Analyze the Break-even Cost of Lithium-ion Battery under Time-of-use Pricing Tariffs

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Abstract—**Lithium-ion batteries can be used by households in a wide range of demand response (DR) programs. This paper examines break-even costs of lithium-ion batteries used in time-of-use (TOU) pricing DR programs. A mixed-integer program is developed to optimize battery capacities and operating schedules. Battery degradation is explicitly considered using a piecewise linear approximation. The model is tested under two TOU pricing tariffs. Parametric sensitivity analysis is conducted with respect to loan rates and C-rates. The results suggest that the lithium-ion batteries are still prohibitively expensive under prevailing market conditions.**

Index Terms—**Break-even analysis, Lithium-ion battery, Mixed integer program, Demand response, Time-of-use tariff.**

I. INTRODUCTION

Driven by increasing penetration of distributed energy sources and development of smart grid technologies, demand response (DR), as an effective demand-side management approach, has received significant attention in recent decades. In the DR programs, end-use customers play an significant role in reducing or shifting electric load in response to time-based rates or other forms of financial incentives [1]. DR offers a wide range of benefits to various power market participants, including direct financial benefits to end-use customers, reduced demand volatility to load serving entities, and relieved congestion and improved system reliability in transmission and distribution networks [2].

A variety of DR programs have been offered by utility companies. Although different classifications exist, these programs can be roughly categorized into three groups: rate-based or price-driven DR programs, incentive or even-based DR, and demand reduction bids [2]. Price-driven DR programs use electricity prices as signals to encourage end-use customers to shift their demand from peak hours to off-peak hours, while incentive-based DR provides financial incentives to reward customers for load reduction upon a variety of triggering events. Customers participate in the demand reduction bids program by submitting their bids, which typically consist of the available demand reduction capacity and the requested price.

Based on the pricing schemes, price-driven DR programs can be further categorized into time-of-use (TOU) pricing, critical peak pricing (CPP), and real-time pricing (RTP) [1]. The TOU pricing program is a static pricing scheme where each day is divided into multiple periods over which the rates are fixed. The TOU pricing normally places higher rates at peak hours during weekdays and lower rates at off-peak hours and weekends. Since the TOU pricing is static, it is easy for the utilities to implement and for the customers to follow.

In general, participating customers of DR programs may change their electricity usage through three possible strategies: load curtailment, load shifting, or backup generators. While load curtailment and shifting can be implemented without additional equipment, response with backup generators such as on-site energy sources can avoid compromise of customer comfort and demand spikes right after the price drop [3]. Batteries are widely viewed as an effective backup source of electricity in DR programs due to their fast response times [4] and a large amount of studies on optimally sizing of battery capacities or determining operating schedules can be found in the literature. A recent study shows at the end of 2016 over 80% of U.S. large-scale battery storage power capacity is provided by lithium-ion based batteries due to its high cycle efficiency, high power, and energy density [4], [5].

However, deployment of batteries incurs additional cost. A study in 2015 suggests that the levelized cost of electricity associated with lithium-ion batteries is among the highest compared with other similar products [6]. Despite of steep decrease in lithium-ion battery prices due to strong growth of demand driven primarily by electric vehicles, in 2016 the prices of lithium-ion batteries are still around 273 $/kWh [7]. Therefore, it remains debatable whether the bill savings from the DR programs can outweigh the investment associated with batteries.

This study presents a break-even analysis for lithium-ion batteries used in TOU pricing DR programs. We developed a mixed integer program to jointly optimize the battery size and operating schedules given long-term load forecast of university campus buildings from 2013 to 2020. The break-even cost is derived using a binary search algorithm under different techno-economic parameters of battery. This paper is structured as follows: Section II introduces the mathematical formulation of our model, Section III presents the results, and Section IV concludes with discussion and future work.

II. METHODOLOGY

The battery break-even analysis is formulated as a mixed-integer programming (MIP) model. The aim of this model is to

minimize total costs of the system by optimally sizing battery capacities and determining operating schedules. The decision variables are listed in Table I. The constraints are defined in Eqs. 2 to 9 and the objective function is defined in Eqs. 14 - 16.

Variables	Units	Notes
x	kWh	Initial battery capacity.
x_t^R	kWh	Residual capacity at the end of t.
y_t	kW	Improved demand.
$y_{k,a,m}^p$	kW	Peak demand k in month (a, m).
z_t^+, z_t^-, z_t	kWh	Battery charge during period t.
q_t, q_t^a, q_t^b	kWh	Energy throughput at the end of t.
w_t^a		Binary variable in the degradation function.
s_t	kWh	Battery energy level at the end of t.

A. Demand representation

Real-world demand is a random and noisy continuous process, which is typically discretized using average values over time intervals. A critical challenge in demand representation is the tradeoff between temporal resolution and computational performance. A refined demand representation can reflect real-world demand variation precisely and obtain a much more accurate solution at the cost of slower computation performance due to more decision variables. In addition, modeling TOU pricing tariffs requires separate time slices of on-peak and off-peak periods, since most TOU rates are defined over hourly scales. Therefore, in this study one year is divided into 576 time slices: two days per month (one weekday and one weekend), with each day including 24 time-of-days to create a representative hourly profile. Since one month actually consists of 28 to 31 days, the number of hours in one time slice depends on the number of days in the month where the time slice resides. The demand in an individual time slice (day d, time-of-day h) is given by averaging the hourly demands during time-of-day h over all actual days in month m. Figure 1 compares the approximated load duration curve with the actual load duration curve. Note the approximated profile fails to fully capture the maximum and minimum demand due to the relaxed temporal resolution.
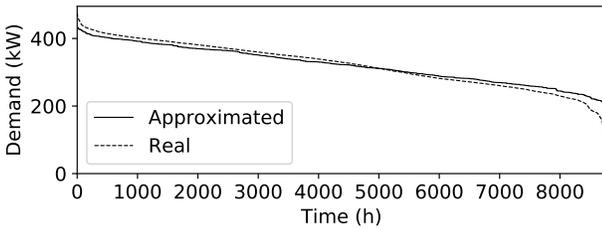

Fig. 1. The actual load duration curve (dash line) and the demand apportioned by model time slice within this study (solid line).

In this study, we denote a time slice using a quadruple (a, m, d, h) that indicates combinations of any year $a \in \mathbf{A}$, month $m \in \mathbf{M}$, day $d \in \mathbf{D}$, and time-of-day $h \in \mathbf{H}$. For simplicity, we also use a single letter $t \doteq (a, m, d, h)$ to represent one time slice. The set of all considered time slices t in this study is denoted with $\mathbf{T}$.

B. The TOU pricing tariff

A TOU pricing tariff typically consists of three terms: a fixed monthly service charge, energy charges on a per use basis and monthly demand charges based on demand peaks over one or more time intervals. Since the monthly demand peaks are captured over different time intervals, we use set $\mathbf{T}_{a,m}^k$ to include all time slices that are included in the time interval associated with peak $k \in \mathbf{K}$ during month m in year a, where set $\mathbf{K}$ represents the monthly demand peaks captured by a tariff.

Given any month $m \in \mathbf{M}$ in year $a \in \mathbf{A}$, the monthly tariff charge ($C_{a,m}^T$) is given by summing up service charge $C_{a,m}^S$, energy charge $C_{a,m,d,h}^E$, and demand charge $C_{k,a,m}^D$:

$$C_{a,m}^T = C_{a,m}^S + \sum_{d,h} C_{a,m,d,h}^E \cdot y_{a,m,d,h} + \sum_k C_{k,a,m}^D \cdot y_{k,a,m}^p \tag{1}$$

where, $y_{a,m,d,h}$ represents improved demand during time slice (a, m, d, h) and $y_{k,a,m}^p$ represents peak demand k in month (a, m), which is determined by the following equation:

$$y_{k,a,m}^p \geq y_{a,m,d,h}, \forall (a, m, d, h) \in \mathbf{T}_{a,m}^k, \tag{2}$$

C. The battery model

Given time slice $t \in \mathbf{T}$, the initial demand is D_t and the improved demand after load-shifting becomes y_t. The following equations hold:

$$y_t = D_t + \eta_I \sqrt{\eta} \cdot \frac{z_t}{\tau_t} \tag{3}$$

$$z_t = z_t^+ - z_t^- \tag{4}$$

where, z_t^+ and z_t^- are electric energy charge and discharge, z_t represents net energy change of the battery, and τ_t gives the length of time slice t in hours. Besides, the charging and discharging rates are bounded by C-rate (r_C):

$$0 \leq z_t^-, z_t^+ \leq r_C \cdot \tau_t, \forall t \in \mathbf{T} \tag{5}$$

The energy level in the battery s_t at the end of each time slice t is given by the following equation:

$$s_t = s_{t-1} + z_t, \forall t \in \mathbf{T} \tag{6}$$

Note that we assume the initial energy level $s_0 = 0$. In addition, we limit the maximum and minimum energy level using a healthy depth of discharge (δ) by the following constraint to extend battery life:

$$(1 - \delta)x \leq s_t \leq \delta x, \forall t \in \mathbf{T} \tag{7}$$

Substantial efforts have been made on development of battery degradation models over the past decades. A significant amount of studies suggest battery degradation is a complex non-linear process that is dependent on many factors [8], [9]. According to [8], the percentage of capacity loss (Q^{loss}) of a lithium-ion battery rated at 2.2 Ah can be expressed as a

function of C-rate r_C, temperature (T), and electric charge throughput (Ah):

$$Q^{loss} = \frac{1}{100}B \cdot \exp(\frac{-31700 + 370.3 \cdot r_C}{RT}) \cdot Ah^{0.55}$$

where, B is a function of r_C. When $r_C = 1$, $B = 30,330$, and R is the gas constant.

The above degradation function is a nonlinear and the model becomes intractable. Therefore, it is approximated using a two-segment piece-wise linear function:

$$Q_t^{loss} = k^a Ah_t^a + k^b Ah_t^b$$

where, the charge throughput Ah_t at the end of time slice t is splitted into $Ah_t^a + Ah_t^b$ and multiplied by pre-determined slopes k^a and k^b. By further assuming the charge throughput Ah_t is proportional to energy throughput q_t, the residual battery energy capacity x_t^R at the end of time slice t is given by:

$$x_t^R = (1 - Q_t^{loss})x = (1 - k^a Ah_t^a - k^b Ah_t^b)x$$

where,

$$q_t = \sum_{i=1}^{t}(z_i^+ + z_i^-) = \frac{Ah_t}{2.2} \cdot x$$

therefore, x_t^R becomes:

$$x_t^R = x - 2.2k^a q_t^a - 2.2k^b q_t^b \qquad (8)$$

In addition, since the degradation function is non-convex, we need the following constraints for q_t^a and q_t^b:

$$0 \leq q_t^a \leq \frac{Ah_0^a}{2.2}x \qquad (9)$$

$$q_t^a - \frac{Ah_0^a}{2.2}x \geq -\inf \cdot(1 - w_t^a) \qquad (10)$$

$$0 \leq q_t^b \leq \frac{Ah_0^b - Ah_0^a}{2.2}x \qquad (11)$$

$$q_t^b \leq \inf \cdot w_t^a \qquad (12)$$

$$w_t^a \in \{0, 1\} \qquad (13)$$

D. Objective function

The objective of our model is to minimize total system costs, which consist of two parts: battery cost (f_1) and tariff cost (f_2).

$$\min f = f_1 + f_2 \qquad (14)$$

The battery costs include a one-time fixed installation cost term (C^I) and a capital cost term which is proportional to the battery capacity (C^C). In this study, we also account for salvage values of battery when the model horizon is less than the battery lifetime. The salvage value can be recovered at the end of model horizon, thus it is subtracted from the total costs. We assume the salvage rate S is determined collectively by its residual capacity x_t^R and its remaining lifetime at the end of model horizon:

$$S = \frac{(1 + g)^{-\min(l_B, l_M)} - (1 + g)^{-l_B}}{1 - (1 + g)^{-l_B}}$$

where, l_B and l_M represent the battery life time and the model horizon length, respectively. g is the global discount rate that reflects social rate of time preference, which is determined by macroeconomic indicators.

Most batteries are still in their early stage of commercialization and faced with great uncertainties. To reflect investment risks associated with batteries, a technology-specific hurdle rate r and loan period l_N are introduced. We first amortize the investment using the hurdle rate and loan period into cash flow of annual payments, then convert annual payments into a lump sum of net present value using the global discount rate g and loan period l_N. Therefore, the net present value of battery investment costs becomes:

$$f_1 = (C^I + C^C x - C^C Sx_{|\mathbf{T}|}^R) \cdot \frac{r}{1 - (1 + r)^{-l_N}} \cdot \frac{1 - (1 + g)^{-l_N}}{g} \qquad (15)$$

where, $x_{|\mathbf{T}|}^R$ represents battery residual capacity at the end of model horizon.

The other term in the objective function is the tariff costs. By summing up all monthly charges given in Eq 2 and discounting future monetary values into the first year, the total monthly tariffs become:

$$f_2 = \sum_a \frac{1}{(1 + g)^{a - a_0}} \sum_m C_{a,m}^T \qquad (16)$$

E. Break-even analysis

In the TOU pricing DR program, batteries shift demand from peak hours to off-peak hours to reduce tariff costs. However, it may not be cost-competitive to do so if costs associated with batteries outweigh the savings. The break-even cost represents the threshold of capital cost at which the batteries become cost-competitive. Examining break-even costs can benchmark the cost-competitiveness of current technologies and provide insights in formulating politic and financial incentives. In this study, the break-even cost is derived using a binary search method.

F. Data preparation

In this study, the demand data of campus buildings in the University of Texas at Dallas from 2013 to 2020 is used. The data consists of historical record from 2013 to 2017, and the data from 2018 to 2020 is forecasted using a support vector machines algorithm in a rolling-window fashion, i.e., a year's data is forecasted using previous two years' record. Approximately 5% of the historical data is missing or abnormal and interpolated using neighboring observations.

The TOU tariffs are drawn from two utility companies in the U.S. The first one is from Consolidated Edison Company of New York, Inc. (ConEd), a New York based utility company [10]. The one-time service charge is 10.57 $ per month and the per-use energy charge is fixed at 0.79 cents/kWh. The other one is from Denton County Electric Cooperative (CoServ), Inc., a Texas based utility company [11]. The one-time service charge is 35 $ per month and the per-use energy charge is fixed at 0.8 cents/kWh. The prices and time intervals of the captured

demand peaks from both tariffs are shown in Figure 2 and it indicates the demand prices in the ConEd tariff is higher than the CoServ tariff.
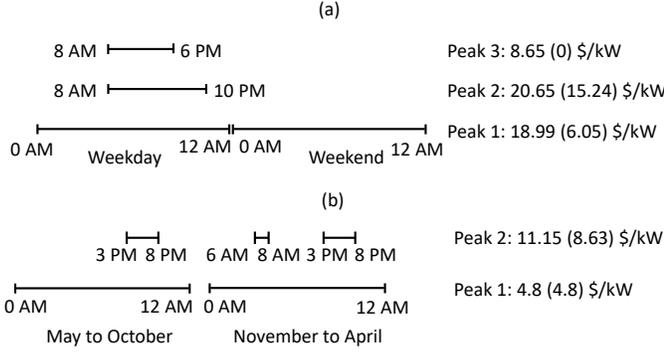

Fig. 2. The prices of demand peaks in (a) the ConEd tariff and (b) the CoServ tariff. Lines represent time intervals over which demand peaks are captured. Note that the prices from the winter months are put in parenthesis. The winter months are from October to May in the ConEd tariff, and from November to April in the Coserv tariff.

The techno-economic parameters of lithium-ion batteries are listed in Table II. The data is drawn from [12]. Note that we conduct a sensitivity analysis for discount rate r and battery charge rate r_C.

TABLE II
TECHNO-ECONOMIC PARAMETERS OF BATTERIES.

Notations	Notes	Values	Units
r_C	C-rate	0.5, 1, 2	h^{-1}
δ	Healthy depth of discharge	0.9	
η	Battery round-trip efficiency	0.80	
η_I	Inverter efficiency	0.95	
C^I	Installation cost	2,000	$
C^C	Battery capital cost	0–100	$/kW
r	Hurdle rate	5%, 10%	
g	Global discount rate	5%	
l_B	Battery lifetime	20	yrs
l_M	Model horizon length	8	yrs
l_N	Loan length	10	yrs

III. RESULTS

We first examine the effects of batteries on demand. Figure 3 shows both the original and improved demand after 900 kWh of battery is deployed. As illustrated, there are 12 pairs of peaks and each pair represents one month. The wider peaks represent weekdays while the narrower ones correspond to weekends. Note that the demand profiles present a clear seasonal pattern where the highest demand in a year occurs during the summer months. With the battery deployed, the peaks of the improved demand are flatter than the original demand. In addition, it shows that the load is curtailed only during weekdays due to higher prices of demand peaks.

The battery operating schedules and state of charge (SOC) are shown in Figure 4. The SOC shows a clear charging/discharging cycles. Note that the SOCs range from 0.05 to 0.95, due to the healthy depth of discharge settings. Although

there are 24 demand peaks as shown in Figure 3, the battery energy level only displays 12 peaks, which correspond to the curtailed load during weekdays, since there is no battery charge or discharge due to lower tariff prices during weekends.
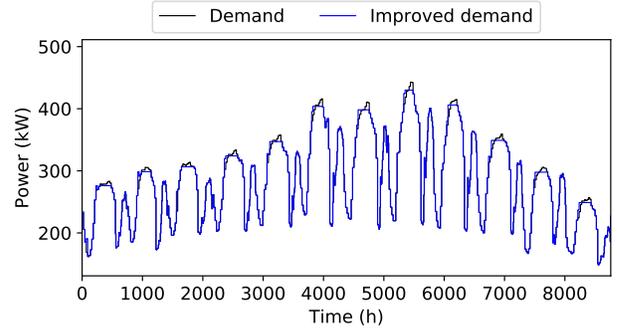

Fig. 3. The demand profil in 2013 under the ConEd tariff when discount rate $r = 0.05$, C-rate $r_C = 1$, and capital cost $C^C = 20$ $/kWh. Note that the optimal battery capacity is 900 kWh in this case.
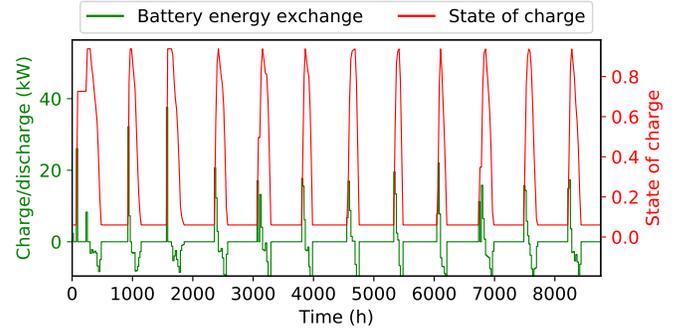

Fig. 4. The battery net energy change and state of charge as a function of time in 2013 under the ConEd tariff when $r = 0.05$, $r_C = 1$, and $C^C = 20$ $/kWh. The optimal battery capacity is 900 kWh.

The optimal battery capacities and total costs under the ConEd tariff are displayed in Figure 5a. As the battery capital costs increase from 5 $/kWh to 100 $/kWh, the optimal battery capacities drop from around 900 kWh to 0, while the total costs increase from 2,555 thousand $ to 2,575 thousand $. This implies that as the battery capital costs increase, net savings, which are given by subtracting battery costs from bill savings, are decreasing. When the battery costs outweigh the bill savings, deployment of batteries are no longer cost-competitive. Similar trends are also displayed in Figure 5b, where the total costs range from 2,150 to 2,170 thousand $ due to overall lower tariff prices in Denton County, TX.

One insight drawn from Figure 5 is that the optimal battery capacities are affected by C-rates only when the capital costs C^C are low. Figure 5 shows that when the capital costs are lower than 20 $/kWh, higher C-rates result in higher optimal battery capacities: the optimal battery capacities drops from 957 kWh when C-rate $r_C = 2$ to 900 kWh when $r_C = 0.5$. In contrast, the profiles of optimal battery capacities of different C-rates overlap when the capital costs are over 20 $/kWh

under both tariffs, suggesting less sensitivity of the optimal battery capacities to C-rates. This indicates that C-rates are more likely to affect the cost-competitiveness of batteries when battery costs are low. Given that the battery capital costs in this study are on a per unit energy capacity basis, this implies that when batteries are equipped with enough energy capacity, lower power capacities start to restrict the battery performance in load shifting and curtailment, thus place negatively impacts on their cost-competitiveness.
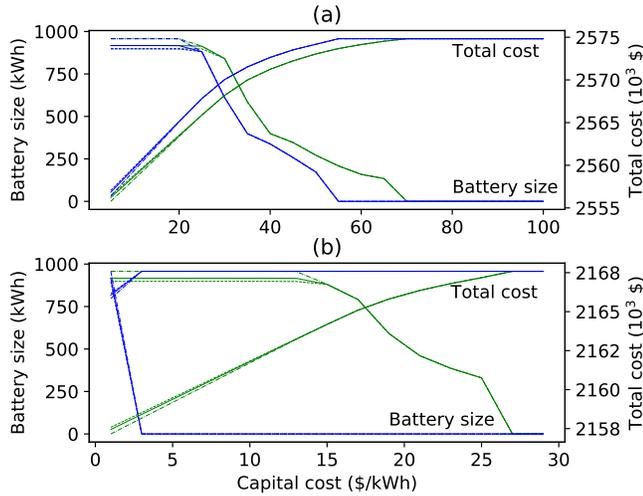

Fig. 5. Optimal battery capacities (left axis) and total system cost (right axis) as a function of battery cost under the ConEd tariff (a) and the CoServ tariff (b). Note that loan rates are distinguished by colors, where blue is 10% and greens is 5%, and C-rates are represented by different line styles: solid line is 1 h^{-1}, dash line is 0.5 h^{-1}, and dash-dot line is 2 h^{-1}.

As shown in Figure 5, the break-even costs are determined by many factors. Results from both tariffs indicate that higher discount rate decreases the break-even cost: when the discount rate increases from 5% to 10%, the break-even cost drops from 70 $/kWh to 50 $/kWh under the ConEd tariff, and from 24 $/kWh to less than 5 $/kWh under the CoServ tariff. In addition, comparing results from two tariffs suggests higher tariff prices result in higher break-even costs, where batteries are more likely to be cost-competitive. In contrast, the break-even costs are not sensitive to C-rates, since when the costs per unit energy capacity are high, the bill savings are reduced by limited energy capacities primarily, while the effects of power capacities are negligible. This observation is consistent with a previous study, where the results suggest the break-even costs are not affected by C-rates [13].

IV. CONCLUSION

By optimally sizing household battery capacities and determining their operating schedules, this study suggests that the break-even costs of lithium-ion batteries in TOU pricing DR programs range from less than 5 $/kWh to over 70 $/kWh, and comparison across cases indicates that the break-even costs are less sensitive to the C-rates, while lower discount rates lead

to higher break-even costs. In addition, the break-even costs are also dependent on the tariff prices.

Although costs of lithium-ion battery have been driven down drastically in the past few years by technology improvements and economies of scale, latest estimates show that the prices of lithium-ion batteries range from 200 to 400 $/kWh [5], [7]. Therefore, our study suggests the costs of lithium-ion batteries are still prohibitively expensive in TOU pricing DR programs in short term. However, the costs of lithium-ion batteries are projected to fall significantly [7]. In EIA's Annual Energy Outlook [14], large-scale battery storage capacity is projected to reach 40 GW by 2050 in the U.S. In the long term, the lithium-ion batteries are most likely to be a promising technology in a diverse set of applications. Our break-even analysis can provide insightful information into policy information and financial subsidy to incentivize deployment of lithium-ion batteries for utilities or policy makers.

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