

Article

Minimization of Global Adjustment Charges for Large Electricity Customers Using Energy Storage—Canadian Market Case Study

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Abstract: Recently, the interest in utilizing energy storage systems (ESSs), particularly batteries, has increased. ESSs are employed for several enhancement tasks in power systems on both the operation and planning scales. On the operation side, ESSs play a main role in offering several ancillary services. In the context of planning, ESSs are used for asset upgrade deferral among other grid applications. This work employs a battery energy storage system (BESS) to minimize the electricity bill charges associated with global adjustment for large consumers in the jurisdiction of Ontario, Canada. An optimization formulation for sizing and scheduling the BESS, to minimize the utility charges and gain profits from other revenue streams, such as energy price arbitrage (EPA), was developed and implemented. The results show the economic feasibility of the developed algorithm to minimize the annual bills of real customers and gain profits. A sensitivity analysis was also carried out to show the potential of the proposed method in providing significant benefits and gains for customers.

Keywords: energy storage; energy price arbitrage; global adjustment; utility charges; battery optimization

1. Introduction

Energy storage systems (ESSs) represent a promising technology for incorporation with existing power systems. Lately, interest in using ESS has been rekindled, especially considering the perfect services that ESSs can offer. Applications of ESSs in power systems are usually motivated by technical and/or economic benefits ([1,2]).

For economic purposes, ESSs can be used by the utility and end-user customers to gain benefits. On the utility side, the literature shows several algorithms for optimizing the deployment of ESS for the deferral of feeder capacity upgrades [1–6]. One of the early studies to investigate the potential of storage systems in the deferral of distribution grid upgrades was published in 1998 [3]. In [4], the optimal size of distribution feeders with a battery and a photovoltaic system was determined. Sandia National Laboratories analyzed the impact of modular storage systems on deferring asset upgrade projects for electric utilities at the transmission and distribution levels [5]. Zhang et al. proposed an algorithm for utility distribution planning benefiting from the deferral potentials of storage systems [6].

On the other hand, energy storage is used by end-users to minimize utility charges, e.g., demand charges (DCs), in some jurisdictions. Energy price arbitrage (EPA) is an interesting way to gain profit by owning energy storage. EPA refers to energy trading, when allowable, within an electricity market, by purchasing energy from the grid (charging ESS) at a low price and selling it back to the grid (discharging ESS) at times of significantly higher grid prices. Therefore, battery systems may take advantage of the spot price volatility from off-peak time to peak time to gain profit. The literature

shows several efforts that have been devoted to optimizing the deployment of BESSs for the purpose of maximizing EPA revenue [7–12].

Recently, an optimization algorithm for BESSs to maximize EPA benefits and provide power factor corrections was presented in [7]. Lin et al. developed another algorithm for EPA based on BESS's liquid air technology [8]. In [9], the economic viability of BESSs was assessed for EPA in the Chilean power system. A scheduling algorithm for BESSs (employed for both the frequency response service and EPA) was proposed in [10]. A multi-objective technique to optimize several technologies for BESSs was presented in [11]. Walawalkar et al. evaluated the economic potential of a BESS for EPA in New York [12].

In the context of decreasing the energy bills for end-user customers, several studies have been conducted to minimize utility charges, such as DC [13–16]. In this paper, a technique that employs battery systems to minimize the global adjustment charges (GACs) of class-A customers in Ontario is presented. The GAC of a class-A customer is based on the contribution of the customer's facility to the provincial load during the top five peak hours over a twelve-month period. In the literature, some attempts to control the GAC are presented based on the prediction of Ontario's top five peak hours, such that clients can reduce their loads, and therefore their contributions to the total provincial demand during the five annual peaks [17–19]. The GAC is defined by the Independent Electricity System Operator (IESO) of Ontario, as "global adjustment covers the cost of building new electricity infrastructure in the province, as well as delivering Ontario's conservation programs—ensuring that enough electricity supply will be available over the long term" [20]. The global adjustment amount to be paid by class-A customers is set monthly by the IESO to reflect two main items; firstly, the differences between the wholesale market price for electricity, known as Hourly Ontario Energy Price (HOEP) and, the sum of regulated rates for Ontario Power Generation's nuclear and hydroelectric generating stations and payments for building or refurbishing infrastructure, such as gas-fired and renewable facilities and other nuclear facilities, as well as the contracted rates paid to a number of generators across the province. Secondly, the cost of delivering conservation programs.

As per the IESO definition, the coincidental peak hours are the top five hours of energy consumption in Ontario, where class-A customers pay (GAC) according to their relative contribution to these top five peaks [21]. Figure 1 shows that the average GAC keeps increasing every year. For instance, in 2019, the GAC was almost equal to five times the average energy cost, as shown in the following figure [22].



Figure 1. Historical Ontario average global adjustment price and average weighted energy price [22].

Class-A customers are defined by (the IESO) as “Customers with peak demand greater than 1 MW but less than or equal to 5 MW”. Moreover, “Customers who participate in the Industrial Conservation Initiative (ICI), pay global adjustment (GA) based on their percentage contribution to the top five peak Ontario demand hours over a twelve-month period. Customers participating in this initiative are referred to as Class A” [23].

Different from publications available in the literature, this paper proposes a methodology to figure out the optimal system size and scheduling profile of BESS to minimize the utility charges (specifically GAC and DC) for class-A customers in Ontario. The research work is motivated by and specific to the class-A tariff structure and the jurisdiction regulations of the IESO in Ontario. Such tariff and regulations together add significant financial benefits to the classical peak shaving service energy storage can offer to large commercial and industrial facilities. Furthermore, the proposed formulation considers profit maximization through stacking more revenue streams, such as energy arbitrage and participation in IESO demand response programs. In addition, the proposed BESS provides backup power supply services to the class-A facilities during grid outages which increases the overall supply resiliency. The model is developed, coded, and tested based on actual load profile data of existing class-A facilities and the corresponding IESO energy market data. The results show the effectiveness of the developed optimization algorithm in minimizing the energy bills of the customer. Findings of this research work also maximize the overall profits of the system such that a viable investment opportunity can be pursued. In other words, value stacking and revenue maximization of the BESS increases the return on investment (ROI) of the project above the threshold that attracts investors into the business. The contributions of this work can be summarized as follows. Firstly, a novel solution is presented to minimize the annual energy bill for large electricity customers in Ontario. Secondly, a methodology is developed to obtain the optimal size of BESS units that minimizes total energy costs, including the global adjustment cost, for class-A customers. Various revenue streams are stacked to maximize the total gain. The proposed technique is flexible and can be applied to different class-A facilities with different load profiles and operation schemes. Thirdly, the proposed straightforward optimization model has a commercial opportunity to attract a great deal of attention from many class-A customers in Ontario, the IESO, and independent third-party energy market investors. Finally, the proposed methodology can be extended to other markets and jurisdictions wherever the total energy cost can be controlled through a behind-the-meter distributed energy resource like a BESS.

It should be emphasized that the work reported in the literature does not include any methodology of optimally sizing and dispatching a battery system for the purpose of reducing energy cost at large facilities. The present paper introduces a first attempt on attaining the optimal size and dispatch profile of a behind-the-meter battery which yields maximum profit for a large commercial or industrial facility. The technique has been tailored to fit the IESO market regulations in Ontario, but could be extended to other jurisdictions whose rules allow a certain level of energy cost control via distributed energy resources. Similar to the case in Ontario, it is anticipated that other markets will have an ROI level which encourages investments by facility owners, utilities, and independent energy investors.

2. Profit-Maximizing Several Revenue Streams for a BESS

In this part of the paper, the developed mathematical formulation that optimally size and schedule the battery, such that decreasing the customer energy charges, mainly considering the global adjustment and demand charges, is presented.

2.1. Major Objectives

The developed mathematical formulation aims to maximize the battery revenue from several streams while minimizing the overall utility charges for the large customer who will adopt the battery solution. The problem is formulated on annual basis.

- Objective function:

The following objective function in (1) minimizes the utility charges and the battery cost while maximizing the battery revenue. Full description of each of these cost and revenue terms are provided in the following set of Equations (2)–(7).

$$\text{Minimize } \{ACC_B + AEC + AGAC + ADCC - ARV_{EA} - ARV_{DR}\} \quad (1)$$

- Battery investment cost per year:

The term of the battery investment cost on annual basis ACC_B is formulated in (2). This annual cost term counts for both the energy capacity of the battery and the power capacity of the interfacing converter unit as in (2). The annual battery cost takes into consideration the interest rate and the investment period in order to yield a present value of the cost.

$$ACC_B = (R_{EB} \cdot \overline{EB} + R_{PB} \cdot \overline{PB}) \cdot \frac{r}{1 - (1 + r)^{-N_y}} \quad (2)$$

- The total customer energy cost per year (AEC):

The energy cost of the customer who adopts the battery solution is estimated based on the net exchange power at the point of common coupling between the customer and the distribution grid, and is formulated in (3) on annual basis. The cost function accounts for the hourly load profile and hourly spot price.

$$AEC = \sum_{t=1}^{N_t} T_t \cdot P_t^T \cdot Rsp_t \quad (3)$$

- Cost of global adjustment per year (AGAC):

The global adjustment cost is a unique utility charges for the province of Ontario, Canada. It has been formulated in (4). It is evaluated on monthly basis such that representing the individual contribution of the customer into the five coincident peaks of the whole province. This cost depends on the monthly announced charges by the Independent Electricity System Operator (IESO) [24–26]:

$$AGAC = \sum_{m=1}^{12} PDF \cdot R_m^{GAC} \quad (4)$$

- The cost of demand charges per year (ADCC):

The annualized cost of demand charges is formulated in (5). Based on monthly calculation the demand charge cost is estimated accounting for the peak demand load for this month:

$$ADCC = \sum_{m=1}^{12} \max(P_t^T)_m \cdot R_m^{DC} \quad (5)$$

- Energy arbitrage revenue per year (ARV_{EA}):

This energy arbitrage revenue is counting for the profit gained from the fluctuation of the energy price from hour to hour, where the battery can charge during the low-price hours and discharging during the high-price hours. This revenue is calculated on annual basis as shown in (6):

$$ARV_{EA} = \sum_{t=1}^{N_t} T_t \cdot P_t^{B+} \cdot Rsp_t \quad (6)$$

- Demand response revenue per year (ARV_{DR}):

The demand response revenue is formulated in (7). This revenue is gained based on two bases as shown in (7). First, the annual demand response contract. Second, the hourly demand response revenue which is calculated based on the corresponding energy price market. The formulation assumes participation in the winter demand response program of the IESO. During summer, the BESS is anticipated to operate mainly for GA peak shaving which more lucrative and comes at a higher priority.

$$ARV_{DR} = \sum_{t=1}^{N_t} KDR \cdot \overline{PB} + T_t \cdot P_t^{DR} \cdot Rsp_t \quad (7)$$

2.2. The Set of Constraint

Based on the multi terms objective function in (1) and the terms described in (2)–(7), a set of constraints are mathematically developed to consider the technical and the economical constraints of the system.

- Hourly power of battery:

This constraint is formulated to count for the charging and discharging modes of the battery. In the charging mode, the battery power is assumed to have a negative value, while in the discharging mode the battery power has a positive value. The net battery power is assumed to be the sum of the charging and discharging power such that the battery is only operating in one of these two modes.

$$PB_t = P_t^{B+} + P_t^{B-} \quad (8)$$

- Battery power at discharging mode:

During the discharging mode the battery power is restricted based on (9). The integer variable u_t , is employed to distinguish between the charging and discharging modes of the battery such that the value of this integer will be one for the discharge mode and zero for charging mode.:

$$0 \leq P^{B+} \leq \overline{PB} \cdot u_t \quad (9)$$

- Battery power at charging mode:

Akin to (9), the charging power is limited to the battery capacity during charging mode as in (10), the integer u_t has a zero value during the charging mode:

$$- \overline{PB} \cdot (1 - u_t) \leq P^{B-} \leq 0 \quad (10)$$

- Peak demand factor (PDF):

This factor describes the share of this customer into the aggregate loading of the province during the five coincidental peaks as in (11). The PDF is the key variable that determines the GA charges during the following adjustment period.

$$PDF = \frac{\sum_{q=1}^5 P_q^T}{\sum_{q=1}^5 \overline{PD}_{PS}}, q \in \Omega_{5PH} \quad (11)$$

- The battery intertemporal constrain:

This battery intertemporal constraint describes the relation between the battery power and energy from time to time as in (12) and (13).

$$0 \leq E^0 - P_t^{B+} \cdot \eta^+ + P_t^{B-} \cdot \eta^- \leq \overline{EB} \quad (12)$$

$$-\sum_{t \in N_t} P_t^{B+} \cdot \eta^+ + \sum_{t \in N_t} P_t^{B-} \cdot \eta^- = 0 \quad (13)$$

- The life cycle limit:

The actual battery cycle life is calculated based on the charging and discharging profile, and has been limited to be less than or equal to the battery manufacturer cycle life as in (14):

$$\sum_{t=1}^{N_t} u_t \cdot (u_t - u_{t-1}) \cdot \frac{P_t^{B+}}{\overline{PB}} \leq \overline{NC} \quad (14)$$

- Power balance constrain:

The power balance for the individual large customer bus is formulated as in (15).

$$P_t^T + PB_t = P_t^D - P_t^{DR} \quad (15)$$

- The battery deployment during the considered set of peak hours:

As the global adjustment is the biggest utility cost for large customers in Ontario, Equation (16) is formulated to enforce the battery discharging to cover the customer load during the set of considered peak hours (Ω_{PH}). This set of peak hours are estimated based on the historical data to avoid the uncertainty of forecasting of the five coincident peaks of this year. The coefficient KD represents the percentage of the customer demand load which will be supplied by the battery during the peak hours:

$$PB_{ph} \geq KD \cdot P_{ph}^D, ph \in \Omega_{PH} \quad (16)$$

- Limits to the battery capital cost:

In constrain (17), the battery capital cost is limited to the annual budget available for battery purchasing. It is important to mention that the maximum budget depends on many factors. However, our application is very specifically tuned to eliminate the GAC, so the budget based on the historical data of the paid bills for a class-A customer. We can estimate the average budget that will make this investment economically feasible. In other words, this investment budget should be returned to the customer in the form of GAC savings within the planning horizon:

$$AIC_B \leq \overline{IC_B} / N_y \quad (17)$$

- C-rate (ratio between \overline{PB} and \overline{EB}):

This constrain defines the limit of the battery power to energy ratio which is defined as C-rate. According to the purpose of the battery deployment and applications, the upper and lower limits are defined as in (18).

$$\underline{C_{rate}} \leq \frac{\overline{PB}}{\overline{EB}} \leq \overline{C_{rate}} \quad (18)$$

- Depth of discharge (DOD):

In order to keep the linearity of the formulation, a five-segment linearized curve [15] is used to specify the relation between the battery depth of discharge (DOD) and its cycle life (NC) as in (19). In Equation (20), an integer IU is used for each segment and ensures that only one segment of the curve will be used as shown in Figure 2.

$$NC = \sum_{w=1}^5 IU_w \cdot (\gamma_w \cdot DOD + \beta_w) \quad (19)$$

$$\sum_{w=1}^5 IU_w = 1 \quad (20)$$

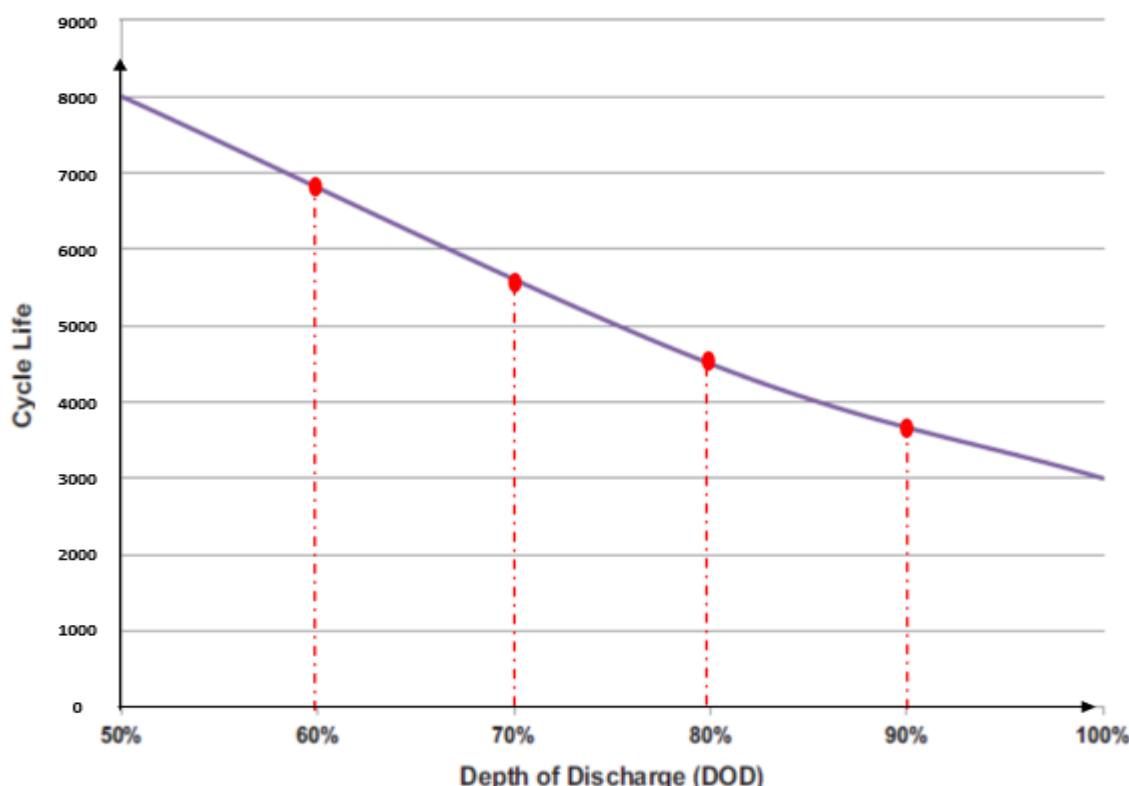


Figure 2. The linearized five segment curve between the battery depth of discharge (DOD) and cycle life (NC).

3. Solution Algorithm

For the purpose of validation, a greedy algorithm 1 is developed to demonstrate the solution procedure for sizing and scheduling the BESS as follows. Furthermore, the developed mathematical formulation of Section 3 is coded and implemented as a mixed integer nonlinear problem and solved using a commercial optimization solver.

Algorithm 1 Battery storage scheduling for energy arbitrage maximization.

1. Read all the model parameters including $\{R_t^{SP}, P_t^D, \overline{PD}_{PS}, r, Ny, \gamma_w, \beta_w, \eta^-, \eta^+, \overline{IC}_B, R_{EB}, R_{PB}, R_m^{GAC}, R_m^{DC}, KDR, \overline{NC}, KD\}$
2. Set $P_{t=1}^B = 0, E_{t=1}^B = 50 \text{ kWh}$ (small initial value), $C-rate_{in} = 0.5$
3. **for** $ph \in \Omega_{PH}$
 4. Calculate $P_{ph}^B = P_{ph}^{B+} = P_{ph}^D$ where $ph \in \Omega_{PH}$
 $u_{ph} = 1, \dots$ where $ph \in \Omega_{PH}$
 5. Calculate \overline{P}_{in}^B and \overline{E}_{in}^B
 $\overline{P}_{in}^B = \max(P_{ph}^B)$ where $ph \in \Omega_{PH}$
 $\overline{E}_{in}^B = \frac{\overline{P}_{in}^B}{C-rate_{in}}$
 6. **if** $(R_{EB} \cdot \overline{E}_{in}^B + R_{PB} \cdot \overline{P}_{in}^B) \cdot \frac{r \cdot Ny}{1 - (1+r)^{-Ny}} \leq \overline{IC}_B$
 7. $\overline{E}_{in}^{B*} = \overline{E}_{in}^B, \overline{P}_{in}^{B*} = \overline{P}_{in}^B$
 8. **else:**
 9. $\overline{P}_{in}^B = \text{the following peak of } P_{ph}^B$ where $ph \in \Omega_{PH}$ $\overline{E}_{in}^B = \frac{\overline{P}_{in}^B}{C-rate_{in}}$
 10. Return back to 6
 11. Calculate $C-rate_{in}^* = \frac{\overline{P}_{in}^{B*}}{\overline{E}_{in}^{B*}}$
 12. **for** $t \in \Omega_{DR}$
 13. $P_t^{DR} = P_t^B * K_{DR}$
 14. **else:**
 15. $P_t^{DR} = 0$
 16. **for** $t \in W, W = \{T = \{1 : 8760\} \setminus \Omega_{PH} \setminus \Omega_{DR}\}$
 17. **if** $R_{t+1}^{SP} > R_t^{SP}$ && $E_t^B \geq 0$
 18. $P_{t+1}^B = P_{t+1}^{B+} = \min(\max(P_1^B : P_t^B, \overline{P}_{in}^{B*}), \frac{E_t^B}{\Delta t})$
 $\overline{P}_{in}^{B*} = \max(P_1^B : P_t^B, \overline{P}_{in}^B)$
 $P_{t+1}^{B-} = 0, u_{t+1} = 1.0$
 19. **else if** $R_t^{SP} - R_{t+1}^{SP} > R^{DC}$ && $E_t^B \leq \overline{E}_{in}^B$
 20. $P_{t+1}^B = P_{t+1}^{B-} = \max(-\min(P_1^B : P_t^B, \overline{P}_{in}^{B*}), \frac{-E_t^B}{\Delta t})$
 $\overline{P}_{in}^{B*} = \max(P_1^B : P_t^B, \overline{P}_{in}^B)$
 $P_{t+1}^{B+} = 0, u_{t+1} = 0$
 21. **else:**
 22. $P_{t+1}^B = 0$
 23. Calculate $P_t^T = P_t^D - P_t^B - P_t^{DR}$
 $E_{t+1}^B = E_t^B - P_t^{B+} \cdot \eta^+ \cdot T - P_t^{B-} \cdot \eta^- \cdot T$
 $\overline{E}_{in}^{B*} = \max(E_1^B : E_{t+1}^B, \overline{E}_{in}^B)$
 24. **if** $(R_{EB} \cdot \overline{E}_{in}^{B*} + R_{PB} \cdot \overline{P}_{in}^{B*}) \cdot \frac{r \cdot Ny}{1 - (1+r)^{-Ny}} \leq \overline{IC}_B$
 25. $\overline{E}_{in}^B = \overline{E}_{in}^{B*}, \overline{P}_{in}^B = \overline{P}_{in}^{B*} \& C-rate = \frac{\overline{P}_{in}^{B*}}{\overline{E}_{in}^{B*}}$
 26. **Return** back the output values $\overline{P}_{in}^{B*}, \overline{E}_{in}^{B*}, P^B[1 : T], E^B[1 : T], P^T[1 : T], u[1 : T]$, and C-rate
 27. Calculate $PDF = \frac{\sum_{q=1}^{N_t} P_q^T}{\sum_{q=1}^{N_t} \overline{PD}_{PS}}, q \in \Omega_{5PH}$
 28. Calculate $ARV_{EA} = \sum_{t=1}^{N_t} T_t \cdot P_t^{B+} \cdot R_t^{SP}$
 $ACC_B = (R_{EB} \cdot \overline{E}_{in}^{B*} + R_{PB} \cdot \overline{P}_{in}^{B*}) \cdot \frac{r}{1 - (1+r)^{-Ny}}$
 $AEC = \sum_{t=1}^{N_t} T_t \cdot P_t^T \cdot R_t^{SP}, AGAC = \sum_{m=1}^{12} PDF \cdot R_m^{GA}$
 $ADCC = \sum_{m=1}^{12} max(P_t^T)_m \cdot R_m^{DC}, ARV_{DR} = \frac{KDR \cdot \overline{P}_{in}^{B*}}{2} + \sum_{t=1}^{N_t} T_t \cdot P_t^{DR} \cdot R_t^{SP}$
 29. **Return** back the output objective function
 $O.F = \{ACC_B + AEC + AGAC + ADCC - ARV_{EA} - ARV_{DR}\}$

4. Results

A practical data for a large customer (Class-A) is employed to check the performance of the developed model. The energy market price including, global adjustment cost, demand charges, hourly energy price are adopted from the available data of IESO in Ontario, Canada [24–26]. It is important to mention here that the uncertainty in the load demand and market prices is fully considered in the data processing step. This analysis is based on the long-term planning forecasted data of IESO, which is available in [26]. This study has considered the average forecasted data for the prices and the global demand load profile over the study horizon (5 years). For the class-A customer data, we have used the available historical data to forecast the average customer load over the study horizon (5 years).

The proposed mixed integer nonlinear mathematical formulation was coded in the AMPL optimization platform [27] and solved using the KNITO commercial solver. Figure 3 shows the daily peak demand power for a class-A customer in Ontario during 2016 and Figure 4 shows a typical hourly maximum demand for 24 hours. As per the IESO regulations the analysis period should start from 1st May of current year to 31st April of the next year.

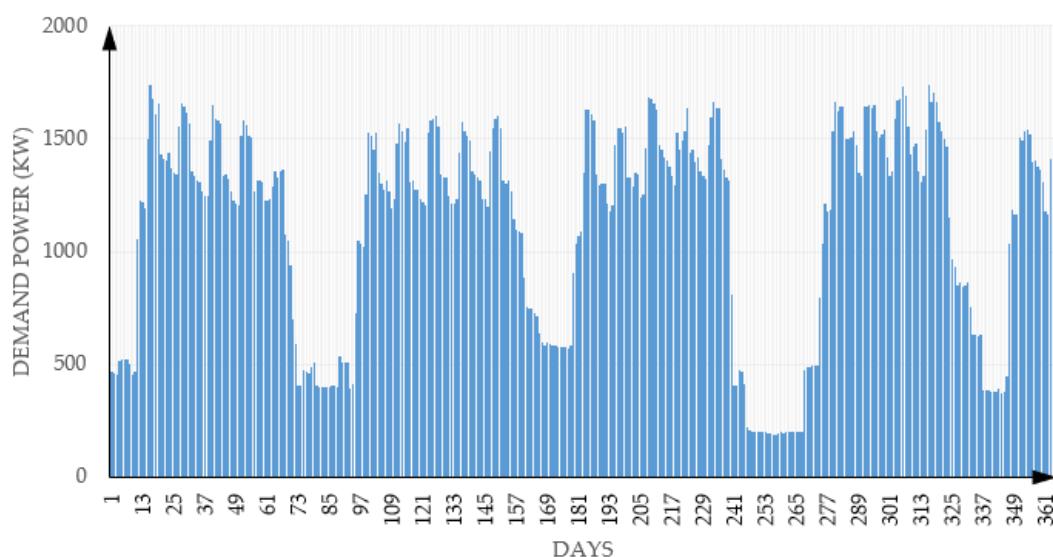


Figure 3. The daily maximum demand for a class-A customer in Ontario during the analyses period (2016).

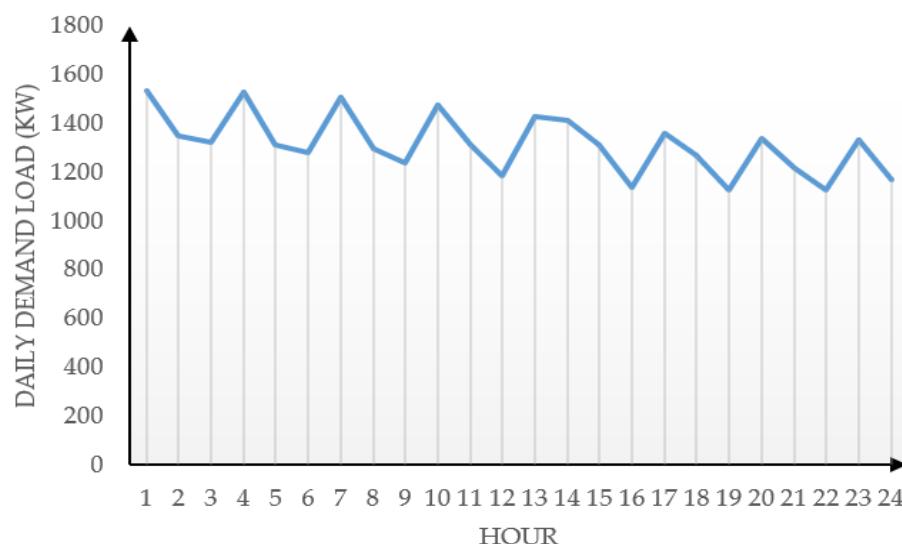


Figure 4. Typical hourly maximum demand for a class-A customer in Ontario (2016).

In Figure 5 the one line diagram of the considered class-A customer is presented. As per IESO regulations the BESS is connected behind the customer meter. The main parameters for the base case are assumed as follows. The maximum allowable budget for the BESS is considered to be \$2 million. The horizon (the planning timeline for the study) is assumed to be 5 years. As per the market price, the battery energy and power cost coefficient are considered to be \$344/kWh and \$125/kW, respectively. As the proposed analysis is annual, the annual interest rate is set to be 6%. The limit of the C-rate is assumed to guarantee a two-hour discharging during the enforced deployment of the peak hours. Finally, the loading factor (KD) is considered to be 100%. The assumptions for obtaining the base case results are summarized in Table 1.

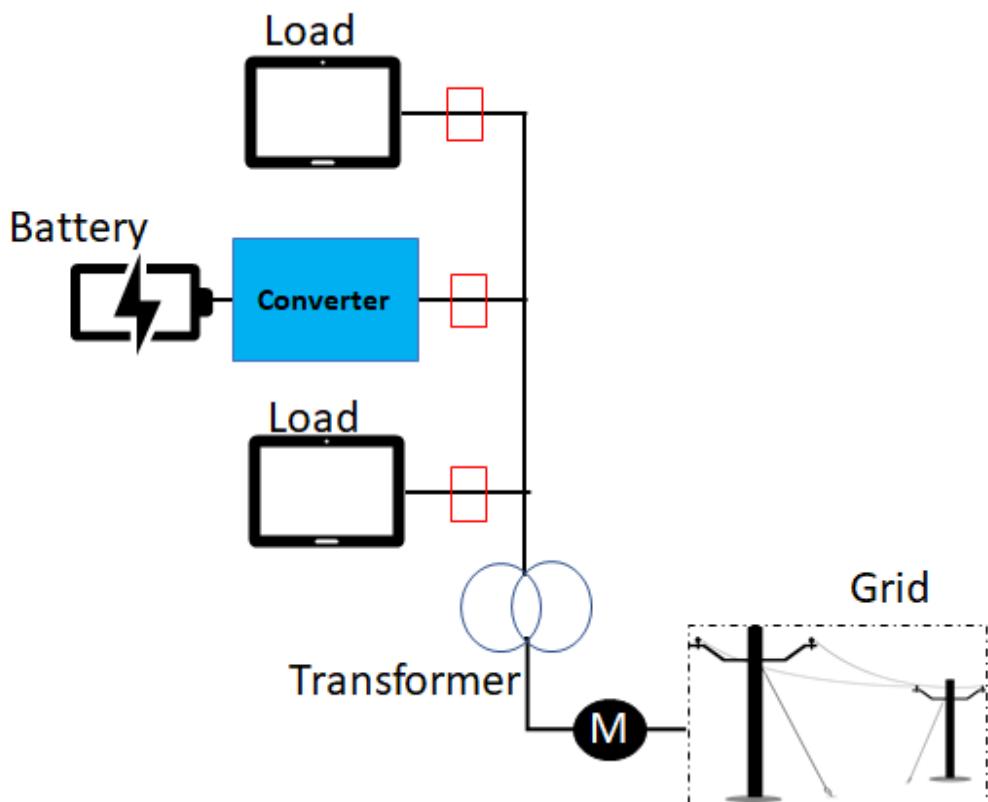


Figure 5. The considered customer one line diagram.

Table 1. Assumptions for the base case.

Maximum allowable budget for the BESS (\overline{IC})	\$2.00 Million
Number of operational years (Ny)	5 years
Battery power cost factor (R_{PB})	\$125/kW
Battery energy cost factor (R_{EB})	\$344/kWh
r (interest rate)	6%
C_{rate}	Less than half
KD	1.0

4.1. Base Case Results

This subsection presents the base case results of the total annual bill for a class-A customer in Ontario before and after applying the proposed deployment algorithm. The base case results show that the optimal sizes for the battery are 1.826 MW and 3.7916 MWh.

The comparison between the customer bill on annual basis is provided before and after the battery deployment as in Table 2. The comparison considers the annual component values of the bill without the battery and showing how these components will be reduced after the battery deployment. The optimal ROI is calculated after the battery deployment and has a value of 18.43% which ensure the viability of the proposed battery deployment method. It is believed that this ROI is attractive for independent energy-sector investors as well as class-A facility owners to finance battery projects which make use of the proposed model.

Table 2. Comparison between the bill components before and after the battery deployment.

	Before	After
Energy cost per year	\$205,004.01	\$296,505.21
Demand Charge cost per year	\$42,470.00	\$40,375.86
Global Adjustment cost per year	\$860,176.24	0.0
Capital cost per year	-	\$363,604.81
Revenue of Energy Price Arbitrage per year	-	\$87,428.57
Demand Response revenue per year	-	\$35,164.28
Saving of GAC per year	-	\$860,176.24
Total Annual bill	\$1,107,650.25	\$700,485.88

4.2. Comparison with the Results of the Developed Greedy Algorithm

This subsection validates the results obtained by KNITRO solver with those obtained from the greedy algorithm. In Figure 6 below, a comparison between the results of the annual revenues of EA and DR, battery size, C-rate, annual commodity cost, annual DC cost, and annual capital cost between the greedy algorithms and optimization solver is shown. The comparison illustrates the good performance of the proposed solution algorithm.

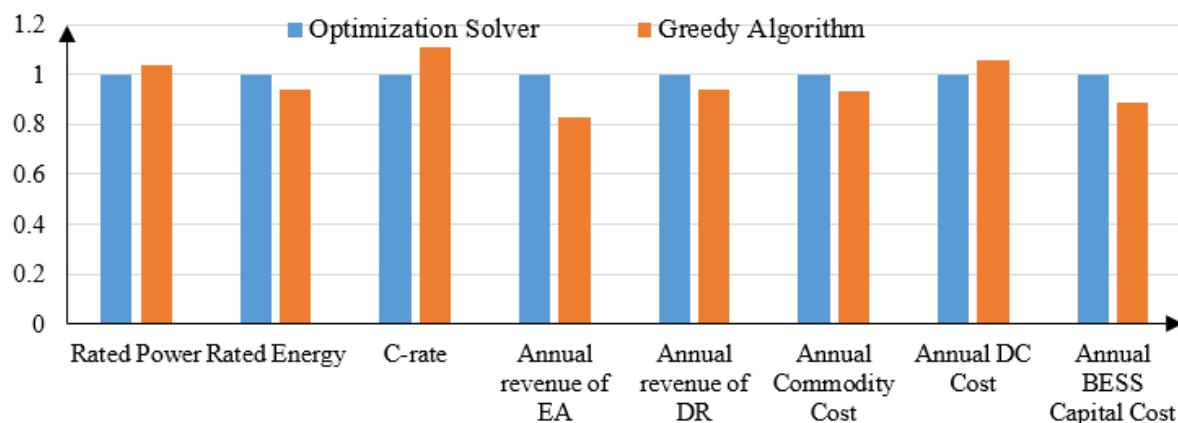


Figure 6. Comparison between the normalized results of the greedy algorithm and optimization solver.

4.3. Comparison with an Existing Sizing Problem for Energy Storage

For validation purposes, the proposed mathematical formulation has been compared with an existing BESS sizing algorithm for demand charge reduction [15]. Since the model of [15] only counts for DC, the energy charge and demand charge terms have been considered in the objective function of the proposed formulation, while the rest of the charges like GAC and revenues (DR and EPA) are not considered in order to maintain a consistent comparison. The sizing algorithm of [15] has been coded and tested on the data set of the considered Ontario class-A customer presented in Figure 7. The two methods are tested based on the base case assumption given in Table 1. The demand charge cost is adopted from [15] to be \$13/KW. The obtained results have been compared and tabulated as follows

in Table 3. The comparison shows that the results are very close, demonstrating that the proposed method is accurate. It is important to note that the major benefit of the proposed method is counting for multi-revenue streams; energy arbitrage and demand response, as well as the savings from utility charges; demand charges and global adjustment charges, as reported in the previous subsection.

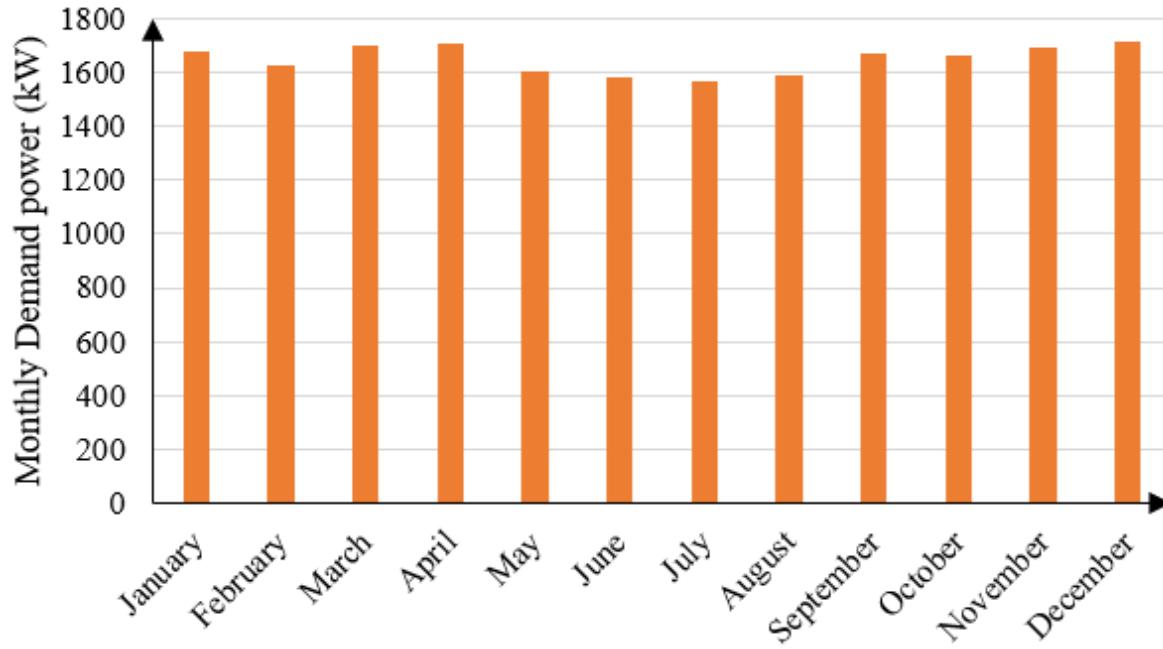


Figure 7. The monthly maximum power of class-A customer in Ontario.

Table 3. Comparison results of the existing battery energy storage system (BESS) sizing for demand charges (DC) [15] and the proposed method.

	Existing BESS Sizing for DC [15]	Proposed Method
Annual energy cost	\$213,486.5	\$213,624.8
Annual DC cost before BESS deployment	\$206,418.0	
Annual DC cost after BESS deployment	\$158,672.0	\$157,946.0
Annual Saving of DC	\$47,746.00	\$48,472.00
Annual BESS capital cost	\$40,987.90	\$40,943.23
BESS size	352 KW	356 KW
	374 KWh	372 KWh

Different sensitivity cases are conducted to check the performance and the effectiveness of the developed battery deployment model.

4.4. Sensitivity Case—Maximum Available Budget for Battery Purchasing

A sensitivity case study depends on different values of the available purchasing budget ($\overline{IC_B}$) are developed. This sensitivity analysis considers four cases, which include percentage values of the available purchasing budget based on the base case, as follows: 80%, 70%, 60%, and 50%. In Figure 8 optimal battery sizes of the four considered cases are illustrated.

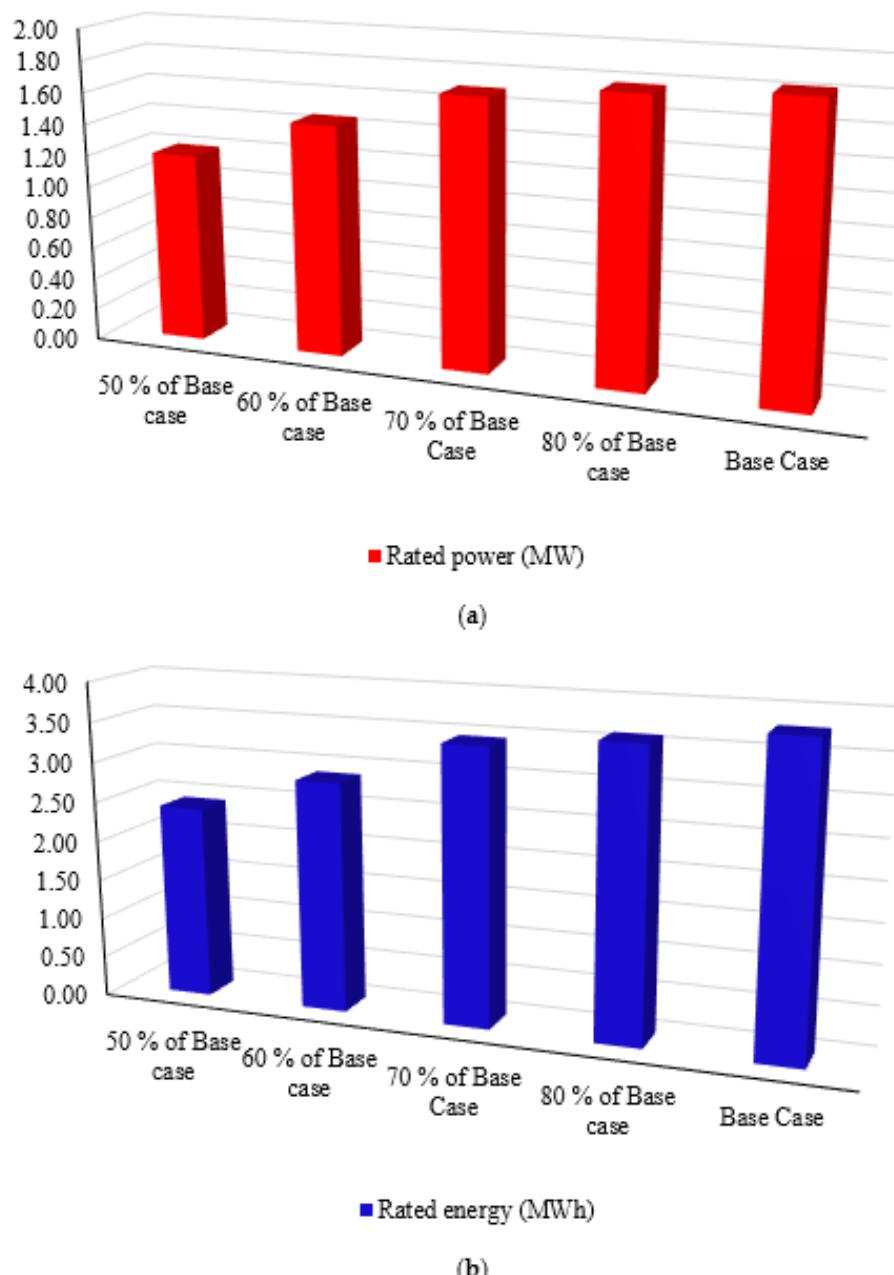


Figure 8. Optimal sizing of the BESS as a result of the sensitivity analysis on the maximum allowable budget (a) for power (MW) and (b) for rated energy (MWh).

The comparison results between the annual accumulated costs of each considered case are presented in Figure 9. The results demonstrate that restricting the battery purchasing budget will limit the battery size leading to increase the global adjustment cost.

The annual revenues of the BESS are presented in Figure 10. The results show that the achieved revenues of the battery from EPA and DR keep decreasing with a reduction in the allowable BESS budget.

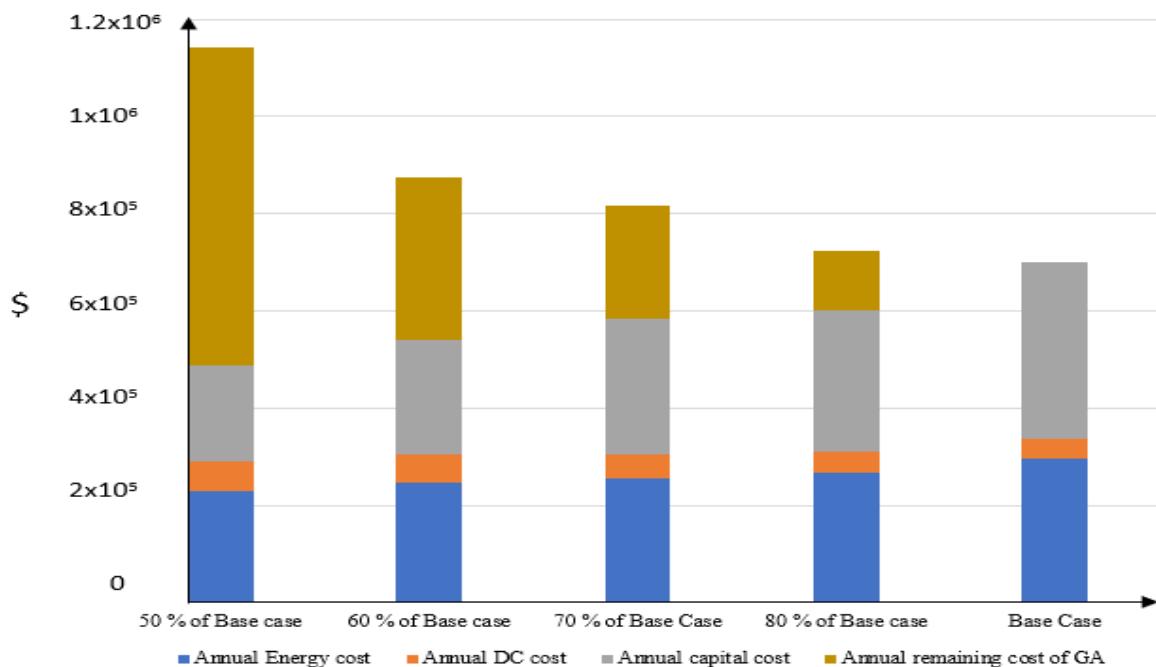


Figure 9. Results of available purchasing budget sensitivity case study in terms of the cost components.

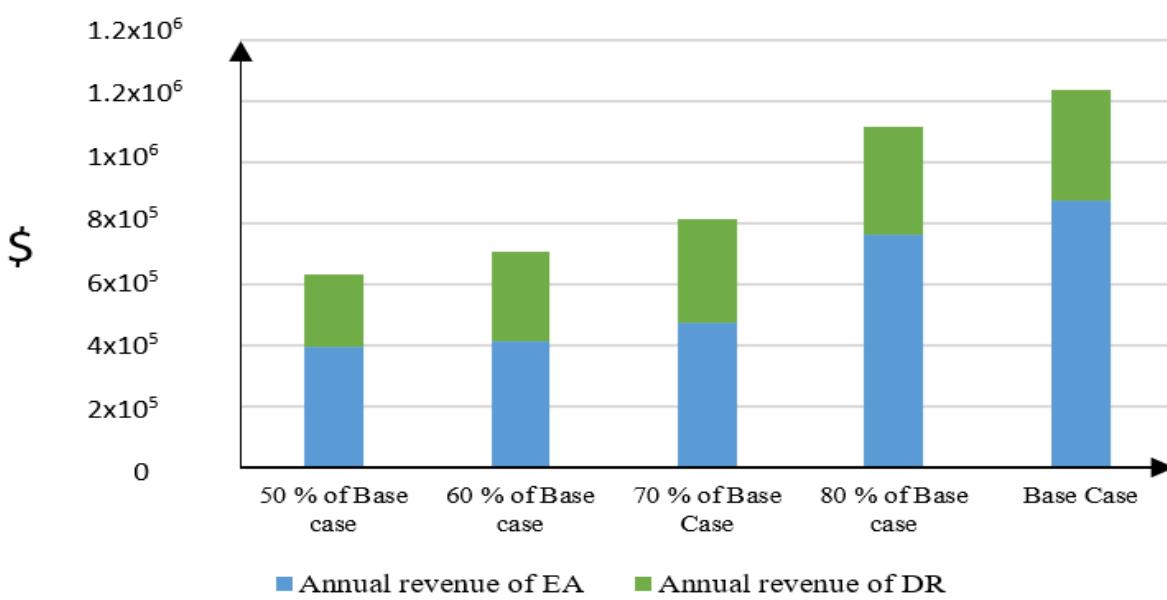


Figure 10. Results of available purchasing budget sensitivity case study in terms of the revenue components.

4.5. Sensitivity to C-Rate Results

Based on constrain (18), several values for the C-rate ranges are considered as: “0.4–0.6”, “0.6–0.8”, “0.8–1.0”, “0.3–0.4”, and “0.2–0.3”, which corresponding to these cases, CASE I, CASE II, CASE III, and CASE IV, respectively. The battery sizes correspond to the aforementioned cases are illustrated in Figure 11.

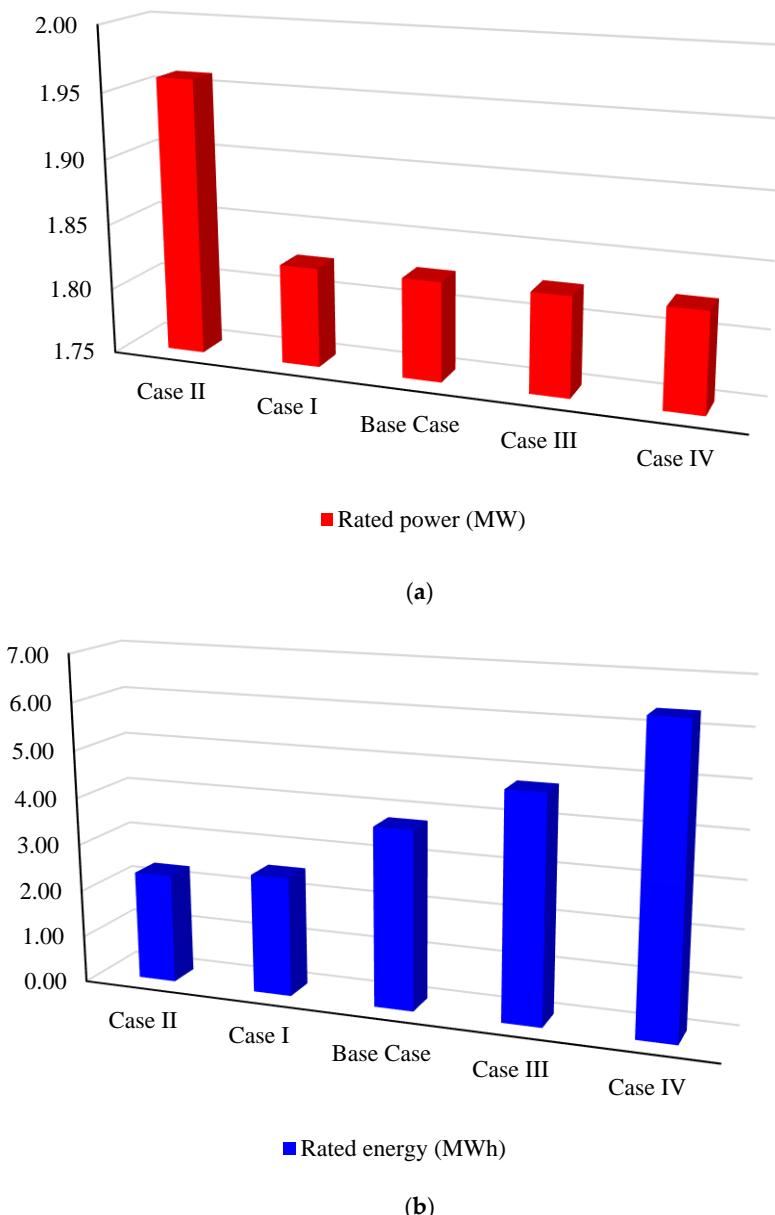


Figure 11. Optimal sizing of the BESS results for the C-rate sensitivity case study (a) for power (MW) and (b) for rated energy (MWh).

Values for the ROI and C-rate of the battery are illustrated below in Figure 12. Note that ROI (Return On Investment) is a ratio between net profit and the cost of investment. The results show that an optimal ROI of the base case has a value of 18.43% and its C-rate has a value of 0.48. As can be shown, the two cases I and II with high C-rate have an economically negligible ROI. Cases III and IV show that a lower C-rate leads to a larger energy capacity of the BESS. A higher energy capacity for the BESS is concomitant with a higher capital cost and definitively higher revenues; however, the surge of revenue does not match the growth of the capital cost of the BESS.

The comparison results between the annual accumulated costs of each considered case are presented in Figure 13. The results show that higher C-rate could save the battery capital cost. But it will affect the battery size leading to higher PDF value and higher Global Adjustment cost a relatively high C-rate may save the capital investment costs of BESS; however, it will lead to a higher GAC as the PDF of this customer keeps increasing. In other words, the lower the size of the incorporated BESS on

the customer microgrid (with a higher C-rate), the higher the contribution of this class-A customer to the peak demand hours of the whole province of Ontario.

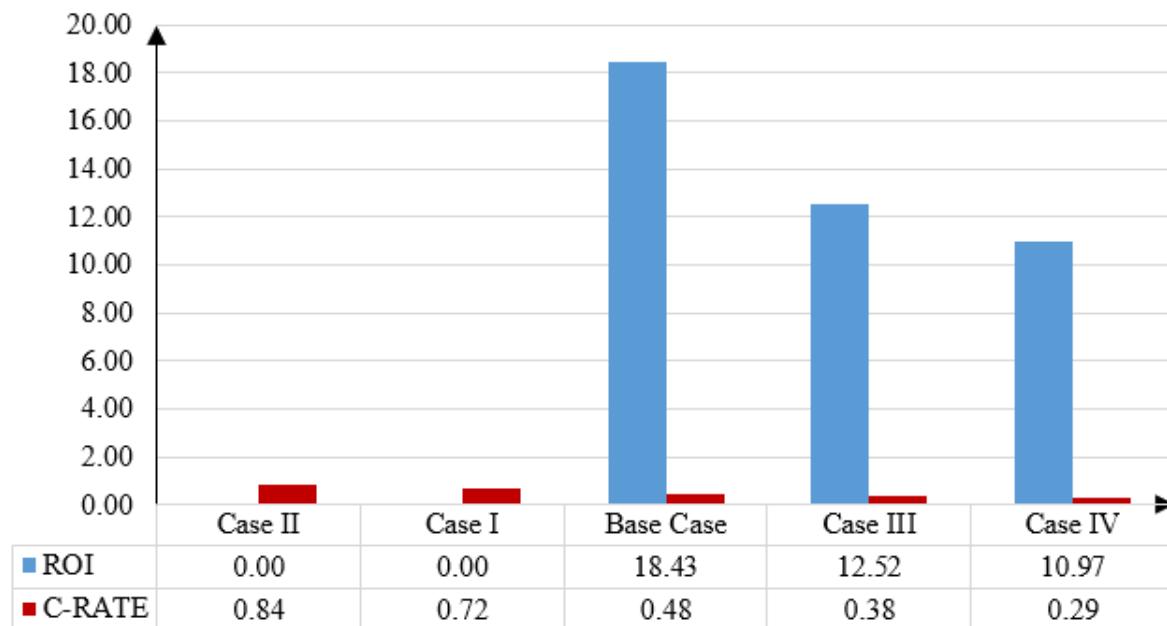


Figure 12. The results of C-rate sensitivity case study in terms of ROI (Return On Investment).

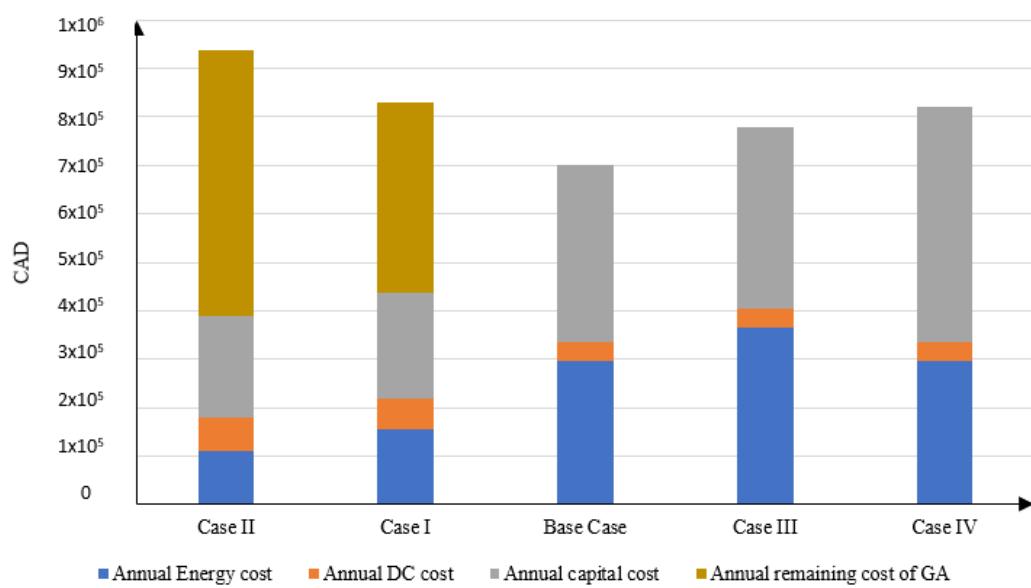


Figure 13. Results of the C-rate sensitivity case study in terms of the cost components.

The annual revenues of the BESS from EPA and DR are presented in Figure 14. The results show that relatively low C-rate values (with higher energy capacity and so higher capital cost) will allow the BESS to achieve higher revenues.

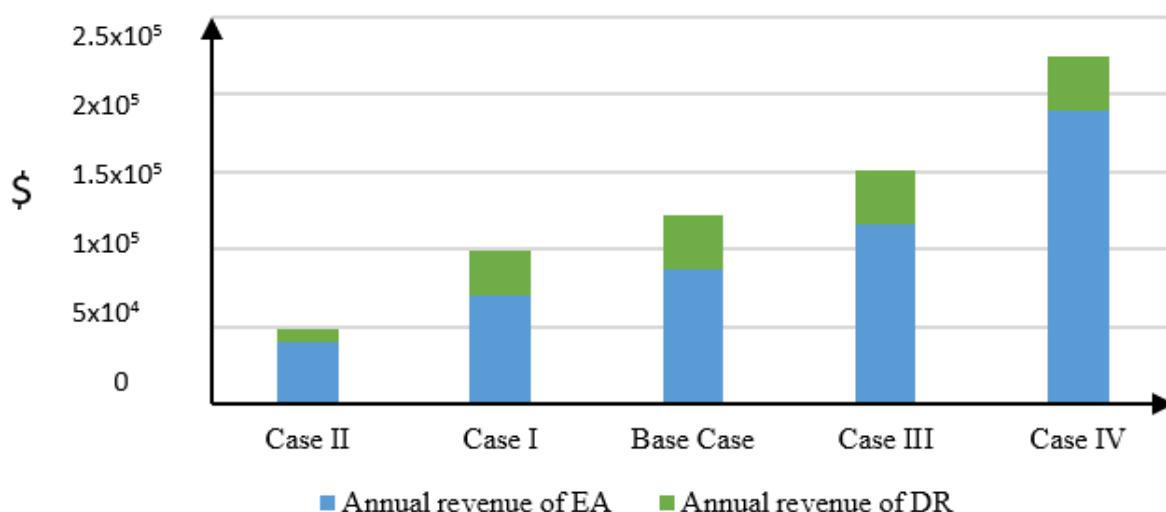


Figure 14. Results of the C-rate sensitivity case study in terms of the revenue components.

5. Conclusions

This paper presents a methodology to optimally size and dispatch a battery energy storage unit for electricity cost minimization for large consumers in Ontario, Canada. The algorithm proposed in this paper particularly minimizes the charges associated with the global adjustment costs for class-A customers. Moreover, other utility charges, such as demand charges, are considered and explicitly minimized by the algorithm. Moreover, energy price arbitrage and participation in the IESO demand response programs are considered as revenue streams. A single comprehensive mathematical formulation is developed to encompass all these revenue streams in one optimization problem abiding by the regulations of the jurisdiction. For quality and performance assurance, the proposed method is applied to real class-A customer data and the corresponding market spot prices in Ontario. The contributions of this work are twofold. Firstly, the developed methodology attains the optimal size of BESS units to minimize total energy costs, including GAC for class-A customers in Ontario. Various revenue streams are stacked to maximize the total gain. The proposed technique can be applied to different class-A facilities with different load profiles and operational features. Secondly, the straightforward optimization model and its results open the doors wide for a viable investment opportunity with obvious technical and financial merits. The results demonstrate that a class-A customer employing a BESS with the optimal battery size and dispatch schedule, can achieve significant savings in energy bills. The results show the efficacy of the developed method in attaining a favorable investment ROI in a short-term financing plane.

Furthermore, the proposed algorithm takes into consideration the jurisdiction regulations, which can be flexibly modified and updated to match the regulations of other jurisdictions. Various sensitivity analyses were conducted to explore the impact of some solution parameters on the results. Another sensitivity analysis based on C-rate changes was also performed. For future work, benefits to the grid reliability, resiliency, stability and profitability may be important to consider.

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Nomenclature

Indices

T	Hourly index of the time
M	Monthly index of the time
Ph	Index of forecasted peaks
Q	Five coincident peaks for Ontario province, Canada
W	five-segments for the linearized depth of discharge (DOD) curve

Parameters

p^{DR}	Demand response power (decision variable)
Rsp_t	Spot price at t (\$/MWh)
\overline{NC}	Battery's rated cycle life
NC	Battery actual cycles life
\overline{IC}	Allowable maximum budget for the battery
R_{PB}	Battery cost factor for power
R_{EB}	Battery cost factor for energy
PD_{PS}	Peak demand load for Ontario province
C_{rate}	Battery C_{rate} ($\overline{PB} / \overline{EB}$)
P_t^T	Total exchange power
P_t^D	Power demand at t
R_m^{GAC}	Charges for global adjustment per month
R_m^{DC}	Demand charges per month
η^+	Battery efficiency (discharging)
η^-	Battery efficiency (charging)
E^0	Initial BESS energy value
KDR	Demand response contract (\$/Mw)
KD	Battery loading coefficient during the coincident peak hour
R	Annual interest rate
N_y	Total number of operational years
γ_w, β_w	Linearization parameters of DOD curve

Variables

ACC_B	Batter capital cost per year (\$/year)
AEC	Total energy cost per year (\$/year)
$AGAC$	Cost of global adjustment per year (\$/year)
$ADCC$	Cost of the demand charge per year (\$/year)
ARV_{EPA}	Energy price arbitrage revenue per year (\$/year)
ARV_{DR}	Demand response revenue per year (\$/year)
\overline{EB}	Battery maximum energy (MWh) (decision variable)
\overline{PB}	Batter maximum power (MW) (decision variable)
T	Time step
DOD	Depth of discharge of the battery.
PB_t	Hourly Battery power at t
P_t^{B+}	Discharging battery power at t (decision variable)
P_t^{B-}	Charging battery power at t (decision variable)
PDF	Peak demand factor
Ω_{5PH}	Set of the five peaks for the Ontario Jurisdiction
Ω_{PH}	Set of the forecasted peaks

Integer variables

IU	Integer of the 5-segments of the linearized DOD curve
u	Integer of battery discharging

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