Break-even Analysis of Battery Energy Storage in Buildings Considering Time-of-use Rates

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***Abstract*—As energy consumption in residential and commercial buildings continues to grow, demand-side management (DSM) for energy systems becomes crucial, because DSM can shift energy use from peak to off-peak hours. In order to realize peak load shifting, energy storage systems (ESSs) can be integrated into buildings to store energy during off-peak hours and discharge energy in peak hours. However, installing a large number of ESSs in individual buildings can complicate DSM and increase the overall capital cost. In this paper, a cost-effective DSM strategy is proposed to address this energy management challenge. The break-even cost of battery storage in a building is explored through a process of two-step optimization in conjunction with different tariff structures. A number of scenarios are performed to conduct cost analyses of the storage-based building energy system under different time-of-use rate structures. The performance of the DSM strategy in the battery break-even cost, is explored using a particle swarm optimization algorithm based on the size of energy storage and priced-based constraints of the energy system. Results of a case study show that the proposed approach can reduce the peak-to-average ratio of the total energy demand to the total energy costs. In addition, as the percentage reductions in yearly maximum energy peaks increase, the optimal battery cost becomes progressively more economical to building owners.**

***Index Terms*—Energy Storage, Demand Side Management, Time of Use, Particle Swarm Optimization, Battery Break-even Cost.**

I. Introduction

Peak demand denotes the maximum power requirement of a system at certain times of a day. It puts considerable stress on the electric grid due to deficiencies in peak generation capacity. Consequently, up to 20% of the total installed electricity generation capacity in the United States is used to meet the peak load in a relatively short period, which is neither efficient nor economical. Approaches that aim to influence quantities or patterns of energy use have traditionally been referred to as demand-side management (DSM) strategies [1]. To be specific, "DSM strategies are the changes in electric usage by end-use customers from their normal consumption patterns in response to changes in the price of electricity over time, or to incentive payments designed to induce lower electricity use at times of high wholesale market prices or when system reliability is jeopardized" [2].

A significant amount of DSM research reported in the literature is based on improving the energy efficiency of loads, namely spending less power to perform the same load tasks [3], [4]. Recently, researchers have also started to develop methods based on time of use (ToU) and demand response (DR) to manage energy consumption [5], with the aim to encourage customers to use less energy during peak hours and to alleviate the maximum power generation for utility companies. However, most of the existing DSM research seeks to optimally manage the demand from a single aspect. For example, Chiu *et al.* [5] used energy storage in DSM to implement load shifing more economically. Thus, the full benefits of using DR and ToU in DSM are still not well studied, especially the economic benefits to residential and commercial building owners. In addition, the break-even cost of energy storage, especially battery storage, is not well understood in the use of DSM.

Recently, price-based DSM research has also been conducted. For example, Soliman *et al.* [6] used game theory and energy storage devices to minimize energy costs on the demand side. A different approach was used by Janocha *et.al* [7] who analyzed the benefit of DSM through optimizing the electric shiftable loads instead of using energy storage storage. In this price-based DSM paper, we develop an innovative battery storage-based DSM strategy in commercial buildings by considering dynamic energy prices. A particle swarm optimization (PSO) algorithm is used to determine the optimal nominal capacity of the battery storage. Then a break-even analysis of battery storage cost is explored, based on the optimal storage size and dynamic electricity prices. This strategy could help residential and commercial building owners to optimally determine the battery energy storage size, thereby reducing the energy storage cost.

The remainder of the paper is organized as follows. Section II describes the battery storage system model, the ToU tariff model, and the two-step optimization framework. Section III applies the storage-based DSM to case studies under different payback years and ToU scenarios. Section IV provides concluding remarks and future work.

II. Methodology

The research framework in this study is formulated as a two-step optimization to find the break-even cost of the battery storage system. In the first step of this framework, a nominal capacity optimization of the battery storage system is conducted by minimizing the electricity cost for a peak load reduction of interest, expressed as:

$$\begin{aligned} &\Lambda^* = \arg\min \left[\mathbb{P}(L^w(\Gamma,\Lambda))\right] \\ &\textit{subject to} \\ &\Lambda \in \mathbb{Z}_{>0} \\ &\phi < \kappa < \frac{1+\phi}{2} \\ &0 \leq R \leq R^{ub} \end{aligned} \tag{1}$$

In Eq. 1, L^w represents the storage-based DSM grid loads in a peak month (a peak month herein is a month with a maximum recorded peak load, expressed in 15-minute intervals); $\mathbb{P}$ is the electricity cost function; Λ is an integer design variable that denotes the capacity of storage; κ denotes the state of charge of the battery; ϕ is the depth of discharge of the battery; R is the rate of (dis-)charge; Γ is the demand limit estimated based on the peak load reduction of interest (ζ), and is calculated by:

$$\Gamma = (1-\zeta) \times \max\{L\} \tag{2}$$

where L represents the non-storage grid loads. The optimal capacity of the storage, Λ^*, will then be used in the second step optimization to find the break-even cost of the battery storage while maximizing the annual profit. Here, the annual profit is the annual tariff charge reduction minus the annualized storage equipment, installation, and financing cost. The general form of this optimization problem is expressed as:

$$\begin{aligned} &\Upsilon = \max_{\nu_{1,2,3,\dots,12}} \left(\sum_{n=1}^{12} \left[\mathbb{P}(L_n) - \mathbb{P}(L_n^w(\nu_n, \Lambda^*)) \right] \right) \\ &\textit{subject to} \\ &\text{Battery storage system constraints} \end{aligned} \tag{3}$$

where Υ is the optimal annual profit; L_n and L_n^w are the non-storage and the storage-based DSM grid loads in month n, respectively; ν_n is the demand limit in month n [8]. Here, ν_n is used to define the battery dispatch strategy – the date and interval pairs (e.g., (D,t)) in month n when the battery is in charging mode (S^C), discharging mode (S^D), or in neutral mode (S^N), expressed as

$$\begin{aligned} &S^C = \{(D,t) \mid L_n > \nu_n \ \&\ 1-\phi < \kappa < \frac{1+\phi}{2}\} \\ &S^D = \{(D,t) \mid L_n < \nu_n \ \&\ 1-\phi < \kappa < \frac{1+\phi}{2}\} \\ &S^N = \{(D,t) \mid L_n = \nu_n \ OR \ L_n = 0\} \end{aligned} \tag{4}$$

The break-even cost of the battery storage with different payback time, Y (in year), is then estimated by

$$\mathbb{H} = \frac{(\Upsilon/\zeta) - C_{fixed}}{\Lambda^*}, \ where\ \zeta = \frac{r \times (1+r)^Y}{(1+r)^Y - 1} \tag{5}$$

TABLE I: Battery storage properties

Parameter	value
Round-trip efficiency (η_R)	80 [%]
Efficiency of the inverter (η_I)	95 [%]
Depth of discharge (χ)	.88

where r denotes the annual interest rate (here 10%); C_{fixed} is a fixed installation cost (here assumed to be $2,000 [8]).

The properties used to model the battery storage in this study are reported in Table I. The average of the depth of discharge and round-trip efficiency in advanced battery technologies (including lithium-ion, sodium sulfur, sodium nickel chloride, vanadium redox, zinc bromine, nickel zinc, and zinc manganese dioxide batteries [8]) are used for κ and ϕ, respectively. In this study, three different C-rates (i.e., 0.5C, 1C, and 2C) are considered as a maximum rate of (dis-)charge (R^{ub}) in the break-even analysis.

A. Time of Use (ToU) Tariff Model

The ToU tariff is a price-based DSM technique, which divides a day (or a week) into different time periods that have different electricity prices. A ToU rate structure includes the energy charge (C^E in [\$/kWh]), demand charge (C^D in [\$/kW − kWpeak]), and fixed monthly service charge (C^S in [\$]) in each billing period:

$$\begin{aligned} &C = C^E + C^D + C^S \\ &\textit{where} \\ &C^E = \sum_{k=1}^{NC} r_k^E \times L_k^E \\ &C^D = \sum_{m=1}^{ND} r_m^D \times L_m^D \\ &C^S = \text{Monthly service charge} \end{aligned} \tag{6–8}$$

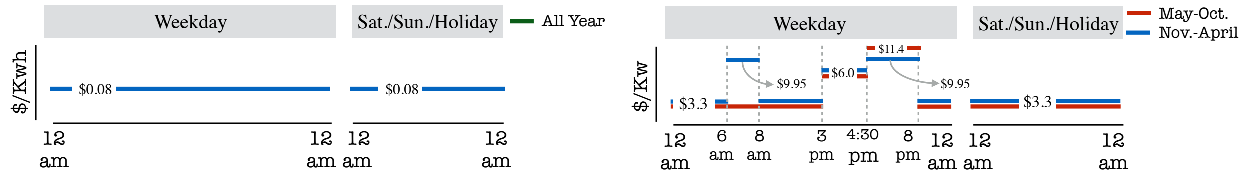
In Eqs. 7 and 9, r^E and r^D represent energy and demand rates, respectively; NC and ND are the number of energy and demand rates in a tariff structure, respectively; and L_k^E and L_m^D are calculated by

$$L_k^E = \{max\big(L(D,t)\big) \mid (D,t) \in S_k^E\} \tag{9}$$

$$L_m^D = \{\sum \big(L(D,t)\big) \mid (D,t) \in S_m^D\} \tag{10}$$

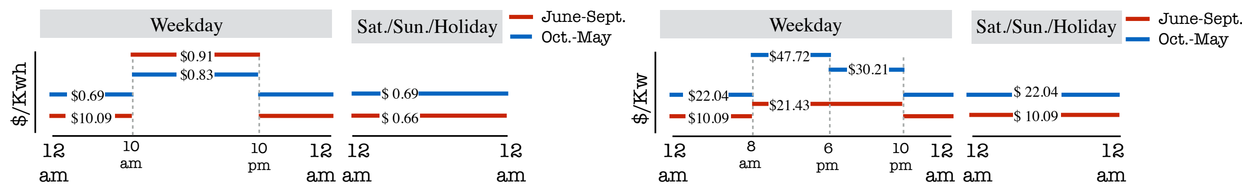
where S_k^E and S_m^D, respectively, represent the date and interval pairs of the k^{th} energy rate and m^{th} demand rate in a tariff structure.

In this study, two representative tariff structures are used to determine the electricity cost, which are: (i) Tariff Model 1: the Commercial ToU tariff, available from Denton Electric Co. of Texas [9] as illustrated in Fig. 1, and (ii) Tariff Model 2: the SC9-Rate III ToU tariff, available from Consolidated Edison Company of New York, Inc. [10] as illustrated in Fig. 2



(a) Energy Rate $/kWh (b) Demand Rate $/kW

Fig. 1: Tariff Model 1: Commercial ToU demand-based tariff from Denton Electric Co. in Texas (C^S=$35.00) [9].



(a) Energy Rate $/kWh (b) Demand Rate $/kW

Fig. 2: Tariff Model 2: SC9-Rate III ToU demand-based tariff from ConEdison in New York (C^S=$9.53) [10]

B. Optimization Method

Heuristic algorithms have been widely used in energy systems design and demand response optimization to improve the thermal comfort, minimize the energy consumption, and reduce the life cycle cost of equipment systems. For example, Xu *et al.* [11] applied a PSO algorithm to deploy intelligent control of pre-cooling and pre-heating for commercial and residential buildings. Yang and Wang [12] implemented a multi-objective PSO to explore the balance between the energy consumption and occupants' comfort, and provided the tradeoff solutions for decision-making. In this study, the optimization is performed using an advanced implementation of PSO developed by Chowdhury *et al.* [13]. An adaptive diversity-preservation technique is implemented in the adopted PSO, which characterizes the population diversity at each iteration.

III. Case Study

A. Data Summary

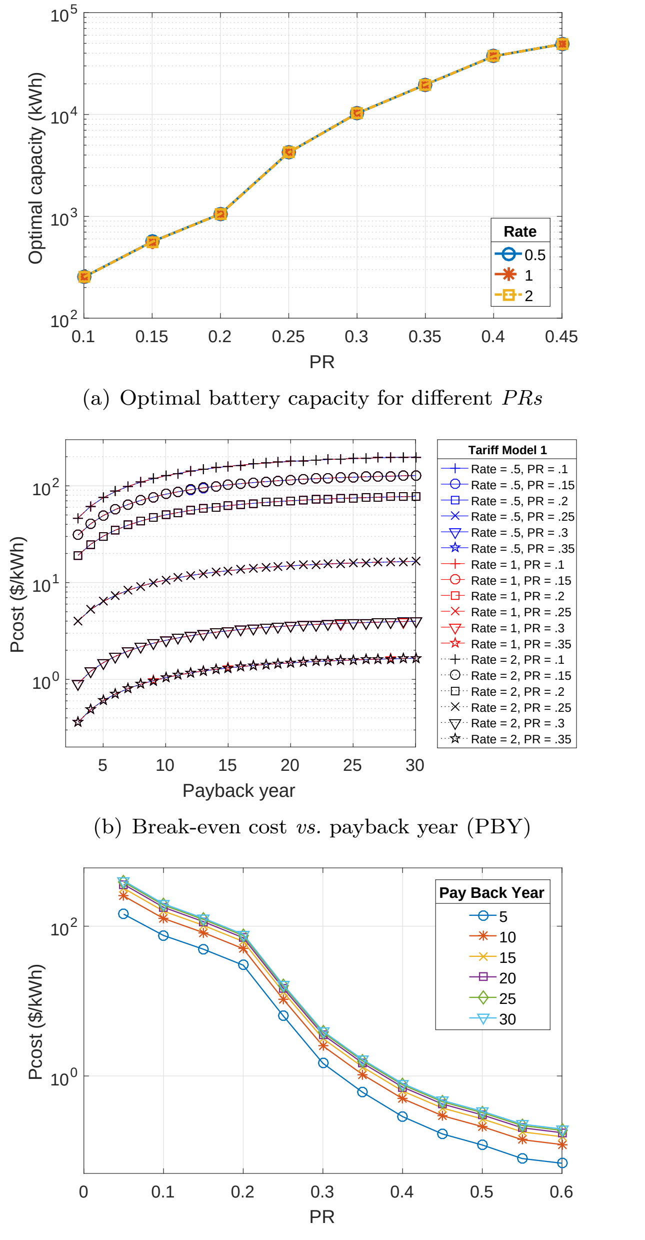
In this case study, the load consumption of a building at the University of Texas at Dallas (UTD) in 2016 is used. Due to events such as maintenance of the power system or network, nearly 5% of the historical data is missing or becomes unusually extreme in nature. This paper aims to determine the optimal size of the battery storage and then performs the break-even battery cost analysis based on the yearly ToU model. Thus, to obtain a full year's load data, the missing or extreme values in the load profile are replaced with estimates from a polynomial regression. According to the 2016 historical loads, the optimal battery storage size and the break-even energy cost are determined by the two-level optimization model. To perform the break-even analysis of battery energy storage, several parameters as listed in Table II are analyzed. By changing the values of these parameters in Table II, the optimal capacity and the break-even cost of battery storage are calculated and compared under the two tariff models in the following subsections.

TABLE II: Tuning parameters in optimization

Parameter	Description
Rate	Ratio of charge rate/discharge rate
PR	A required percentage reduction in yearly maximum peak load value ($0 < PR < 1$)
TP	A tunable parameter in finding the optimal battery capacity ($1 < TP < 10$)
Pcost	Break-even cost, which is the maximum affordable cost

B. Tariff Model 1: Commercial ToU Tariff Model

The results of the battery capacity and break-even cost under the Commercial ToU tariff structure are compared using different optimization parameters in Table II. Figure 3(a) illustrates the relationship between the optimal battery nominal capacity and the percentage reduction in yearly maximum peak value (PR) under different ratios of charge rate/discharge rate. It is seen that the optimal battery nominal capacity shows an exponential growth with an increase in PR value. It also shows that the rate (the ratio of charge rate/discharge rate) has little or no influence on the growth of optimal capacity in this case. Figure 3(b) shows the relationship between the break-even cost and the payback year under different rates and PR values. In this figure, PR, the tunable parameter in the optimal capacity determination, is defined to be 5. It is seen that the battery break-even cost is highly sensitive to the PR and the payback year. The break-even cost significantly increases with the payback year when payback is less than 10 years. Beyond 10 years, the battery break-even cost's increases at a slower rate. In addition, the battery break-even cost is significantly decreased, exponentially, with the increasing PR value. This is partially due to the large size of the battery system resulting from the large PR

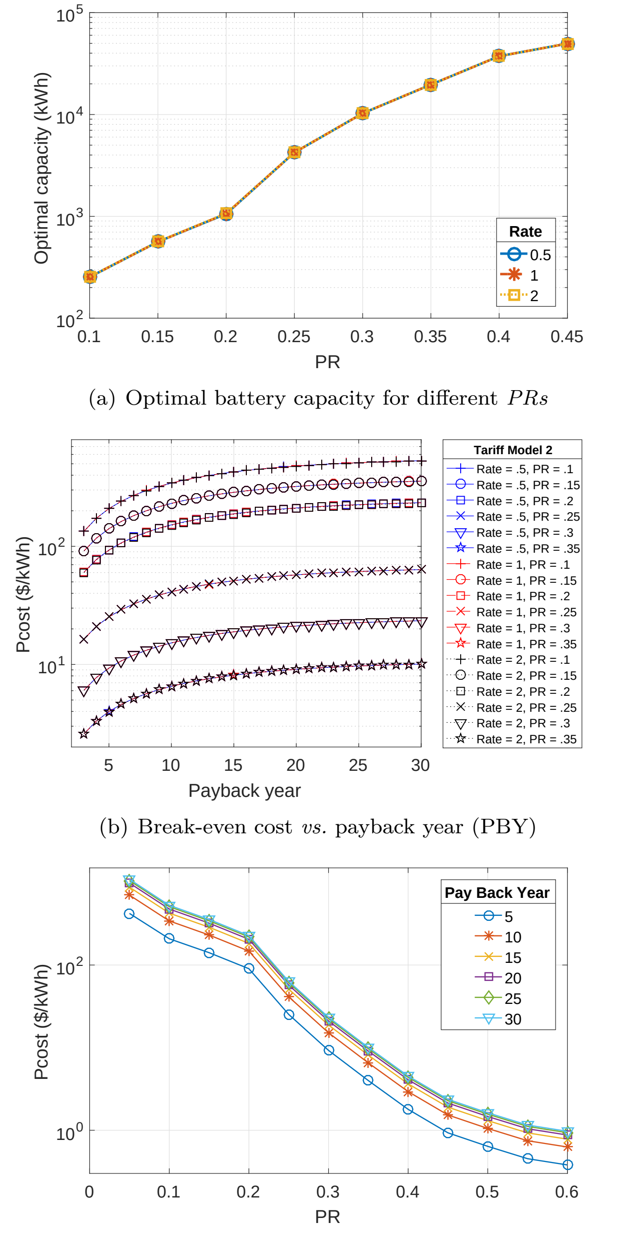


(a) Optimal battery capacity for different PRs

(b) Break-even cost *vs.* payback year (PBY)

(c) Break-even cost for different PRs

Fig. 3: The optimal battery capacity and break-even cost with different *Rate* and PR values under the Commercial ToU Tariff Model (Tariff Model 1)



(a) Optimal battery capacity for different PRs

(b) Break-even cost *vs.* payback year (PBY)

(c) Break-even cost for different PRs

Fig. 4: The optimal battery capacity and break-even cost with different *Rate* and PR values under the SC9-Rate III ToU Tariff Model (Tariff Model 2)

value. It is expected a larger size battery system will have a smaller break-even cost, which is further explained in Fig. 3(c). It is seen from Fig. 3(c) that the battery break-even cost shows an exponential decay with the increasing PR value.

C. Tariff Model 2: SC9-Rate III ToU Tariff Model

Similar to the results of Tariff Model 1, Fig. 4 compares the different break-even battery storage costs of the SC9-Rate III ToU Tariff Model with different parameters. Figure 4(a) shows a similar result in the optimal battery capacity, which has approximately a 1% difference from the results of Tariff Model 1.

In Fig. 4(b), the increasing trend of Pcost is also similar to the results of Tariff Model 1. In addition, it is observed from both tariff models that the Pcost is significantly larger if $PR \leq 0.25$. This can be further illustrated in Figs. 3(c) and 4(c). Figure 4(c) shows a similar trend as Fig. 3(c), however, with a more distinct observation at the point of $PR = 0.2$. This is due to the much higher energy rate and demand rate in Tariff Model 2, which then corresponds to a much high Pcost.

D. Comparison between Two ToU Tariff Models

As illustrated in Figs. 1 and 2, the energy rate P^{EC} is fixed in the Commercial ToU demand-based tariff (*Tariff Model 1*). Two different energy rates are used on weekdays in the SC9-Rate III ToU tariff (*Tariff Model 2*), which are approximately eight to ten times of that in Tariff Model 1. Also, the unit cost for P^{DC} in Tariff Model 2 is approximately five to seven times of that in Tariff Model 1. Even though the fixed monthly service in Tariff Model 1 is $35.00, which is much higher than the $9.53 in Tariff Model 2, the overall electricity cost in Tariff Model 2 is still much higher and is the main reason for the higher energy cost in Tariff Model 2.

Due to the higher energy rate and demand rate in Tariff Model 2, the optimal battery capacity and break-even cost in Tariff Model 2 are also larger than those in Tariff Model 1. It is seen from both tariff models that the percentage reduction in the yearly maximum peak load value, PR, has a significant impact on both the optimal capacity and break-even cost of the battery. A more interesting finding is that there exists a PR threshold value (i.e. $PR = 0.2$ in this case study) for the battery break-even cost's changing rate. When the PR is large than 0.2, that is more storage is needed to reduce the peak load value, the benefits of battery storage will be more significant with a lower break-even cost. In other words, a larger size battery energy storage will be more economic for building applications.

IV. Conclusion

A cost-effective demand-side management (DSM) strategy was developed in this paper. The optimal capacity and break-even cost of battery energy storage for buildings were explored by using a two-step optimization framework, under two time-of-use (ToU) tariff structures. Results of the case study showed that the optimal capacity and break-even cost are significantly affected by the percentage reduction (PR) in yearly maximum peak load value. The battery break-even cost is $10-500/kWh with the SC9-Rate III ToU tariff model under different PR values that are less than 0.4, which are approximately four to five times the break-even costs with the Commercial ToU tariff model.

According to the survey of energy storage from [14], the current cheapest price of lithium-ion battery is almost $500/kWh, which is close to the maximum break-even cost in Tariff Model 2 with a smaller PR value. However, it is predicted that the energy storage system cost would be decreased by up to $300/kWh in the next 10 years [15]. With the increasing power usage and decreasing battery storage cost, the storage-based demand-side management will play a more important role in energy systems management. This study is limited to commercial buildings and limited ToU data. As a result, its feasibility in a residential building needs further justification. Moreover, the capacity decay and degradation model need to be considered in the future. In this study, we have adopted the fixed load for 20 years and the uncertainty in the building load is not considered. A stochastic model that includes the long-term forecasted building load will be developed in future work.

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