Degradation-aware Valuation and Sizing of Behind-the-Meter Battery Energy Storage Systems for Commercial Customers

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***Abstract*—The optimal dispatch, valuation, and sizing of behind-the-meter battery energy storage systems are crucial in reducing the electricity bill for commercial customers. This paper develops a novel battery dispatch and valuation algorithm for commercial customers, which takes battery degradation into consideration. A battery sizing algorithm based on heuristic optimization approach is also developed to determine the optimal power and energy ratings of battery energy storage systems. Simulation studies are performed for commercial customers with real-world smart meter data. The simulation results show that the proposed degradation-aware battery dispatch and valuation algorithm produces significantly higher net present value than that of the based model, which does not explicitly consider degradation in the optimization framework. The simulation results also show that the proposed battery sizing optimization algorithm is capable of finding near-optimal battery energy and power ratings for commercial customers.**

***Index Terms*—Battery energy storage system, behind-the-meter, commercial customer, degradation, heuristic optimization.**

I. INTRODUCTION

As the penetration level of distributed renewable energy continues to increase, battery energy storage systems (BESS) become more important in reducing the cost of electricity for end-use customers and maintaining reliability in the distribution network. High demand charges and the significant difference between on-peak and off-peak electricity rates have incentivized many commercial customers to adopt BESS. However, excessive cycling of BESS could cause premature failure. Hence, commercial customers need a BESS dispatch and sizing optimization algorithm, which considers the impacts of battery cycling operations on the state-of-health of BESS. With the availability of granular smart meter data [1], the BESS dispatch and sizing optimization algorithm can be easily adopted by the commercial customers.

The existing literature on battery dispatch and sizing optimization can be classified into two groups. The first group determines the optimal dispatch and sizing of BESS by only considering the peak load shaving application. In [2], a BESS dispatch and sizing framework is developed for peak shaving. Dynamic programming is adopted to find the optimal battery operation strategy. The optimal sizing is found by exhaustively searching all possible BESS settings while assuming a fixed battery operation strategy. The state-of-health of BESS is evaluated by comparing the number of charge/discharge cycles incurred and the maximum number of cycles. [3] presents a heuristic method to determine the appropriate size of BESS. In this method, batteries are expected to shave all peaks that exceed a pre-defined load threshold while having zero failure event. The lifetime valuation of BESS is conducted based on the simulation results from one-year battery operation simulation.

The second group of literature considers energy arbitrage in addition to peak load reduction when determining the size of BESS. The BESS sizing problem for commercial buildings is solved by minimizing the building's annual electricity cost [4]. The annualized BESS initial costs and a predetermined number of operation cycles are considered in the optimization. [5] and [6] present a similar formulation for commercial customers. They assume that there is an approximately linear relationship between the depth of discharge and the number of operation cycles. The battery simulation is conducted over a one-year horizon while the battery lifetime is assumed to be 15 years.

Most of the existing literature on BESS valuation and sizing use highly simplified battery degradation models. They either assume a fixed number of lifetime cycles or a linear relationship between the depth of discharge and the number of operation cycles. However, the degradation of BESS is a highly nonlinear function of the depth of discharge, the current rate, and the mean state-of-charge of the cycles. Hence, the existing methods can not provide a reliable estimation for the value or optimal size of BESS.

In this paper, we fill the knowledge gap by developing a degradation-aware BESS dispatch optimization algorithm for commercial customers. The peak shaving and energy arbitrage benefits of BESS are simultaneously modeled. The proposed algorithm minimizes the electricity bill of commercial customers over the lifetime of BESS while explicitly considering degradation effects of battery. The proposed degradation-aware algorithm achieves higher lifetime net present value for BESS by limiting the charging and discharging rates and usable range of battery when BESS provide less valuable energy shifting service. This paper also develops an optimal battery sizing

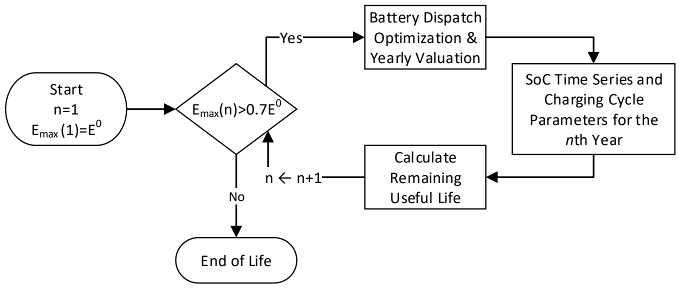

Fig. 1: Battery lifetime valuation framework

algorithm based on heuristic optimization, which considers the nonlinear degradation effects of battery. The proposed algorithm is capable of finding near-optimal energy and power ratings of BESS for commercial customers.

The unique contributions of this paper are as follows. First, this paper proposes a degradation-aware BESS dispatch optimization algorithm, which can significantly reduce the electricity bill for commercial customers. Second, this paper develops a comprehensive lifetime valuation framework for BESS. Third, we also developed a heuristic BESS sizing algorithm which determines the optimal energy and power ratings of battery for commercial customers.

The rest of this paper is organized as follows. Section II presents the degradation-aware BESS operation and valuation models. Section III describes the algorithm for solving the BESS sizing problem. Section IV presents the simulation results. Section V states the conclusion.

II. Degradation-aware Battery Energy Storage System Operation and Valuation

In this section, we develop a methodology to perform lifetime valuation of battery storage systems for commercial customers. A degradation-aware optimal operation strategy is also developed to extract maximum value from BESS.

A. BESS Lifetime Valuation Framework

The lifetime valuation framework of BESS is illustrated in Fig. 1. The valuation process starts in year 1, where the initial battery energy rating $E_{max}(1) = E^0$. A battery dispatch optimization engine then determines the optimal hourly dispatch schedules of BESS in the next year. The state-of-charge (SoC) time series and the parameters of charging cycles are then calculated for the corresponding year. The remaining battery useful life and energy rating can then be estimated based on the battery charging cycles information. If the remaining battery energy rating is less than 70% of its original energy rating, then the battery has reached its end of life. Otherwise, the energy rating of the battery is updated and the battery dispatch optimization is carried out for the next operating year. The battery dispatch optimization algorithm and the remaining energy rating calculation procedure are covered in the following two subsections.

B. BESS Operation Optimization

In this subsection, we develop two battery operation optimization algorithms, the base model and the degradation-aware model. The base optimization model determines the optimal battery operation schedule, which maximizes the monthly electricity bill reduction without considering the battery degradation effects. In contrast, the degradation-aware optimization model imposes additional constraints on battery usable range and charging/discharging rates to achieve higher electricity bill reduction for commercial customers over the lifetime of BESS. The details of the two optimization models are presented below.

1) Base Optimization Model: The base battery operation optimization model selects the optimal hourly charging and discharging schedules of BESS to minimize the monthly electricity bill of commercial customers. The base optimization model does not explicitly consider the impacts of charging and discharging activities on the state-of-health of BESS.

The problem formulation of the base optimization model is listed blow. The objective (1) of the optimization problem is to minimize commercial customers' monthly electricity bill, which consists of the energy charge and the demand charge. The decision variables are the hourly battery charging and discharging rates. The operational constraints of BESS are modeled by (2)-(8).

$$\min_{c_m(h),d_m(h)} \sum_{h\in H_{mn}} \{x_m(h) - [d_m(h) - c_m(h)] \cdot (1\ hr.)\} \cdot C^E(h) + P(m) \cdot C^D(m), \quad m \in M_n \tag{1}$$

subject to:

$$S_m(h+1) = S_m(h) \cdot (1-\gamma) - (d_m(h) - c_m(h)) \cdot (1\ hr.) - (d_m(h) + c_m(h)) \cdot (1\ hr.) \cdot (1-\sqrt{\kappa}), \quad h \in H_{mn} \tag{2}$$

$$0 \le S_m(h) \le E_{max}(n), \quad h \in H_{mn} \tag{3}$$

$$c_m(h) \cdot (1\ hr.) \le E_{max}(n) - S_m(h), \quad h \in H_{mn} \tag{4}$$

$$d_m(h) \cdot (1\ hr.) \le S_m(h), \quad h \in H_{mn} \tag{5}$$

$$0 \le d_m(h) \le P_{max}, \quad h \in H_{mn} \tag{6}$$

$$0 \le c_m(h) \le P_{max}, \quad h \in H_{mn} \tag{7}$$

$$x_m(h) - (d_m(h) - c_m(h)) \cdot (1\ hr.) \le P(m), \quad h \in H_{mn} \tag{8}$$

where H_{mn} denotes the set of all hours in the mth month of the nth year. $x_m(h)$ is the electric load of hour h in the mth month. $d_m(h)$ and $c_m(h)$ are the hourly battery discharge and charge rates at hour h in the mth month. $P(m)$ is the maximum load of the mth month. $C^E(h)$ is the electricity price for hour h under the time of use (TOU) rate and $C^D(m)$ is the demand charge of the mth month. $S_m(h)$ stands for the battery state of charge at hour h of the mth month. γ is the self discharge rate. κ is the battery round trip efficiency. $E_{max}(n)$ is the battery energy rating at the beginning of the nth year. P_{max} is the battery power rating.

Equation (2) is the update equation for the battery's state of charge (SoC). (3) ensures SoC is within the feasible range. Constraints (4)-(7) limit the battery SoC, charging, and discharging rates. Constraint (8) makes sure the hourly electric load never exceeds the maximum load of the month.

The outputs of the above optimization problem are the hourly battery charging and discharging schedules for a battery energy storage system with a given energy and power rating. It should be noted that the battery operation schedule generated from the base optimization strategy minimizes the current month's electricity bill without considering the degradation effects and the long-term value of BESS.

2) Degradation-aware Optimization Model: The base optimization model does not limit the battery usable range or charging/discharging rate. This may lead to overused batteries with accelerated degradation. To mitigate this problem, we develop a degradation-aware battery operation optimization model. Recognizing that the majority of the electricity bill is demand charge for most commercial customers, we propose to limit the battery usable range and charging/discharging rates based on the customer's daily electric demand level. On *heavy loading* days, the full capability of batteries should be used to reduce the customers' peak load and demand charge. On *non-heavy loading* days, we should limit the charging rates, discharging rates, and usable range of the battery because the value provided by energy shifting service is not as high as that of the peak reduction service. The *heavy loading* days and *non-heavy loading* are defined as a function of the minimum achievable peak demand and battery usage index for peak load reduction, which are derived as follows.

a) Minimum Achievable Peak Demand and Battery Usage Index: The minimum achievable peak demand is defined as the minimum customer peak demand, which can be achieved by operating the battery energy storage system. The minimum achievable peak demand of year n month m, $X^n_{max}(m)$, can be calculated by solving the following optimization problem.

$$\min_{c_m(h),d_m(h)} \max_{h\in H_{mn}} \left[x_m(h) - (d_m(h) - c_m(h)) \cdot (1\ hr.)\right] \quad (9)$$

subject to:

$$Constraints\,(2)\text{ - }(8)$$

The battery usage index for peak load reduction is defined as:

$$\mu_m(d) = \frac{\sum_{t=1}^{24} \max\{0, L_d(t)\}(2-\sqrt{\kappa})}{E_{max}(n)},\ d \in D_{mn} \quad (10)$$

where D_{mn} is the set of all days in the mth month of the nth year. $L_m(h) = x_m(h) - X^n_{max}(m)$ is defined as the difference between the customer's original load $x_m(h)$ and minimum achievable peak demand $X^n_{max}(m)$. $L_d(t) = L_m(h)$ for all hours h in month m, where $t = h \bmod 24$ and $d = \left\lceil \frac{h}{24} \right\rceil$.

When the battery usage index for peak load reduction $\mu_m(d) \geq 1$, the full capacity of the battery energy storage system has to be utilized for peak load reduction purpose on day d. Hence, $\mu_m(d) = 1$ is used to separate *heavy loading* days and *non-heavy loading* days. When $\mu_m(d) \geq 1$, i.e., during *heavy loading* days, we do not place additional operational constraints on batteries except (2)-(8). When $\mu_m(d) < 1$, i.e., during *non-heavy loading* days, additional constraints will be enforced to reduce the wear and tear of BESS. These additional battery usable range and charging/discharging rates constraints are described below.

b) Additional Battery Operational Constraints: On *non-heavy loading* days, additional battery operational constraints on battery SoC $S_m(h)$ and charging/discharging rates $c_m(h)$, $d_m(h)$ are enforced to extend the battery life.

Tighter battery SoC bounds are enforced as follows:

$$U_m(d)E_{max}(n) \leq S_m(h) \leq (1 - U_m(d))E_{max}(n), h \in H_{mn} \quad (11)$$

where the lower bound of the usable range $U_m(d)$ is determined by the following equations:

$$u_m(d) = \frac{1}{2}\left[1 - \mu_m(d)\right], \quad d \in D_{mn} \quad (12)$$

$$U_m(d) = \min\{u_0, u_m(d)\}, \quad d \in D_{mn} \quad (13)$$

The lower bound of the usable range $U_m(d)$ equals the smaller of the default usable range lower bound u_0 and $u_m(d)$, which is derived from the battery usage index for peak load reduction $\mu_m(d)$. This constraint ensures that during peak hours of *non-heavy loading* days, the battery will not discharge more power to reduce the hourly demand lower than the minimum achievable peak demand $X^n_{max}(m)$ of the month.

Since constraint (11) on SoC is tighter than that of base optimization model (3), the charging/discharging rates constraints (4) and (5) should be tightened accordingly:

$$c_m(h) \cdot (1\ hr.) \leq (1 - U_m(d))E_{max}(n) - S_m(h), h \in H_{mn} \quad (14)$$

$$d_m(h) \cdot (1\ hr.) \leq S_m(h) - U_m(d)E_{max}(n), h \in H_{mn} \quad (15)$$

To avoid high current rate in charging cycles, additional constraints on charging/discharging rates are imposed. First, we define the average charging rate ν_{ch} and discharging rate ν_{dis} on a typical weekday of *non-heavy loading* days as follows:

$$\nu_{ch} = \frac{(1 - 2U_m(d))E_{max}(n)}{T_{off}(d)} \quad (16)$$

$$\nu_{dis} = \frac{(1 - 2U_m(d))E_{max}(n)}{T_{on}(d)} \quad (17)$$

$T_{off}(d)$ and $T_{on}(d)$ denote the length of off-peak and on-peak hours on day d.

The charging and discharging rates on hours excluding P_{mn} are limited as follows. P_{mn} is the set of hours that require a discharge rate higher than the average discharge rate to reduce the load level to minimum achievable peak demand.

$$0 \leq c_m(h) \leq \min\{P_{max}, \nu_{ch}\}, \quad h \in H_{mn} \setminus P_{mn} \quad (18)$$

$$0 \leq d_m(h) \leq \min\{P_{max}, \nu_{dis}\}, \quad h \in H_{mn} \setminus P_{mn} \quad (19)$$

(18) and (19) ensure that for hours that do not require fast discharging/charging, the charge and discharge rates are smoothed out over the entire on-peak/off-peak hours.

What remains to be considered are the charging/discharging rates constraints for hours which require a discharge rate exceeding the average discharge rate. The constraints for these hours P_{mn} can be described by an if-else statement below.

If $L_m(h) - \nu_{dis} \cdot (1\ hr.)$ is positive, then the following inequality constraint is required to shave the load to $X^n_{max}(m)$.

$$d_m(h) \cdot (1\ hr.) - x_m(h) + X^n_{max}(m) \leq 0,\ h \in P_{mn} \quad (20)$$

If $L_m(h) - \nu_{dis} \cdot (1\ hr.)$ is non-positive, the above constraint does not need to be enforced.

By using the binary variable trick, the above if-else statement can be equivalently represented by the following constraints where M is a real number that is sufficiently large.

$$L_m(h) - \nu_{dis} \cdot (1\ hr.) < M\alpha, \quad h \in P_{mn} \quad (21)$$

$$d_m(h) \cdot (1\ hr.) - x_m(h) + X^n_{max}(m) \leq M(1-\alpha), \quad h \in P_{mn} \quad (22)$$

$$\nu_{dis} \cdot (1\ hr.) - L_m(h) \leq M(1-\alpha), \quad h \in P_{mn} \quad (23)$$

$$d_m(h) \cdot (1\ hr.) \geq -M\alpha, \quad h \in P_{mn} \quad (24)$$

In sum, on *non-heavy loading* days, the following constraints must be enforced in the degradation-aware optimization model: (2), (11), (14)-(19), and (21)-(24).

c) Degradation-aware Optimization Model Summary: The degradation-aware optimization model is summarized as follows:

$$\min_{c_m(h), d_m(h), \alpha} (1)$$

subject to:

non-heavy loading days : (2), (11), (14)-(19), (21)-(24)

heavy loading days : (2)-(8)

Note that the objective function of the degradation-aware optimization problem is the same as that of base optimization model. The set of constraints enforced on *heavy loading days* and *non-heavy loading days* are different.

C. Battery State-of-health Estimation

In general, the degradation of BESS depends on four factors: the number of operating cycles, the depth of discharge, the current rate, and the mean SoC of each cycle. In order to accurately estimate the energy rating of the battery at the end of each year, we adopt a semi-empirical battery degradation model presented in [7]. The remaining battery capacity in the beginning of year $(n+1)$ is given by

$$E^{(n+1)}_{max} = r_1 e^{-r_2 \sum_{\eta=1}^{n} deg_\eta} + (1-r_1) e^{\sum_{\eta=1}^{n} -deg_\eta} \quad (25)$$

where r_1 and r_2 are two constants. The first term on the right-hand side (RHS) stands for the degradation incurred with the solid electrolyte interphase (SEI) layer buildup. The second term on the RHS accounts for a slower degradation process due to ion loss. deg_η is the battery degradation rate of ηth year. It can be estimated as a function of the number of operating cycles, the depth of discharge, the current rate, and the mean SoC of each cycle as shown in [8]. The rainflow-counting algorithm (RCA) [9] is applied to derive the battery cycle parameters based on the battery SoC time series.

III. Battery Sizing Optimization

This section develops an algorithm to determine the optimal battery size for a commercial customer. The goal of the battery sizing optimization is to select the best energy and power ratings for a battery, which has the maximum net present value (NPV). The NPV of the battery can be calculated by subtracting the initial cost of the battery from the sum of discounted reduction in electricity bill for a commercial customer over the lifetime of the battery.

The battery sizing optimization problem is formulated as follows. The optimization problem maximizes the NPV of BESS. $C_0(E^0, P_{max})$ denotes the initial cost of the battery. C_n is the reduction in electricity bill of the nth year for a commercial customer with the help of the battery. C_n includes the energy charge reduction and the demand charge reduction components.

$$\max_{E^0, P_{max}} \sum_{n=1}^{N} \frac{C_n}{(1+r)^n} - C_0(E^0, P_{max}) \quad (26)$$

subject to:

$$C_n = \sum_m \{ \sum_{h \in H_{mn}} [d_{mn}(h) - c_{mn}(h)] C^E(h) + [\max_{h \in H_{mn}} (x_m(h) - P(m))] \cdot C^D(m) \} \quad (27)$$

$$(d_{mn}(h), c_{mn}(h)) \leftarrow f_{dispatch}(E_{max}(n), P_{max}) \quad (28)$$

$$E_{max}(n) \leftarrow f_{deg}(E_{max}(n-1)), \quad \forall n \geq 2 \quad (29)$$

$$E_{max}(1) = E^0 \quad (30)$$

where r is the annual discount rate. (28) and (29) correspond to the degradation-aware battery operation optimization algorithm and the battery state-of-health estimation algorithm, respectively. (30) defines the initial battery capacity.

The nonlinearity of the battery degradation estimation function makes the battery sizing optimization problem a highly nonlinear one. Thus, we adopt the genetic algorithm (GA) to search for the optimal battery energy and power ratings. The flow chart of the genetic algorithm for battery sizing optimization is shown in Fig. 2.

The GA algorithm starts from a population of randomly generated individuals with different battery energy ratings E^0 and power ratings P_{max}. Then the fitness function is calculated for each individual in the population. In this case, the fitness function is the NPV of BESS. The next generation population is then generated by selecting individuals from the previous generation with high fitness values and executing mutation and crossover operations. The fitness function evaluation and population evolution procedures are carried out iteratively until a predefined termination criterion is met.

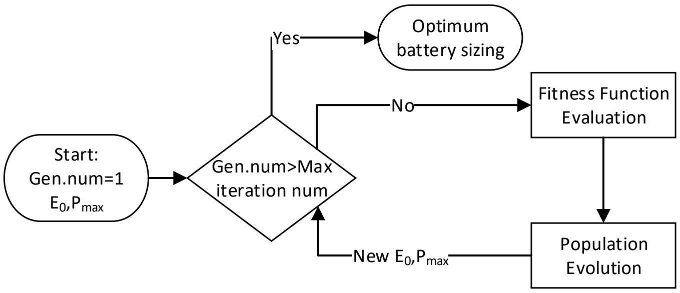

Fig. 2: Genetic algorithm flow chart

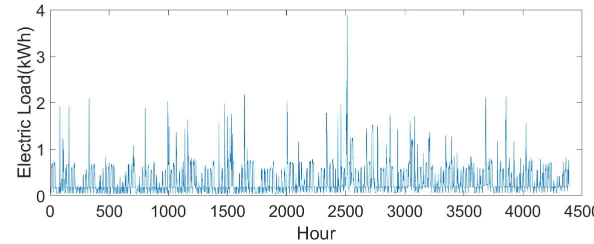

Fig. 3: Load profile of sample customer 1

IV. Numerical Studies

In this section, numerical studies are carried out to validate the effectiveness of our proposed degradation-aware battery operation optimization algorithm and the battery sizing optimization algorithm. The simulation setup is presented in subsection IV.A. Subsection IV.B compares the performance of two battery operation optimization algorithms: the base optimization model and our proposed degradation-aware optimization model. Subsection IV. C validates the applicability of the GA algorithm for selecting the optimal battery size. Two commercial customers' load profile used in the study are from Southern California. The hourly load data recorded by smart meters are from 2015. To generate long-term electric load time series for battery life-time evaluation, the original load data is repetitively used for future years. The electricity price paid by commercial customers are based on Southern California Edison (SCE)'s general service rates for business customers. The electricity price for on-peak, mid-peak and off-peak hours are 0.2974\$/kWh, 0.0982\$/kWh, and 0.05443\$/kWh, respectively. On weekdays, the on-peak hours are from 12 PM to 18 PM and the off-peak hours are from 23 PM to 8 AM. The rest of the hours on weekdays are mid-peak. All hours on weekends and holidays are considered off-peak hours. The demand charge for commercial customers is 18.34\$/kW. The power-based and energy-based capital costs of the battery are 551\$/kW and 614\$/kWh [10]. The battery death line is assumed to be 70% of its initial energy rating.

A. *Effectiveness of the Degradation-aware Operation Strategy*

In order to demonstrate the advantage of the proposed degradation-aware battery optimization model, we compare its performance with that of the base optimization model. The testing battery is assumed to have an energy rating of $E^0 = 1.2$ kWh and power rating of $P_{max} = 0.6$ kW. The default lower bound of the usable range of the battery is chosen as $u_0 = 0$. It means that the full usable range of the battery can be utilized to reduce the commercial customer's electric load. The hourly load profile of sample commercial customer 1 who installed BESS is shown in Fig. 3.

Both the base optimization model and the degradation-aware optimization model are used to determine the hourly charging/discharging schedules of BESS on a yearly basis. The lifetime valuation of BESS is conducted according to the framework presented in Section II. The energy ratings at the end of each year and the yearly battery revenue under both optimization models are depicted in Fig. 4 and Fig. 5. As shown in Fig. 4, the blue and green lines are the remaining battery capacity curves for the base model and degradation-aware model, respectively. The red line is the death line (70% of the initial battery capacity). When operated under the base optimization model and the degradation-aware model, the usable life of the battery are 11.417 years and 14.167 years, respectively. The proposed degradation-aware optimization model extends the usable life of the battery by around 3 years. In addition, the degradation-aware optimization model produces a higher NPV for BESS. The NPV of the battery operated under the base optimization model is \$1999.3, while the NPV of the battery operated under the degradation-aware model is \$2386.5. As shown in Fig. 5, although the based model yields a slightly higher revenue than the degradation-aware model in the first 11 years, it fails to let the battery generate any revenue in years 12 to 14. The simulation results show that the degradation-aware model avoids deep cycles for energy shifting purposes, which leads to higher lifetime value than that of the base optimization model.

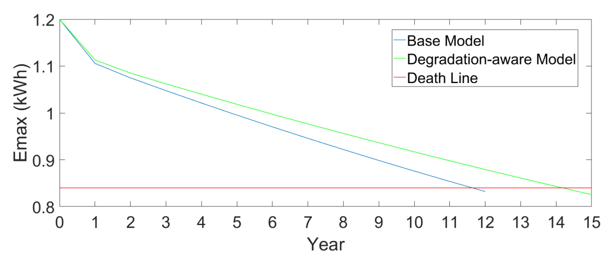

Fig. 4: Yearly energy rating of the battery under two operating strategies

B. *Battery Sizing Optimization*

The effectiveness of the proposed GA based battery sizing optimization algorithm is validated through a comparison with the exhaustive grid search approach. The validation is carried out through a case study on another sample commercial customer in Southern California. The hourly load profile of the customer is shown in Fig. 6.

The GA setup is as follows. The number of individuals in each generation is set at 20. The generation gap and the

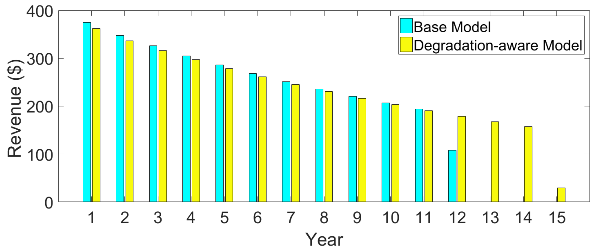

Fig. 5: Yearly net revenue of the battery under two operating strategies

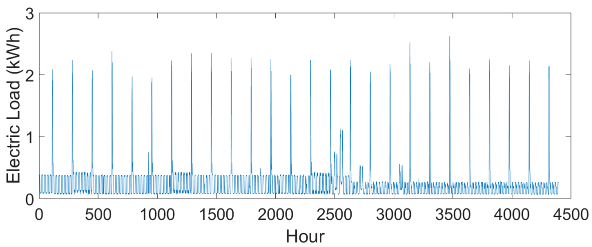

Fig. 6: Load profile of sample customer 2

mutation rate are chosen to be 0.9 and 0.05, respectively. The energy ratings of the batteries in the first generation are sampled from a uniform distribution $U(0.5, 5)$ kWh. The number of working hours of the batteries in the first generation are sampled from a uniform distribution $U(1, 4)$ hours. The default battery usable range is set to be 10%-90%. The initial cost of the battery is the same as the setup in Section IV.B. 8-digit binary strings are used to represent the energy ratings and working hours. The program will terminate when the number of iterations reaches 100 or the standard deviation of the 20 individuals in one generation is less than \$100.

The optimal energy and power ratings found by the GA are 2.83 kWh and 0.98 kW (2.87 working hours). With the degradation-aware optimization, this battery is expected to last 16 years and 6 months and has a lifetime NPV of \$1743.45.

To validate the optimality of battery setting found by the GA, a grid search is conducted with 56 different battery sizes for sample customer 2. In the grid search, 8 different values for energy ratings equally spaced between 0.5 kWh and 4 kWh and 7 different values for the number of working hours of a battery equally spaced between 1 hour and 4 hours are selected. Under each battery size, a lifetime battery valuation is conducted with the degradation-aware optimization algorithm. The NPVs of all battery sizes and the corresponding NPV surface are shown in Fig. 7. The red point represents the optimal battery size found by the GA. The best energy and power rating pair found by the grid search is 3 kWh and 3 working hours which has a NPV of \$1650.91 with a 16 years and 4 months battery life. The NPV of the optimal battery configuration found by the GA is 5.6% higher than that of the exhaustive grid search.

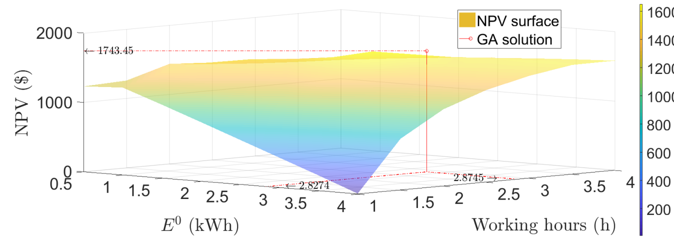

Fig. 7: NPV of BESS with different sizing configurations for sample customer 2

V. Conclusion

To improve the profitability of BESS, this paper develops an innovative degradation-aware dispatch optimization algorithm. The proposed method explicitly considers the battery degradation effects and limits the charging/discharging rates when it provides less valuable energy shifting service. A comprehensive battery lifetime valuation framework is built on top of the degradation-aware dispatch optimization algorithm to estimate the NPV of BESS. At last, an optimal battery sizing algorithm is developed based on the heuristic optimization approach. Numerical studies based on real-world smart meter data from commercial customers in Southern California are carried out to validate the proposed algorithms and methods. The simulation results show that compared to the base optimization algorithm, the degradation-aware dispatch optimization algorithm increases the NPV of the battery by almost 20%. The simulation results also show that the proposed GA based battery sizing algorithm can find near-optimal battery energy and power ratings for commercial customers.

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