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RESEARCH ARTICLE

Sizing Merchant Energy Storage for Maximum Revenues Considering Net Metering and Ancillary Services

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ABSTRACT As prices for energy storage (ES) decline, merchant-owned ES units have an opportunity to be profitable if they earn revenue from multiple streams. Most papers in the literature provide a simplistic view, and do not capture practical tariff structure of commercial customers connected via load meters billed via net-metering scheme. In this paper, we present a flexible and comprehensive mathematical model to enable merchant-owned ES owners to maximize their profits by considering multiple revenue streams. The main contribution is a model that fully captures the economic picture by including displaced electricity costs, i.e., net-metering scheme, for behind-the-meter installations. It also includes operating costs, annual investment costs, and ES connected to the distribution system. The inclusion of net metering is novel, as well as simultaneously including all of ancillary services, energy costs, investment costs, net metering, and local generation. These elements can be crucial in building the business case for ES in Ontario to ensure profitability. We test our model on a large commercial customer. The load has a peak load of 1,500 kW and a solar generation capacity of 2,500 kW connected on a 13.8 kV feeder, with a limit of 5,000 kW capacity. The results show two cases. The first considers only energy arbitrage and costs $4,812,909, which is less than the cost without storage at $9,299,623. The second scenario allows for energy arbitrage and revenue via participation in local and bulk system ancillary services and yields a total benefit of $11,004,225. Both scenarios indicate benefits from purchase of storage. The second scenario is clearly more beneficial when storage investment is considered and opportunity is available. We also provide a stochastic implementation to consider uncertainty in any input parameter and demonstrate this method with energy prices.

INDEX TERMS Electricity markets, energy storage, power system economics, state of charge.

NOMENCLATURE

NYS	Is the number of year scenarios.
NYD	Is the number of years with the same data.
$KINFL$	Is the rate of inflation.
$KAIR$	Is the annual interest rate.
$\mathrm{KROR10S_y}$	Is the rate of revenue for operating reserve, 10-minute synchronized.
$\mathrm{PCOR10S_y}$	Is the power capacity for operating reserve, 10-minute synchronized.
$\mathrm{KROR10N_y}$	Is the rate of revenue for operating reserve, 10-minute non-synchronized.
$\mathrm{PCOR10N_y}$	Is the power capacity for operating reserve, 10-minute non-synchronized.
$\mathrm{KROR30_y}$	Is the rate of revenue for operating reserve, 30-minute.
$\mathrm{PCOR30_y}$	Is the power capacity for operating reserve, 30-minute.
$\mathrm{KRRS_y}$	Is the rate of revenue for regulation service.
$\mathrm{PCRS_y}$	Is the power capacity for regulation service.
$\mathrm{KRBS_y}$	Is the rate of revenue for black start service.

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$\mathrm{PCBS_y}$	Is the power capacity for black start service.
$\mathrm{KRTDR_y}$	Is the rate of revenue for transmission connected demand response service.
$\mathrm{PCTDR_y}$	Is the power capacity for transmission connected demand response service.
$\mathrm{KRDDR_y}$	Is the rate of revenue for distribution connected demand response service.
$\mathrm{PCDDR_y}$	Is the power capacity for distribution connected demand response service.
$\mathrm{KRRSVC_y}$	Is the rate of revenue for reactive support and voltage control service.
$\mathrm{QCRSVC_y}$	Is the power capacity for reactive support and voltage control service.
$NTB_{y,m}$	Is the net metering bill for year 'y', month 'm'.
NMS	is the number of month scenarios with similar pattern.
NY	Is the number of years for the study.
KPB	Is the cost per unit of power for storage.
$\overline{PS}$	Is the power rating of the storage unit.
KEB	Is the cost per unit of energy for storage.
$\overline{ES}$	Is the energy rating of the storage unit.
$ESB_{y,m,t}$	Is the state of charge of the storage unit.
KBC	Is the constant maintenance charge for storage, as a function of the capital cost.
KBV	Is the variable maintenance charge for storage, as a function of the capital cost.
$NMD_{y,m}$	Is the number of similar months data.
TD	Is the time duration in hours for each time interval, one hour in this study.
ND	Is the number of days in a month.
NH	Is the number of hours in a day.
$PNT_{m,t}$	Is the total power drawn from the network.
$HOEP_{m,t}$	Is the hourly Ontario energy price in the bulk electricity system available to class A and select class B customers.
$WMST_y$	Are the Wholesale Market Service Charges.
$MP_{y,p}$, $TP_{y,p}$	Are sets of indices for months and hours where 5 CP occurs.
$\mathrm{QS_{yq}}$	Is the intermediate variable that sectionalizes reactive power requirements into linear sections for P-Q relationship.
$PNT_{y,m,t}$	Is the hourly network demand.
$PG_{y,m,t}$	Is the hourly generation at the facility.
$PSB_{y,m,t}$	Is the hourly power drawn by the storage unit.
$PD_{y,m,t}$	Is the hourly demand at the facility.

I. INTRODUCTION

Energy storage (ES) has the potential to deliver numerous benefits to electricity systems [1] and thereby generate multiple streams of revenue. In many cases, these multiple revenue streams are necessary and crucial for the profitability merchant-owned ES systems. Therefore, in this paper, we present a profit maximization formulation that considers multiple revenue streams from the perspective of merchant-owned ES. This is a more complete and realistic economic model as it considers revenue streams including various ancillary services and energy arbitrage, while also allowing for offsetting costs for behind-the-meter installations.

The purpose of this proposed merchant ES sizing formulation is to enable more ES to be installed for economic and environmental benefits. ES can lead to greater social welfare, more economic efficiency, and lower market prices. However, many ES will be privately owned by merchants. Therefore, it is important to find effective sizing strategies for merchant-owned ES in order to build sound business cases to justify the investments by looking at the full economic picture, where revenues can be stacked and investment costs are considered.

A. LITERATURE REVIEW

ES has been considered for numerous applications. Energy applications include: arbitrage; renewable energy time shift; demand charge reduction; time-of-use charge reduction; transmission and distribution upgrade deferral; and grid resiliency. Power applications include: frequency regulation; voltage support; small signal stability; frequency droop; synthetic inertia; and renewable capacity firming [2].

ES can also manifest in a variety of configurations. They can be owned by utilities or by private merchants; they can be large, grid-scale installations or small, behind-the-meter applications. They can be controlled by a utility, independently, or through an aggregator. They could also be operating under market conditions or within a vertically-integrated utility [2].

Among all these possibilities for application and configurations, this paper explores the situation for merchant-owned energy storage connecting in Ontario, Canada. Ontario has transmission markets for energy and several ancillary services, and the distribution side is operated by regulated utilities, many of which are municipally-owned. We consider that the same ES unit can simultaneously participate in multiple energy and ancillary service markets as well as behind-the-meter applications.

The business model from the perspective of merchant-owned ES has been studied in literature, however, to our knowledge, none of the studies have included the complete economic model that we present in this paper. Spatiotemporal energy arbitrage, in which excess generation is stored for use by loads at later times, was the sole revenue stream considered for one study, whose main goal was to locate and size ES units [3]. To complement this planning problem, the scheduling and bidding problem has been explored for spatiotemporal energy arbitrage as well, taking care to consider the impacts of state-of-charge [4]. In a microgrid context, ES capacity allocation has been optimized with the objective of minimizing costs [5]. The main purpose of this study was to consider the uncertainties associated with solar, wind, and demand in the system, rather than maximizing all potential revenue sources. Spatiotemporal energy arbitrage in day-ahead markets was the only revenue stream in another study that captured the influence of transmission expansions, although the authors noted that additional profit streams from capacity, ancillary services, and hourly markets could be added to the profit calculation, despite being out of scope for their study [6].

Additional studies consider ES systems co-located with renewables [7], [8], [9], [10], [11], [12], [13]. A couple of studies consider residential applications using ES and renewable generation [7], [8]. Both household load and ES are scheduled to minimize overall system costs. One study minimizes the monthly charges for both time-of-use volumetric tariffs and demand charge tariffs for an energy storage system with photovoltaics (PV) () [9]. Another study proposes an energy management system that schedules a microgrid with PV, wind turbine (WT), fuel cell, micro turbine, and battery energy storage system considering uncertainty of PV, WT, load forecasting, and grid prices ()() [10]. Net grid electrical energy was minimized for the schedule for a nearly Zero Energy Building (nZEB) with PV and ES [11]. Integrated energy microgrids, comprising energy storage with solar PV and microturbines, were scheduled using a reinforcement learning-based scheduling strategy that minimizes operating costs [12]. ES merchants who also had wind generation maximized their expected rewards while also being large enough to influence electricity prices [13]. We build upon these past studies that include renewable generation by considering net metering, ancillary services, and investment costs together.

Revenue from ancillary services for merchant-owned ES were considered in several studies for optimal scheduling [14], [15], [16]. One study included ancillary services for the scheduling of underground pumped hydro energy storage, considering the unique geometry and physical characteristics of the facility [14]. Another study scheduled ES for energy, reserve, and balancing with an objective to maximize profit [16]. Still another study was for a stand-alone ES connection [15]. ES units could be installed behind-the-meter of an existing load in order to reduce both energy and demand charges, thereby enhancing their profitability. Also, the operating costs and annual investment costs were not considered. We build on this past work by including these aspects in our mathematical model.

Additional merchant ES scheduling problems have been considered from a variety of perspectives. Compressed air energy storage plants have been scheduled to maximize profits [17] and to take advantage of energy arbitrage while considering price forecasting errors [18]. Uncertainties in locational marginal prices were also considered for ES scheduling in both the day-ahead and real-time markets [19]. The perspective of the overall distribution system, where total social welfare was maximized, was the goal in another study that scheduled merchant-owned ES [20].

TABLE 1. Comparison of merchant ES studies.

	Ancillary services	Energy costs	Investment costs	Net metering	Generation
Shafiee et. al., 2016 [18]	No	Yes	No	No	No
Dvorkin et. al., 2017 [3]	No	Yes	Yes	No	Yes
Wang et. al., 2017 [4]	No	Yes	No	No	No
Babacan et. al., 2017 [9]	No	Yes	No	No	Yes
Nojavan et. al., 2018 [17]	No	Yes	No	No	No
Fang et. al., 2018 [19]	No	Yes	No	No	No
Li et. al., 2018 [7]	No	Yes	No	No	Yes
Xie et. al, 2018 [5]	No	Yes	Yes	No	No
Dvorkin et. al., 2018 [6]	No	Yes	Yes	No	No
Toubeau et. al., 2019 [14]	Yes	Yes	No	No	No
Abdolahi et. al., 2020 [20]	No	No	No	No	Yes
Tómasson et. al., 2020 [21]	No	Yes	No	No	Yes
Luo et. al., 2020 [10]	No	Yes	No	No	Yes
Georgiou et. al., 2020 [11]	No	Yes	No	No	Yes
Opathella et. al., 2020 [15]	Yes	Yes	Yes	No	No
Liu et. al., 2021 [22]	No	Yes	No	No	No
Toubeau et. al., 2021 [16]	Yes	Yes	No	No	No
Bouakkaz et. al., 2021 [8]	No	Yes	Yes	No	Yes
Zhou et. al., 2022 [12]	No	Yes	No	No	Yes
Liu et. al., 2022 [13]	No	Yes	No	No	Yes
Proposed in this paper	Yes	Yes	Yes	Yes	Yes

A specialized branch-and-bound algorithm that applies a linear quasi-relaxation of the profit-maximizing merchant storage problem was proposed [21]. Finally, the market price impact of the merchant ES's actions was considered as the ES maximized their profits [22].

Table 1 summarizes the approaches in the merchant ES studies discussed above. The model proposed in this paper builds upon these previous works by comprehensively including all of ancillary services, energy costs, investment costs, net metering, and local generation. In particular, none of the other works address net metering at all; this is a new contribution first proposed here.

B. TARIFF STRUCTURE

The model proposed in this paper follows the tariff structure in Toronto, Ontario, Canada for interval meter-billed customers [23], who are typically industrial customers with demand greater than 50 kW. Very similar tariff structures are used in other jurisdictions, so this model can be applied to those areas by adjusting the input parameters, which capture the local conditions such as prices for energy and ancillary services.

Customers pay two types of charges: energy charges (based on kWh) and demand charges (based on kW). Energy (volumetric) charges are the hourly market energy price and the wholesale market service charge. (This modeled below in (14).) Demand charges comprise global adjustment charge, capacity based recovery charge, and distribution charge. (This modeled below in (15).)

Net metering allows consumers to send excess energy to the grid [24], [25], [26]. Instead of payment for that energy, they are given credit on their electricity bills to displace charges from other times. If the credit is not fully used during the billing month, it can be carried forward to future months for up to 12 months.

C. CONTRIBUTIONS OF THIS PAPER

In this paper, we introduce a complete and realistic mathematical model to maximize profits for merchant ES owners. The main new contribution is the inclusion of net metering, which allows behind-the-meter ES installations to displace energy and demand charges. In addition, our proposed model assesses the full economic investment model, including all of ancillary services, operating costs, annual investment costs, and on-site generation.

Our multi-year model also allows for the evaluation of opportunity costs; in particular, ES owners can consider trade-offs between and impacts of actions in different time periods. By scheduling the ES unit over a longer time horizon, the ES owner is also able to optimally size their unit for maximum profits. Furthermore, we consider uncertainty in future energy prices through our stochastic model.

Our proposed model reflects the perspective of a private, merchant-owned facility including ES. Therefore, the owner is solely concerned with affairs within their facility and not the distribution network to which they are connected. They do not have the interest or ability to include the distribution network in their analysis, and therefore the network is out of scope in our proposed model.

In summary, our proposed model enables the merchant owner of a facility to optimally size their ES by scheduling it over a long time horizon to maximize their profits.

D. ORGANIZATION OF PAPER

This paper is organized as follows: our model for the maximization of energy storage profits is presented in Section II; in Section IV, data, results, and potential applications of an Ontario case study are described; in Section V, results are discussed; and in Section VI, the conclusions are outlined.

II. METHODS AND PROCEDURES

The set of equations that describe the revenue stacking optimization challenge is described in this section. The formulation is an enhancement of [15] with additional elements such as net metering added. Ancillary services have been considered as potential revenue streams for the merchant facility. Specific ancillary services included are: 10-minute synchronized operating reserve; 10-minute non-synchronized operating reserve; 30-minute non-synchronized operating reserve; regulation service; black start capacity service; demand response service; and reactive support and voltage control service. This is consistent with ancillary services in Ontario, Canada. This model is for a merchant-owned energy storage facility. The private merchant is concerned with the technical and economic situation within their own facility and not the distribution network. Therefore, the distribution system itself is not modelled for this situation; however, relevant system properties such the hourly energy price, wholesale market service charges, and prices for ancillary services are included. Furthermore, while solar was used in this example, the proposed model is flexible to accommodate any type of generation, renewable or otherwise. Generation output is included in $PG_{y,m,t}$.

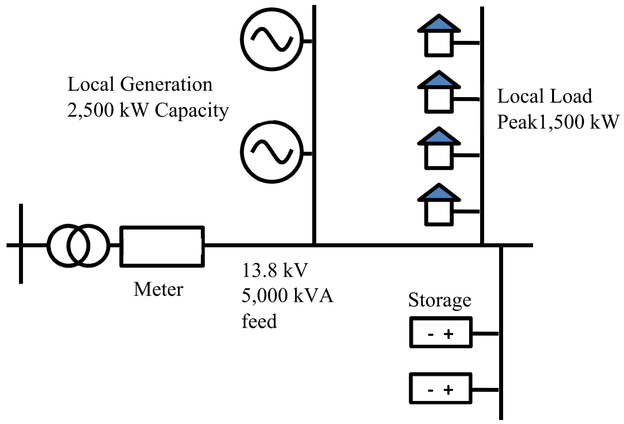

FIGURE 1. Sketch of a possible electric single line for storage system, with local load and generation.

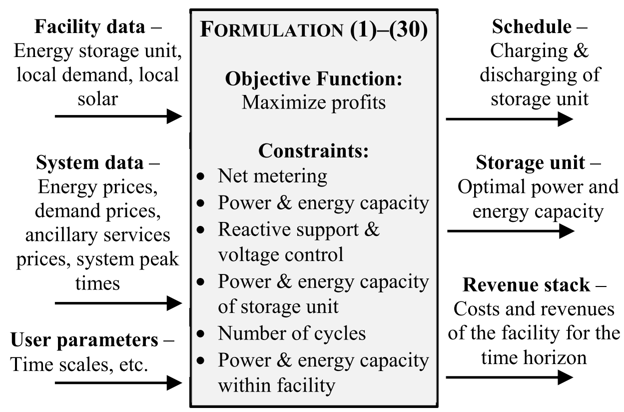

FIGURE 2. Methodology overview.

Fig. 1 provides a sketch of a possible electric single line diagram for a facility with ES, with local load and generation, all behind-the-meter. Numbers are for the case study discussed later in this paper.

Fig. 2 provides an overview of the methodology.

A. OBJECTIVE FUNCTION

The objective function is the maximization of total profits. Each term is computed for a future year 'y'. Thereafter, each term is reflected to the present year. The revenue is, therefore, computed for the present year for a uniform computation.

$$\begin{aligned} \mathit{Maximize\ Profits} = \mathit{Revenues\ Expenses} = \mathit{Revenues} \\ - \mathit{Costs}\ (MWh + MW) - \mathit{Asset\ Costs} \end{aligned} \tag{1}$$

Please refer to the Nomenclature section at the beginning of this article. The naming convention includes N designating numbers, K designating constants and rates, P designating real power, Q designating reactive power, and E designating energy.

1) REVENUE IN OBJECTIVE FUNCTION

The terms for the revenue equation (2), as shown at the bottom of the page, are explained further in equations (3) – (10).

The revenues comprise: (a) operating reserve for 10-minute synchronized; (b) operating reserve for 10-minute non-synchronized; (c) operating reserve for 30-minute non-synchronized; (d) regulation service; (e) black start capacity; (f) demand response for transmission-connections; (g) demand response for distribution-connections; and (h) reactive support and voltage control.

a: OPERATING RESERVE CAPACITY SERVICE

ES can earn revenues from operating reserve capacity service. In alignment with jurisdictions like the Independent Electricity System Operator (IESO) in Ontario, Canada, service providers can be paid for three forms of operating reserve capacity: 10-minute synchronized; 10-minute non-synchronized; and 30-minute non-synchronized.

Revenue for 10-minute synchronized OR in year y is:

$$\mathrm{KROR10S_y} \cdot \mathrm{PCOR10S_y} \tag{3}$$

Revenue for 10-minute non-synchronized OR in year y is:

$$\mathrm{KROR10N_y} \cdot \mathrm{PCOR10N_y} \tag{4}$$

Revenue for 30-minute non-synchronized OR in year y is:

$$\mathrm{KROR30_y} \cdot \mathrm{PCOR30_y} \tag{5}$$

b: REGULATION SERVICE

The revenue earned through frequency regulation service and automatic generation control (AGC) for year y is:

$$\mathrm{KRRS_y} \cdot \mathrm{PCRS_y} \tag{6}$$

c: BLACK START CAPACITY SERVICE

The revenue earned through black start capacity for year y is:

$$\mathrm{KRBS_y} \cdot \mathrm{PCBS_y} \tag{7}$$

d: DEMAND RESPONSE SERVICE

Demand response revenue could be earned from both transmission (8) and distribution (9) connections for year y:

$$\mathrm{KRTDR_y} \cdot \mathrm{PCTDR_y} \tag{8}$$

$$\mathrm{KRDDR_y} \cdot \mathrm{PCDDR_y} \tag{9}$$

e: REACTIVE SUPPORT AND VOLTAGE CONTROL SERVICE

The revenue earned from reactive support and voltage control service for year y is:

$$\mathrm{KRRSVC_y} \cdot \mathrm{QCRSVC_y} \tag{10}$$

2) COSTS FROM NET METERING BILL IN OBJECTIVE FUNCTION

The energy and demand charges are the sum of the monthly net metering costs:

$$\left[\sum_{y=1}^{NYS}\left(\left[\sum_{yy\in NYD_y}\frac{(1+KINFL)^{yy}}{(1+KAIR)^{yy}}\right]\cdot\left[\sum_{m=1}^{NMS}NTB_{y,m}\right]\right)\right] \tag{11}$$

3) COSTS FROM ASSET – CAPITAL, OPERATING AND MAINTENANCE IN OBJECTIVE FUNCTION

These costs from assets owing from capital, operations and maintenance, reflected to the present year are:

$$\begin{pmatrix} KPB\cdot\boxed{PS} \\ + \\ KEB\cdot\boxed{ES}\end{pmatrix}\cdot\left[1+KBC\cdot\sum_{y=1}^{NY}\frac{(1+KBV)^y}{(1+KAIR)^y}\right] \tag{12}$$

B. CONSTRAINTS – NET METERING

Net metering is when consumers use behind-the-meter resources to displace their consumption fees during a defined time period (e.g. one year). Net metering customers cannot be paid for their generation; they only get to reduce their electricity bills [24].

The net metering costs ($NTB_{y,m}$) are the greater of zero or the sum of the monthly energy ($MEC_{y,m}$) and demand charges ($MDC_{y,m}$), less the net metering credits ($NTC_{y,m}$). Therefore, $NTB_{y,m}$ must be greater than zero and cannot be negative. Computed for year 'y' and month 'm' as below.

$$NTB_{y,m} = +max\left\{MEC_{y,m}+MDC_{y,m}-NTC_{y,m},0\right\} \tag{13}$$

The monthly energy cost for year 'y' and month m is:

$$MEC_{y,m} = NMD_{y,m}\cdot TD\cdot ND\cdot\sum_{t=1}^{NH}\left(PNT_{m,t}\right)\cdot\left(HOEP_{m,t}+WMST_{y}\right) \tag{14}$$

The monthly demand charge for month m (MDC_m) is defined in (15). The monthly demand charge comprises the global adjustment charge ($GAC_{y,m}$) and the capacity based recovery amount ($CBR_{y,m}$), both of which are functions of the peak demand factor (PDF), which in turn is defined in (16).

$$Revenue = +\left[\sum_{y=1}^{NYS}\left(\left[\sum_{yy\in NYD_y}\frac{(1+KINFL)^{yy}}{(1+KAIR)^{yy}}\right]\cdot\left[\begin{array}{l}\mathrm{KROR10S_y}\cdot\mathrm{PCOR10S_y}+\mathrm{KROR10N_y}\cdot\mathrm{PCOR10N_y}\\+\mathrm{KROR30_y}\cdot\mathrm{PCOR30_y}+\mathrm{KRRS_y}\cdot\mathrm{PCRS_y}\\+\mathrm{KRBS_y}\cdot\mathrm{PCBS_y}+\mathrm{KRTDR_y}\cdot\mathrm{PCTDR_y}\\+\mathrm{KRDDR_y}\cdot\mathrm{PCDDR_y}+\mathrm{KRRSVC_y}\cdot\mathrm{QCRSVC_y}\end{array}\right]\right)\right] \tag{2}$$

There is also a demand charge (DC), which is a function of peak demand ($\left(PNT_{y,m,t}\right)$).

$$MDC_{y,m} = NMD_{y,m} \cdot PDF_y \cdot \left(GAC_{y,m} + CBR_{y,m}\right) + NMD_{y,m} \cdot DC \cdot max\left(PNT_{y,m}\right) \quad (15)$$

The global adjustment charge ($GAC_{y,m}$) encompasses the transmission network charge, transmission connection charge and the transformer allowance charge. The three charges are nearly proportional, and errors are minor when compared to the reduction in mathematical complexity. The peak demand factor, assuming that Ontario's peak demand is known, is:

$$PDF_y = \frac{\sum_{p=1}^{NP} \max\{PNT_{y,m=MP_{y,p},t=TP_{y,p}}, 0\}}{\sum_{p=1}^{NP} OSPD_{y,p}} \quad (16)$$

The monthly net metering credit ($NTC_{y,m+1}$), which starts at zero yearly, is:

$$\begin{aligned} &NTC_{y,m+1} \\ &= max\left\{+NTC_{y,m} + NTB_{y,m} - MEC_{y,m} - MDC_{y,m}, 0\right\}; \\ &NTC_{y,m=1} = 0 \end{aligned} \quad (17)$$

C. CONSTRAINTS – POWER AND ENERGY CAPACITY

The energy needed for servicing operating reserve capacity is:

$$\mathrm{KEPOR10S} \cdot \mathrm{PCOR10S_y} + \mathrm{KEPOR10N} \cdot \mathrm{PCOR10N_y} + \mathrm{KEPOR30} \cdot \mathrm{PCOR30_y} \quad (18)$$

The regulation service energy requirement, which is net zero over an hour for a maximum period of 30 minutes, is:

$$\mathrm{KEPRS} \cdot \mathrm{PCRS_y} \quad (19)$$

The energy required for black start service is:

$$\mathrm{KEPBS} \cdot \mathrm{PCBS_y} \quad (20)$$

The energy required for transmission-connected and distribution-connected demand response services are defined in (21) and (22) respectively:

$$\mathrm{KEPTDR} \cdot \mathrm{PCTDR_y} \quad (21)$$

$$\mathrm{KEPDDR} \cdot \mathrm{PCDDR_y} \quad (22)$$

D. CONSTRAINTS – REACTIVE SUPPORT AND VOLTAGE CONTROL SERVICE

Real power capacity needed for reactive support and voltage control ($\mathrm{PCRSVC_y}$) is a function of the reactive power ($\mathrm{QCRSVC_y}$) needed.

$$\mathrm{QCRSVC_y} \leq \sum_{\mathrm{q=1}}^{\mathrm{NQ}} \mathrm{QS_{yq}} \quad (23)$$

$$\begin{aligned} &\mathrm{PCRSVC}_y = \sum_{\mathrm{q=1}}^{\mathrm{NQ}} \mathrm{KQS_q} \cdot \mathrm{QS_{yq}}; \\ &\mathrm{KQS} = [0.12, 0.35, 0.53, 0.66] \end{aligned} \quad (24)$$

E. CONSTRAINTS – NUMBER OF CYCLES

The number of maximum number of cycles (KNC) as defined must be respected, as per below. Annual number of cycles is first computed (NC_y) for this relation.

$$KNC \geq \sum_{y=1}^{NYS} \left(NYD_y \cdot NC_y\right) \quad (25)$$

$$NC_y = \frac{1}{\bar{ESB}} \cdot \sum_{m=1}^{NMS} \left[NMD_{y,m} \cdot ND \cdot \sum_{t=1}^{NH} max\left\{ESB_{y,m,t} - ESB_{y,m,t-1}, 0\right\}\right] \quad (26)$$

F. CONSTRAINTS – LIMITS ON POWER AND ENERGY CAPACITY OF STORAGE

The upper and lower power limits of the storage unit are limited as below.

$$-\overline{PSB} + \left[\begin{array}{c} \mathrm{PCOR10S_y} + \mathrm{PCOR10N_y} + \mathrm{PCOR30_y} \\ +\mathrm{PCRS_y} + \mathrm{PCBS_y} \\ +\mathrm{PCTDR_y} + \mathrm{PCDDR_y} \\ +\mathrm{PCRSVC}_y \end{array}\right] \leq PSB_{y,m,t} \leq \overline{PSB} - \mathrm{PCRS}_y \quad (27)$$

The upper and lower energy limits of the storage unit are limited as below.

$$\left[\begin{array}{c} \mathrm{KEPOR10S{\cdot}PCOR10S_y} \\ +\mathrm{KEPOR10N{\cdot}PCOR10N_y} \\ +\mathrm{KEPOR30{\cdot}PCOR30_y} \\ +\mathrm{KEPRS{\cdot}PCRS_y} \\ +\mathrm{KEPBS{\cdot}PCBS_y} \\ +\mathrm{KEPTDR{\cdot}PCTDR_y} \\ +\mathrm{KEPDDR{\cdot}PCDDR_y} \end{array}\right] \leq ESB_{y,m,t} \leq \left[\begin{array}{c} \overline{\mathrm{ESB}}- \\ \mathrm{KEPRS{\cdot}PCRS_y} \end{array}\right] \quad (28)$$

G. CONSTRAINTS – POWER AND ENERGY RELATIONSHIP WITHIN FACILITY

Power must be balanced within the ES facility as below.

$$PNT_{y,m,t} + PG_{y,m,t} + PSB_{y,m,t} = PD_{y,m,t} \quad (29)$$

Equation (30) describes the relationship between energy and power within the storage facility. The energy level within the storage unit ($ESB_{y,m,t}$) is dependent on the level at the previous time segment ($ESB_{y,m,t-1}$), hourly self-discharge rate (KSD) and power for storage ($PSB_{y,m,t}$). Self-discharge is increased to account for power losses in the converter.

$$\begin{aligned} &ESB_{y,m,t} = ESB_{y,m,t-1} \cdot KSD_m - PSB_{y,m,t} \cdot TD; \\ &if\ t = 0, t-1 = NH \end{aligned} \quad (30)$$

The formulation (1) – (30) is the overall formulation. Several of these equations are further broken down into smaller equations for implementation in the

TABLE 2. Data for solar generation (kW).

Hour	Months 01 and 02	Months 03 and 04	Months 05 and 06	Months 07 and 08	Months 09 and 10	Months 11 and 12
1	0	0	0	0	0	0
2	0	0	0	0	0	0
3	0	0	0	0	0	0
4	0	0	0	0	0	0
5	0	0	1.334724	1.380749	0	0
6	0	0.618269	116.0791	38.13937	0.951183	0
7	0	106.0477	501.4519	368.2459	38.06521	0.015853
8	15.47535	518.3891	1033.356	844.4356	349.8507	12.11326
9	279.5782	968.5532	1544.731	1348.655	826.5416	231.6345
10	639.007	1419.11	2071.445	1835.906	1165.344	487.8372
11	914.6166	1735.18	2274.698	2268.28	1456.039	652.3944
12	1084.608	1923.319	2378.269	2469.823	1703.14	761.6955
13	1154.62	1955.259	2422.865	2290.893	1644.504	772.3702
14	1100.717	1937.135	2289.628	2225.937	1427.728	676.9978
15	915.9837	1720.022	2231.297	2089.319	1196.747	502.9446
16	665.3634	1345.706	1796.155	1626.185	949.7387	316.6846
17	308.5334	902.8541	1329.387	1329.953	516.2085	64.01103
18	48.81771	437.9901	847.7939	797.7663	173.8128	0
19	0	72.9859	372.6934	329.723	12.52391	0
20	0	0	54.83058	38.86042	0	0
21	0	0	0	0	0	0
22	0	0	0	0	0	0
23	0	0	0	0	0	0
24	0	0	0	0	0	0

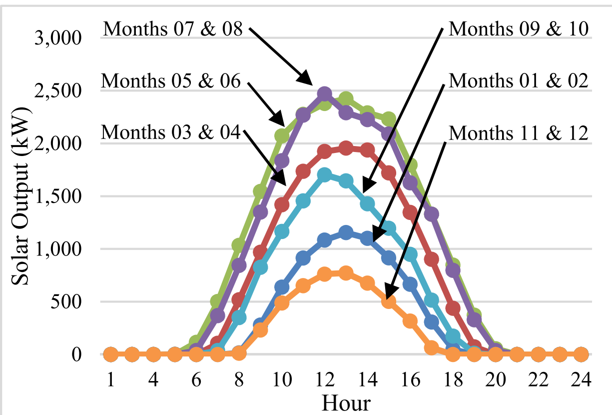

FIGURE 3. Solar generation at the facility.

commercial solver, MOSEK®, while retaining accuracy of the formulation and ensuring that the formulation remains linear and convex yielding the same optimal solution consistently. All the constraints are satisfied to a low tolerance (4e-09). This formulation was solved in MATLAB.

H. ASSUMPTIONS

Several assumptions are made for this model. The prices and rates for energy, demand charges, and ancillary services are assumed to be known before this optimization problem is solved. The generation output and demand are also known beforehand. Furthermore, we expect the ES vendor to provide us with reliable equipment. The vendor is liable for any loss of revenue due to reliability through a performance clause in the supply contract.

TABLE 3. Data for load (kW).

Hour	Months 01 and 02	Months 03 and 04	Months 05 and 06	Months 07 and 08	Months 09 and 10	Months 11 and 12
1	1438.395	604.9708	902.2919	1075.939	1075.725	1314.213
2	1414.594	605.7097	888.1929	1045.151	1034.786	1320.044
3	1418.216	605.0158	925.5618	1054.296	1052.425	1300.168
4	1432.95	604.2784	907.4609	1024.815	1026.229	1313.003
5	1407.696	610.8801	923.2916	1050.769	1032.733	1303.902
6	1399.25	606.2308	1013.814	1169.434	1142.472	1320.345
7	1425.513	628.7807	1106.339	1268.285	1221.761	1344.123
8	1487.829	634.4462	1158.461	1334.432	1269.521	1403.989
9	1500	583.6489	1183.618	1381.811	1270.018	1467.105
10	1492.18	568.3974	1183.575	1413.208	1278.483	1460.864
11	1494.641	546.7634	1188.175	1434.024	1289.504	1455.617
12	1477.874	536.7128	1203.116	1434.807	1271.805	1490.523
13	1477.27	531.3435	1211.593	1440.643	1265.463	1476.843
14	1481.951	530.4958	1240.069	1448.176	1264.676	1495.573
15	1470.38	500	1240.399	1446.26	1263.47	1486.396
16	1458.526	511.2263	1247.944	1448.35	1258.221	1484.673
17	1458.935	554.6424	1239.529	1438.901	1259.356	1488.328
18	1453.071	545.3655	1200.645	1417.694	1256.089	1467.618
19	1444.437	564.59	1126.517	1388.953	1234.969	1450.094
20	1456.615	573.0235	1107.811	1373.755	1222.851	1422.955
21	1454.141	595.7476	1081.928	1353.985	1199.343	1413.613
22	1446.68	602.1345	1018.554	1302.774	1166.034	1387.961
23	1437.313	586.5854	945.0447	1190.554	1118.845	1374.88
24	1429.335	593.7343	908.9909	1136.948	1134.779	1353.141

III. STOCHASTIC IMPLEMENTATION

The model presented in (1) – (30) is a deterministic optimization model. To implement it stochastically, we expand the model as below for a set (S) of scenarios (s) each with probability p^s:

$$Maximize\ Profits = p^s \cdot \sum_{s \in S} Revenue^s - Expenses^s \tag{31}$$

Subject to equality and inequality constraints from (13) – (30) as compactly shown below for each scenario:

$$g\left(X^s\right) = b^s \tag{32}$$
$$h\left(X^s\right) \leq c^s \tag{33}$$

Based upon determination of scenarios, the optimization is solved and probable profits and optimal storage sizes are estimated.

IV. CASE STUDY: INDUSTRIAL FACILITY IN TORONTO, ONTARIO, CANADA

A. DATA

Fig. 1 provides a sketch of a possible electric single line for storage system, with local load and generation. This is based on an actual industrial consumer with solar and energy storage behind-the-meter in Toronto, Canada. Since it is a merchant-owned facility and not the distribution system, an IEEE bus test system is not appropriate in this case.

The loads and generation patterns are represented by six 24-hour data sets. Each 24- hour data set is average day of 2-month period. This data set, cumulatively, represents a year. Similar years are bunch together for a scenario. For this study, three scenarios, each lasting for five (5) years is considered. Prices for ancillary services for each scenario is taken different.

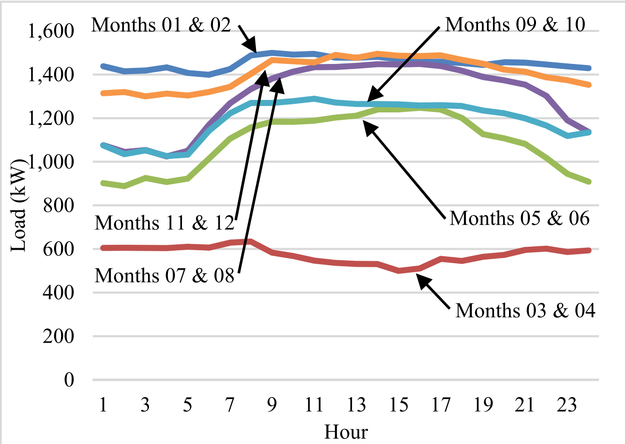

FIGURE 4. Load at the facility.

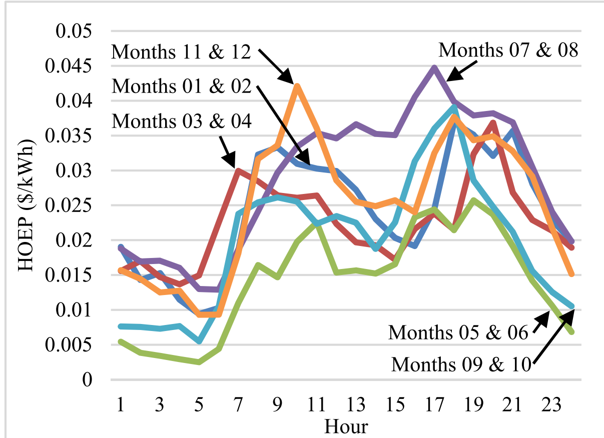

FIGURE 5. HOEP for a year, represented by six similar months.

TABLE 4. HOEP for a year, represented by six similar months ($/kWh).

Hour	Months 01 and 02	Months 03 and 04	Months 05 and 06	Months 07 and 08	Months 09 and 10	Months 11 and 12
1	0.019042	0.015589	0.005435	0.018803	0.00763	0.015692
2	0.014294	0.017017	0.003847	0.01693	0.007558	0.014471
3	0.015287	0.014715	0.003415	0.017049	0.007301	0.012512
4	0.011485	0.013671	0.00295	0.016037	0.007686	0.012768
5	0.009423	0.014975	0.002509	0.013001	0.005491	0.0093
6	0.010284	0.022539	0.004416	0.012901	0.010513	0.009321
7	0.018522	0.029964	0.010986	0.018658	0.023776	0.018124
8	0.032295	0.028473	0.016439	0.024127	0.025437	0.031644
9	0.033337	0.026452	0.014682	0.029701	0.026152	0.033637
10	0.030956	0.026093	0.019787	0.033416	0.025556	0.042123
11	0.030276	0.026411	0.022534	0.035375	0.022368	0.036037
12	0.029929	0.022357	0.01536	0.034617	0.023448	0.028572
13	0.027215	0.019683	0.015679	0.036639	0.022493	0.025535
14	0.023048	0.019272	0.015217	0.035252	0.018745	0.024876
15	0.020334	0.017215	0.016578	0.035069	0.022552	0.025725
16	0.019166	0.021599	0.023294	0.040567	0.03134	0.024016
17	0.024459	0.023826	0.024418	0.04473	0.036008	0.03248
18	0.036859	0.021498	0.021436	0.039863	0.03908	0.037695
19	0.035132	0.03237	0.025735	0.037906	0.028581	0.034337
20	0.032089	0.036864	0.023677	0.038206	0.024801	0.034922
21	0.035696	0.026832	0.019165	0.036918	0.021218	0.032784
22	0.028085	0.022907	0.014194	0.030505	0.015582	0.029173
23	0.022916	0.021375	0.010649	0.024099	0.012583	0.021786
24	0.019847	0.018948	0.006852	0.019823	0.010545	0.015154

Table 2 provides data for solar generation at the site for a year, represented by six similar months.

Fig. 3 provides data for solar generation at the site for a year, represented by six similar months.

Table 3 provides data for site load at the site for a year, represented by six similar months.

Fig. 4 provides data for site load at the site for a year, represented by six similar months.

Table 4 provides data for HOEP for a year, represented by six similar months. [27] This data is from 2018. Extreme variants are removed and averaged, hourly, over 2 months.

Fig. 5 provides data for HOEP for a year, represented by six similar months. This data is from 2018. Extreme variants are removed and averaged, hourly, over 2 months.

Table 5 provides the fixed costs that lead to demand-based charges.

TABLE 5. Fixed costs that lead to demand-based charges.

	Global adjustment charge for a year ($/kW)	Capacity based recovery ($/kW)	WMST Wholesale market service tariff ($/kWh)	KDC (distribution charge) ($/kW)
Months 01 & 02	791,550,000	3,950,000	0.003499	0.43
Months 03 & 04	950,300,000	3,050,000	0.003499	0.43
Months 05 & 06	1,076,050,000	3,600,000	0.003499	0.43
Months 07 & 08	894,100,000	3,600,000	0.003499	0.43
Months 09 & 10	991,300,000	4,400,000	0.003499	0.43
Months 11 & 12	894,800,000	4,050,000	0.003499	0.43

TABLE 6. Data for the Ontario system five coincident peaks (5CP).

Ontario System Load (kW)	Months of Occurrence	Hour of Occurrence (hours)
23,240,000	Months 09 and 10	18
23,046,000	Months 09 and 10	16
23,039,000	Months 09 and 10	17
23,031,000	Months 09 and 10	19
22,872,000	Months 09 and 10	15

Table 6 provides the Ontario five system peak data for computing Peak Demand Factor. These are used to factor the Global adjustment charges and capacity-based recovery charges.

Table 7 provides data for Storage Units. [28] This data is used in the optimization. Note that the self-discharge parameter (KSD) accounts for battery degradation over the course of the 18 time periods.

Table 8 provides data for revenue calculation, as per prevailing market rates.

Table 9 provides basic data used for optimization. It includes length of month scenarios, year scenarios, inflation rate, interest rate, etc.

B. RESULTS

1) CASE 1: ENERGY ARBITRAGE ONLY

This section presents results for the case using data set presented above in the formulation (1) – (30). This considers

TABLE 7. Data for storage units.

Value	Unit	Variable Used in the Formulation	Description
40	$/kW	KP	Storage power cost
500	$/kWh	KE	Storage energy cost
0.015	Factor of the capital cost	KBC	Maintenance costs – constant value
0.02	Factor of the capital cost	KBV	Maintenance costs – variable value
5,000	kW	PSmax	Maximum power capacity for storage opportunity
10,000	kWh	ESmax	Maximum energy capacity for storage opportunity
8,000	Number	KNC	Total number of cycles, lifetime
See Below	Factor	KSD	Self Discharge

Months 01 & 02	Months 03 & 04	Months 05 & 06	Months 07 & 08	Months 09 & 10	Months 11 & 12
0.8	0.9	0.9	0.95	0.9	0.9

TABLE 8. Data for revenue calculation.

Description	Operating reserve for 10-minute synchronized	Operating reserve for 10-minute non-synchronized	Operating reserve for 30-minute non-synchronized	Regulation service
Variable in formulation	KROR10S	KROR10N	KROR30	KRRS
Units	$/kW-year	$/kW-year	$/kW-year	$/kW-year
Data for 1 – 5	438	201.48	192.72	0
Data for 6 – 10	0	0	0	0
Data for 11 - 15	438	201.48	192.72	0

Description	Black start capacity	Demand response for transmission-connections	Demand response for distribution-connections	Reactive support and voltage control
Variable in formulation	KRBS	KRTDR	KRDDR	KRRSVC
Units	$/kW-year	$/kW-year	$/kW-year	$/kW-year
Data for 1 – 5	377	856.436	856.436	0
Data for 6 – 10	0	0	0	0
Data for 11 - 15	377	856.436	856.436	0

only energy arbitrage. Fig. 6 shows these results. Table 10 presents the Case 1: Energy Arbitrage only results considering Monthly Bill Data for 15 years.

In the absence of net metering, the facility would not get credit for any generation returned to the grid, as shown in the last column of Table 10. This would mean that the facility would need to pay an additional $40,784 (the difference between the totals of the Net Meter Bill and Regular Load Meter Bill in present day dollars) over the full 15-year study period.

Table 11 and Fig. 7 present power and energy data for a day in Months 07 and 08. This is a sample day from the results.

TABLE 9. Basic data.

0.02						Inflation Rate
0.0395						Annual Interest Rate
1						Time duration for each step in hours
24						Number of time durations in a day
30						Number of days in a month
6						Number of month scenarios in a year
2	2	2	2	2	2	Number of months per month scenario
3						Number of Year scenarios
5		5		5		Number of years per Year scenario
6,109,180						Energy Cost for 15 years, reflected to the present year ($)

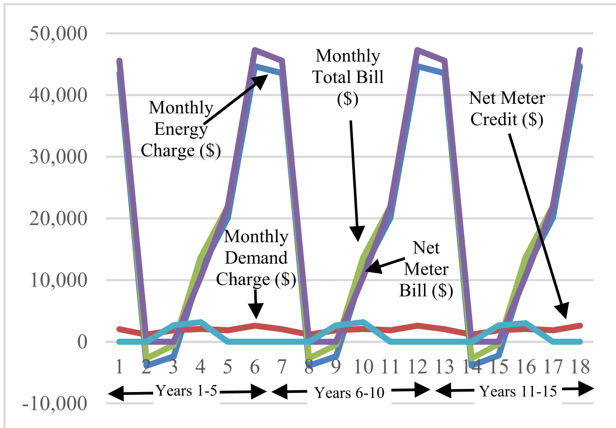

FIGURE 6. Case 1: Energy arbitrage only results.

Table 12 presents Case 1: Energy Arbitrage Only result for optimization with optimal Storage Sizes.

Storage Optimal Power Capacity is determined to be 1,873 kW and Storage Optimal Energy Capacity is determined to be 5,194 kWh.

Table 13 presents Case 1: Energy Arbitrage Only result for Optimal Power Capacity Sizes, Number of Cycles and Peak Demand Factor. It can be seen that power capacities for services are set to zero. The number of cycles is about equally spread for those years. The peak demand factor is reduced to zero, thereby minimizing the demand-based charges.

Table 14 provides the value stack for the storage unit. It clearly shows that cost of energy from the net meter bill is $6,109,180, cost of storage for power is $89,480, cost of storage for energy is $3,100,963. The benefit from energy arbitrage $4,486,713. Hence the total cost is $4,812,909 and it significantly less than the original bill amount.

Fig. 8 provides the revenue and cost stacks for the storage owner.

2) CASE 2: ENERGY ARBITRAGE AND ANCILLARY SERVICES

This section presents results for the case using data set presented above in the formulation (1) – (30). This considers energy arbitrage and ancillary services. Fig. 9 shows these

TABLE 10. Case 1: Energy arbitrage only, monthly bill data for 15 years.

Years	Months	Monthly Energy Charge ($)	Monthly Demand Charge ($)	Total Bill ($)	Net Meter Bill ($)	Net Meter Credit ($)	Regular Load Meter Bill ($)
1 – 5	01-02	43,561	2,040	45,601	45,601	0	45,601
1 – 5	03-04	-3,872	1,183	-2,689	0	0	0
1 – 5	05-06	-2,388	1,872	-516	0	2,689	0
1 – 5	07-08	11,652	2,085	13,737	10,532	3,205	13,737
1 – 5	09-10	20,080	1,868	21,948	21,948	0	21,948
1 – 5	11-12	44,689	2,616	47,304	47,304	0	47,304
6 – 10	01-02	43,561	2,040	45,601	45,601	0	45,601
6 – 10	03-04	-3,867	1,183	-2,684	0	0	0
6 – 10	05-06	-2,378	1,872	-506	0	2,684	0
6 – 10	07-08	11,652	2,085	13,737	10,547	3,190	13,737
6 – 10	09-10	20,080	1,868	21,948	21,948	0	21,948
6 – 10	11-12	44,689	2,616	47,304	47,304	0	47,304
11 – 15	01-02	43,561	2,040	45,601	45,601	0	45,601
11 – 15	03-04	-3,867	1,183	-2,684	0	0	0
11 – 15	05-06	-2,237	1,872	-365	0	2,684	0
11 – 15	07-08	11,652	2,085	13,737	10,687	3,049	13,737
11 – 15	09-10	20,080	1,868	21,948	21,948	0	21,948
11 – 15	11-12	44,689	2,616	47,304	47,304	0	47,304
Total (Present Day Dollars)					1,622,462		1,663,246

TABLE 11. Case 1: Energy arbitrage only, power and energy data for a day in months 07 and 08.

Hour	Load Power (kW)	Generator Power (kW)	Storage Power (kW)	Network Power (kW)	Storage Energy (kWh)
1	1,076	0	0	1,076	0
2	1,045	0	0	1,045	0
3	1,054	0	0	1,054	0
4	1,025	0	-1,400	2,425	1,400
5	1,051	1	-1,375	2,425	2,705
6	1,169	38	-1,293	2,425	3,863
7	1,268	368	-1,524	2,425	5,194
8	1,334	844	-260	750	5,194
9	1,382	1,349	886	-853	4,048
10	1,413	1,836	1,873	-2,296	1,972
11	1,434	2,268	1,873	-2,708	0
12	1,435	2,470	0	-1,035	0
13	1,441	2,291	0	-850	0
14	1,448	2,226	-104	-674	104
15	1,446	2,089	-1,873	1,230	1,972
16	1,448	1,626	-99	-79	1,972
17	1,439	1,330	1,873	-1,765	0
18	1,418	798	0	620	0
19	1,389	330	0	1,059	0
20	1,374	39	0	1,335	0
21	1,354	0	0	1,354	0
22	1,303	0	0	1,303	0
23	1,191	0	0	1,191	0
24	1,137	0	0	1,137	0

TABLE 12. Case 1: Energy arbitrage only, results for optimization for optimal storage sizes.

Maximum Load (kW)	Generation Capacity (kW)	Total Load Energy (kWh)	Total Generated Energy (kWh)
1,500	2,470	151,483,441	71,351,909
Storage Optimal Power Capacity (kW)	Storage Optimal Energy Capacity (kWh)		
1,873	5,194		

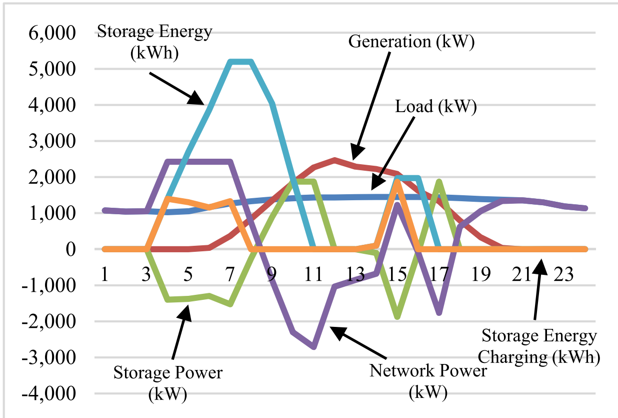

FIGURE 7. Case 1: Energy arbitrage only, power and energy hourly data for a day in months 07 and 08.

TABLE 13. Case 1: Energy arbitrage only, result for optimization for optimal power capacity sizes, number of cycles and peak demand factor.

	Unit	Years 1–5	Years 6–10	Years 11–15
Operating reserve for 10-minute synchronized	kW	0	0	0
Operating reserve for 10-minute non-synchronized	kW	0	0	0
Operating reserve for 30-minute non-synchronized	kW	0	0	0
Regulation service	kW	0	0	0
Black start capacity	kW	0	0	0
Demand response for transmission-connections	kW	0	0	0
Demand response for distribution-connections	kW	0	0	0
Reactive support and voltage control	kW	0	0	0
Number of Cycles in the Year Scenario	#	2,706	2,696	2,598
Peak Demand Factor (annual) in the Year Scenario x 10^{-6}	#	0	0	0

results. Table 15 presents the Case 2: Energy Arbitrage and Ancillary Services results considering Monthly Bill Data for 15 years.

Table 16 and Fig. 10 present power and energy data for a day in Months 07 and 08.

Table 17 presents Case 2: Energy Arbitrage and Arbitrage result for optimization with optimal Storage Sizes.

Storage Optimal Power Capacity is determined to be 5,000 kW and Storage Optimal Energy Capacity is determined to be 2,220 kWh. It can be seen that power size is higher, in fact maximized allowed by the location, 5,000 kW. The energy is reduced from 5,194 kWh, even though the maximum allowed as 10,000 kWh. Clearly the emphasis of the optimization is laid on to the ancillary services in years 1 – 5 and 11 – 15. In between years, 11 – 15, the emphasis is on energy arbitrage as the revenue from ancillary services is reduced to zero due to a lack of opportunity.

Table 18 presents Case 1: Energy Arbitrage Only result for Optimal Power Capacity Sizes, Number of Cycles and Peak

TABLE 14. Case 1: Energy arbitrage only, revenue stack.

Description	Unit	Cost (-) Benefit (+)	
Cost of Energy – Net Meter Bill	$	(-)	6,109,180
Cost of Storage – Power	$	(-)	89,480
Cost of Storage – Energy	$	(-)	3,100,963
Benefit from Energy Arbitrage	$	(+)	4,486,713
Operating reserve for 10-minute synchronized	$	(+)	0
Operating reserve for 10-minute non-synchronized	$	(+)	0
Operating reserve for 30-minute non-synchronized	$	(+)	0
Regulation service	$	(+)	0
Black start capacity	$	(+)	0
Demand response for transmission-connections	$	(+)	0
Demand response for distribution-connections	$	(+)	0
Reactive support and voltage control	$	(+)	0
Total	$	(-)	4,812,909

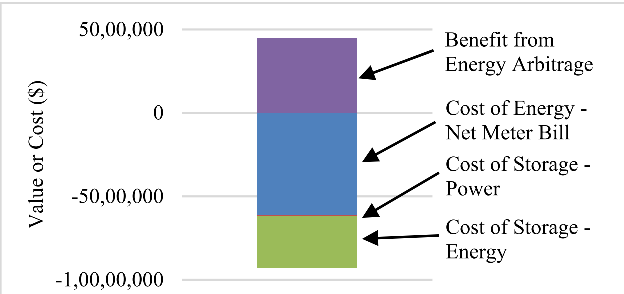

FIGURE 8. Value and cost stacks for Case 1: Energy arbitrage only.

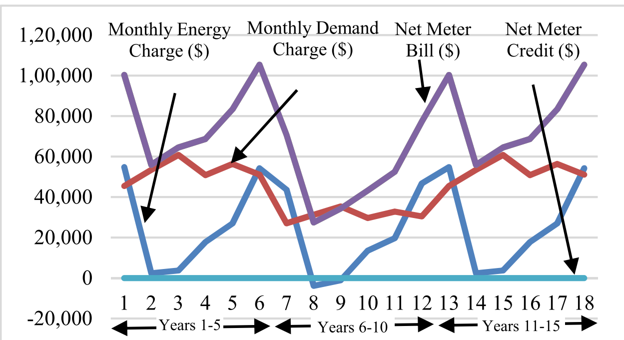

FIGURE 9. Case 2: Energy arbitrage and ancillary services results.

TABLE 15. Case 2: Energy arbitrage and ancillary services, monthly bill data for 15 years.

Years	Months	Monthly Energy Charge ($)	Monthly Demand Charge ($)	Total Bill ($)	Net Meter Bill ($)	Net Meter Credit ($)
1 – 5	Months 01 and 02	54,850	45,512	100,361	100,361	0
1 – 5	Months 03 and 04	2,396	53,505	55,900	55,900	0
1 – 5	Months 05 and 06	3,762	60,793	64,555	64,555	0
1 – 5	Months 07 and 08	17,861	50,876	68,737	68,737	0
1 – 5	Months 09 and 10	26,963	56,381	83,344	83,344	0
1 – 5	Months 11 and 12	54,235	51,123	105,358	105,358	0
6 – 10	Months 01 and 02	43,654	27,063	70,717	70,717	0
6 – 10	Months 03 and 04	-3,803	31,267	27,464	27,464	0
6 – 10	Months 05 and 06	-1,045	35,360	34,315	34,315	0
6 – 10	Months 07 and 08	13,560	29,682	43,242	43,242	0
6 – 10	Months 09 and 10	19,707	32,848	52,554	52,554	0
6 – 10	Months 11 and 12	46,764	30,457	77,221	77,221	0
11 – 15	Months 01 and 02	54,850	45,512	100,361	100,361	0
11 – 15	Months 03 and 04	2,396	53,505	55,900	55,900	0
11 – 15	Months 05 and 06	3,762	60,793	64,555	64,555	0
11 – 15	Months 07 and 08	17,861	50,876	68,737	68,737	0
11 – 15	Months 09 and 10	26,963	56,381	83,344	83,344	0
11 – 15	Months 11 and 12	54,235	51,123	105,358	105,358	0

TABLE 16. Case 2: Energy arbitrage and ancillary services, power and energy data for a day in months 07 and 08, Years 1 – 5.

Hour	Load Power (kW)	Generator Power (kW)	Storage Power (kW)	Network Power (kW)	Storage Energy (kWh)
1	1,076	0	-60	1,135	1,190
2	1,045	0	-173	1,218	1,304
3	1,054	0	-238	1,292	1,477
4	1,025	0	-238	1,263	1,641
5	1,051	1	-238	1,287	1,797
6	1,169	38	-238	1,369	1,946
7	1,268	368	-238	1,138	2,086
8	1,334	844	-238	728	2,220
9	1,382	1,349	-111	144	2,220
10	1,413	1,836	-111	-312	2,220
11	1,434	2,268	919	-1,753	1,190
12	1,435	2,470	-238	-797	1,369
13	1,441	2,291	110	-960	1,190
14	1,448	2,226	-238	-540	1,369
15	1,446	2,089	-238	-405	1,539
16	1,448	1,626	-238	60	1,700
17	1,439	1,330	424	-315	1,190
18	1,418	798	-60	679	1,190
19	1,389	330	-135	1,194	1,266
20	1,374	39	-34	1,369	1,237
21	1,354	0	-15	1,369	1,190
22	1,303	0	-60	1,362	1,190
23	1,191	0	-60	1,250	1,190
24	1,137	0	-60	1,196	1,190

Demand Factor. The number of cycles is about equally spread for those years. The peak demand factor is reduced during years 11 – 15, due to arbitrage and demand charge reduction opportunities. It may be noted that, without energy storage, peak demand factor for the site was 30e-6.

Similarly, the number of cycles is extensively used during years 11 – 15, as the profits depend on arbitrage. During years 1 – 5 and 11 – 15, as revenue is primarily driven from ancillary services, the number of cycles is significantly lesser.

Table 19 provides the value stack for the storage unit. It clearly shows that cost of energy from the net meter bill is $6,109,180, cost of storage for power is $238,803, cost of storage for energy is $1,325,441. The benefit from energy arbitrage is $665,735, which is lesser than Case 1 amount of $4,486,713. The revenue from the storage unit is $11,004,225, which is reversing the cost situation of Case 1 equaling $4,812,909 and it significantly reversing the original bill amount of $6,109,180.

Fig. 11 provides the revenue and cost stacks for the storage owner.

TABLE 17. Case 2: Energy arbitrage and ancillary services - result for optimization for optimal storage sizes.

Maximum Load (kW)	Generation Capacity (kW)	Total Load Energy (kWh)	Total Generated Energy (kWh)
1,500	2,470	151,483,441	71,351,909
Storage Optimal Power Capacity (kW)	Storage Optimal Energy Capacity (kWh)		
5,000	2,220		

TABLE 18. Case 2: Energy arbitrage and ancillary services - result for optimization for optimal power capacity sizes, number of cycles and peak demand factor.

	Unit	Years 1–5	Years 6–10	Years 11–15
Operating reserve for 10-minute synchronized	kW	4,762	0	4,762
Operating reserve for 10-minute non-synchronized	kW	0	0	0
Operating reserve for 30-minute non-synchronized	kW	0	0	0
Regulation service	kW	0	0	0
Black start capacity	kW	0	0	0
Demand response for transmission-connections	kW	0	0	0
Demand response for distribution-connections	kW	0	0	0
Reactive support and voltage control	kW	0	0	0
Number of Cycles in the Year Scenario	#	771	4,817	771
Peak Demand Factor (annual) in the Year Scenario x 10^{-6}	#	28	16	28

TABLE 19. Case 2: Energy arbitrage and ancillary services – revenue stack.

Description	Unit	Cost (-) Benefit (+)	
Cost of Energy – Net Meter Bill	$	(-)	6,109,180
Cost of Storage – Power	$	(-)	238,803
Cost of Storage – Energy	$	(-)	1,325,441
Benefit from Energy Arbitrage	$	(+)	665,735
Operating reserve for 10-minute synchronized	$	(+)	18,011,915
Operating reserve for 10-minute non-synchronized	$	(+)	0
Operating reserve for 30-minute non-synchronized	$	(+)	0
Regulation service	$	(+)	0
Black start capacity	$	(+)	0
Demand response for transmission-connections	$	(+)	0
Demand response for distribution-connections	$	(+)	0
Reactive support and voltage control	$	(+)	0
Total	$	(+)	11,004,225

C. CASE 3: COMPARISON WITH EXISTING APPROACHES

As shown in Table 1, no other works considered net metering. In order to showcase the benefits for net metering, the data for the industrial facility in the previous section was modified so that the storage power cost (KP) was $10/kW and the storage energy cost (KE) was $190/kWh. The solar generation output was also increased by 150%.

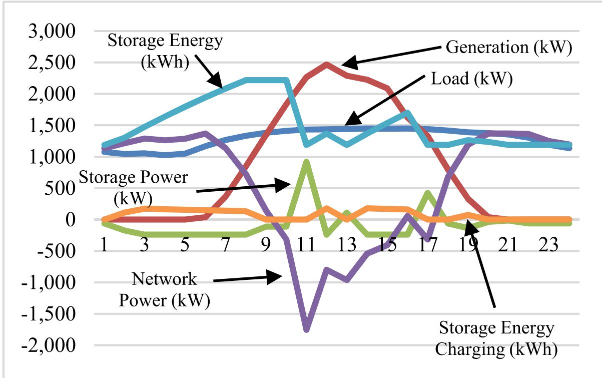

FIGURE 10. Case 2: Energy arbitrage and ancillary services, power and energy hourly data for a day in months 07 and 08, Years 1 – 5.

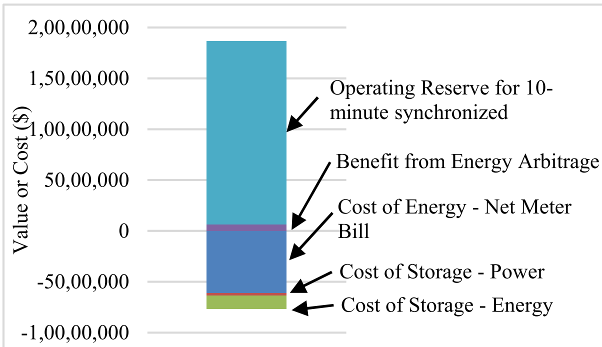

FIGURE 11. Value and cost stacks for Case 2: Energy arbitrage and ancillary services.

TABLE 20. Stochastic implementation with HOEP uncertainty.

	Method Proposed in the Paper (With Net Metering)	Existing Approaches (Without Net Metering)
Cost of Energy – Net Meter Bill	- $6,109,180	- $6,109,180
Cost of Storage – Power	- $26,865	- $34,703
Cost of Storage – Energy	- $824,192	- $824,192
Benefit from Energy Arbitrage	$5,356,890	$4,900,307
Total Value Stack (Benefits – Costs)	**- $1,603,348**	**- $2,067,768**

Table 20 has a comparison of the results with and without net metering. It clearly shows that the method proposed in this paper (which includes net metering) has a lower total cost at $1,603,348 than existing approaches (which do *not* include net metering) at $2,067,768. This yields a total savings of $464,421.

D. CASE 4: STOCHASTIC CASE STUDY

Using the stochastic implementation method described in Section III above, a series of ten scenarios were generated by scaling the HOEP higher and lower. This represents uncertainty in future grid energy prices. Probabilities for each scenario were assigned. HOEP multipliers, associated

TABLE 21. Comparison of results with existing approaches.

Scenario	Probability	HOEP Multiplier	Storage Optimal Power Capacity (kW)	Storage Optimal Energy Capacity (kWh)	Total Value Stack
1	0.1	0.6	1,397	5,194	-$4,327,510
2	0.15	0.8	1,630	5,194	-$4,573,159
3	0.2	1	1,873	5,194	-$4,812,909
4	0.15	1.2	2,214	5,194	-$5,048,354
5	0.1	1.4	2,404	5,194	-$5,279,926
6	0.1	1.6	2,500	5,194	-$5,508,961
7	0.08	1.8	2,734	5,194	-$5,735,515
8	0.06	2	2,734	5,194	-$5,960,145
9	0.04	2.5	2,870	5,194	-$6,519,859
10	0.02	3	3,713	5,194	-$7,073,282
Total	**1**		**2,153**	**5,194**	**-$5,136,158**

probabilities, and results are shown in Table 21. In this case, the ES merchant anticipates that HOEP prices are more likely to rise than fall. Taking this into account, the merchant would purchase a larger ES unit at 2,153 kW rather than at 1,873 kW when no uncertainty was considered. The total value stack is also less at -$5,136,158 rather than at -$4,812,909.

This demonstrates one possible example of stochastic implementation. The user may choose any input parameters for which there is uncertainty and use this method to account for the probabilities of the various scenarios.

V. DISCUSSION

The two case studies show that revenues from ancillary services are important for building a favorable business case for using ES. Collecting revenues from both energy arbitrage and ancillary services (Case 2) yields a total benefit of $11,004,225, whereas energy arbitrage alone (Case 1) would cost a total of $4,812,909. The ES is still worthwhile in Case 1, because the total cost without it would otherwise have been much larger ($9,299,623), however, ancillary service enables the ES to make money, not just reduce costs.

Furthermore, the net metering arrangement in both cases allows the ES to be used in displacing local load, considering the real-time energy market prices (i.e. HOEP) that need to be paid at the time. This reflects a realistic scenario for as large industrial and commercial loads are promising potential users of ES, and this proposed model allows for the full range of potential benefits from ES.

In terms of scalability, larger systems and more granular time periods will naturally be more computationally complex and take more time to solve. To build a business case for ES investment, this is less of a concern as it is reasonable to group together similar days, as we have in the case study above. For day-to-day scheduling, this will require more time periods and therefore more computational time. However, this is still not a major issue as the hourly schedule can be easily produced well ahead of time. Larger systems will also take time, but again, this can be solved beforehand to avoid any issues.

VI. CONCLUSION

In this paper, we present a comprehensive and realistic mathematical model to maximize profits for merchant ES owners. The main contribution is the allowance for net metering benefits through behind-the-meter installations to displace energy and demand charges. This is new and has not been done before. It also considers the full investment model, including operating costs, and annual investment costs. Furthermore, our multi-year model also allows for the evaluation of opportunity costs; in particular, ES owners can consider trade-offs between and impacts of actions in different time periods. We also provide a stochastic implementation to consider uncertainty in any input parameter and demonstrate this method with energy prices.

While our proposed method provides guidance to ES owners to make sound investment decisions, it also enables system operators and policymakers to predict the uptake of ES. This can then be used to model the impact on electricity prices and carbon emissions. Further, the input parameters can be adjusted to suit many jurisdictions or circumstances.

The cases studied are for: (1) energy arbitrage only, and (2) energy arbitrage with ancillary services. Clearly, it can be seen in Case 1 that energy arbitrage reduced the net costs of the facility. Case 2 shows a handsome profit with storage considering benefits from ancillary services.

We show that net metering participation yields tangible benefits to the ES merchants. In Case 1, net metering saved the ES owner $40,784 in present day dollars over the course of 15 years. In Case 3, the ES owner saved $464,421 over the 15-year study period by using our proposed method rather than existing approaches.

This paper is limited by the assumptions made, particularly around foreknowledge of prices, demand patterns, and solar output. Future work could include:

- Uncertainty in the generation output, demand charges, load profiles, rates for ancillary services, and more
- The initial investment costs for the generation facility
- Testing this model in other jurisdictions
- Testing this model for other purposes, such as to assess the impact of merchant ES on policymakers, regulators, utilities, and system operators.

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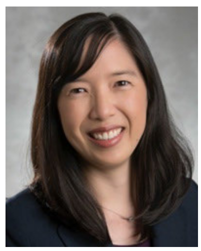

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