Optimizing Price-Informed Operation of a Battery Storage System in an Office Building

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Abstract
New prescriptive efficiency requirements amended to US model energy codes historically have been evaluated using an average, blended electricity rate, which obscures demand charges. Post 2019, new measures can be evaluated using a representative time-of-use (TOU) tariff yet more sophisticated analysis methods are needed to consider a variety of TOU tariffs and assess price-informed control. To address these needs, this study couples building prototype simulation model with varying-in-sophistication battery storage operating strategies for different electricity TOU tariffs. The analysis compares the impact of operating a battery storage system following simpler rule-of-thumb methods versus a semi-optimized priced-informed heuristic approach. The investigation demonstrates that the heuristic approach results in greater electricity cost savings and is practical to implement.

Key Innovations
- Investigating battery system operation and utility rate assumptions to better inform energy policy
- Developing a semi-optimized battery charge and discharge strategy that’s customizable for different building types and TOU tariffs

Practical Implications
The findings indicate the level of simulation complexity needed to effectively assess building battery storage cost savings to inform energy code development and energy policy. The results also indicate the value for building owners to incorporate sophisticated demand projection algorithms to improve energy storage operation for sites with TOU tariffs.

Introduction
Today’s marginal costs to produce peak electricity is much higher in many regions than base generation costs. In addition as clean grid policies are more widely adopted, the increase in contributions from variable, intermittent renewable energy resources presents challenges for maintaining grid stability. (Kropski and Pratt 2014). Since buildings are large electricity consumers, totalling 48% globally (IEA 2018) and 75% in the US (EIA 2019), they have an important role to play in achieving a clean, resilient electricity grid. Specifically, buildings are capable of load flexibility, which can be used to dynamically balance the supply and demand for electric power (Huang et al. 2020).

Demand flexibility measures (DFMs) and behind-the-meter distributed energy resources (DERs) can postpone or reduce electric load based on a price or other grid signal, which supports achieving grid-interactive efficient buildings and energy resilience. However, considering DFMs and DERs in energy policy creates a new set of analysis challenges that needs to be addressed.

To encourage building owners and users to implement DFMs and invest in DERs, utilities are starting to offer dynamic electricity pricing. However, these tariffs are not yet widely applied due their dependence on smart meter installation and building automated demand response capabilities (Hu et al. 2014). Yet time-of-use (TOU) electricity tariffs that specify different rates for each hour are widely available. For example, over 70,000 TOU tariffs are currently available to U.S. commercial building customers across 3,300 utilities.2 Franconi et al. (2020) studied the impact of electric utility rates on measure cost effectiveness in order to inform energy code development. The results revealed that the higher the capital cost of the measure, the more critical it is to use the actual rate instead of a national representative rate. The study included three groups of measures, each with increasing first costs, including: 1) demand flexibility operational control, 2) equipment efficiency, and 3) battery storage. Thus, the study indicates the importance of considering local or regional TOU rates in energy policy development for battery storage and other high capital cost, load shifting technologies.

There are many existing studies related to the optimization battery storage operation (Bayod-Rújula et al. 2017; Subramani et al. 2017). Dufo-López and Bernal-Agustín (2015) presented a methodology to evaluate the performance of a grid-connected system with storage under a TOU electricity tariff. The results showed that storage has the capability of smoothing power demand, reducing peak demand, and customer electricity cost. In addition, battery storage is often combined with photo-voltaic (PV) systems (Hassan et al. 2017; Zhang and Tang 2019; Nottrott et al. 2013; Berglund et al. 2019). Hassan et al. (2017) proposed a PV-battery system with feed-in tariff incentive. The objective was to maximize the feed-in tariff revenue streams and minimize the grid

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1 As indicated when comparing the levelized cost of energy of conventional base power plants to peaker plants, such as that published by Lizard, "Levelized Cost of Energy and Levelized Cost of Storage 2020". 19 October 2020. Retrieved 14 April 2021.

2 As extracted from the OpenEI U.S. Utility Rate Database, which is available for download at https://openei.org/apps/USURDB/.
electricity import. The result illustrated the cost effectiveness of the PV-battery system. Furthermore, Milis et al. (2018) and Ren et al. (2016) studied the energy and cost performance under different scenarios and electricity tariffs, which varied case-by-case.

These studies provide many insights for optimizing the operation of battery storage. However, they are complex and usually require application of different methods for different cases. And while advanced optimization methods may be warranted when assessing multiple systems and dynamic pricing, energy policy assessments do not require the same level of treatment. Instead, they need to balance the ability to analyze performance across building types and climate zones while maintaining enough customization to address variation in the most influential parameters. This paper investigates such considerations for assessing battery storage to inform a practical and efficient analytical approach to be applied in energy code development.

Methods

Approach

This research explores using a heuristic method to develop a semi-optimized, customized strategy to charge and discharge battery storage. Since it is heuristic based, it is practical to integrate into building simulation analysis studies to inform energy policy. It also has the potential for implementation in a building energy management and control system. To verify the effectiveness of the proposed semi-optimized battery operation strategy, we compare it to two simpler rule-of-thumb battery operating strategies. We conduct the analysis for two demand-based TOU tariffs applied to a large and medium office building in three locations representing hot-humid, mixed-humid, and cool-humid conditions.

Assumptions

In developing the operating strategies, we assume that the building’s 15-minute or hourly electricity usage time-series data are available for one or more calendar years. Such information can be acquired from electricity utility meter or monitoring data from previous years. While there can be wide variations in a building’s hourly demand profile across the day and seasons, we assume the abstracted statistics of these profiles, such as the maximum or average demand of each hour in a month, have limited variance between different years, assuming the building’s activity and space usage does not change significantly. Moreover, an advanced load prediction method designed specifically for fast demand response can be applied, such as the time-of-week and temperature model (Mathieu et al. 2011).

The selection of the battery size for a specific building is not the focus of this paper. In this study, we size the battery according to the 5 watt-hour of nominal capacity per square-foot-of-floor-area specification noted in ASHRAE Standard 189.1 (ASHRAE 2018). Additionally, we assume an energy to power ratio of 4 hours\(^3\), a usable battery fraction of 0.80, and a charge/discharge roundtrip efficiency of 0.83 according to Mongrid et al. (2019).

Office Building Prototypes

The medium and large office building simulation models used in this analysis are part of a suite of EnergyPlus (2020) building models developed by Pacific Northwest National Laboratory to inform and assess the impact of model energy code development.\(^4\) The characteristics of the medium and large office building prototype are summarized below.

\(3\) Discharging the fully charged battery occurs in no less than 4 hours.

\(4\) The residential and commercial building prototype models used to inform code development can be accessed from https://www.energycodes.gov/development.
and is applied in this study. The second rate is also considered. It is published as the Consolidated Edison New York City, Rate III, General Large Voluntary Time-of-Day (ConEd tariff) and represents a high-demand charge rate. Key features of the rates are summarized below and graphically depicted for a summer and winter week in Figure 1.

![Figure 1. Comparison of ASHRAE and ConEd Rates](image)

**Table 3: TOU Tariff Descriptions**

<table>
<thead>
<tr>
<th>Tariff Name</th>
<th>Description</th>
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| ASHRAE TOU  | October - May  
$0.0946 per kWh, peak hours  
$0.0571 per kWh, off-peak hours  
$5.59 per kW, base  
No peak kW charges  
Peak: Monday–Friday, 6 AM to 10 AM and 5 PM to 9 PM  
June – September  
$0.1104 per kWh, peak  
$0.0586 per kWh, off-peak  
$ 5.59 per kW, base  
$10.99 per kW, peak  
Peak: Monday–Friday, 1 PM to 9 PM |
| ConEd       | October – May  
$0.1197 per kWh, all hours  
$5.26 per kW, base  
$12.43 per kW, peak  
Peak: Monday–Friday, 8 AM to 10 PM  
June – September  
$18.36 per kW, base  
$28.15 per kW, peak 1  
$19.20 per kW, peak 2  
Peak 1: Monday–Friday, 8 AM to 6 PM  
Peak 2: Monday–Friday, 6 PM to 10 PM |

Monthly energy (kWh) cost is equal to the product of the energy consumed and the cost per unit energy. The determination of the monthly electric demand (kW) cost is more complex. The base demand charge is applied to the maximum peak demand for the billing month regardless if it occurs during an off-peak or on-peak period. The peak period demand charge is applied to the maximum demand occurring during the period. The total monthly charge for demand can be determined from Equation 1, where \( n \) is the number of peak demand periods in the electric rate for the month.

\[
\text{Monthly kW Cost} = kW_{\text{max month}} \cdot kW_{\text{Cost base}} + \sum_{i=1}^{n} kW_{\text{max peak period}} \cdot kW_{\text{Cost peak period}}.
\]

The TOU tariff calculation is implemented as a Python script which takes a building’s annual electricity demand time series and the TOU tariff information encoded in OpenEI’s JSON schema and computes the building’s monthly and annual kWh, kW, and total cost. **Battery operation strategies**

In this study, we develop and analyze three battery operation strategies to test the value of conducting battery and other DER analyses with greater specificity to better inform energy policy and actual battery system operation. The analysis process is depicted in Figure 2.

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5 The ASHRAE 90.1 Standard is identified as the model energy code by the US DOE.
In this study, the battery operation strategies are implemented as Python scripts that post-process annual hourly demand time series data from EnergyPlus simulation output and calculate the annual hourly battery charge/discharge time series profile.

The evaluated strategies are referred to as 1) Simple, 2) Simple TOU, and 3) Optimized TOU. Strategies (1) and (2) require anticipating each day’s building demand load profile. Strategy (3) requires anticipating each day’s demand profile over each electric billing period month. Strategies (2) and (3) also require knowledge of the TOU peak demand periods. All three strategies discharge the battery during the “daytime” hours, from 5 AM – 10 PM, and the battery recharge occurs evenly across each hour during “night-time” from 10 PM to 5 AM. More details about the strategies are provided below. Figure 3 depicts the effect of applying the three battery operation strategies to the medium office building in Tampa on July 21.

Figure 3. Battery Operation Comparison

Simple and Simple TOU

For the Simple strategy, the battery capacity is discharged equally during the hours with the highest demand. Similarly, for the Simple TOU strategy, the battery is discharged evenly for hours with the highest demand within the TOU rate peak-demand period. For either case, if the building’s instantaneous demand is lower than the assigned discharge value, then the battery will discharge only enough to reduce the demand to 0 kWh.

To apply either of these strategies, the number of hours that the battery discharges in a day must be specified. For this study, we determined the value based on the building type, climate zone, and TOU rate. To do so, we investigated potential values for the number of hours ranging from 1 to 12 for each case and determined the impact on annual electricity cost savings. To fairly compare the cost savings, we normalize the annual battery savings by the nominal capacity of the battery. We refer to this scalar indicator as the normalized annual battery-savings, with units of $/kWh. The results are shown in the Figure 4.

Figure 4. Results of Grid Search to Determine Simple Strategies Battery Discharge Hours

As the data indicate, the optimal number of discharge hours is most affected by the TOU rate. The medium and large office buildings with the ASHRAE TOU rate generally have an optimal number of discharge hours totaling about 4. However, for a few cases, namely the offices in Tampa following the Simple TOU strategy, higher savings are achieved with discharge for 9 hours. With the ConEd rate, the higher savings are achieved with more discharge hours, in the range of 8 or 9 hours per day. In the study, we opted to use the number of discharge hours that resulted in the highest energy savings for each building type-climate zone-TOU rate combination based on the assessment.

To apply the approach more broadly across TOU rates, we can extract a general principle based on the analysis value, and is only for illustration of the strategies’ characteristics.
results shown in Figure 4. The results imply that the optimal number of discharge hours is roughly equal to the number of regular building operating hours falling within the TOU peak demand period. For the office building prototypes, this totals approximately 4 hours for the ASHRAE TOU rate and 9 hours for the ConEd TOU rate.

**Optimized TOU strategy**

The third strategy relies on anticipating each day’s demand load profile in the electric billing cycle month. The applied semi-optimized heuristic approach is designed to minimize monthly demand costs. It provides a customized battery operation strategy based on the building load profile and the TOU rate peak-demand period. The procedure is outlined below.

1. Specify the “night-time” period in which the building’s electricity demand is at its minimal and the TOU rate has the lowest demand charge. The period is 10 PM to 5 AM in this analysis. The battery is charged evenly each hour over this period to achieve full capacity.

2. Based on the building’s historic hourly electricity time-series data, identify the “worst” demand day for each month.
   a. For each month, denote the period with the peak demand rate as period $P_{m,\text{max}}$.
   b. If the month’s TOU rate includes a peak demand period, identify its “worst” day as the day that contains the highest hourly demand, $HD_{m,\text{max}}$, in period $P_{m,\text{max}}$ after applying the battery’s full discharge potential across the hours with the highest demand in period $P_{m,\text{max}}$.
   c. If the month’s TOU rate does not contain a peak demand period, consider all non “night-time” hours as the peak period $P_{m,\text{max}}$ and identify the “worst” day and $HD_{m,\text{max}}$ the same way as above.

During the building’s real-time operation, the battery is discharged for each month during its $P_{m,\text{max}}$ hours if that hour’s instantaneous demand, $P_t$, is higher than the month’s $HD_{m,\text{max}}$. The discharge power for that hour is $(HD_{m,\text{max}} - P_t)$ or based on the available battery discharging power at that time, whichever is less. In short, the battery operation strategy aims to maintain the monthly building peak demand during $P_{m,\text{max}}$ to be no larger than $HD_{m,\text{max}}$. The result of applying this approach is shown in Figure 3. Ideally, it will levelize demand across the hours in the month with the highest demand. This reduces the cost associated with the maximum peak demand while minimizing the discharge of the battery during hours when there is no cost benefit.

**Results**

The annual electricity cost savings were determined for the two building types, three climate zones, two TOU rates, and three battery system operation strategies. The results are presented as bar charts in Figure 5 and indicate the variation in annual electricity cost saving per unit battery capacity ($$/kWh capacity) for each of the 36 cases analysed. The charts indicate the following.

- The Simple TOU strategy achieves better savings than the Simple strategy for the ASHRAE tariff. However, for the ConEd tariff, the trend is reversed. The Simple strategy achieves better savings than the Simple TOU strategy. This can be attributed to the fact that the number of hours included in the “daytime” exceed the hours in the ConEd max peak period ($P_{m,\text{max}}$) for both winter and summer months. This, in combination with the base demand rate being very high, results in meaningful demand reductions in the early hours (e.g., 5 AM – 8 AM) with the Simple strategy.

- The Optimized TOU strategy provides greater savings than the simple strategies for all cases analysed. It achieves an average of 43% greater savings for both the medium office and the large office compared to the Simple TOU strategy for the ASHRAE rate. It achieves 29% greater savings for the medium office and 16% savings for the large office compared to the Simple strategy for the Coned rate.

Due to the high capital cost of battery systems, it is important to consider the impact of the operating strategy on battery life. The cycle life for conventional batteries is a function of its depth of discharge. Cycle life is reported as 3500 for Li-Ion batteries based on an 80% depth of discharge (as assumed in the analysis), and typical battery life is reported as 10 years (Mongrid et al. 2019).

Figure 6 presents the number of annual discharge cycles determined for the three battery operation strategies evaluated. Annual discharge cycles are defined as the total annual energy discharged divided by 80% of the battery discharge capacity. As the charts indicate, the two simple strategies result in a full depth of discharge of the battery each weekday. As a result, they cause greater wear on the battery compared to the Optimized TOU strategy, which aims to levelize demand strategically to reduce monthly cost. This approach discriminates between hours that impact the monthly peak demand cost and those that do not, which results in less battery cycling.

Figure 6 also indicates the total annual energy discharged by the battery. The greater the annual energy value, the greater the embedded battery charge/discharge losses (based on the assumed 0.83 round-trip efficiency). Specifically, the Optimized TOU strategy averages about a 60% and 40% reduction in annual capacity for the medium and large office buildings, respectively, for the ASHRAE rate compared to the simple strategies. For the ConEd rate, the impact is larger. The reduction averages about 75% and 50% for the medium and large office buildings, respectively. Thus, the Optimized TOU strategy may provide additional cost benefit by increasing the battery life by 40% to 75%.
Discussion

The simple strategies are easier to implement compared to the semi-optimized approach. However, there is one caveat in their design, which is the choice of the number of hours to discharge the battery each day. Yet based on the results from the grid search analysis, one may be able to reasonably establish the optimal number of discharge hours by assessing the number of regular building operating hours falling within the TOU peak demand period.

Of course, the consequence of implementing one of the simpler methods instead of a semi-optimized approach is the reduction in annual electricity cost savings, which reduces the cost effectiveness of the battery system investment. For the ASHRAE rate, the results suggest that a more optimized approach provides additional savings to be \$5 - $8 per year per kWh battery capacity based on the office buildings analysed. For the ConEd rate, the additional savings are \$5 - $10 / per year kWh. Perhaps more importantly though, is the impact that a simplified approach has on battery cycling and its life. For example, Li-Ion battery system cost is estimated at $360/kWh capacity with the battery storage cost comprising $190/kWh of the total (Mongrid et al. 2019). Levelizing the capacity cost over a 10-year life results in a $19/kWh/year cost. Comparing this average annual cost to the incremental savings of the semi-optimized solution (~ $5 - $10 / kWh/year) indicates the first cost benefit that can be realized by improving the battery life by 40% to 70% may of equal magnitude as the operating cost savings.
In practice, a limitation of applying the Optimized TOU strategy is the ability to accurately project the building instantaneous demand profile for each month. An inaccurate estimate may result in the battery not reducing the demand sufficiently for hours occurring during the \( P_{m,\text{max}} \) period to be lower than \( HD_{m,\text{max}} \). In such a case, \( HD_{m,\text{max}} \) for the remaining days in the month shall be adjusted to the new highest hourly peak demand value and used to direct the battery discharge for the remainder of the month.

Another limitation of the Optimized TOU strategy is that it only accounts for one peak demand period – the one with the highest demand cost. As indicated in the ConEd case, TOU rates can include multiple peak demand periods. Thus, an improved version of the Optimized TOU strategy would be to expand the method to balance loads across multiple peak demand periods. In addition, the Optimized TOU strategy does not take into account variations in TOU energy rates. It only considers demand. However, based on the rates utilized in this study, the variations in demand rates had a much larger impact on electricity cost than the variations in energy rates.

**Conclusion**

In current practice, there lacks a systematic method to develop a general battery discharge strategy to inform energy policy, such as building energy codes. Establishing such a strategy is further complicated by the wide variations in demand rates and peak demand periods identified from published TOU tariffs.

The cases assessed in this study, including three battery system operation strategies and two TOU tariffs applied to medium and large office buildings located in three climate zones, indicate that applying a semi-optimized strategy always provides additional annual electricity cost savings compared to more simplified methods. In addition, methods that target reducing monthly electricity cost instead of addressing daily hourly demand, result in reduced cycling, less wear on the battery, and increased life. This may result in levelized first cost savings that are of the same order of magnitude as the additional annual electricity cost savings offered by the semi-optimized approach.

The Optimized TOU strategy proposed in this study is practical to implement and integrate within a whole-building simulation analysis. It also has the potential to be deployed in buildings to improve battery system operation effectiveness and the resulting electricity cost savings. In either application though, it is important to customize the approach based on the local TOU tariff. This requires tapping into utility rate database resources, such as the OpenEI Utility Rate Database, and adapting energy policy building modelling studies to take a more regionalized approach when considering utility rates.

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