implementation with SJE data are described in this chapter. Then the chapter will describe materials and resources that are available to SJE to reduce demand during peak hours. Also, the SJE billing model, costs and system constraints are presented.

3.1 SJE resources

Saint John Energy is a local electricity distribution company that provides electric power to more than 36,500 residents of the city of Saint John, New Brunswick, Canada. Their electricity rates are the lowest in the region and account for 10% and 3% less expensive for residential and commercial customers respectively [46]. NB Power is the wholesale electricity supplier and uses a demand rate of approximately $15.00 for the monthly maximum kW demand [46]. The peak demand charge, based on this rate, ranges from over 1 million in early summer to over 3 million dollars during the coldest month of each year [47].

SJE has invested in various solutions to reduce the maximum demand and, therefore, to reduce the cost of electricity and the rates applied to their customers. The goal has been to shift the energy from peak demand hours to non-peak hours by using alternative, less expensive, distributed generation and demand side management strategies in the form of direct load control of aggregation of customer loads. Table 1 shows the list of energy resources that SJE is currently using as part of a peak load demand reduction pilot project that should be extended in the future upon its success. With the current set of EERs, maximum, and optimistic, peak demand reductions ranging from 6% to 14% are expected.

Table 1. List of SJE Embedded Energy Resources and maximum capacities

Energy Resource		**Number of units**	**Maximum capacity**
	Diesel generator	4	3.2 MW
	Utility scale battery	1	1.25 MW
	PV generation	1	500 kW
Aggregations of TCLs	*RB*	50	367 kW
	EWH	1500	6.15 MW
	HP	200	800 kW
	BBH	85	148 kW
	ETS	50	300 kW
Total			**12.72 MW**

3.1.1 SJE TCLs

TCLs can store energy, which may be used by DSM strategies for load balancing in LDCs like Saint John Energy. In direct load control strategies, ON/OFF and setpoint controls are typically used with TCLs, and there are a number of control algorithms that allow managing the demand of aggregations of these devices using these controls. Some of these algorithms are Direct Temperature Feedback Control (DTFC) and Stochastic Blocking Control (SBC). Some of the TCLs used by SJE provide information about temperature values, setpoints, and the device status, which can be accessed remotely. The EWH used in the pilot project, for example use Aquanta [48] controllers, ETSs use proprietary APIs from their manufacturer (Stash) [49], BBHs use Mysa controllers [50], and HPs use controllers from Intesis [51]. The TCL models used in this study have been developed previously by the research group at UNB [7, 52, 53] and include the information and controllability provided by these existing controllers. DTFC, SBC, OFF-control, and Setpoint controllers were modified by these previous works to be compatible with the features and behaviour of the SJE controllers. Although SJE and the UNB research group have gathered data from a subset of TCLs already deployed, the amount of information is not significantly large, it has been enough to validate the load models.

Electric water heaters and Heat Pumps HPs

EWHs and HPs are attractive candidates to participate in peak shaving strategies because they are common appliances that are used all year long. The 1500 EWH units currently available for SJE pilot project have power rates (3, 4.5 and 4.8kW) can reduce up to 6.15MW in the event of turning them all off concurrently. The strategy followed with an aggregation of EWHs has been to provide the maximum energy capacity they can without sacrificing the comfort that users expect from them. Details of the models and control algorithms used by these aggregations can be found in [7, 52].

HPs, like EWHs, can be used to support peak load demand shifting any time of the year due to their heating/cooling modes. SJE currently has 200 remotely controllable units. The total maximum capacity of the aggregation is 800 kW however, the available energy capacity that the aggregation of HPs can provide is calculated considering the residential user comfort associated to their preferred setpoint settings [7]. Setpoint control is the default control method to modify the energy demand during peak hours.

Baseboard Heaters and Electric Thermal Storage units

Baseboard Heaters and ETSs are room heating devices that are only used during winter months. SJE utilizes Mysa controllers to turn ON or OFF the BBHs. The controllers can also provide information about user settings and the temperature values of the rooms they are heating. As with other EERs, the operation of the aggregated load of BBHs is simulated with computer models, but the control algorithm uses setpoint control [7, 52]. The aggregation of 85 BBH units used in the pilot project has a maximum capacity of 148 kW with individual units power ratings between 1 kW and 2.5 kW.

SJE employs aggregated power of ETSs using Stash controllers. The number of 50 expected as part of the pilot project is 50 and the individual capacities range between 2.4 kW and 9 kW. The maximum total nominal capacity of the aggregation of these units is 300 MW. Maintaining user comfort levels during the cold months is the basis for calculating the available aggregated capacity of both BBHs and ETSs.

3.1.2 Battery energy storage devices

SJE has deployed one utility energy storage systems from Tesla to use for peak load reduction purposes. The battery interconnects to the grid via a Tesla bi-directional inverter. The system is configurable for 2 to more than 6 hours continuous charge/discharge, managed by SJE's SCADA system. The maximum power output of 1,250 kW and the maximum nominal energy production is 2325 kWh.

SJE also uses residential batteries as EERs available for peak shifting. The RBs employed by SJE are combined battery-storage and electronics systems managed by a cloud-based software platform from Sunverge. The pilot project uses 50 RB units with nominal capacities ranging from 2.5 to 9.7 kW, for a total maximum capacity of 367 kW.

3.1.3 Dispatchable generation

SJE utilizes four Diesel generation units. Two DGs are owned by the utility and the other two are rented. The largest generator has a maximum nominal output of 1250kW, seconded by one 750 kW unit and two others 600kW generators. The total capacity of the aggregation of four DGs is 3.2 MW. DGs have the highest operation costs among the other resources mentioned so far due to fuel costs and renting conditions.

3.1.4 Other available resources for reducing the peak demand

Conservation Voltage Reduction (CVR) is extensively used for two primary purposes: peak-load reduction and minimizing annual energy usage. CVR is also closely connected to carbon emission reductions. Moreover, decreased voltages enhance the life of transformers since iron losses are proportional to operational voltage levels [46]. CVR is one of the most cost effective, easiest to utilize methods to adopt during peak shaving. SJE CVR mechanism is setup to execute in 5 stages (Stages 0 to 4) where stage ‘0’ is normal SJE load where CVR is in restored or off and stage 4 would be full CVR applied which results in ~3.77% total load decrease. Figure 1 shows example of the application of the conservation voltage reduction to reduce peak demand. Table 2 shows SJE CVR configurations in each stage:

Table 2. SJE CVR Configuration

CVR Stage	**Approximate % of Voltage Reduction**	**voltage setpoint equivalent**
0	0%	Nominal Voltage 7.46kv
1	0.98%	Voltage setpoint 7.39kv
2	1.75%	Voltage setpoint 7.35kv
3	2.50%	Voltage setpoint 7.28kv
4	3.77%	Absolute minimum voltage setpoint 7.19kv

When CVR is triggered, the CVR program enters stage 1 and taps the voltage to the stage 1 setpoints, if the load is maintained, no further action is taken, and the load is continuously monitored. If the load begins to increase or continues to increase, the CVR is advanced to stage 2, then monitored, etc., until stage 4 is reached. CVR returns to stage 1 when the load falls below the peak value minus a bandwidth value, and to stage 0 (off) if the load continues to decrease.

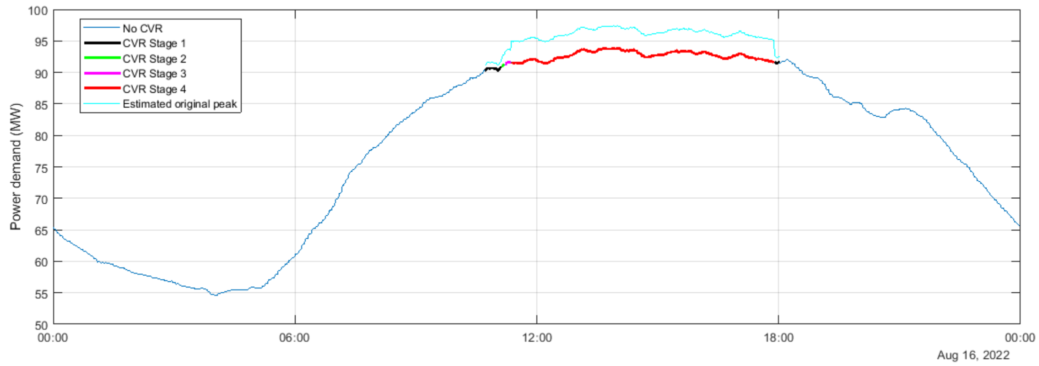


Figure 1. Example of the application of the conservation voltage reduction to reduce peak demand.

3.2 SJE data forecasting, investment cost, billing model, and constraints

The following section discusses SJE data forecasting, investment cost, billing model and constrains.

3.2.1 SJE electricity demand forecasting

SJE receives daily forecasts that predict the next 30 days ahead of the electricity demand the utility is expected to supply. The forecasts have one hour resolution and are mainly used by the utility to predict future peak loads. These forecasts are instrumental for scheduling system resources that help reduce the peak demand and the cost associated with the demand charge. Knowing in advance when the maximum peak demand is likely to happen helps the utility to charge energy storage resources prior the biggest demand, to create demand response actions preventing some loads to operate during the peak period, and to contract small generation resources. However, the prediction error that forecasts inevitably have may affect this process. In the worst-case scenario, a non-predicted maximum demand will invalidate all the efforts made to accommodate energy resources. Detecting a peak erroneously may increase operation costs because resource scheduling and operation may not have the impact expected and may incur in other costs that cannot be compensated for. Therefore, it is convenient to have shorter term forecasts with higher accuracy to reschedule resources in the event of corrected forecasts. For this reason, SJE also uses 24 hours ahead and 7 days ahead forecasts. The mean absolute percentage error (MAPE) for the 24-hour ahead forecast is below 3%, which allows to have more certainty when scheduling resources.

Figure 2 shows the forecast generated for August 16th, 2022, as an example of the forecast accuracy achieved, in this case MAPE was 1.63%.

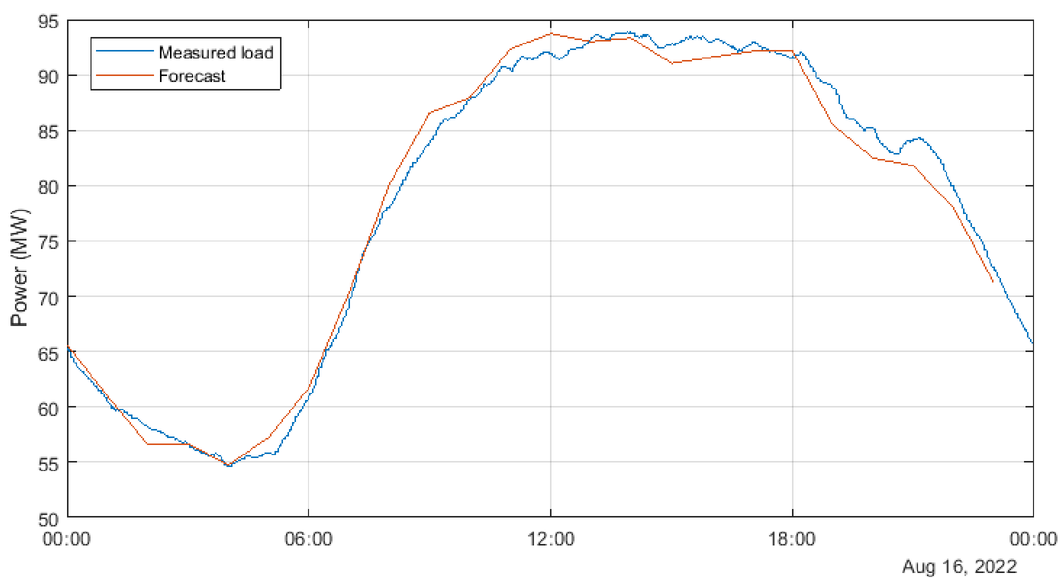


Figure 2. Example of a 24-hours ahead load forecast

3.2.2 Peak shaving associated costs

Peak reduction strategies have several associated costs. One of the first ones is to contract and/or deploy the resources that will be used for peak demand reduction. For example, SJE has customer incentive programs that allow the utility to remotely access their thermostats and modify their temperature setpoints to modify their demand. Typical appliances involved in these programs are EWHs, HPs, BBHs and ETSs. Other costs are related to instrumentation investments necessary to upgrade standard (non-smart) appliances and their communication mechanisms. Equations 5-8 and Table 3 describe various reference costs that SJE incurs since it began the pilot project for reducing their peak demand with embedded energy resources. Investment costs in Eq. 5 and also Eq. 8 sum of the costs of purchased units plus other miscellaneous costs calculated over the period of one years. Miscellaneous costs (Eq. 7) include maintenance, installation, and control costs. Table 4 shows the disaggregation of costs per user appliances included in the pilot project in SJE.

Table 3. Variable names in Eq. 5 - 7

Symbols and abbreviations		**Symbols and abbreviations**	
$Cost_{Invest}$	investment cost of unit	$Cost_{MisCont}$	Controller cost
$Cost_{Mis}$	Miscellaneous cost	$Cost_{MisMain}$	Maintenance cos
$Cost_{U}$	Unit cost	$Cost_{MisIns}$	Installation cost
$Cost_{UEWH}$	EWH Unit cost	$Cost_{UBBH}$	BBH Unit cost
$Cost_{UHP}$	HP Unit cost	$Cost_{UETS}$	ETS Unit cost

$$Cost_{Invest} = Cost_{U} + Cost_{Mis} \qquad \text{(Eq. 5)}$$

$$Cost_{U}(\text{ per 10 years}) = Cost_{UEWH} + Cost_{UBBH} + Cost_{UHP} + Cost_{UETS} \qquad \text{(Eq. 6)}$$

$$Cost_{Mis}(\text{per 10 years}) = Cost_{MisIns} + Cost_{MisCont} + Cost_{MisMain} \quad \text{(Eq. 7)}$$

$$Cost_{invest}(\text{per month}) = \frac{Cost_{invest}(\text{per 10 years})}{120} \quad \text{(Eq. 8)}$$

Table 4. Investment costs per customer appliance involved in SJE's pilot project

Aggregator	**EWH**	**BBH**	**HP**	**ETS**
Number of Devices	1500	85	200	50
$\boldsymbol{Cost_U}$ *(CAD)*	400.00	150.00	1,400.00	400.00
$\boldsymbol{Cost_{MisIns}}$ $(\boldsymbol{CAD\ per\ 10\ years})$	200.00	200.00	200.00	200.00
$\boldsymbol{Cost_{MisCont}}$ $(\boldsymbol{CAD\ per\ 10\ years})$	200.00	200.00	200.00	200.00
$\boldsymbol{Cost_{MisMain}}$ $(\boldsymbol{CAD\ per\ 10\ years})$	200.00	200.00	200.00	200.00
$\boldsymbol{Cost_{invest}}(\boldsymbol{CAD\ per\ month})$	5,005.00	111.00	2,338.00	172.00
Total investment cost per month (CAD)				**7,626**

3.2.3 SJE billing model

SJE is billed for the energy it supplies to their customers on a monthly basis. NB Power is the energy provider and offers competitive rates to the utility. As a very large business/industrial costumer, SJE energy bill has two separate charges. The first one is the energy charge, which is 6.7 cents/kWh that accounts for the use of energy. The second component is the demand charge, 14.60 CAD /kWh as per July 2022, which penalizes maximum power demand. The maximum demand is defined as the peak demand within the billing cycle that is sustained for at least 15 minutes. Reducing the demand charge is instrumental to reduce the billing charge as shown in Figure 3 and Table 5. Figure 3 shows the averages of total, demand, and energy charges during the last two years. As expected, charges are higher during colder months, but the contribution of the demand charges can be deemed significant. Table 5 presents monthly charges in more detail, showing that demand charges account for around 30% of the total charge. Figure 4 to Figure 7 depict load demand during four months in 2021. These examples let us conclude that peak demands are complex, sometime difficult to forecast if there are similar days with high demands, and that reducing a single maximum peak does not equate to significant demand charge reductions. Therefore, one of the goals for reducing the supply costs is to reduce the maximum peak demands along with improving the load factor ($load\ factor\ = \frac{average\ load}{peak\ load}$) of the network.

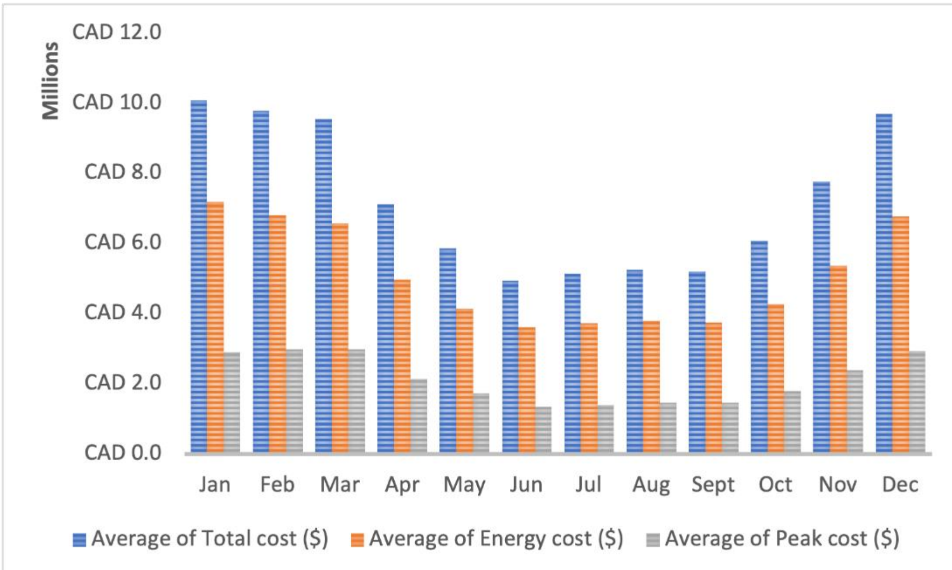


Figure 3. Average monthly billing charges. Period Jan 2020 to Dec 2022**.**

Table 5. Billing charge examples to SJE

	November 2021		**December 2021**		**January 2022**		**February 2022**	
	CAD	%	CAD	%	CAD	%	CAD	%
Energy cost	5,217,520	68.58	6,875,187	70.62	8,189,103	71.58	7,011,435	69.41
Demand cost	2,390,896	31.42	2,859,600	29.38	3,251,289	28.42	3,089,535	30.59
Total	7,608,416	100	9,734,787	100	11,440,392	100	10,100,970	100

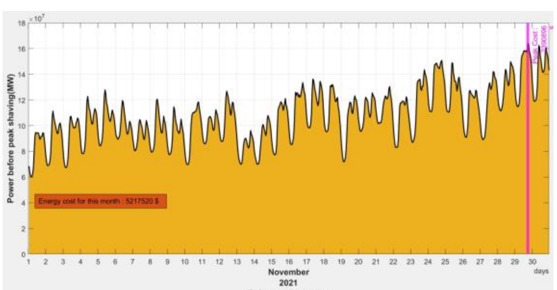


Figure 4. Load demand before peak shaving in November 2021

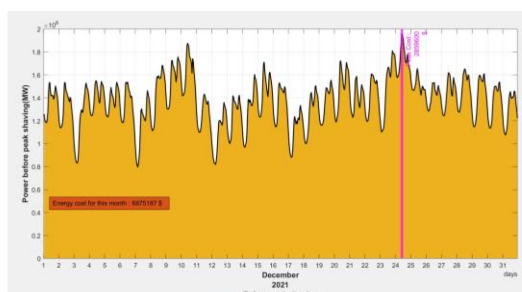


Figure 5. Load demand before peak shaving in December 2021

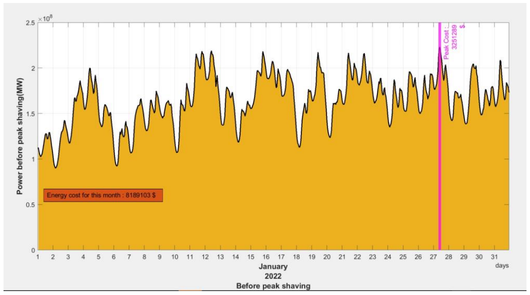


Figure 6 Load demand before peak shaving in January 2022

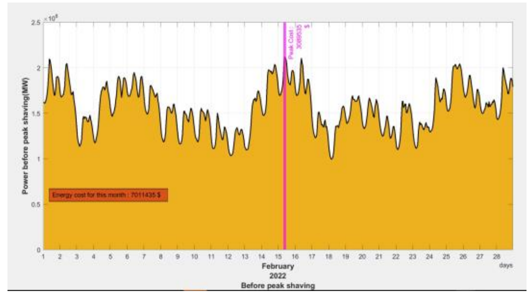


Figure 7 Load demand before peak shaving in February 2022

***3.2.4 SJE constraints on the use of energy** resources*

There are several constraints that SJE operators and scheduling systems must be aware of to utilize the resources available fully and efficiently for reducing the maximum electricity demand in the system. Keeping end-user comfort when remotely controlling customer appliances is a constrain, that when it is not considered, costumers tend to drop out the demand side management program. If such happens, the available resources may be reduced drastically. Diesel generators also have constraints associated with maintenance schedules, maximum utilization times and starting time conditions that may prevent their utilization in real time or if scheduled when unavailable. For example, diesel generators are only used for a maximum of 8 hours of generation per month and a minimum of one hour per day every time a generator was engaged. The utility scale battery has also constraints on the maximum number of discharge periods per month. These and other constraints are to be included in the solutions proposed in this work.

3.3 Research methodology and control algorithm

The peak electricity demand can be reduced by making use of the energy stored by load aggregators, battery systems and by the low-cost energy generated by other renewable and/or dispatchable generation resources. The first step to consider by the any peak reduction algorithm is to accurately detect or predict the occurrence of peak demands. Once the peaks are identified, available resources will be scheduled and engaged to supply the energy needed to reduce the demand charge.

As aforementioned, forecasts play a significant role in this process, but other factors like historic peaks for each specific billing cycle, may also be considered to reduce the risk associated with forecast errors. Initially, a demand threshold is estimated using 30-days ahead forecast, historic peak values and maximum capacities of available resources. Resources are scheduled to reduce the highest peak but are updated daily to allow maximum reduction. Figure 8 replicates the load demand during January 2021 (as in Figure 6) along with the initial threshold. As can be seen, in order to reduce the demand charge, not only the maximum peak on the 27th needed reduction because other lower but very similar peaks occurred around the 12th, 16th, 19th, 22nd and 23rd of the said month.

A peak shaving mechanism based on the identified SJE system constraints and their currently available resources is shown in the flowchart in Figure 9. It includes three stages and 10 sub-blocks, namely load forecasting and peak detection, optimization and calculation/output. The mechanism operates as follows:

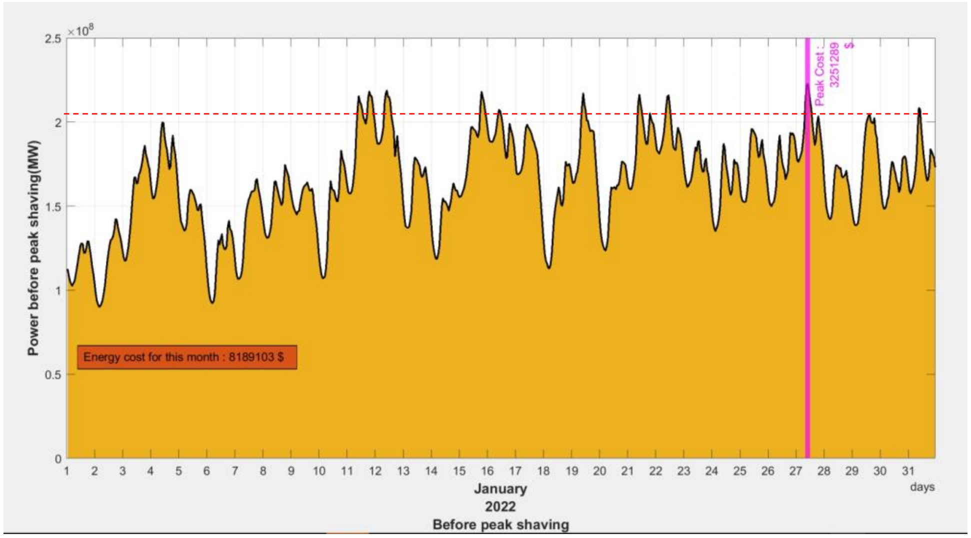


Figure 8. Example of demand threshold (red dashed line) estimated at the beginning of a billing cycle

Initially, the available actual and forecasted load demand data are received and read, as shown in block 1 of Figure 9,. Then the initial threshold for the first day of the billing cycle is obtained by averaging daily peaks that occurred during the same billing cycle in the previous years, as well as one month ahead forecast. The peak shaving mechanism is scheduled to engage when the forecasted peak is above the estimated threshold. Load forecasts are available by 03:30 every day and communication with the VPPs and EERs takes place at this time.

The more probable peak loads demands are selected based on the forecasted data, and a plan is made to use DG and UB, considering their respective usage constraints (blocks 2-3). Following this a priori selection, an optimization algorithm using a genetic algorithm (GA) is executed (blocks 5-8). The optimization procedure uses a genetic algorithm because the nature of each EER is stochastic, variable, and the potentially long duration of peak shaving commitment of aggregated EERs makes it difficult to use direct mathematical solutions. Mathematical solutions may not converge or be computationally expensive. Common types of stochastic optimization algorithms include simulated annealing, genetic algorithms, and particle swarm optimization. We have adopted a GA solution because it is a random-searching algorithm with strong global searching capabilities that rapidly selects the ideal solution by simulating a principle of natural selection. Genetic algorithms model natural selection and inheritance processes like as crossover and mutation. Starting with a random starting population, it develops a group of people who are more suited to the environment by using random selection, crossover, and mutation processes, such that the population progresses to a better and better area of the search space. After generations of continuous reproduction and evolution, the optimal solution to a problem will finally converge on a group of people who are best adaptive to their environment [59]. There are a number of studies which have utilized GA for peak shaving. One example is the study conducted by J.M. Lujano-Rojas et al [60]. This study [60] focuses on a GA for direct-load control, allowing to determine the best scheduling window when loads may begin and end their enrollment in peal shaving. This solution aims to mitigate the influence of DLC on customer satisfaction by correlating daily forecasts of renewables and meteorological data with a genetic algorithm to efficiently deploy DR resources so as to maximize renewable energy resources integration and minimize battery discharge.

During the optimization step, depicted in Figure 9, there are two important variables: 1. Duration of using EERs aggregation and 2. Magnitude of power demand of EERs. The optimization algorithm finds the optimal contribution of each local system resources (aggregators, utility scale battery, diesel generators, CVR, etc.) for the purpose of minimizing peak costs satisfying a diversity factor equation (Eq.9) [55]. The genetic algorithm optimizes the use of the available capacity of EERs, prioritizes those resources that have lower costs and limits the use of the most expensive ones such as diesel generators.

The optimization process occurs as follows: at first (block 5), the genetic algorithm produces an initial population according to the EER-related variables 1. Duration of using each EERs aggregation and 2. Magnitude of power demand of EERs. Then based on the initial population, the VPP requests aggregators and other system resources to get an estimation of the energy that those resources can commit to the peak shaving event and schedule the time and magnitude of the contribution expected during the peak period. Then it sorts the results of the initial population from the point of view of the objective function (diversity factor) from low to high and selects the top 80% and performs mutation and crossover operations and produces a new population. This process is repeated until the elite selection is found.

After optimization is completed, the maximum available capacity of EERs is determined according to all the restrictions and calculations related to net benefit and then the cost savings are performed (block 9). The peak estimation and shaving process is executed until the end of the billing cycle to ensure that the maximum peak is never missed (block 10).

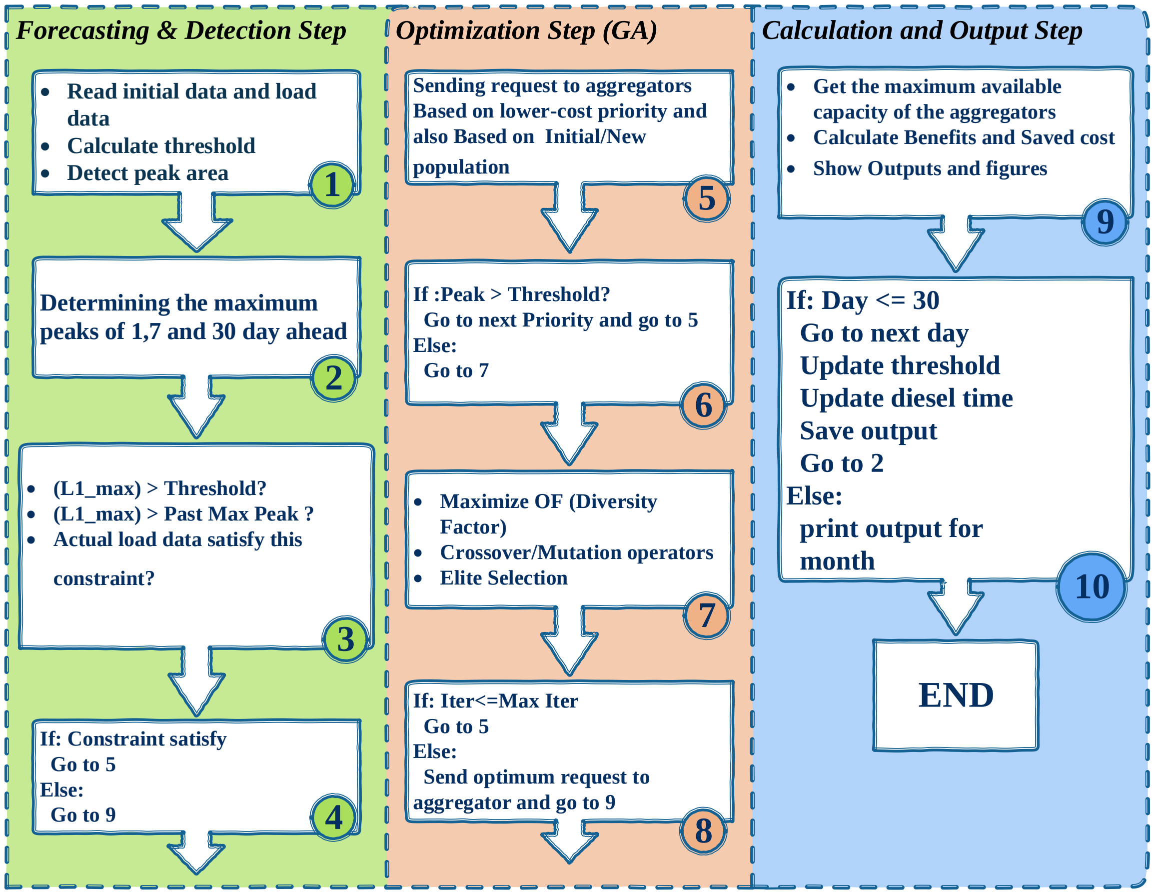


Figure 9. Proposed peak-demand shaving mechanism

Equations 10 - 13 and table 6 are used to calculate the amount of cost savings during each billing cycle.

Table 6. Variable names in Eq. 9 - 13

Symbols and abbreviations		**Symbols and abbreviations**	
$\boldsymbol{\beta_{on}}$	Demad charge rate	***load***	*Demand load*
β_{off}	Energy charge rate	Aggregator (i)	*Power of Aggregator (i)*

$$Maximize\ (Diversity\ factor_{at\ peak\ time}) = Maximize\ \left(\frac{\sum_{i=1}^{n} \max\ (Aggregator\ (i))}{\max\ (load)}\right) \quad \text{(Eq. 9)}$$

$$\text{Cost saving}_{\text{peak}} = (\text{max. load}_{\text{ no Peak Shav.}} \text{-max load}_{\text{ with Peak Shav.}}) \times \beta_{\text{on}} \quad \text{(Eq. 10)}$$

$\text{Cost saving}_{\boldsymbol{energy}} = (\text{Energy Cost}_{\text{no Peak Shav}} - \text{Energy Cost}_{\text{with Peak Shav}}) \times \beta_{\text{off}}$ (Eq. 11)

$\text{Cost saving} = \left(\text{Cost saving}_{\text{peak}} + \text{Cost saving}_{\boldsymbol{energy}}\right)$ (Eq. 12)

$\text{Cost saving}_{\boldsymbol{total}} = \text{Cost saving - } Cost_{invest} \text{(per month)}$ (Eq. 13)

Figure 10 shows the technique employed to account for inevitable forecast errors. At first, planning is done based on forecast load but a real-time operation that monitors actual data is also implemented. Full peak shaving is performed in times when both load forecast and actual load exceed the threshold, which means that all aggregators and sources, including diesel generators, use their maximum available capacity to participate in peak shaving when needed. If only the load forecast is above the threshold and the actual load is below the threshold, peak shaving will not be performed. If the actual load is above the threshold and the forecast load is below the threshold, only CVR and UB, which are more accessible than other sources, participate in peak shaving. If both loads (forecast and actual) are lower than the threshold, peak shaving will not be performed.

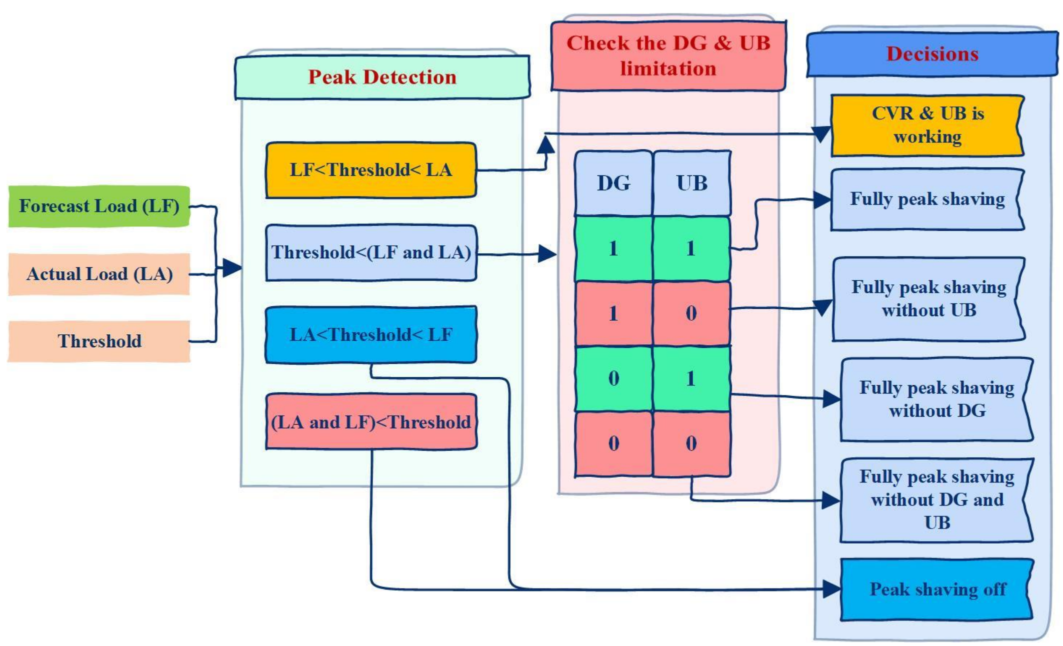


Figure 10. Peak shaving mechanism in the presence of inevitable forecast errors

All simulations have been created and evaluated using MATLAB-based UNB smart grid simulation platform. In line with the limits imposed on utility size batteries and diesel generators, the next chapter tests two situations, one with and one without constraints.

Chapter 4 System Optimization and Economic Analysis

4.1 Introduction

This chapter provides the results of applying the proposed optimization method to shave peak demands of a local utility. The optimization solution is applied to scenarios with different constraints to demonstrate the effectiveness of the method. The set of resources used for reducing electricity peak demands were described in Chapter 3 and are listed in Table 1 and Table 2 corresponding to SJE, an actual utility in the province of New Brunswick, Canada. The dataset used in the evaluation comprises two years of load data from the local utility. An economic analysis is also presented to identify the benefits of the optimization method.

4.2 Optimization scenarios

To evaluate the performance of the proposed optimization method, the following scenarios with different constraints have been chosen.

- **Scenario 1** uses all the energy resources available for peak shaving in Saint John Energy (see Table 1 and Table 2). The scenario includes limitations for the use of UB and DGs that the local utility currently uses. Therefore, it reproduces realistic setups to estimate potentially realistic outcomes.
- **Scenario 2** replicates the same cases as Scenario 1 but without the limitations imposed to UB and DGs usage. This scenario is designed to quantify the impact on peak shaving and on cost that limitations to UB and DGs power generation bring to the system.

4.2.1. Experiment design for both scenarios

A simulation for estimating peak shaving gains was performed using the proposed algorithm with the available energy resources to the local utility of SJE. As mentioned earlier, these resources include DGs, UB, CVR and aggregations of EERs such as HP, EWH, RB, ETS and BBH. The sizes of the aggregations used in the simulation match current aggregations managed by SJE and shown in Table 1. The simulation utilizes the following datasets:

- Two years of minutely data of the total load demand of the utility.
- Two years of day-ahead, seven-days-ahead, and thirty-days-ahead load demand forecasts with one minute resolution. Forecasts were generated once per day.
- Other data from aggregated EERs were generated during the simulation by running dynamic models [7, 52, 53, 57].

It was decided to consider net benefit (maximum and minimum net benefit) as the basis for months to be selected and discussed further in scenarios to avoid randomness. It was also decided to choose one month that showed the highest value in peak load within the past two years in scenarios.

4.2.2 Scenario 1

The first scenario uses the following constraints according to recommendations, and current constraints, from Saint John Energy:

- Diesel generation is limited to a maximum of eight hours per month.

  The reason for this limitation includes the cost of renting DGs, other DG commitments and limitations of maintenance cycles.

- Utility-scale batteries can be used as energy resource for peak shaving up to a maximum of 7 days per month.

  The reason for this limitation is a current policy of SJE to limit the number of charging/discharging cycles of the utility battery for peak shaving purposes.

The MATLAB simulation of the optimization method was executed for billing cycles available in the load demand dataset, where each billing cycle has a duration of one

Table 7. Energy contribution to peak shaving from each embedded energy resource in Scenario 1.

Billing Cycle	DG (MWh)	EWH (MWh)	HP (MWh)	BBH (MWh)	ETS (MWh)	RB (MWh)	UB (MWh)	CVR (MWh)	*Total (MWh)*
Jul-20	1.66	3.68	2.78	0	0	2.93	12.15	93.08	*116.28*
Aug-20	7.28	8.17	4.33	0	0	4.75	13.94	128.71	*167.17*
Sept-20	13.5	8.59	7.16	0	0	5.09	8.67	165.02	*208.03*
Oct-20	7.23	7.02	5.74	1.36	0.24	3.93	8.88	166.75	*201.15*
Nov-20	1.66	3.15	1.76	0.61	1.15	1.78	12.04	208.51	*230.66*
Dec-20	14.55	6.71	4.84	1.46	1.37	4.82	6.5	322.97	*363.22*
Jan-21	18.48	7.03	3.56	1.07	2.07	2.76	12.46	227.39	*274.82*
Feb-21	20.64	4	2.55	0.68	0.25	1.97	10.02	187.11	*227.23*
Mar-21	10.96	3.46	1.68	0.65	0.18	1.89	5.75	178.44	*203.01*
Apr-21	7.23	2.63	1.16	0.87	0.21	1.68	7.98	130.15	*151.9*
May-21	11.69	3.53	2.48	0	0	2.18	13.88	119.47	*153.23*
Jun-21	7.23	4.54	3.21	0	0	3.53	9.79	95.71	*124.01*
Jul-21	2.84	13.14	9.72	0	0	8.66	15.06	161.87	*211.29*
Aug-21	3.18	12.5	7.52	0	0	7.46	10.83	236.06	*277.56*
Sept-21	8.38	5.48	3.49	0	0	4.42	13.83	114.26	*149.86*
Oct-21	7.28	8.97	6.58	1.68	1.03	6.11	13.13	193.51	*238.28*
Nov-21	14.54	9.28	4.17	1.38	1.29	4.09	12.06	253.38	*300.19*
Dec-21	21.9	9.35	7.06	1.62	1.02	4.61	9.69	315.44	*370.69*
Jan-22	13.87	5.14	3.68	1.17	1.39	2.9	13.79	322.34	*364.29*
Feb-22	14.49	3.98	3.78	0.64	0.12	1.94	11.96	167.58	*204.47*
Mar-22	11.68	2.22	0.73	0.42	0.19	0.91	4.33	85.85	*106.33*
Apr-22	7.28	2.92	1.91	0.77	0.12	2.06	8.63	140.51	*164.17*
May-22	14.55	3.53	2.19	0	0	1.59	8.69	82.8	*113.36*
Jun-22	4.32	10.41	8.97	0	0	6.79	14.73	170.97	*216.18*
Jul-22	2.16	15.59	9.11	0	0	9.46	13.94	202.92	*253.19*
Total	**248.58**	**165.02**	**110.16**	**14.38**	**10.63**	**98.31**	**272.73**	**4470.8**	***5390.57***

month. Table 7 presents simulation results that show the energy contribution to peak shaving of each energy resource during each billing cycle. The first outstanding fact from

Table 7 is the significantly higher contribution of CVR for peak shaving, which ranges from 73% to over 90%. The use of CVR occurs more during early winter months, as shown graphically in Figure 11. This is an expected outcome as there will be more engagements of this resource during months when forecasts are less reliable.

The least contributing resources are ETS and BBH aggregations. These customer appliances operate only during winter months, which reduces their total contributions. Another fact for the small energy capacities shown by these aggregations is the number of enrolled users (see Table 1).

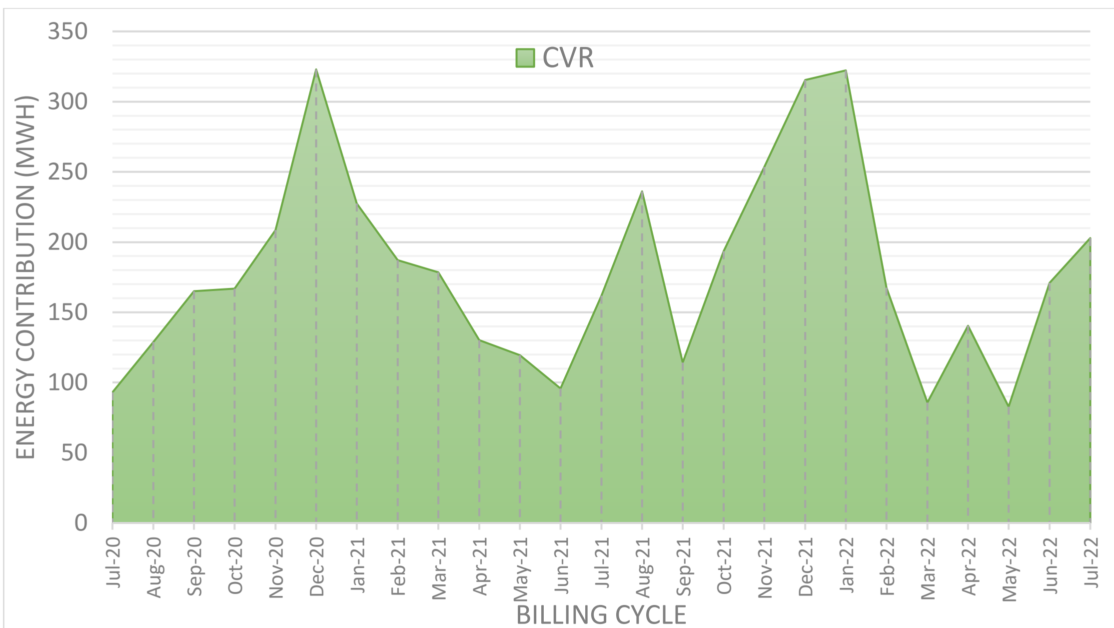


Figure 11. Monthly energy participation of CVR in the last two years in scenario 1

However, BBH aggregations can have a higher positive impact as the number of customers that own them are significant (approximately 60,000 customers own baseboard heaters in Saint John according SJE). Figure 12 graphically shows individual contributions of all the available resources, except for CVR. The figure clearly depicts the marginal contribution of ETS and BBH aggregations.

The utility battery and diesel generators are the next bigger contributors to peak shaving, and they are more heavily used during winter months, but are the other two resources that

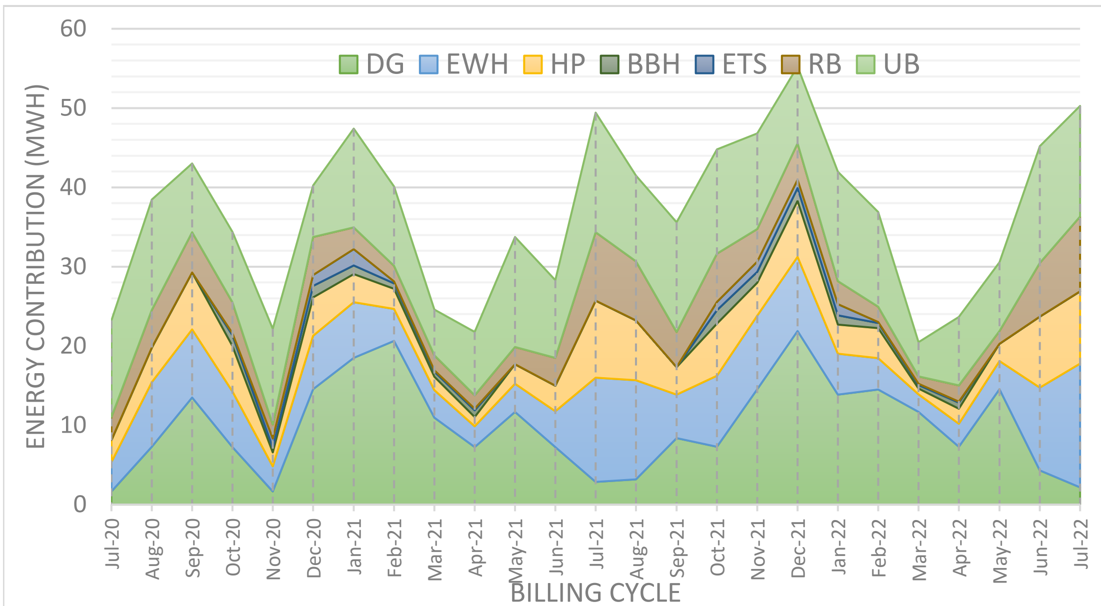


Figure 12. Monthly energy participation of EERs in the last two years in scenario 1

the optimization algorithm selects to reduce peak demands. However, water heater and heat pump aggregations are also used. These two resources have more capacity during summer months and the optimization algorithm can use them instead of more expensive and limited resources as DG and UB. Unfortunately, during winter months these resources do not have enough capacity and more expensive resources are used. Finally, residential batteries are good candidates for peak shaving but their contribution in winter is reduced, probably because of their utilization by their owners in reducing their electricity bill.

Table 8. Benefit and load factor in the last two years in scenario 1

Billing Cycle	Gross profit (k$)	Production cost (k$)	Investmen t cost (k$)	Net Benefit (k$)	load factor before	load factor after
Jul-20	56.40	0.60	7.60	48.20	80%	83%
Aug-20	50.40	2.40	7.60	40.30	80%	83%
Sept-20	108.00	4.50	7.60	95.90	74%	76%
Oct-20	99.20	2.40	7.60	89.10	68%	72%
Nov-20	78.40	0.60	7.60	70.20	70%	72%
Dec-20	113.80	4.90	7.60	101.30	67%	70%
Jan-21	111.70	6.20	7.60	97.90	74%	77%
Feb-21	157.80	6.90	7.60	143.30	70%	74%
Mar-21	169.90	3.70	7.60	158.60	68%	71%
Apr-21	164.90	2.40	7.60	154.80	68%	72%
May-21	54.60	3.90	7.60	43.10	73%	76%
Jun-21	21.40	2.40	7.60	11.40	81%	82%
Jul-21	32.60	0.90	7.60	24.00	82%	84%
Aug-21	56.10	1.10	7.60	47.40	78%	81%
Sept-21	22.60	2.80	7.60	12.20	81%	82%
Oct-21	36.10	2.40	7.60	26.00	77%	79%
Nov-21	93.40	4.90	7.60	81.00	66%	68%
Dec-21	212.70	7.30	7.60	197.80	73%	77%
Jan-22	110.60	4.60	7.60	98.40	76%	79%
Feb-22	133.20	4.80	7.60	120.70	69%	72%
Mar-22	231.50	3.90	7.60	219.90	66%	70%
Apr-22	110.40	2.40	7.60	100.40	73%	76%
May-22	116.70	4.90	7.60	104.20	72%	77%
Jun-22	29.40	1.40	7.60	20.30	82%	84%
Jul-22	35.50	0.70	7.60	27.10	81%	83%
Total	**2407.30**	**83.00**	**190.00**	**2133.50**	**74%**	**77%**

Table 8 presents estimations of production costs, investment costs, plus gross and net benefit. Gross profit is the sum of the cost saved during the peak shaving process by decreasing peak costs. The calculations were made using current (as per 2022) rates to which SJE buys from its wholesale provider. The net benefit subtracts production and investment costs from the gross profit. Load factors before and after peak shaving during each billing cycle are also displayed. Load factors do not change drastically in this

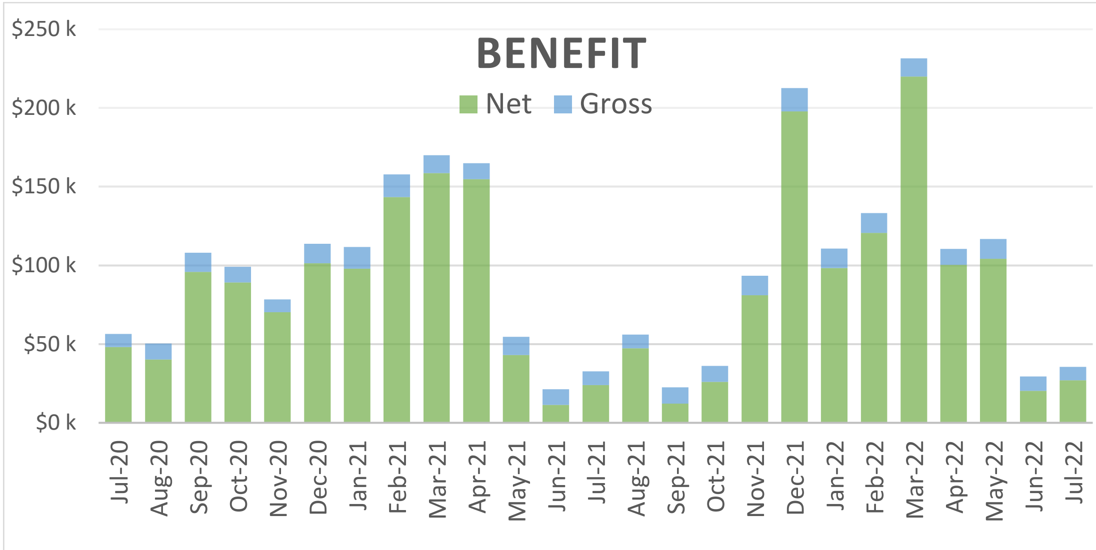


Figure 13.Monthly net and gross benefit of EERs and CVR in the last two years in scenario 1

scenario, showing an average improvement of 3% and a maximum increase of 5%. This result is, nonetheless, expected because of the low capacities of the available resources (Table 1).

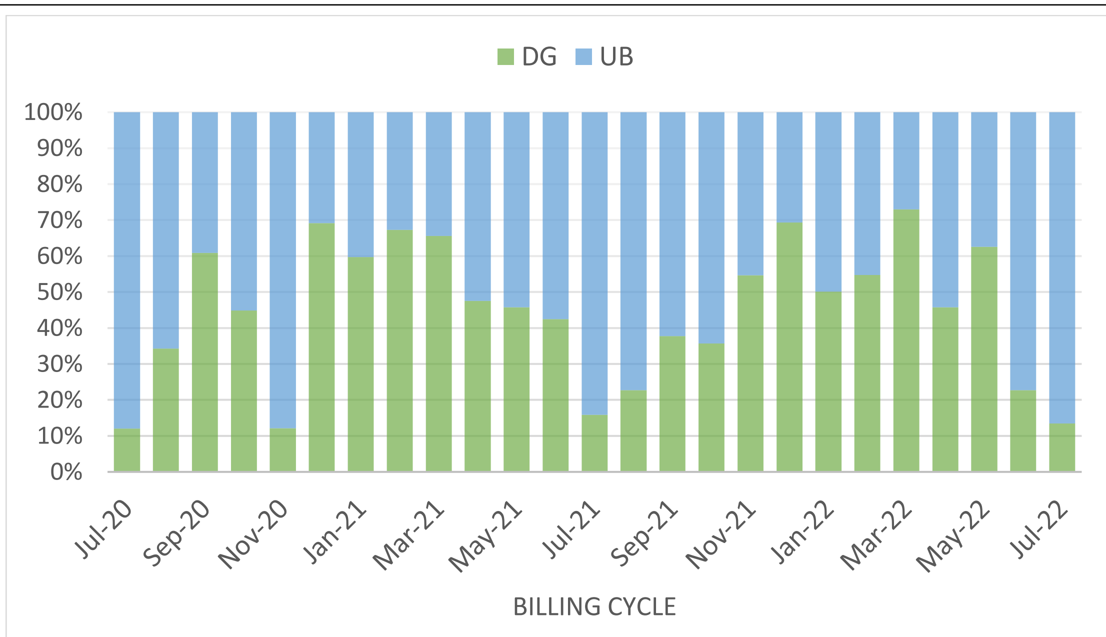


Figure 14. Monthly percentage energy participation of DG and UB in the last two years in scenario 1

Figures 11 to 13 graphically show net benefit, monthly energy participation of EERs & CVRs and monthly energy participation of DG and UB respectively within the past two years. Figure 13 demonstrates that March shows a higher net benefit compared to other months of the year. During March often the load curve is descending, as a result, if the forecast predicts the correct actual load, a smaller number of peak days would be achieved based on fewer engagements of available resources and production cost would be minimized. According to Figure 13, the lowest net benefit has mostly been observed during warm months of the year, because there are more engagements in these times, due to the fact that more load factors occur at these times and the amount of maximum daily peaks during the month is almost at the same level. Hence, production costs increase, and net benefit decrease because of that. Generally, December every year shows an increasing load curve according to this figure. This results in more engagements according to the proposed peak shaving method. More engagements result in more energy participation of EERs and CVRs.

Tables 7 and figures 12-13 yield the following results:

When the monthly load demand curve ascends, more engagements will be expected based on threshold and peak shaving mechanisms. As a result, the energy participation of EERs may increase. For example, in Table 7, DGs energy participation for February 2021 and December 2021 shows the highest values. It is crucial to notice that the error between forecast and the load demand is minimal. In the case EWHs energy participation, June and August 2021 show the highest values in Table 7. UB energy participation shows the highest value during June 2021. CVR energy participation's highest value has been during December 2020. As energy participation of CVR is mainly used among other aggregators, it could be deduced that total energy participation is highest in December 2020 and December 2021.

Closer look at specific bill cycles

Three billing cycles have been selected to further analyze the performance of the optimization algorithm: June 2021, January 2022, and March 2022. June 2021 has shown the minimum net benefit, January 2022 exhibited the highest peak amplitude, and March 2022 had the maximum net benefit in the two years that the dataset includes.

Maximum Net Benefit March 2022

The maximum net profit of the two years studied was achieved in the billing cycle of March 2022, showing a CAD 219,945.00 profit. Based on the load and threshold curves shown in Figure 15, there is a limited number of engagements to find the peak during the billing cycle and because all EERs and CVRs have been participating at the maximum available capacity the EERs provided, maximum profit was achieved during the peak shaving. Two engagements were experienced this month, on March 1st and March 4th 2022, the highest peak being recorded on March 1st. The algorithm began with a low threshold to identify the peaks and, according to this threshold, March 1st had a long peak and very high peak. The optimization method then used the available capacities and all resources to reduce the peak component as much as possible. A total of 106.33Mwh participation engagements during the peak shaving were achieved. The load factor was able to increase from 66% to 70% after peak shaving. Figure 19 shows the contribution from aggregators and generation resources along with the demand that could not be shaved with the available resources.

Figure 16 to Figure 18 show peak shaving participation of load and resources during March 1st, 2022. These figures show the order of energy participation of different aggregators on this day: 1. CVR; 2. DGs; 3. UB; 4. EWH; 5. RB; 6. HP; 7. BBH and 8. ETS .

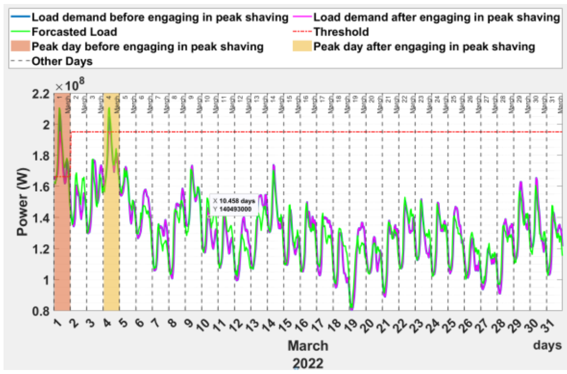


Figure 15. Peak engaging and shaving on load demand during the billing cycle in scenario 1 in March 2022

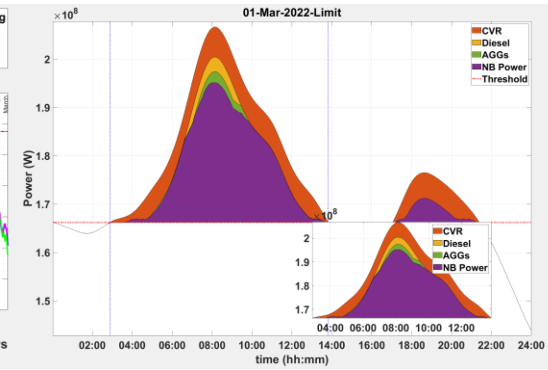


Figure 16. The load demand and peak shaving by EERs in scenario 1 on March 01, 2022

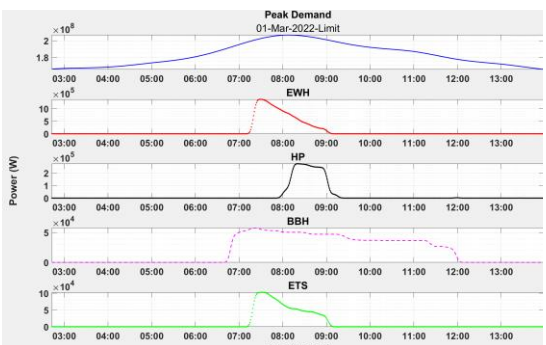


Figure 17. EWH, HP, BBH and ETS participation in peak period in scenario 1 on March 01, 2022

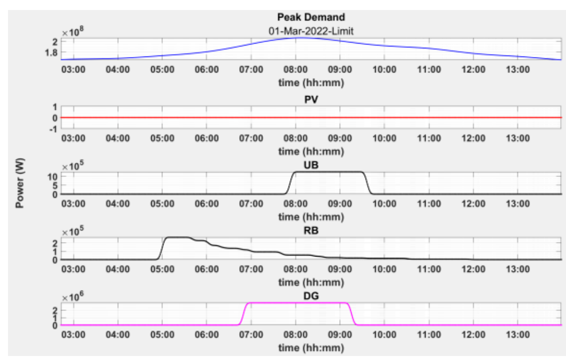


Figure 18. PV, UB, RB and DGs participation in peak period in scenario 1 on March 01, 2022

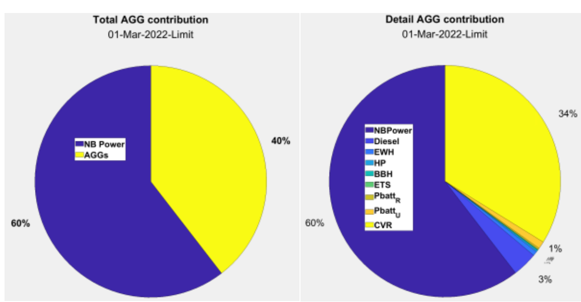


Figure 19. EERs participation in peak period in scenario 1 on March 01, 2022

As shown in table 8, in March 2022, DG participation has been 11.68Mwh at 281 minutes within two days. UB participation at the same period has been 4.33Mwh at 208 minutes within two days.

Table 9. DG and UB participation in peak shaving in March 2022 (scenario 1)

March 2022	**Diesel Generator**	**Utility Battery**
Duration of operation per month (minutes)	281	208
Number of participation days per month	2	2
Energy stored or consumed in engagements per month (MWh)	11.68	4.33

Maximum Peak Demand January 2022

The coldest day during the two years considered in this study was January 27th, 2022. The forecasted load predicted a load demand lower than the expected peak shaving threshold for this day; however, the actual load was much higher than the threshold. Hence, based on the mechanism taken (Chapter 3, page 43) in scenario 1 only CVR and UB participate in peak shaving on this day as shown in Figure 21 and Table 10. There have been 9 engagements during the same month with EERs participation. 364.29Mwh participation during the peak shaving by CVR has been achieved. The load factor was slightly increased from 76% to 79% by peak shaving. The net profit for this month was CAD 98,371.00.

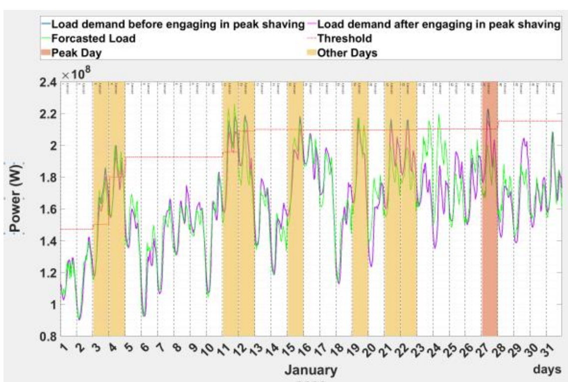


Figure 20. Peak engaging and shaving on load demand during the billing cycle in scenario 1 in January 2022

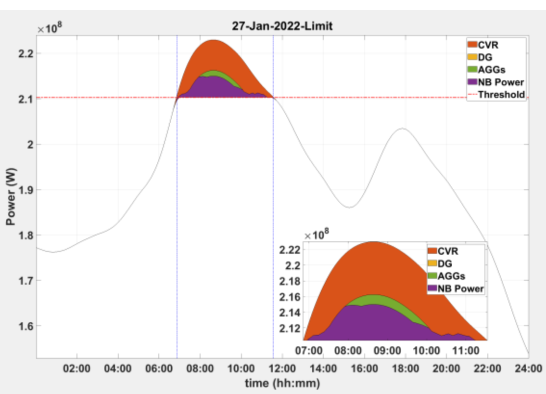


Figure 21. The load demand and peak shaving by EERs in scenario 1 on January 27, 2022

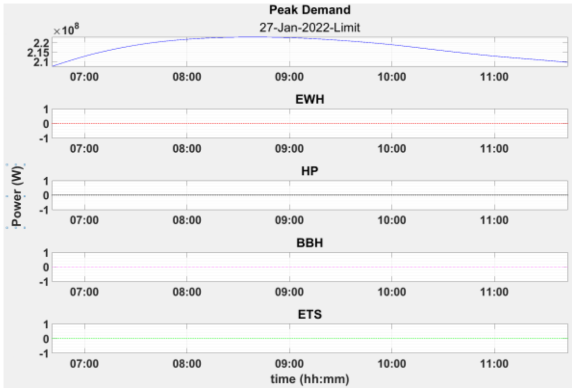


Figure 22. EWH, HP, BBH and ETS participation in peak period in scenario 1 on January 27, 2022

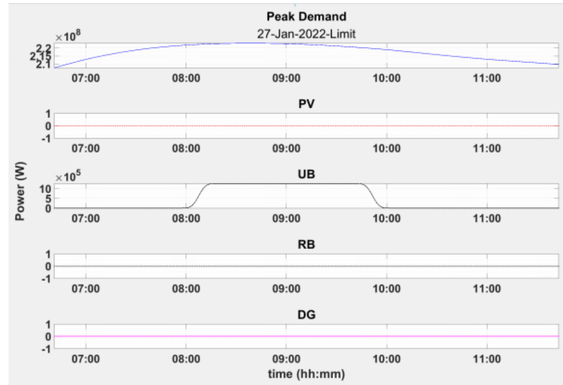


Figure 23. PV, UB, RB and DGs participation in peak period in scenario 1 on January 27, 2022

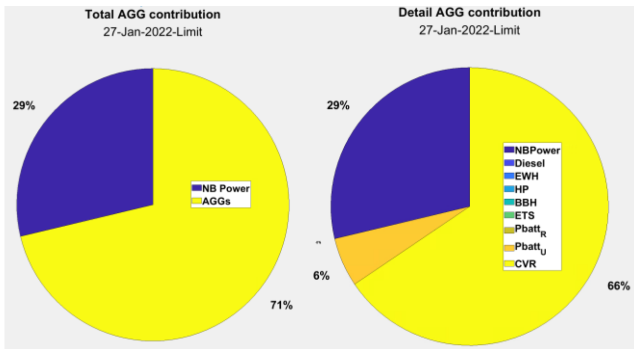


Figure 24. EERs participation in peak period in scenario 1 on January 27, 2022

Table 10. DG and UB participation in peak shaving in January 2022 (scenario 1)

January 2022	**Diesel Generator**	**Utility Battery**
Duration of operation per month (minutes)	402	662
Number of participation days per month	3	7
Energy stored or consumed in engagements per month (MWh)	13.87	13.79

Minimum Net Benefit June 2021

The least amount of profit achieved has been on June 2021 with only CAD 11,400.00. There were 14 resource engagement events during the billing cycle (Figure 25). The load factor after peak shaving shows only a 1% increase, reaching 82%. The predicted maximum peak demand was June 9th. DGs did not participate during the peak duration on June 15th due to the existing constraint of no more than 8 hours of operation in a month.

Using DGs was not anticipated on this day according to the load forecast, leaving the remaining operation time for other days where load demand was predicted to be higher. During warm months, load aggregators do not provide much capacity, as ETSs and BBHs are mostly turned off. EWHs & HPs are operating, with HPs running on cooling mode. Two peaks during the same day have been identified in June, as the example shown in Figure 26. The control strategy employed dictates that in cases when two peaks have been identified, the higher peak will use all the available EER aggregations plus CVR. During the lower peak, only CVR is utilize as the stored energy of aggregators is likely to be depleted.

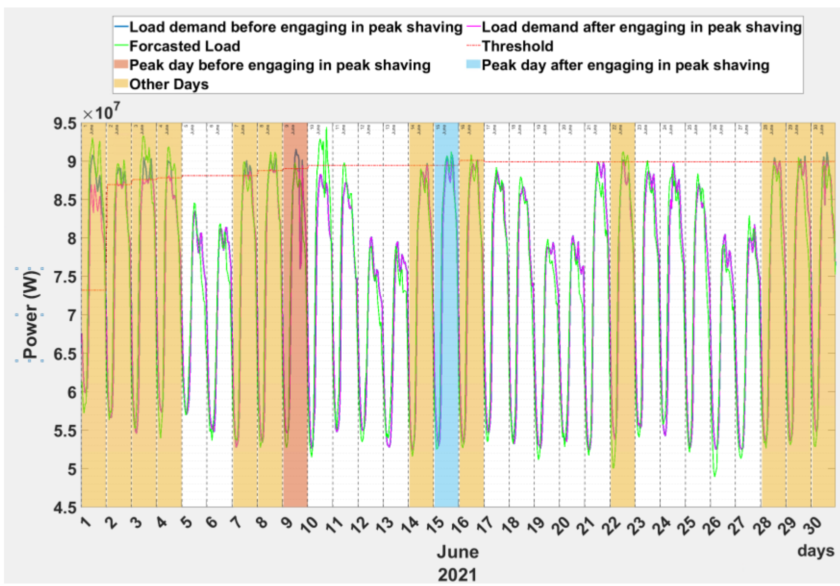


Figure 25. Peak engaging and shaving on load demand during the billing cycle in scenario 1 in June 2021

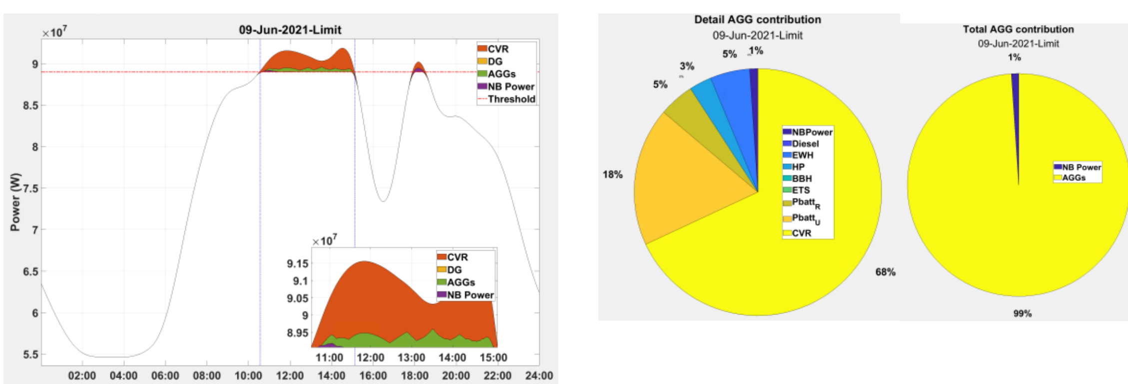
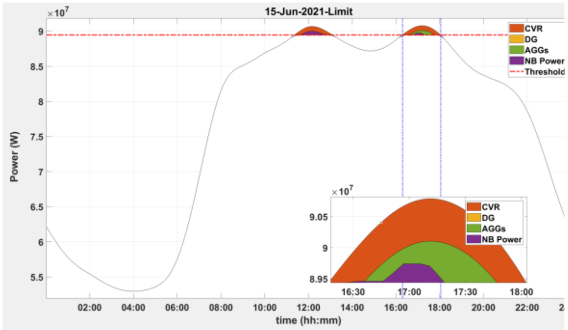


Figure 26. The load demand and peak shaving by EERs in scenario 1 on June 09, 2021

Figure 27. EERs participation in peak period in scenario 1 on June 09, 2021



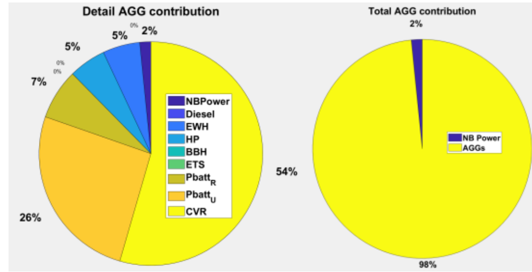
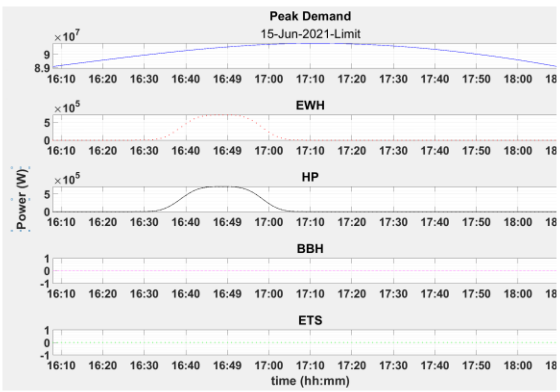


Figure 28. The load demand and peak shaving by EERs in scenario 1 on June 15, 2021

Figure 29. EERs participation in peak period in scenario 1 on June 15, 2021



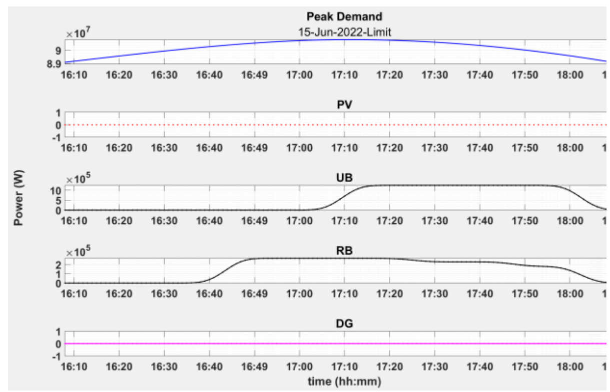


Figure 30. EWH, HP, BBH and ETS participation in peak period in scenario 1 on June 15, 2021

Figure 31. PV, UB, RB and DGs participation in peak period in scenario 1 on June 15, 2021

4.2.3 Scenario 2

The second scenario uses the following constraints:

- Diesel generation has no monthly usage limitation
- Utility-scale battery has no monthly limitations

Table 10 and 11 shows data gathered in the same fields as table 6, however, the data is based on the second scenario, which considers a similar situation as scenario 1, except that there is no monthly usage limitation for DGs and UB. Due to the elimination of restrictions in this scenario, the total energy participation of DG and UB has become 670 and 551 MWh, respectively. These numbers represent increases of 270% and 200%, respectively in comparison with scenario 1. The rest of the EERs have changed by about 1 to 7 MWh, which is a small amount for two years. As shown in figures 34-37, due to the lack of monthly usage limitation of DGs, production cost has increased, resulting in lower net benefit.

Table 11. Energy contribution to peak shaving from each embedded energy resource in Scenario 2.

Billing Cycle	DG (MWh)	EWH (MWh)	HP (MWh)	BBH (MWh)	ETS (MWh)	RB (MWh)	UB (MWh)	CVR (MWh)	*Total (MWh)*
Jul-20	16.23	3.65	1.20	0.00	0.00	3.07	24.19	120.54	*168.87*
Aug-20	28.47	6.11	2.86	0.00	0.00	4.24	23.60	137.89	*203.18*
Sept-20	30.77	7.93	3.94	0.00	0.00	4.28	20.52	186.14	*253.58*
Oct-20	27.48	10.75	6.76	1.64	0.89	6.04	27.98	202.69	*284.23*
Nov-20	19.47	4.05	1.79	0.59	0.34	1.57	15.52	220.91	*264.24*
Dec-20	53.75	9.52	4.47	1.57	1.64	5.19	23.54	386.17	*485.86*
Jan-21	21.48	6.92	3.18	0.86	1.46	2.62	12.75	198.18	*247.45*
Feb-21	29.10	4.20	2.49	0.79	0.28	2.02	16.56	211.78	*267.21*
Mar-21	18.23	3.47	1.25	0.62	0.14	1.88	7.92	178.78	*212.28*
Apr-21	21.68	2.63	0.84	0.87	0.22	1.68	10.83	135.06	*173.80*
May-21	27.07	4.17	3.43	0.00	0.00	2.67	15.56	125.47	*178.36*
Jun-21	10.56	5.60	4.67	0.00	0.00	4.06	25.33	117.23	*167.46*
Jul-21	43.76	16.58	7.67	0.00	0.00	9.85	41.08	252.15	*371.09*
Aug-21	38.01	14.66	7.71	0.00	0.00	7.81	38.58	284.94	*391.71*
Sept-21	13.35	4.79	2.13	0.00	0.00	2.77	23.35	116.99	*163.39*
Oct-21	22.21	6.05	4.52	1.38	0.80	4.98	34.06	200.77	*274.77*
Nov-21	58.00	9.48	4.56	1.70	2.07	4.71	27.42	319.59	*427.53*
Dec-21	48.06	7.58	6.32	1.69	1.33	4.27	22.67	356.02	*447.93*
Jan-22	28.49	5.16	3.63	1.18	1.40	2.91	18.13	335.72	*396.60*
Feb-22	14.58	3.98	3.78	0.64	0.12	1.94	11.96	167.58	*204.56*
Mar-22	11.68	2.22	0.73	0.42	0.19	0.91	4.33	85.85	*106.33*
Apr-22	21.78	3.94	1.63	0.79	0.14	2.06	10.79	145.06	*186.19*
May-22	14.40	3.55	2.21	0.00	0.00	1.59	8.69	82.61	*113.06*
Jun-22	17.39	10.45	5.99	0.00	0.00	7.09	42.15	198.12	*281.19*
Jul-22	34.08	16.06	10.72	0.00	0.00	9.83	44.25	262.33	*377.28*
Total	**670.08**	**173.5**	**98.48**	**14.73**	**11.02**	**100.04**	**551.76**	**5028.57**	***6648***

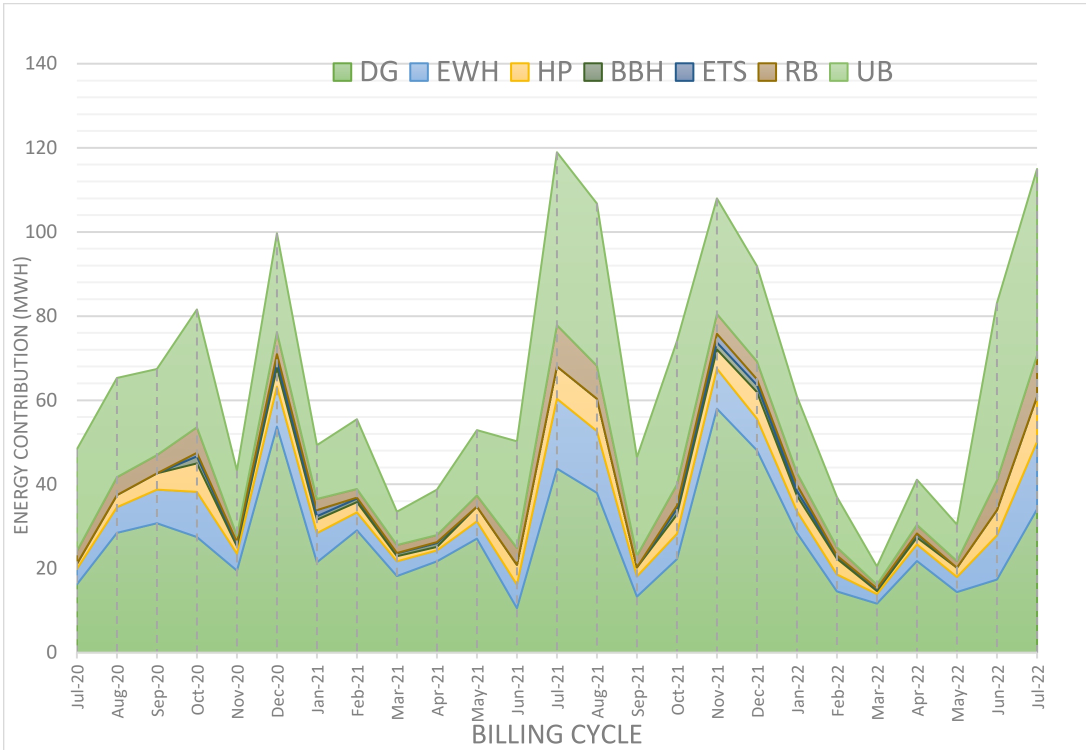


Figure 32. Monthly energy participation of EERs in the last two years in scenario 2

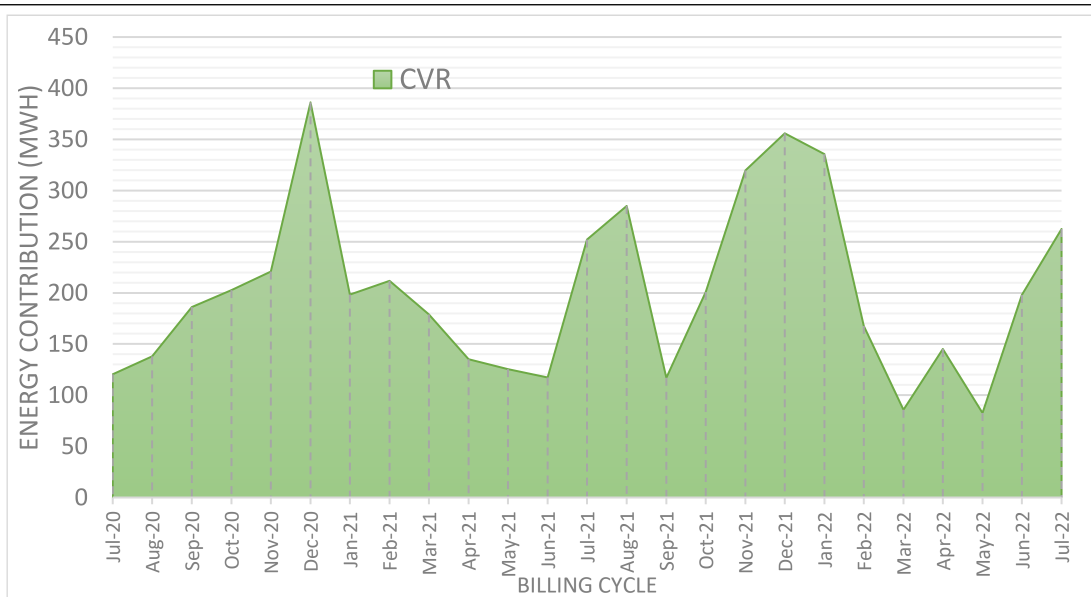


Figure 33. Monthly energy participation of CVR in the last two years in scenario 2

Table 12. Benefit and load factor in the last two years in scenario 2

Billing Cycle	**Gross profit (k$)**	**Production cost (k$)**	**Investment cost (k$)**	**Net Benefit (k$)**	**load factor before**	**load factor after**
Jul-20	89.5	5.4	7.6	76.5	80%	83%
Aug-20	62.8	9.5	7.6	45.7	80%	84%
Sept-20	64.0	10.3	7.6	46.1	74%	77%
Oct-20	133.5	9.2	7.6	116.7	68%	72%
Nov-20	78.4	6.5	7.6	64.3	70%	72%
Dec-20	113.8	18.0	7.6	88.2	67%	70%
Jan-21	158.5	7.2	7.6	143.7	74%	77%
Feb-21	157.8	9.7	7.6	140.5	70%	74%
Mar-21	169.9	6.1	7.6	156.2	68%	71%
Apr-21	164.9	7.2	7.6	150.0	68%	72%
May-21	54.6	9.0	7.6	38.0	73%	75%
Jun-21	24.3	3.5	7.6	13.1	81%	82%
Jul-21	36.3	14.6	7.6	14.0	82%	84%
Aug-21	56.1	12.7	7.6	35.8	78%	81%
Sept-21	22.6	4.5	7.6	10.6	81%	82%
Oct-21	36.1	7.4	7.6	21.0	77%	79%
Nov-21	93.4	19.4	7.6	66.4	66%	68%
Dec-21	212.8	16.1	7.6	189.1	73%	77%
Jan-22	110.6	9.5	7.6	93.5	76%	79%
Feb-22	133.2	4.9	7.6	120.7	69%	72%
Mar-22	231.5	3.9	7.6	219.9	66%	70%
Apr-22	110.4	7.3	7.6	95.5	73%	76%
May-22	116.7	4.8	7.6	104.3	72%	77%
Jun-22	30.3	5.8	7.6	16.9	82%	84%
Jul-22	39.0	11.4	7.6	20.0	81%	83%
Total	**2501**	**223.9**	**190.00**	**2086.7**	**74%**	**77%**

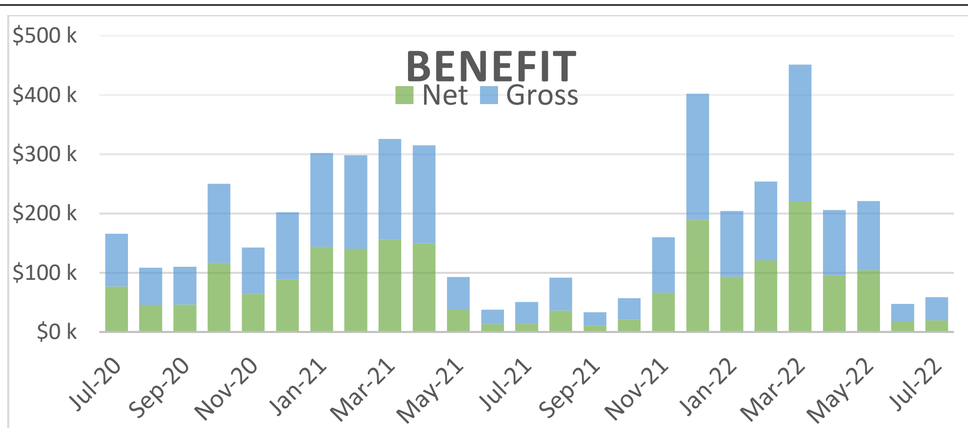


Figure 34. Monthly net and gross benefit of EERs and CVR in the last two years in scenario 2

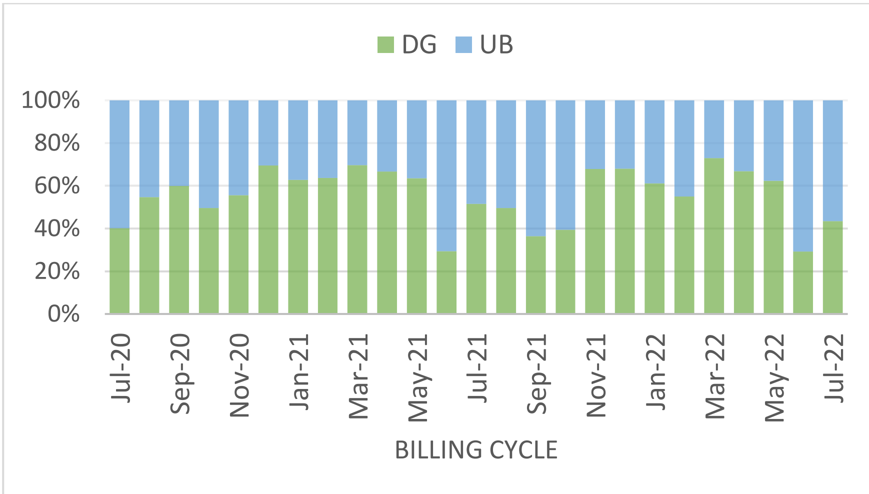


Figure 35. Monthly energy participation of DG and UB in the last two years in scenario 2

Closer look at specific bill cycles

Maximum Net Benefit March 2022

During March 2022, no meaningful differences were observed between scenarios 1 and 2. The reason for this factor is that there have been only two engagements this month and the forecast has correctly predicted the actual load based on the peak shaving mechanism proposed in this study, i.e., all EERs have engaged at the maximum available capacity of the EERs and have shaved the allowed limit in terms of DG and UB usage. Figures 36 and 37 demonstrate this point.

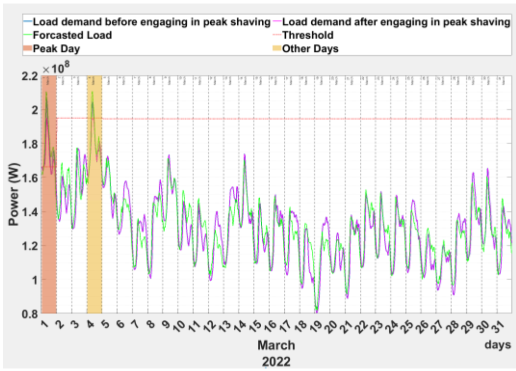


Figure 36. Peak engaging and shaving on load demand during the billing cycle in scenario 2 in March 2022

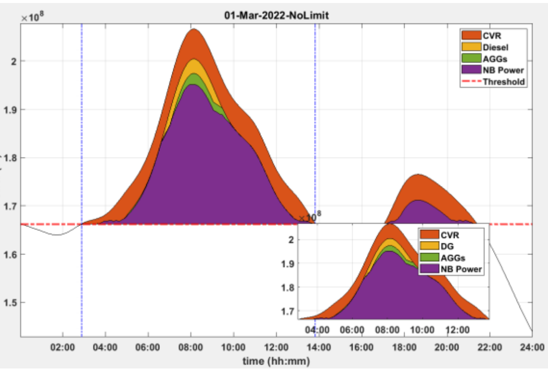


Figure 37. The load demand and peak shaving by EERs in scenario 2 on March 01, 2022

Maximum Peak Demand January 2022

January 2022 shows a lower profit in scenario 2 compared to January 2022 in scenario 1; there has not been any limitation on monthly usage of DGs and UB. Hence, production costs have increased, which has decreased the net benefit. On the other hand, due to errors in the forecast on January 27th, UB and CVR participated in this engagement. Our net benefit cannot be maximized during this month for two reasons: firstly, higher production costs because of increase of the use of DGs. Secondly, forecast errors in this month prevented the usage of the maximum available capacity of EERs. Figures 38 and 39 show the case visually.

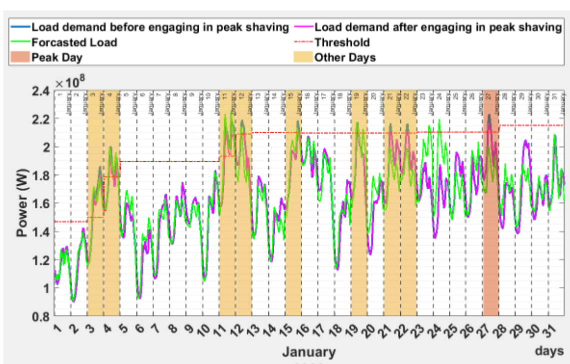


Figure 38. Peak engaging and shaving on load demand during the billing cycle in scenario 2 in January 2022

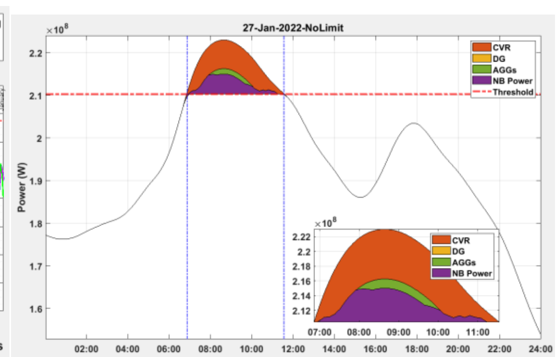


Figure 39. The load demand and peak shaving by EERs in scenario 2 on January 27, 2022

Minimum Net Benefit June 2021

June 2021 showed a slightly higher net benefit compared to the same month in scenario 1 for the following reasons. First, the change in the peak day from 9th to 30th (see figures 40 to 42). Second, although there has not been any UB limitation, as there is no production cost for UB and as production costs of DGs have increased, we see a slight edge in net benefit of UB compared to January 2022 and March 2022 in production costs.

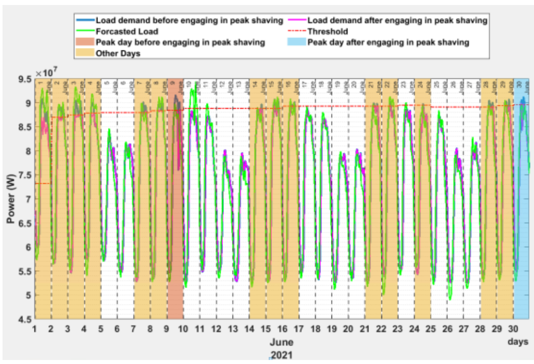


Figure 40. Peak engaging and shaving on load demand during the billing cycle in scenario 2 in June 2021

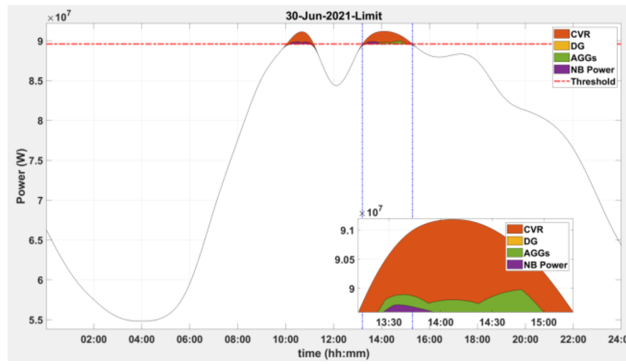


Figure 41. The load demand and peak shaving by EERs in scenario 2 on June 30, 2021

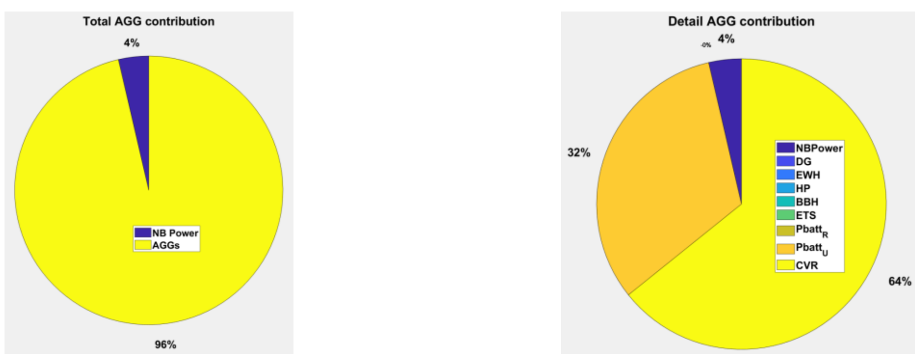


Figure 42. EERs participation in peak period in scenario 1 on June 30, 2021

4.2.4 Comparison between scenario 1 and 2

Table 13 compares output data in scenario 1 and scenario 2 for three months, March and January 2022 and June 2021 in terms of UB and DG participation and net benefit.

There have been only two engagements during March 2022 and there has been no more need to participate in DGs and/or UB in scenario 2 compared to scenario 1, hence, the usage statistics of both are the same.

Net benefit during January 2022 shows a reduction in scenario 2 compared to scenario 1. That is because of production costs, resulting in more participation of DGs during this month.

Both DGs and UB have increased their participation during the billing cycle of June 2021 in scenario 2 when compared to scenario 1. The participation of UB has resulted in higher net benefit.

Table 13. Compare scenarios 1 and 2 in terms of net benefit, UB & DG participation in peak shaving

months	**Net Benefit in scenario 1 $**	**Net Benefit in scenario 2 $**	**UB Participation in scenario 1 (min)**	**UB Participation in scenario 2 (min)**	**DG participation in scenario 1 (min)**	**DG participation in scenario 2 (min)**
March 22	219945	219945	208	208	281	281
January 22	98371	93488	662	870	402	695
June 21	11400	13130	470	1216	145	454

Chapter 5 Conclusions and future work

According to this study, we were able to develop a method to regulate and manage existing EERs in order to achieve maximum shaving performance and to provide solutions for reducing electricity supply costs during peak demand times. Also, the economic benefits of optimizing the dispatch capacity of DERs and load aggregations for peak shaving relying on real characteristic of the billing mechanisms used in LDCs have been studied. The conclusions achieved the results (chapter 4) based on the proposed methods in this study are:

- The expected result is that using diesel generators indiscriminately would increase the cost and not necessarily improve the economy of the network, although it can reduce GHG emissions.
- A load forecast plays an important role in finding peak days in order to schedule and manage EERs, which in turn are necessary for maximizing the available capacity of EERs' on peak days.
- The number of peak shaving engagements in the monthly load according to the threshold mechanism and the proposed peak shaving process shows a direct meaningful relation to ascending/descending load curve, i.e., if the load curve is ascending, then there may be more engagements and vice versa.
- The more incidents of engagement may be in a billing cycle, the energy participation of EERs will increase, leading to increased production costs and lower user comfort.

- The number of engagements is directly related to the load factor. Considering the same situations in terms of ascending or descending load curve in the billing cycle, the smaller number of load factors in a month will lead to lower engagements.
- Considering the same given situations, as the BBHs and ETSs are turned off during warm days and have no role in the peak shaving process, utilizing the maximum available capacity of EERs is possible on cold days. As a result, the net benefit will be maximized on cold days.
- The results open the path for implementing and evaluating further the control algorithms and the resource optimization including load aggregators and distributed generation.
- It is essential to design and develop additional control algorithms for various aggregators and resources in order to meet the industry's performance requirements in terms of control techniques.

The future work is summarized as follows:

1. Considering the uncertainty in the input parameters of aggregators and resources
2. Implementation of robust control and robust optimization for VPP level in line with peak shaving
3. Considering the reliability parameters to reduce the risk caused by the cost increase during the peak time
4. Wind power, if available, may be considered as one of the EERs in VPPs.

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