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

Author
Zhang, Zhenhai

Publication Date
2018

Peer reviewed|Thesis/dissertation

UNIVERSITY OF CALIFORNIA
RIVERSIDE

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

A Thesis submitted in partial satisfaction
of the requirements for the degree of

Master of Science

in

Electrical Engineering

by

Zhenhai Zhang

December 2018

Thesis Committee:

Dr. Nanpeng Yu, Chairperson
Dr. Zhijia Zhao
Dr. Ming Liu

The Thesis of Zhenhai Zhang is approved:

Committee Chairperson

University of California, Riverside

Acknowledgments

To begin with, it was a great pleasure to work with my advisor Nanpeng Yu. Dr.Yu has always been a fatherly figure to me and my lab mates. He is always willing to help when we are faced with some problems in our research. Even though I am not in the power field during my undergraduate study, he encourages me to do independent research and be brave to the unknown challenges.

I thank my thesis committee, Professor Zhijia Zhao, Professor Ming Liu to spare their own time to attend this defense. I appreciate it a lot for they are nice to interact with and be nice to me.

I would like to thank fellow graduate students and lab mates for their help and support. My lab mates Yuanqi Gao, Jie Shi, Wei Wang, Wenyu Wang, Brandon Foggo and Farzana Kabir were also my research collaborators with whom I spent countless hours discussing research and meeting deadlines. They gave me many meaningful and constructive advises and guidance when I have trouble in solving problems in research. It would have been much more difficult for me to accomplish the conference paper and the thesis without cooperation with them.

Finally, I am most grateful to my family for always being there for me. Their continuous support has always been a source of my motivation since I came to US. It has been a challenging several years from them, but I am very pretty sure that we are still as connected as ever.

To my parents for all the support.

ABSTRACT OF THE THESIS

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

by

Zhenhai Zhang

Master of Science, Graduate Program in Electrical Engineering
University of California, Riverside, December 2018
Dr. Nanpeng Yu, Chairperson

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 thesis 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.

Contents

List of Figures

NOMENCLATURE

Decision Variables

$d_m(h)$: Hourly amount of power battery discharge on the customer side at hour h in m-th month [kW].

$c_m(h)$: Hourly amount of power battery charge on the customer side at hour h in m-th month [kW].

State Variables

$S_m(h)$: Hourly battery state of charge at hour h in m-th month [kWh].

$P(m)$: The maximum hourly load in m-th month after optimization [kWh].

Parameters

$x_m(h)$: The electric load at hour h in m-th month [kWh].

$X^n_{max}(m)$: The minimum monthly peak load achieved with full battery usable range in m-th month of n-th year[kWh].

$E_{max}(n)$: Battery energy rating at the beginning of n-th year [kWh].

P_{max}: Battery power rating [kW].

$C^E(h)$: The price of electricity for hour h under the time of use (TOU) rate [$/kWh].

$C^D(m)$: The demand charge in m-th month [$/kW].

η: Round trip efficiency [%].

C_I: Initial cost of the battery [$].

γ: Battery self discharge rate [%/hour].

ρ: Battery resistive loss factor [unitless].

$T_{off}(d)$: Length of off-peak hours on day d.

$T_{on}(d)$: Length of on-peak hours on day d.

$L_m(h)$: Difference between electric load and $X_{min}(m)$ on hour h of m-th month [kWh].

$L_d(\hbar)$: Difference between electric load and $X_{min}(m)$ on hour $\hbar$ of d-th day [kWh].

$U_m(d)$: The lower bound of the battery usable range of d-th day in the m-th month [%].

u_0: The default lower bound of the usable range [%].

$u_m(d)$: Hourly usable range lower bound decided after min-max optimization of d-th day [%].

ν_d: Average discharge rate on a typical weekday. [kW]

ν_c: Average charge rate on a typical weekday. [kW]

α: Binary decision variable decided by the difference between ν and $L_d(\hbar)$.

M: A large enough parameter.

Sets

M_n: Set of all months of n-th year.

H_{mn}: Set of all hours in m-th month of n-th year.

D_{mn}: Set of all days in m-th month of n-th year.

P_{mn}: Set of hours whose peak exceeds $X_{min}(m)$ in m-th month.

P^u_{mn}: Set of hours which $u_m(d)$ is positive.

$H_{mn}(1^+)$: Set of hours that contains H_{mn} and augmented by one additional hour after the last hour of each consecutive chain of hours of H_{mn} of n-th year.

Index Variables

h: Hour.

$\hbar$: Hour-of-day.

d: Day.

m: Month.

n: Year.

Chapter 1

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 significance 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 its state-of-health. With the availability of granular smart meter data [1], the BESS dispatch and sizing optimization algorithm can be easily adopted by the commercial customers.

Batteries of BESS are made of stacked cells where-in energy exchange between chemical energy and electricity energy. The primary characteristics of the batteries are: life span (in terms of number of cycles), depth of discharge, energy rating, power rating, and self-discharge. So constructive among the features is the battery energy rating in terms of long-term valuation for commercial customers. In this work, I mainly focus on optimizing the battery size (e.g. energy rating) for commercial customer electricity bill reduction purpose.

1.1 Commercial Customer Bill

As the demand prices charged by utility companies can be as high as 100 times of energy prices, demand charge could account for more than 50% of the monthly electricity bill of a commercial customer [2]. Thus the total cost of the bill can be significantly reduced by discharging the battery during peak hours. An example of the electricity rate from Southern California Edison(SCE) is shown in Fig. 1.1 [3].

	Delivery Service								Generation[9]	
	Trans[1]	Distrbtn[2]	NSGC[3]	NDC[4]	PPPC[5]	DWRBC[6]	PUCRF[7]	Total[8]	UG**	DWREC[10]
Option CPP										
Energy Charge - $/kWh/Meter/Month										
Summer Season On-Peak	(0.00239) (R)	0.00245 (I)	0.00487 (R)	0.00005 (I)	0.01021 (R)	0.00549	0.00046 (I)	0.02114 (R)	0.10130 (I)	0.00000
Mid-Peak	(0.00239) (R)	0.00245 (I)	0.00487 (R)	0.00005 (I)	0.01021 (R)	0.00549	0.00046 (I)	0.02114 (R)	0.05852 (I)	0.00000
Off-Peak	(0.00239) (R)	0.00245 (I)	0.00487 (R)	0.00005 (I)	0.01021 (R)	0.00549	0.00046 (I)	0.02114 (R)	0.03706 (I)	0.00000
Winter Season On-Peak										
Mid-Peak	(0.00239) (R)	0.00245 (I)	0.00487 (R)	0.00005 (I)	0.01021 (R)	0.00549	0.00046 (I)	0.02114 (R)	0.05355 (I)	0.00000
Off-Peak	(0.00239) (R)	0.00245 (I)	0.00487 (R)	0.00005 (I)	0.01021 (R)	0.00549	0.00046 (I)	0.02114 (R)	0.04264 (I)	0.00000
Customer Charge - $/Meter/Month		462.59 (I)						462.59 (I)		
Demand Charge - $/kW of Billing Demand/Meter/Month										
Facilities Related	4.63 (R)	13.66 (I)						18.29 (I)		

Figure 1.1: Sample electricity rate for a commercial customer

The monthly electricity bill for customers is made up of 2 parts: energy charge and demand charge (1.1). Where x is the electric load of the month, C^E is the energy charge price, P is the peak hourly power consumed in the month, and C^D is the demand charge price of the month.

$$J = x \cdot C^E + P \cdot C^D \tag{1.1}$$

Our main objective function is minimize the total cost during the overall battery life, I meed to obtain both the optimum battery dispatch and sizing for commercial customers.

1.2 Literature Survey

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 was 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 the BESS is evaluated by comparing the number of charge/discharge cycles incurred and the maximum number of cycles. [4] presented a heuristic method to determine the appropriate size of BESS. In this method, the battery is expected to shave all peaks that exceed a pre-defined load threshold while having zero failure event. The lifetime valuation of a 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 [5]. The annualized

BESS initial costs and a predetermined number of operation cycles are considered in the optimization. [6], [7] present a similar formulation for commercial customers. They assume that there is an approximately linear relationship between the depth of discharge and number of operation cycles. The battery simulation is conducted over an 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 optimal sizes of BESS.

1.3 Our Contribution

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

The rest of this thesis is organized as follows. Chapter 2 presents the degradation-aware BESS operation and valuation models. Chapter 3 describes the algorithm for solving the BESS sizing problem. Chapter 4 presents the simulation results. Chapter 5 states the conclusion.

Chapter 2

Degradation-aware Battery Storage System Operation and Valuation

In this chapter, I 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 the battery storage system.

2.1 BESS Lifetime Valuation Framework

The lifetime valuation framework of BESS is illustrated in Fig. 2.1. The valuation framework 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 charging cycles parameters 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

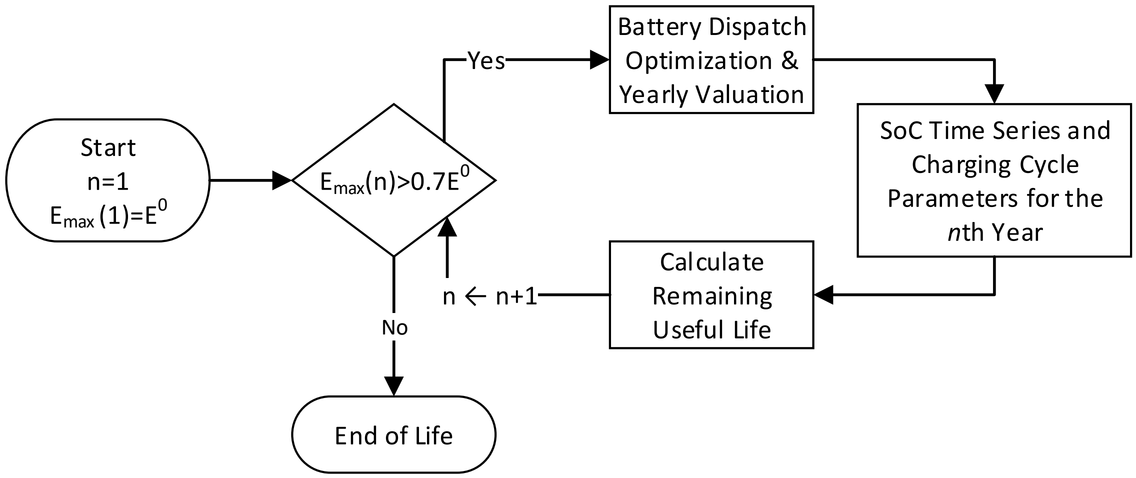

Figure 2.1: Battery lifetime valuation flow chart

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 remaining energy rating calculation procedure are covered in the following two subsections.

2.2 Battery Operation Optimization

In this section, I develop two battery operation optimization algorithms, the base model and degradation-aware model. The based 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 rate to achieve higher electricity bill reduction for commercial customers over the life time of the battery energy storage systems. The details of the two optimization models are presented below.

2.2.1 Base Optimization Model

The base battery operation optimization model selects the optimal hourly charging and discharging schedules of battery energy storage systems which minimizes the monthly electricity bill of commercial customers. The base optimization model does not explicitly consider the impacts of charging and discharging activities on a battery energy storage system's health.

The problem formulation of the base optimization model is listed blow. The objective function (2.1) of the optimization problem is to minimize commercial customer's monthly electricity bill which consists of the energy charge and demand charge. The decision variables are the hourly battery charing and discharging rates. The battery energy storage systems' operational constraints are modeled by (2.2)-(2.8).

$$\min_{c_m(h), d_m(h)} \sum_{h \in H_{mn}} \{x_m(h) - [d_m(h) - c_m(h)] \cdot (1\ hr.)\} \cdot C^E(h) + P(m) \cdot C^D(m), \quad m \in M_n \tag{2.1}$$

subject to:

$$S_m(h+1) = S_m(h) \cdot (1-\gamma) - (d_m(h) - c_m(h)) \cdot (1\ hr.)$$
$$- (d_m(h) + c_m(h)) \cdot (1\ hr.) \cdot (1 - \sqrt{\kappa}), \quad h \in H_{mn} \tag{2.2}$$

$$0 \leq S_m(h) \leq E_{max}(n), \quad h \in H_{mn} \tag{2.3}$$

$$c_m(h) \cdot (1\ hr.) \leq E_{max}(n) - S_m(h), \quad h \in H_{mn} \tag{2.4}$$

$$d_m(h) \cdot (1\ hr.) \leq S_m(h), \quad h \in H_{mn} \tag{2.5}$$

$$0 \leq d_m(h) \leq P_{max}, \quad h \in H_{mn} \tag{2.6}$$

$$0 \leq c_m(h) \leq P_{max}, \quad h \in H_{mn} \tag{2.7}$$

$$x_m(h) - (d_m(h) - c_m(h)) \cdot (1\ hr.) \leq P(m), \quad h \in H_{mn} \tag{2.8}$$

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 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 nth year. P_{max} is the battery power rating.

Equation (2) is the update equation for the battery's state of charge (SoC). (2.3) ensures SoC is within the feasible range. Constraints (2.4)-(2.7) limit the battery SoC, charging and discharging rates. Constraint (2.8) 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 under 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 long-term value of the battery energy storage system.

2.2.2 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, I develop a degradation-aware battery operation optimization model. Recognizing that the majority of the electricity bill is demand charge for most commercial customers, I propose to limit the battery usable range and charging/discharging rate 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, I should limit the charging and 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 in the following sections.

Minimum Achievable Peak Demand and Battery Usage Index

The minimum achievable peak demand is defined as defined as the minimum customer peak demand which can be achieved by operating the battery 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.

$$\min_{c_m(h),d_m(h)} \max_{h\in H_{mn}} [x_m(h) - (d_m(h) - c_m(h)) \cdot (1\ hr.)] \tag{2.9}$$

subject to:

$$Constraints\,(2.2)\text{ - }(2.8)$$

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

$$\mu_m(d) = \frac{\sum_{t=1}^{24} \max\{0, L_d(t)\}(2-\sqrt{\kappa})}{E_{max}(n)},\ d \in D_{mn} \tag{2.10}$$

where D_{mn} is the set of all days in mth month of 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 $d = \lceil \frac{h}{24} \rceil$.

When the battery usage index for peak load reduction $\mu_m(d) \geq 1$, the full capacity of the battery storage system has to be utilized for peak load reduction purpose. 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, I do not place additional operational constraints on batteries expect (2.2)-(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 battery energy storage systems. These additional battery usable range and charging/discharging rate constraints are described below.

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:

$$U_m(d)E_{max}(n) \leq S_m(h) \leq (1 - U_m(d))E_{max}(n), \quad h \in H_{mn} \tag{2.11}$$

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

$$u_m(d) = \frac{1}{2}\left[1 - \mu_m(d)\right], \quad d \in D_{mn} \tag{2.12}$$

$$U_m(d) = \min\{u_0, u_m(d)\}, \quad d \in D_{mn} \tag{2.13}$$

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 achievable peak demand $X^n_{max}(m)$ of the month.

Since the constraint (2.11) on SoC is tighter than that of base optimization model (2.3), the charging/discharging rate constraints (2.4) and (2.5) should be tightened accordingly:

$$c_m(h) \cdot (1\ hr.) \leq (1 - U_m(d))E_{max}(n) - S_m(h), \quad h \in H_{mn} \tag{2.14}$$

$$d_m(h) \cdot (1\ hr.) \leq S_m(h) - U_m(d)E_{max}(n), \quad h \in H_{mn} \tag{2.15}$$

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

$$\nu_{ch} = \frac{(1 - 2U_m(d))E_{max}(n)}{T_{off}(d)} \tag{2.16}$$

$$\nu_{dis} = \frac{(1 - 2U_m(d))E_{max}(n)}{T_{on}(d)} \tag{2.17}$$

where P_{mn} is the set of hours which requires a discharge rate exceeds the average discharge rate to reduce the load level to minimum achievable peak demand. T_{off} and T_{on} denote the length of off peak and on peak hours of day d.

The charging and discharging rates on hours excluding P_{mn} are limited as follows:

$$0 \leq c_m(h) \leq \min\{P_{max}, \nu_{ch}\}, \quad h \in H_{mn} \setminus P_{mn} \tag{2.18}$$

$$0 \leq d_m(h) \leq \min\{P_{max}, \nu_{dis}\}, \quad h \in H_{mn} \setminus P_{mn} \tag{2.19}$$

(2.18) and (2.19) ensure that for hours that do not require fast discharging/charging, the charge and discharge rates could smooth out over the entire on-peak/off-peak hours.

What remains to be considered are the charging/discharging rate constraints for hours which require a discharge rate exceeds 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 equality constraint is required to shave the load to exactly $X^n_{max}(m)$.

$$d_m(h) \cdot (1\ hr.) - x_m(h) + X^n_{max}(m) \leq 0, \quad h \in P_{mn} \tag{2.20}$$

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:

$$L_m(h) - \nu_{dis} \cdot (1\ hr.) < M\alpha, \quad h \in P_{mn} \tag{2.21}$$

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

$$h \in P_{mn} \tag{2.22}$$

$$\nu_{dis} \cdot (1\ hr.) - L_m(h) \leq M(1-\alpha), \quad h \in P_{mn} \tag{2.23}$$

$$d_m(h) \cdot (1\ hr.) \geq -M\alpha, \quad h \in P_{mn} \tag{2.24}$$

In sum, on *non-heavy loading* days, the following constraints must be enforced in the degradation-aware optimization model: (2.2), (2.11), (2.14)-(2.19), and (2.21)-(2.24).

Degradation-aware Optimization Model Summary

The degradation-aware optimization model is summarized as follows:

$$\min_{c_m(h), d_m(h), \alpha} (2.1)$$

subject to:

$$\textit{non-heavy loading days}: (2.2), (2.11), (2.14)\text{-}(2.19), (2.21)\text{-}(2.24)$$

$$\textit{heavy loading days}: (2.2)\text{-}(2.8)$$

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.

2.3 Battery State-of-health Estimation

In general, the degradation of battery energy storage systems depend on four factors: number of operating cycles, depth of discharge, current rate, and mean SoC of each cycle. In order to accurately estimate the remaining capacity of the battery at the end of each year, I adopt a semi-empirical battery degradation model presented in [8] . The remaining battery capacity in the beginning of year $(n+1)$ is given by

$$E_{max}^{(n+1)} = r_1 e^{-r_2 \sum_{\eta=1}^{n} deg_\eta} + (1-r_1) e^{\sum_{\eta=1}^{n} -deg_\eta} \tag{2.25}$$

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 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 number of operating cycles, depth of discharge, current rate, and mean SoC of each cycle as shown in [9]. The rainflow-counting algorithm (RCA) [10] is applied to derive the battery cycle parameters based on the battery SoC time series.

Chapter 3

Battery Sizing Optimization

3.1 Genetic Algorithm Review

Genetic algorithm is a heuristic solution-search or optimization technique, originally motivated by the Darwinian principle of evolution through (genetic) selection. A GA uses a highly abstract version of evolutionary processes to evolve solutions, then I can find the optimal solutions. Each GA operates on a population of artificial chromosomes. The chromosomes are usually represented by binary digits. Each chromosome represents a solution to a problem and has a fitness, a real number which is a measure of how good a solution it is to the particular problem.

Starting with a randomly generated population of chromosomes, a GA simulates a process of fitness-based selection and recombination to produce a successor population–the next generation. During recombination, parent chromosomes are selected and their genetic material is recombined to produce child chromosomes. These then pass into the successor population. As this process is iterated, a sequence of successive generations evolves and the average fitness of the chromosomes tends to increase until some stopping criterion is reached. In this way, a GA evolves a best solution to a given problem.

3.2 Sizing Optimization Formulation

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 rating for a battery which has the maximum net present value. The net present value (NPV) of the battery can be calculated by subtracting the cost of the battery from the sum of discounted reduction in electricity bill for a commercial customer over the life time of the battery.

The battery sizing optimization problem is formulated as follows. The optimization problem maximizes the NPV of the 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 the battery. C_n includes the energy charge reduction and the demand charge reduction components.

$$\max_{E^0, P_{max}} \sum_{n=1}^{N} \frac{C_n}{(1+r)^n} - C_0(E^0, P_{max}) \tag{3.1}$$

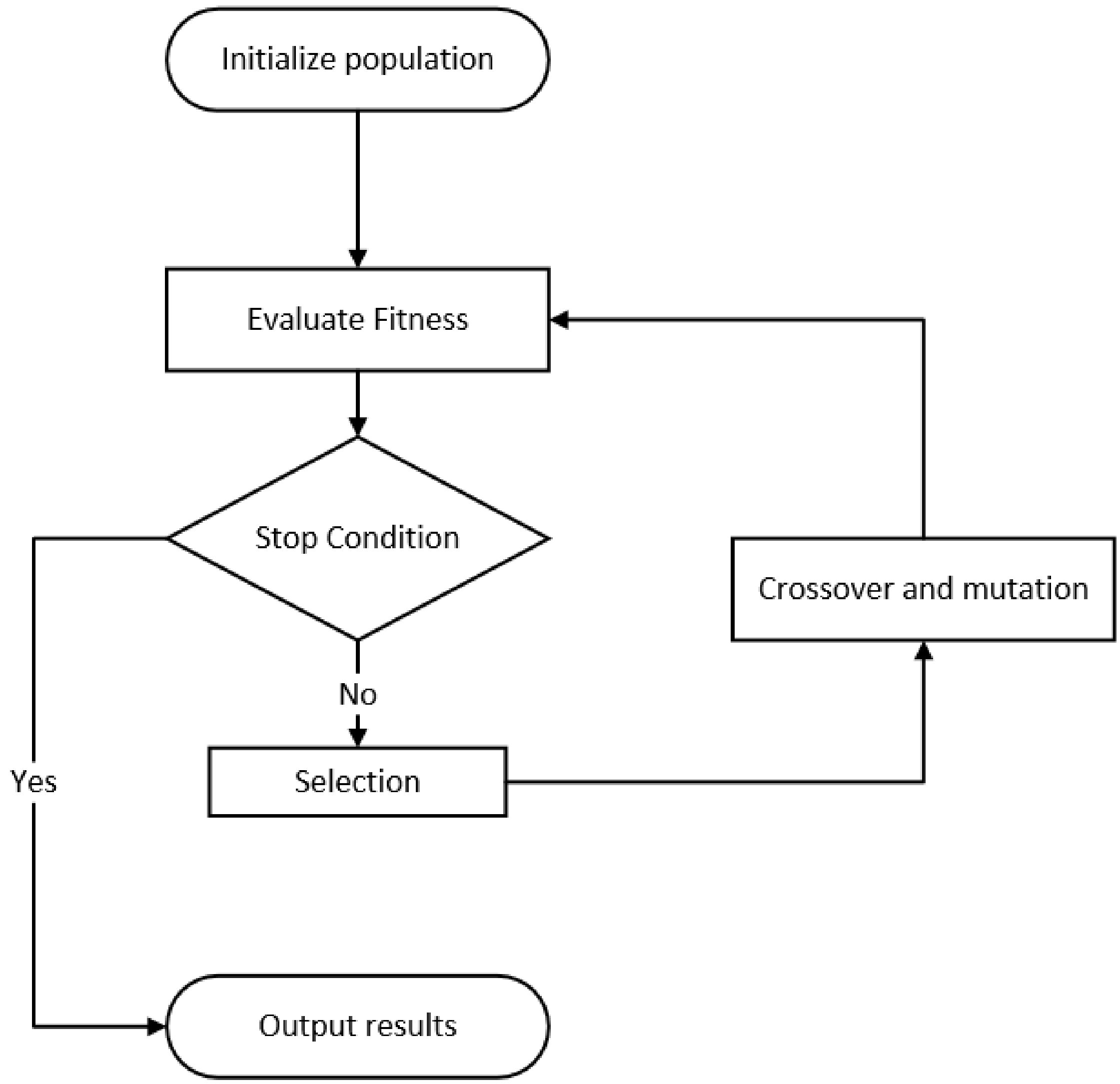

Figure 3.1: General genetic algorithm flow chart

subject to:

$$C_n = \sum_m \{ \sum_{h \in H_{mn}} [d_{mn}(h) - c_{mn}(h)] C^E(h)$$

$$+ [\max_{h \in H_{mn}} (x_m(h) - P(m))] \cdot C^D(m)\} \tag{3.2}$$

$$(d_{mn}(h), c_{mn}(h)) \leftarrow f_{dispatch}(E_{max}(n), P_{max}) \tag{3.3}$$

$$E_{max}(n) \leftarrow f_{deg}(E_{max}(n-1)), \qquad \forall n \geq 2 \tag{3.4}$$

$$E_{max}(1) = E^0 \tag{3.5}$$

where r is the discount rate. (3.3) and (3.4) correspond to the degradation-aware battery operation optimization algorithm and the battery state-of-health estimation algorithm, respectively. (3.5) defines the initial battery capacity.

The nonlinearity of the battery degradation estimation function makes the battery sizing optimization problem a highly nonlinear one. Thus, I 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. 3.2.

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

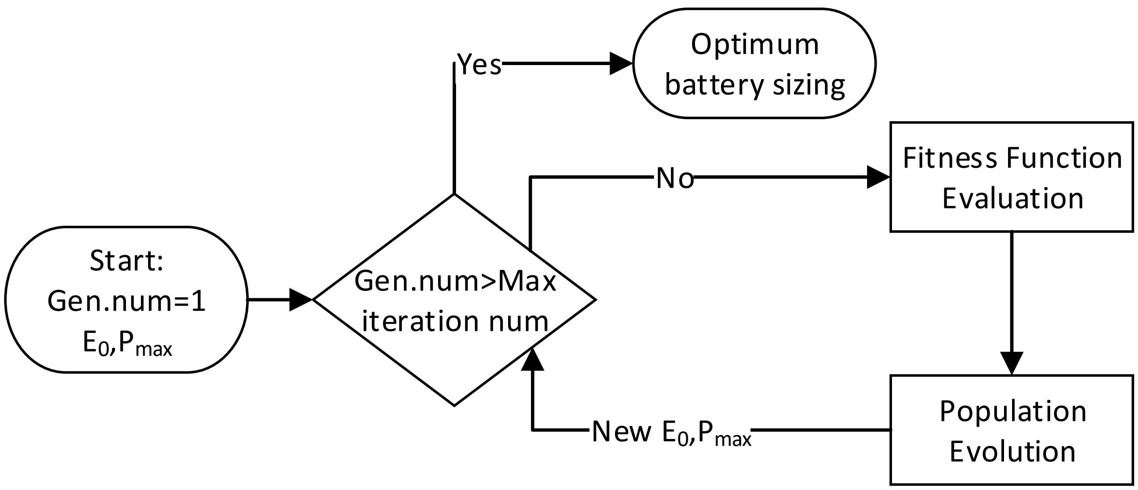

Figure 3.2: Genetic algorithm flow chart for finding optimal battery sizing

Chapter 4

Numerical Studies

In this chapter, 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 section 4.1. Section 4.2 compares the performance of two battery operation optimization algorithms: the base optimization model and our proposed degradation-aware optimization model. Section 4.3 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 energy 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. The on-peak hours are from 12 PM to 18 PM. The off-peak hours are from

23 PM to 8 AM. The rest of the hours are mid-peak. 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 [11]. The battery death line is assumed to be 70% of its initial energy rating.

4.1 Effectiveness of the Degradation-aware Battery 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 respectively. The default lower bound of the usage range of the battery is chosen as $u_m(d) = 0$. 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 the sample commercial customer 1 installed the BESS. The hourly load profile of the customer is shown in Fig. 4.1.

Both the base optimization model and the degradation-aware optimization model are used to determine the hourly charging/discharging schedules of the BESS on a yearly basis. The lifetime valuation of the BESS are conducted according to the framework presented in Chapter 2. The energy ratings at the end of each year and the yearly battery revenue under both operating optimization models are depicted in Fig. 4.2-4.3. As shown in Fig. 4.2, the blue and green lines are the remaining battery energy curves for the base

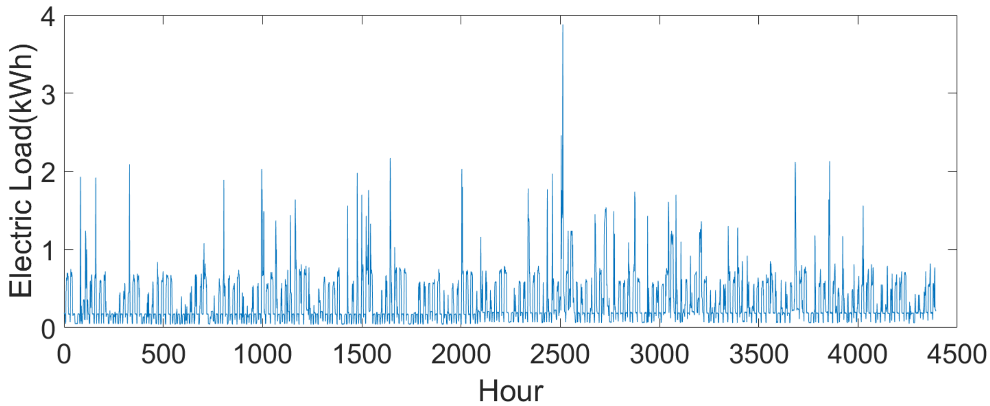

Figure 4.1: Load profile of sample customer 1

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 the battery are 11 years and 7 months and 14 years and 2 months respectively. The proposed degradation-aware optimization model extends the usable life of the battery by 3 years. In addition, the degradation-aware optimization model led to a higher NPV for the 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. 4.3, although the based model yields a slightly higher revenue than the degradation-aware model in the first 11 years, it failed to let the battery generate any revenue in years 12 to 14. Hence, 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.

Based on Fig.4.2-4.3, I made the following suggestions for the commercial customers:

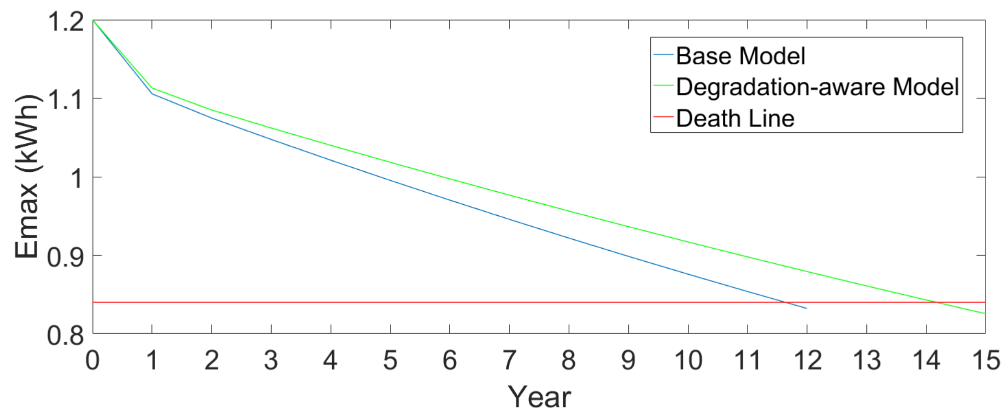

Figure 4.2: Yearly energy rating of the battery under the two operating strategies

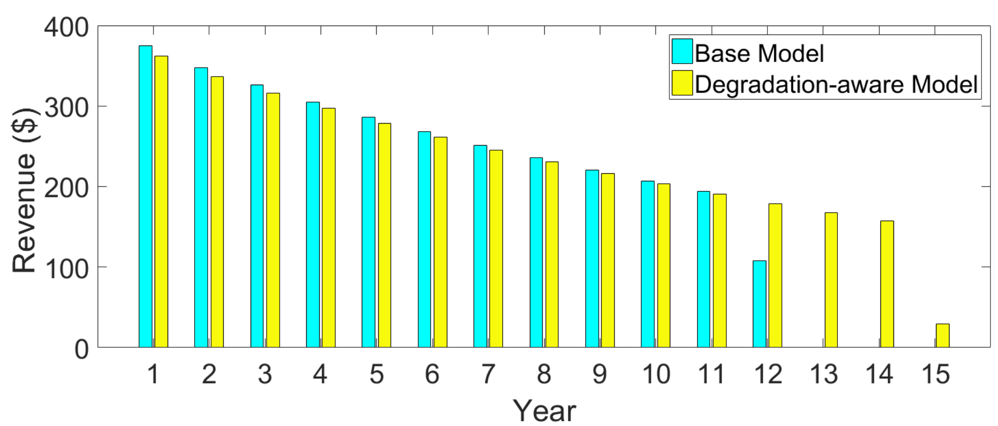

Figure 4.3: Yearly net revenue of the two battery operating strategies

• The battery should avoid full cycle working state as deep depth of discharge will cause a larger degradation rate each year, which reduces the final NPV from BESS;

• The commercial customers should make full use of the length of on-peak and off-peak hours to smooth the current rate. Charging or discharging too fast will also decrease the length of battery life, leading to less NPV from BESS.

4.2 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 Edison. The hourly load profile of the customer is shown in Fig. 4.4.

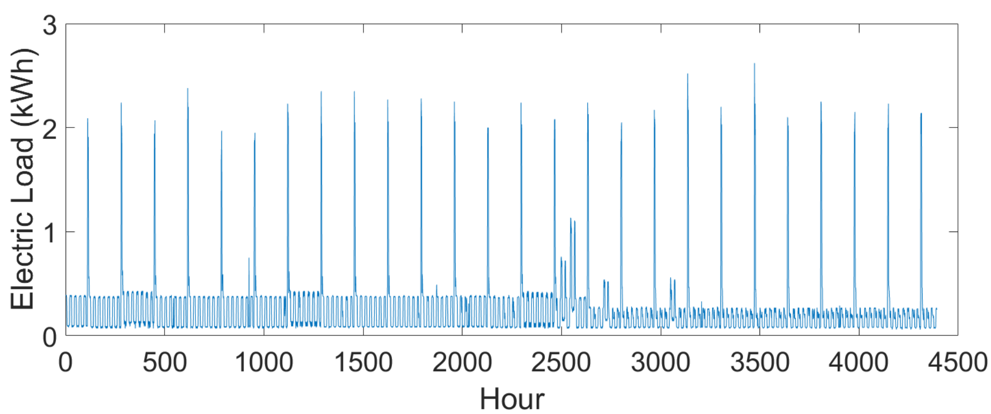

Figure 4.4: Load profile of sample customer 2

The genetic algorithm setup are as follows. The number of individuals in each generation is set at 20. The generation gap and the 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 in the range of 10%-90%. The initial cost of the battery is the same as the setup shown from the start of this chapter [11]. Eight bits of binary numbers are used to represent the energy rating and working hours. The program will stop when the total 100 generations of GA have been run 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 sizing, a lifetime battery valuation is conducted with the degradation-aware optimization algorithm. The resulting NPVs of all battery sizing and the NPV surface are shown in Fig. 4.5. The red point represents the optimal battery sizing solution found by the GA. The best energy and power rating pair found by the grid search are 3 kWh and 1 kW (3 working hours) which has a NPV of $1650.91 with a 16 years and 4 months battery life. The battery energy and power ratings found by the GA increases the NPV of the exhaustive grid search solution by 5.6%.

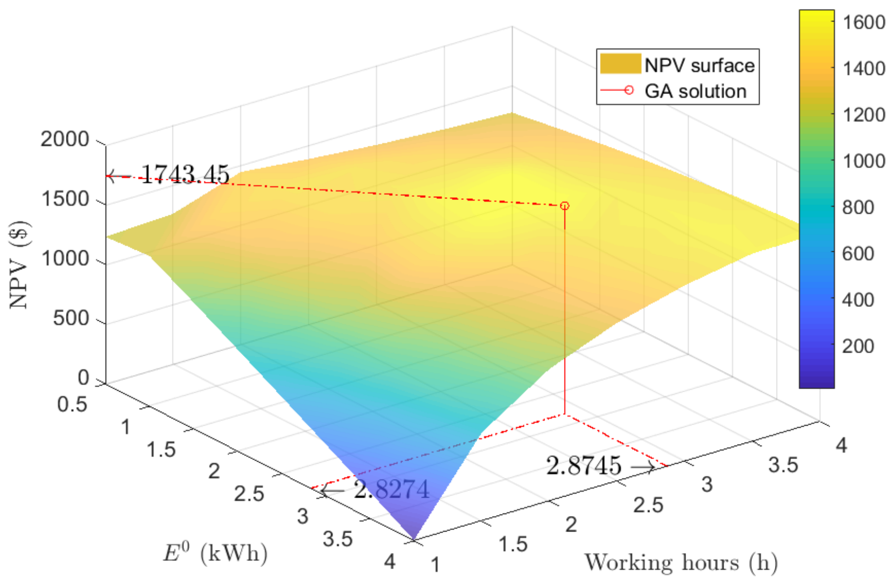

Figure 4.5: NPV of BESS with different sizing configurations for sample customer 2

Chapter 5

Conclusions

To improve the profitability of BESS, this thesis 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, a 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 based 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.

Bibliography

[1] N. Yu, S. Shah, R. Johnson, R. Sherick, M. Hong, and K. Loparo, "Big data analytics in power distribution systems," in *2015 IEEE Power Energy Society Innovative Smart Grid Technologies Conference (ISGT)*, pp. 1–5, Feb 2015.

[2] A. Oudalov, R. Cherkaoui, and A. Beguin, "Sizing and optimal operation of battery energy storage system for peak shaving application," in *Power Tech, 2007 IEEE Lausanne*, pp. 621–625, IEEE, 2007.

[3] `https://www.sce.com/NR/sc3/tm2/pdf/ce30-12.pdf/`.

[4] J. Leadbetter and L. Swan, "Battery storage system for residential electricity peak demand shaving," *Energy and buildings*, vol. 55, pp. 685–692, 2012.

[5] I. Alsaidan, W. Gao, and A. Khodaei, "Battery energy storage sizing for commercial customers," in *Power & Energy Society General Meeting, 2017 IEEE*, pp. 1–5, IEEE, 2017.

[6] D. Wu, M. Kintner-Meyer, T. Yang, and P. Balducci, "Economic analysis and optimal sizing for behind-the-meter battery storage," in *Power and Energy Society General Meeting (PESGM), 2016*, pp. 1–5, IEEE, 2016.

[7] D. Wu, M. Kintner-Meyer, T. Yang, and P. Balducci, "Analytical sizing methods for behind-the-meter battery storage," *Journal of Energy Storage*, vol. 12, pp. 297–304, 2017.

[8] B. Xu, A. Oudalov, A. Ulbig, G. Andersson, and D. Kirschen, "Modeling of lithium-ion battery degradation for cell life assessment," *IEEE Transactions on Smart Grid*, 2016.

[9] B. Foggo and N. Yu, "Improved battery storage valuation through degradation reduction," *IEEE Transactions on Smart Grid*, 2017.

[10] C. Amzallag, J. Gerey, J. Robert, and J. Bahuaud, "Standardization of the rainflow counting method for fatigue analysis," *International journal of fatigue*, vol. 16, no. 4, pp. 287–293, 1994.

[11] N. Yu and B. Foggo, "Stochastic valuation of energy storage in wholesale power markets," *Energy Economics*, vol. 64, pp. 177–185, 2017.