Cost-Optimization of Battery Sizing and Operation

Rami Ariss, Julie Buard, Marc Capelo,
Berengere Duverneuil, Arthur Hatchuel

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Instructor: Professor Scott Moura

Abstract

Batteries will play a major role in the future of the electric grid to address demand constraints, replace traditional grid capacity infrastructure, promote the penetration of intermittent renewable generation, and increase grid reliability flexibility, and resiliency. Currently, batteries are an expensive technology to provide energy storage services. We conduct a case study on numerous building loads on the University of California, Berkeley campus using Pacific Gas & Electric's commercial time-varying tariff, E-19S, and market-based battery pricing based on Tesla's Powerpack. A linear program was developed to optimize battery sizing and operation based on time-varying electricity tariffs and market-based battery costs. Implementation of the program in Python using the Pyomo open-source optimization package and the GLPK solver was efficient and results show that large-scale commercial buildings can generate positive net savings, as high as 26.5%, with optimally sized batteries and operation. The bulk of the savings come from peak demand shaving, with reductions of up to 61% on pre-optimization demand costs. Energy pricing arbitrage using the battery, in contrast, generates reductions of up to 15% of the pre-optimized energy costs. Future work can incorporate other revenue streams generated from energy storage services, such as ancillary services, resource adequacy, critical load backup, and utility dispatch.

1 Introduction

1.1 Motivation and Background

A changing grid. The electric grid is in a state of transition, both in terms of financial and physical topology. The traditionally centralized, unidirectional grid structure is becoming increasingly distributed and meshed in nature. Aggregation of distributed energy resources (DERs) and operation as virtual power plants (VPPs) is expected to make the grid more efficient, offsetting the need for additional peaker plants and infrastructure upgrades. DERs will play an increasingly important role in providing customers with the clean, flexible, and efficient energy they seek, reshaping the grid in the process.

The role of batteries. The current electric grid operates by instantaneously meeting supply and demand. It is economically founded as a commodity market that utilizes extensive capital-intensive infrastructure to do so. Peaker plants, spinning reserves, and ancillary services must be on call to ensure reliability and power quality requirements are met. The fundamental operation of the electric grid would change, however, with large-scale penetration of a means to temporally arbitrage energy. Many types of energy storage technologies are emerging, from flywheels to supercapacitors to electric vehicles to batteries. Each technology has its strengths and limitations, and batteries appear to be some of the most versatile forms of energy storage.

Batteries as an energy storage service for the electric grid are currently very expensive technologies, yet their versatility allows them to take advantage of multiple revenue streams. For behind-the-meter batteries, energy and demand charge arbitrage of a customer's electricity tariff provides an opportunity for significant cost savings. In order for arbitrage opportunities to be present, the tariff must have time-varying charges, typically in the form of time-of-use or real-time pricing. Dynamic charges allow batteries to temporally arbitrage between high cost peak periods and low cost off-peak periods. For large commercial and industrial customers, utilities typically impose demand charges based on the customers peak monthly demand corresponding to various time-of-use periods. Such costs are justified by the high price the utility must pay to procure sufficient capacity during system-wide peak use periods. Demand charges present large revenue opportunities for behind-the-meter batteries, helping justify the high capital costs of such energy storage.

Project Goal Our project aims to optimally size behind-the-meter batteries to minimize electricity costs (maximize net savings) based on cost arbitrage of time-of-use electricity tariffs and current market-based battery prices. Linear programming and non-linear programming methods are explored to optimize the operation of a behind-the-meter battery for actual commercial loads. This project is conducted in parallel with our CE264 Behavioral Modeling project where we studied potential financial policy subsidies and incentives necessary to increased the market adoption of batteries. Based on our stated preferences survey and multinomial logit discrete-choice model, we observed interest in market adoption of batteries and estimated a forecast of battery adoption based on varying percentage-based cost reductions through policy incentives. Results are presented in Figure 1

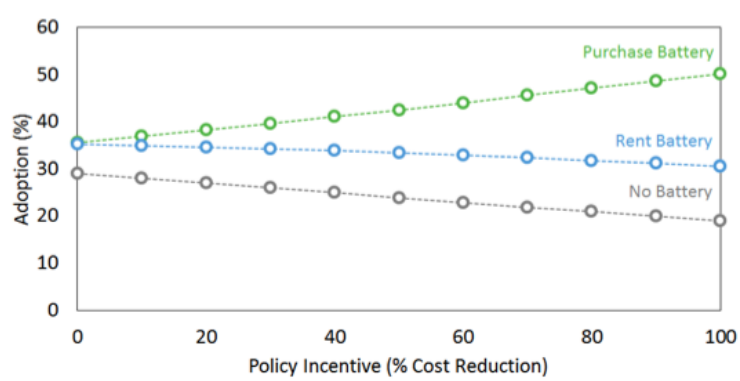

Figure 1: Forecasted demand for battery purchase, rent and no-adoption v. policy incentive.

As mentioned, high capital costs of batteries can be justified by stacking multiple revenue streams. Although our project is primarily focused on tariff cost arbitrage, future work can incorporate optimization of other services, such as resource adequacy, ancillary services, or wholesale market pricing arbitrage. Furthermore, long term objectives can be geared towards cost-optimization of a spatially distributed portfolio of loads as a VPP responsive to utility dispatch signals based on system-wide peak demand, nodal congestion, or high temperatures. Such aggregate dispatch could also include optimization based on grid-level greenhouse gas emissions or offsetting the need for investment in traditional grid infrastructure. As a case study, actual commercial loads on the UC Berkeley campus are cost-optimized under Pacific Gas & Electric (PG&E) time-of-use tariffs for optimal battery sizing and operation.

1.2 Relevant Literature

Demand response (DR) is a change in the power consumption of an electric utility customer to better match the available power supply. The use of batteries to flatten load profiles and reduce costs has been extensively studied as a form of DR. An example of DR is Direct Load Control (DLC) using a Home Energy Controller (HEC) provided the pricing scheme of the utility is a two level tariff with on-peak and off-peak periods (Kishore and Snyder, 2010). In this method, the utility is empowered to control the appliances whenever it is necessary. It has been shown that DLC can successfully reduce the load peak provided the homes can share their load consumption information. However without shared information, aggregated single home energy optimization creates a rebound peak during off peak hours that is even more pronounced.

Another DR method which has been explored is called Real Time Pricing (RTP) in which the price of electricity can freely fluctuate each half hour but is announced in advance to the user who can adapt energy consumption in response. Zhou et al. (2014) extensively studied this method considering a Home Energy Management System (HEMS) which included an electric vehicle, photovoltaic system, batteries and appliances control (flexible loads). The simulation results showed that the proposed control approach demonstrates good performance for scheduling energy consumption while fulfilling the proposed DR requirements.

Although these optimal electric energy consumption schemes show some significant results in shaving peak energy consumption, using a battery for demand response provides other advantages such as protection against power outages or integration with photovoltaic systems that make them an attractive object of study. Semigran and Tsim (2014) quantified the savings derived from using a battery, showing that significant reduction in cost can be achieved to partly compensate for the upfront cost of buying a battery. Cho et al. (2014) studied the integration of Battery Energy Storage Systems (BESS) and presented a method to optimally size a battery in order to reduce a building's annual cost. (Kishore and Snyder, 2010) showed that this optimization scheme can be extended to multiple homes in order to reduce peak demand in a neighborhood while reducing costs. These recent breakthroughs are now reaching a point where commercial solutions are breaking into the market, with start-ups such as STEM and Advanced Microgrid Solutions (AMS) offering services to combine learning algorithms and energy storage solutions to lower costs for private stakeholders.

1.3 Focus of the Study

This study aims to develop a linear program to cost-optimize battery sizes and operation based on time-varying energy and demand charges and market-based battery costs for future development into an optimized aggregated load VPP model.

2 Technical description

2.1 Initial Modeling

The problem that we are trying to model is the cost-optimization of a single load. We want to minimize the monthly electricity bill for a single household or commercial building. In order to do so, it is crucial to understand the tariff structure that is being applied by the utility, in our case, PG&E. For the sake of this study, we will use the standard energy tariff E-19 (PG&E, 2016), a typical time-varying tariff structure that is divided into two major charges of interest:

a. an **energy charge** that corresponds to the price of the amount of kWh being consumed every 15-minute time step. This price is in $/kWh. It varies between summer and winter, peak hours, part-peak hours and off-peak hours.

b. a **demand charge** that charges the maximum demand measured from the customer over a month in $/kW. PG&E charges first the maximum demand over the month and second the maximum demand over the month's peak and part-peak hours.

The first opportunity to optimize one's consumption is to move energy consumption that occurs during peak hours (when cost of electricity is high) to off-peak hours (when cost is low). The battery can charge during off-peak hours and then discharge during peak hours, providing a lower overall energy cost. The second opportunity is to play with that demand charge in order to do load "shaving", that is, discharging the battery to flatten any peak in the load and thus reducing the global monthly demand charge and/or peak demand charges.

2.2 Data used

We use load data from the University of California, Berkeley, campus buildings available here to perform optimizations. Multi-year, 15-minute resolution meter interval data is utilized to optimize battery sizes and operation for various campus buildings. Our results make it possible to formulate propositions to the University of California in terms of battery adoption. Although the university is not served under PG&E tariffs, our methodology and model can easily be adapted to any electricity pricing comprised of energy and demand charges.
Market-based battery costs are approximated from Tesla Energy's Powerpack, using quotes from their "Design your Powerpack system" tool. Costs scale linearly at $65000 per 250 kW bi-directional inverter and $47000 per 100kWh powerpack.

2.3 Battery Modeling

We model our battery as a load with a maximum storage capacity and maximum charge and discharge rate. We assume the battery has no internal or external losses and operate it with perfect with a 100% round-trip efficiency. We note the maximum energy storage capacity

S_{max} and the maximum rate of charge Q_{max} (whic we also refer to as the size of the inverter). We could also consider minimum values S_{min} and Q_{min} but we will assume for the sake of simplicity that $S_{min} = 0$ and $Q_{min} = -Q_{max}$.

2.4 A first intuition: non-linear programming

2.4.1 Definition of the variables

We define N the number of time intervals that we have data on, L the vector of the load such that $L = [L_1, ..., L_N]$ with L_k being the consumption of the building during the k^{th} time interval. We define $C = [C_1, ..., C_N]$ the vector of electricity cost such that C_k is the cost of energy during the k^{th} time interval, $Q = [Q_1, ..., Q_N]$ the consumption of the battery such that Q_k is the consumption of the battery during the k^{th} interval. Finally we define $Z = [Z_1, ..., Z_N]$ the energy stored in the battery such that Z_k represents the energy stored in the battery after the k^{th} time interval. We note $I = \{1, ..., N\}$, I_{peak} (resp. I_{part}) the subset of I that is constituted of the indexes k such that the k^{th} time interval falls in peak (resp. part-peak) hours. Demand tariffs are referred to as: c (all-month demand cost), c_{peak} (peak hours demand cost) and c_{part} (part-peak hours).
We note $\mathcal{C}$ the objective function corresponding to the monthly electricity cost so that:

$$\mathcal{C}_{nl} = (L+Q)^T C + c \cdot \max_I (L+Q) + c_{peak} \cdot \max_{I_{peak}} (L+Q) + c_{part} \cdot \max_{I_{part}} (L+Q) \quad (1)$$

2.4.2 Formulation of the program

We use the equation 1 to define the objective of the program as

$$\min_Q \mathcal{C}_{nl}(Q)$$

Then we have the following constraints:

a. Maximum charge rate:

$$-Q_{max} \leq Q \leq Q_{max}$$

where Q_{max} is the maximum rate of charge of the battery.

b. Battery Dynamics and Maximum Charge of the battery:

$$Z_{k+1} = Z_k + \Delta t \cdot Q_{k+1}$$

with the initial condition $Z_0 = S_0$ representing the initial state of the battery. The following constraint is then:

$$S_{min} \leq Z \leq S_{max}$$

with S_{min} and S_{max} being physical limits for the battery storage capacity.

c. Non-negativity of total demand:

$$L + Q \geq 0$$

d. Anticipation of future optimization:

$$0.95 Z_0 \leq Z_k \leq 1.05 Z_0$$

The battery is forced to return to its initial state because failing to do so might compromise future optimization.

2.4.3 Solution of the problem

We implement this non-linear program (the non-linearity is due to presence of a max in the objective function) with MATLAB, using the `fmincon` solver.

Single-Day Optimization We first test the program on a small period and begin with a single-day optimization. We account for the monthly the demand charge by scaling these charges. The cost function was:

$$\mathcal{C}_{nl}^{day} = (L+Q)^T C + \hat{c} \cdot \max_{I}(L+Q) + \hat{c}_{peak} \cdot \max_{I_{peak}}(L+Q) + \hat{c}_{part} \cdot \max_{I_{part}}(L+Q)$$

$$\hat{c} = c/n \qquad \hat{c}_{peak} = c_{peak}/n \qquad \hat{c}_{part} = c_{part}/n$$

where n is the number of days in the month.
We decided to set S_0 and S_{min} to 0 and tried several values for Q_{max} and S_{max}. Our program also returned the cost with and without battery.

Results We processed the program on a 15 minute dataset representing the consumption of Doe Library on Tuesday March 15th, 2016. The battery parameters were chosen as $S_{max} = 390$ kWh and $Q_{max} = 50$ kW. Results are presented on Figure 2. The blue curve represents the real consumption from the dataset. The red curve represents the battery consumption in order to minimize the total cost and the yellow curve is simply the sum of the blue and the red curve. The dotted purple curve represents the energy stored in the battery. We also plotted the electricity cost. As we can see, constraints are respected: the red curve stays between -50 and 50 kW, the yellow curve stays non-negative, the purple curve remains between 0 and 390 kWh and the battery returns to its initial state at the end of the day. In accordance with our expectation, global cost is reduced, decreasing from \$176.48 without battery to \$152.20 therewith, achieving a 13.8% saving.

Several days optimization We tried to extend this analysis to longer periods of time such as three days, one week or an entire month. However, we obtained very poor results showing that the algorithm proved inefficient in operating such large-scale optimizations, and this without mentioning the fact that computational times were getting unacceptably high.

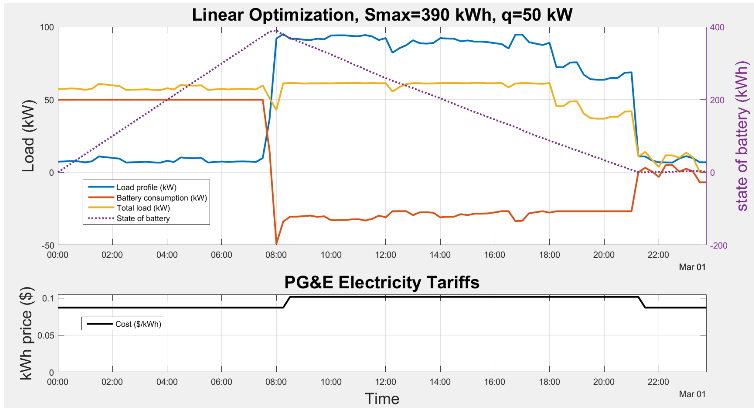

Figure 2: Non-linear single-day optimization for Doe Library, Berkeley, CA. The solid lines are scaled on the left y-axis and the dotted line is scaled on the right y-axis. On top, the loads. At the bottom, the electricity tariffs.

Identification of the limitations The reason why we thought our program was not performing as well as we would have wanted it to do was primarily its non-linearity. Since there are no very efficient methods to solve optimization problems, researchers often resort to similar problems where bulletproof solutions already exist: linear programming, quadratic programming or convex programming for instance. To decrease the program complexity, we also considered averaging our data over the hour instead of having data every 15 minutes.

2.5 A more efficient model: linear programming

2.5.1 Turning the problem linear

We were greatly helped in our research by an idea from Pr. Scott Moura, originating from (Han et al., 2015). The idea consists in introducing new variables to optimize on: P_{max} the maximum demand over the month as well as $P_{max,peak}$ the maximum demand over the month peak hours and $P_{max,part}$ over part-peak hours. Thus the new cost function is given by

$$\mathcal{C}_{lin} = (L+Q)^T C + c \cdot P_{max} + c_{peak} \cdot P_{max,peak} + c_{part} \cdot P_{max,part} \tag{2}$$

and the corresponding linear program:

$$\min_{\substack{Q, P_{max}, P_{max,peak} \\ P_{max,part}}} \mathcal{C}_{lin}(Q, P_{max}, P_{max,peak}, P_{max,part})$$

with new constraints:

$$L_k + Q_k \leq P_{max} \qquad \forall k \in I \tag{3}$$

$$L_k + Q_k \leq P_{max,peak} \qquad \forall k \in I_{peak} \tag{4}$$

$$L_k + Q_k \leq P_{max,part} \qquad \forall k \in I_{part} \tag{5}$$

The attentive reader will have noticed that this formulation is not strictly equivalent to the non-linear one on the grounds that constraints (3), (4) and (5) are not necessarily active. However to the extent they are, this is a totally equivalent problem. The great advantage is that this is a linear program, which can be less computationally intensive.

2.5.2 Formulation

The difficulty of using a linear formulation when dealing with a great number of constraints is to turn this into the conventional linear form:

$$\min_x f^T x \quad \text{s.t.} \quad Ax \leq b, \quad lb \leq x \leq ub$$

We define

$$x = [Q_1, ..., Q_N, P_{max}, P_{max,part}, P_{max,peak}] = [x_1, ..., x_N, x_{N+1}, x_{N+2}, x_{N+3}]$$

We have

$$\begin{aligned} \forall k \in I \quad L_k + Q_k \leq P_{max} &\Leftrightarrow Q_k - P_{max} \leq -L_k \\ &\Leftrightarrow x_k - x_{N+1} \leq -L_k \end{aligned}$$

Similarly we have:

$$\begin{aligned} \forall k \in I_{part} \quad L_k + Q_k \leq P_{max,part} &\Leftrightarrow Q_k - P_{max,part} \leq -L_k \\ &\Leftrightarrow x_k - x_{N+2} \leq -L_k \\ \forall k \in I_{peak} \quad L_k + Q_k \leq P_{max,peak} &\Leftrightarrow Q_k - P_{max,peak} \leq -L_k \\ &\Leftrightarrow x_k - x_{N+3} \leq -L_k \end{aligned}$$

The constraints on the battery charge are:

$$\begin{aligned} \forall k \in I \qquad S_{min} \leq Z_k \leq S_{max} &\Leftrightarrow S_{min} \leq S_0 + \Delta t \cdot (Q_1 + ... + Q_k) \leq S_{max} \\ &\Leftrightarrow \frac{S_{min} - S_0}{\Delta t} \leq Q_1 + ... + Q_k \leq \frac{S_{max} - S_0}{\Delta t} \\ &\Leftrightarrow Q_1 + ... + Q_k \leq \frac{S_{max} - S_0}{\Delta t} \text{ and } -Q_1 - ... - Q_k \leq \frac{S_0 - S_{min}}{\Delta t} \\ &\Leftrightarrow x_1 + ... + x_k \leq \frac{S_{max} - S_0}{\Delta t} \text{ and } -x_1 - ... - x_k \leq \frac{S_0 - S_{min}}{\Delta t} \end{aligned}$$

The linear relationships previously established now make it possible to create the matrix A and the vector b.

We have

$$f = [C_1, ..., C_N, c, c_{part}, c_{peak}]$$

And for the bounds:

$$Q \leq Q_{max} \Leftrightarrow \forall k \in I \; x_k \leq Q_{max}$$
$$Q \geq -Q_{max} \Leftrightarrow \forall k \in I \; x_k \geq -Q_{max}$$
$$L + Q \geq 0 \Leftrightarrow \forall k \in I \; x_k \geq -L_k$$

which become:

$$\forall k \in I, \; \max(-Q_{max}, -L_k) \leq x_k \leq Q_{max}$$

2.5.3 First Results with MATLAB

Now we implement and run this model with MATLAB using the `linprog` solver. Figure 3 shows the results we obtained. Remember that we used scaled values for the demand charge. The comparison with the non-linear program is striking. Not only is the linear solver more efficient, achieving 24.2% of cost reduction instead of 13.8% but it also runs faster: 3.34s instead of 5.43s. We checked that the constraint on maximum demand were active. On Figure 3, one can well see the peak-shaving effect of cost-optimization comparing the blue and the yellow curves. The behavior of the battery is also pretty straightforward: charge until the demand rises then discharge during high-demand period.

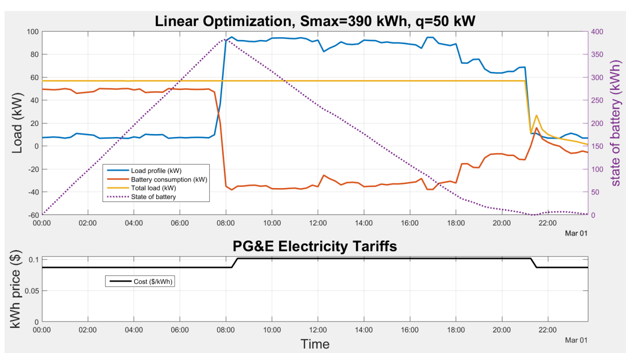

Figure 3: Cost without battery: \$176.48. Cost with battery: \$133.84. Savings: \$42.64 i.e. 24.2%

Then we performed longer optimization. The solver optimized 7 days of battery use in 16s, but 1 month in 10min. Results are shown in Appendix B on Figure 7 and 8. The month optimization was very time-consuming though it represented our full optimization (without scaled costs). Yet, we found that up to 17.5% reduction was achievable in this case (Doe, March 2016). Results for the summer proved even better with saving up to 30% for September 2015 for instance (Figure 9). With almost \$8000 saved over a single month and building, there is potential for huge savings should batteries be deployed throughout campus.

In conclusion, even though the linear algorithm proved more efficient and faster than the non-linear one, we still had long computational times, when optimizing for periods longer than a week. Since MATLAB appeared to be too slow for the scope of our study, we decided to use more powerful tools.

2.5.4 Battery Sizing

In the course of our study, we realized the impact of choosing values for S_{max} and Q_{max} — sizing the battery. We first referred to the values provided by Tesla PowerWall which are $S_{max} = 6.4$ kWh and $Q_{max} = 3.3$ kW but we quickly noticed that those were undersized for applications in buildings as big as the Doe Library or other campus buildings. So at this point, we decided to manually size the battery.
We sized for March 1st at the Doe Library. We ran several optimizations (using our linear algorithm presented further) varying Q_{max} and S_{max}, and looked for the pair (Q^*_{max}, S^*_{max}) that minimize the objective cost. Results are shown in Figure 4. We observe that increasing Q_{max} and S_{max} reduces the minimal achievable cost, which is logical since it is equivalent to weakens the constraints. However, past a certain point, no further improvement in cost reduction can be achieved. The bar diagram shown in Figure 4 presents a threshold. Because we want our battery to achieve the most savings but don't want to pay for an oversized battery, We retained as optimal size for our battery the elbow of the threshold which was approximately $S_{max} = 390$ kWh and $Q_{max} = 50$ kW.

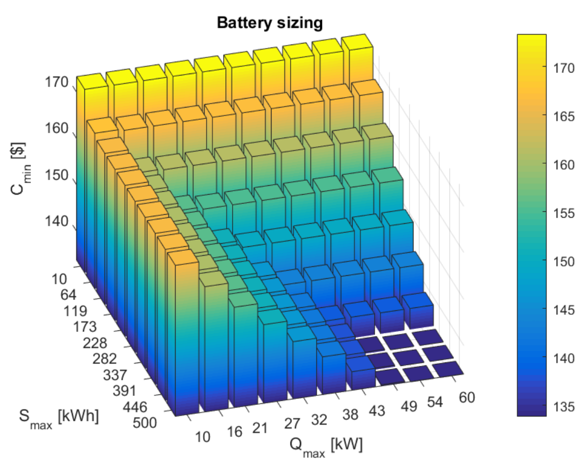

Figure 4: Q_{max} ranges from 10 to 60 kW and S_{max} ranges from 10 to 500 kWh. The color bar is in dollars.

2.6 Linear formulation of cost-optimized battery sizing and operation

A linear program is formulated to concurrently cost-optimize battery sizing and operation. To do so, maximum battery energy capacity, S_{max}, and maximum battery charge rate, Q_{max}, are defined as decision variables rather than fixed parameters. The new set of decision

variables to optimize on is now: $Q, P_{max}, P_{max,peak}, P_{max,part}$, S_{max}, and Q_{max}. Note that the following assumptions are made for the sake of simplicity with regards to the linear formulation: $S_{min} = 0$ and $Q_{min} = -Q_{max}$. In code implementation, a similar formulation is made using scaling factors for battery energy capacity and charge rate on fixed parameters S_{max} and Q_{max}. Mathematically, these formulations are equivalent.
The objective function is adjusted to incorporate battery costs for the battery capacity and inverter size. The new cost function is:

$$\mathcal{C}_{lin} = (L+Q)^T C + c \cdot P_{max} + c_{peak} \cdot P_{max,peak} + c_{part} \cdot P_{max,part} + c_{batt} S_{max} + c_{inv} Q_{max} \quad (6)$$

and the corresponding linear program with sizing included is:

$$\min_{\substack{Q, P_{max}, P_{max,peak} \\ P_{max,part}, S_{max}, Q_{max}}} \mathcal{C}_{lin}(Q, P_{max}, P_{max,peak}, P_{max,part}, S_{max}, Q_{max})$$

with new constraints:

$$X = [Q_1, ..., Q_N, P_{max}, P_{max,part}, P_{max,peak}, S_{max}, Q_{max}]^T$$

Constraint $\forall k \in I \quad L_k + Q_k \leq P_{max}$

$$\begin{bmatrix} 1 & 0 & \cdots & 0 & -1 & 0 & 0 & 0 & 0 \\ 0 & 1 & \cdots & 0 & -1 & 0 & 0 & 0 & 0 \\ \vdots & & \ddots & & \vdots & \vdots & \vdots & \vdots & \vdots \\ 0 & 0 & \cdots & 1 & -1 & 0 & 0 & 0 & 0 \end{bmatrix} X \leq -L$$

Constraint $\forall k \in I_{part} \quad L_k + Q_k \leq P_{max,part}$

$$\begin{bmatrix} \delta_1 & 0 & \cdots & 0 & 0 & -\delta_1 & 0 & 0 & 0 \\ 0 & \delta_2 & \cdots & 0 & 0 & -\delta_2 & 0 & 0 & 0 \\ \vdots & & \ddots & & \vdots & \vdots & \vdots & \vdots & \vdots \\ 0 & 0 & \cdots & \delta_N & 0 & -\delta_N & 0 & 0 & 0 \end{bmatrix} X \leq -L$$

where $\delta_k = 1$ if $k \in I_{part}$, 0 otherwise.
Constraint $\forall k \in I_{peak} \quad L_k + Q_k \leq P_{max,peak}$

$$\begin{bmatrix} \delta_1 & 0 & \cdots & 0 & 0 & 0 & -\delta_1 & 0 & 0 \\ 0 & \delta_2 & \cdots & 0 & 0 & 0 & -\delta_2 & 0 & 0 \\ \vdots & & \ddots & & \vdots & \vdots & \vdots & \vdots & \vdots \\ 0 & 0 & \cdots & \delta_N & 0 & 0 & -\delta_N & 0 & 0 \end{bmatrix} X \leq -L$$

where $\delta_k = 1$ if $k \in I_{peak}$, 0 otherwise.

Constraints on the maximum battery capacity: $\forall k \in I,\ S_0 + \Delta t \cdot (Q_1 + ... + Q_k) \leq S_{max}$

$$\begin{bmatrix} 1 & 0 & \cdots & 0 & 0 & 0 & 0 & -\Delta t^{-1} & 0 \\ 1 & 1 & \cdots & 0 & 0 & 0 & 0 & -\Delta t^{-1} & 0 \\ \vdots & & \ddots & \vdots & \vdots & \vdots & & \vdots & \vdots \\ 1 & 1 & \cdots & 1 & 0 & 0 & 0 & -\Delta t^{-1} & 0 \end{bmatrix} X \leq -\frac{S_0}{\Delta t}$$

Constraints on the minimum battery capacity: $\forall k \in I,\ S_{min} \leq S_0 + \Delta t \cdot (Q_1 + ... + Q_k)$

$$\begin{bmatrix} -1 & 0 & \cdots & 0 & 0 & 0 & 0 & 0 \\ -1 & -1 & \cdots & 0 & 0 & 0 & 0 & 0 \\ \vdots & & \ddots & & \vdots & \vdots & \vdots & \vdots \\ -1 & -1 & \cdots & -1 & 0 & 0 & 0 & 0 \end{bmatrix} X \leq \frac{S_0 - S_{min}}{\Delta t}$$

Constraints on the maximum battery charge rate: $\forall k \in I,\ Q_k - Q_{max} \leq 0$

$$\begin{bmatrix} 1 & 0 & \cdots & 0 & 0 & 0 & 0 & 0 & -1 \\ 0 & 1 & \cdots & 0 & 0 & 0 & 0 & 0 & -1 \\ \vdots & & \ddots & & \vdots & \vdots & \vdots & \vdots & \vdots \\ 0 & 0 & \cdots & 1 & 0 & 0 & 0 & 0 & -1 \end{bmatrix} X \leq 0$$

Constraints on the minimum battery charge rate: $\forall k \in I,\ -Q_{max} - Q_k \leq 0$

$$\begin{bmatrix} -1 & 0 & \cdots & 0 & 0 & 0 & 0 & 0 & -1 \\ 0 & -1 & \cdots & 0 & 0 & 0 & 0 & 0 & -1 \\ \vdots & & \ddots & & \vdots & \vdots & \vdots & \vdots & \vdots \\ 0 & 0 & \cdots & -1 & 0 & 0 & 0 & 0 & -1 \end{bmatrix} X \leq 0$$

A and b are obtained by vertically concatenating the five previous matrices and vectors.
The cost vector now becomes:

$$f = [C_1, ..., C_N, c, c_{part}, c_{peak}, c_{batt}, c_{inv}]$$

where c_{batt} is a normalized cost of the battery capacity in \$/kWh/month and c_{inv} is a normalized cost of the inverter in \$/kW/month.
Bounds:

$$lb = \begin{bmatrix} \max(-Q_{max}, -L_1) \\ \vdots \\ \max(-Q_{max}, -L_N) \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \end{bmatrix} \leq X \leq \begin{bmatrix} Q_{max} \\ \vdots \\ Q_{max} \\ +\infty \\ +\infty \\ +\infty \\ +\infty \\ +\infty \end{bmatrix} = ub$$

2.6.1 Python implementation using Pyomo with GLPK

In order to streamline data processing overhead and dramatically decrease computation time, the cost-optimization of battery sizing and operation model was implemented in Python using Pyomo, an open-source software package with extensive optimization capabilities for formulating, solving, and analyzing optimization models, developed by Hart et al. (2012). Pyomo provides easily scalable programming formulations to define sets, parameters, decision variables, constraints, and objective functions similar to how one would write them on paper. It produces the matrices (which get significantly large over larger time horizons; one month of data consists of roughly 23000 constraints and nearly 6000 decision variables) for use in a linear or non-linear solver.

The linear formulation permitted use of the lightning fast GNU Linear Programming Kit (GLPK). This linear solver takes our linear program formulation created using Pyomo and generates optimal results in a matter of seconds for respectable time horizons, such as a month. More importantly, the linear nature of the model formulation produced more physically realistic battery operation results producing very few "artifacts" of no net gain battery operation. Again, a penalty for battery cycling could be implemented to reduce such artifacts and achieve more realistic battery operation results.

The advantages of linear program formulation were clearly observed via computation time. Running the linear program cost-optimization with sizing model using the GLPK solver for September 2015 data for the Haas School of Business took 6.12 seconds on a Dell Inspiron 15 with an Intel i7 processor and 12 GB of memory. Further tests could be conducted over larger data sets and longer time horizons to better underscore the computational advantages for formulating the problem as a linear versus non-linear program (for example, a year of data took over 18 minutes to cost-optimize in the linear program).

2.6.2 Optimal battery sizing and operation results with Python

The implementation of the linear program in Python using Pyomo and the GLPK solver accommodated rapid cost-optimal battery sizing and operation for multiple UC Berkeley campus buildings. A key observation of the optimal results is a balance between increasing battery size for more savings from energy arbitrage and demand peak shaving and the linearly increasing cost of the battery capacity and inverter. This model is used to generate optimal battery sizes and operation for Wheeler, see Figure 5, and five other buildings on the UC Berkeley campus, see Appendix B. Figure 5 illustrates the significant cost savings that occur due to peak demand shaving. The optimal battery operation focuses on minimizing the on-peak demand since the E-19S tariff (see 2 in Appendix A) attributed the highest costs to that period. Furthermore, the battery is optimally utilized during the on-peak period when demand is below that of the month's maximum on-peak demand. This is seen in the battery discharge spikes that are a result of energy arbitrage from charging in the off-peak period and discharging in the on-peak period.

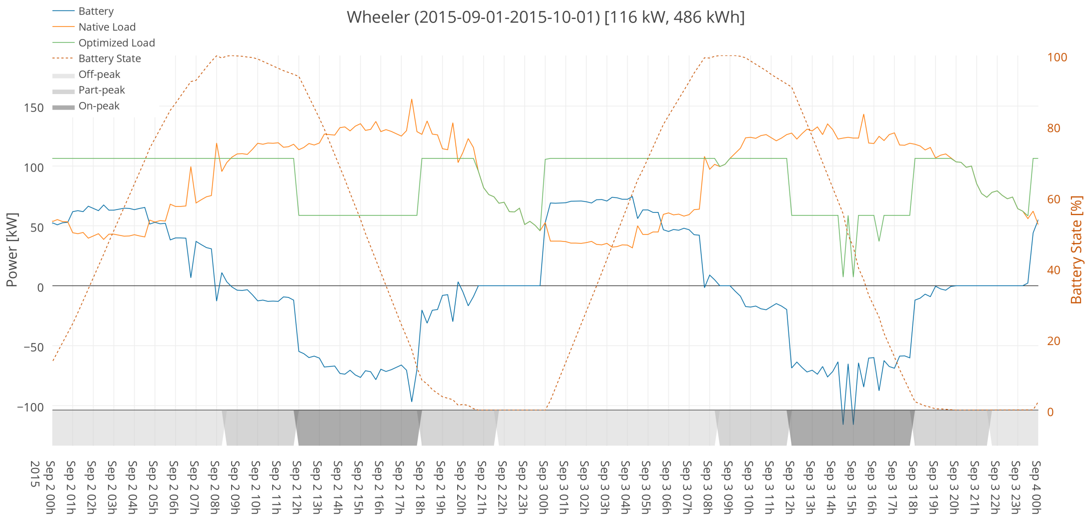

Figure 5: Wheeler auditorium optimized with a 116 kW 486 kWh battery in September 2015 achieving 17% net savings taking into account battery costs.

3 Discussion

3.1 Possible Savings throughout UC Berkeley

We performed battery optimization on various buildings across campus. Results are presented in Table 1 where we present the optimal sizing of the battery for a given building as well as the savings achieved with such a battery on that building during September 2015. The savings also take into account the battery cost. Full results can be found in Appendix A in Table 4 and Table 5. How it can be noticed, the optimal size is very different for each building. We can hypothesize that size is correlated with the total consumption of electricity over the month. The analysis plotted on Figure 6 suggest a linear dependency between the two. Savings percentage also appears to change a lot between each building, ranging from 7.2% to 26.5%. However this time, we can infer from the figures that it is not correlated to optimal size and subsequently to total consumption. The assumption we have here is that the savings achievable will be correlated to the load profile, especially if the initial load is very flat or if it fluctuates a lot.

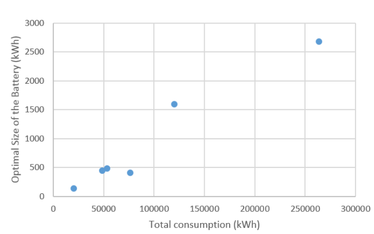

Figure 6: Correlation between optimal size and total consumption.

Table 1: Various buildings optimization results (all results are for September 2015

Building	Optimal Size (kWh)	Optimal Charge Rate (kW)	Pre-opt. Cost ($)	Post-opt. Cost, with battery cost ($)	Savings Achieved (%)
Haas School of Business	2676	442	55227	51237	7,2
Doe Library	444	66	11403	10121	11,2
McLaughlin Hall	139	24	4628	4076	11,9
RSF	411	97	14501	13008	10,3
Memorial Stadium	1596	412	36457	26808	26,5
Wheeler Hall	486	116	12862	10648	17,2

3.2 Limitations and perspectives

A significant limitation of this project is that a single tariff structure is considered (PG&E E-19), whereas there are many flavors of tariffs that depend on peak demand and load type. Tariffs can also vary from non-time-varying pricing to relationship-specific contractual Power Purchase Agreements (PPAs).In order to generalize our results, the optimization could take into account more tariff structures and pricing schemes. Furthermore, UC Berkeley operates is own electric grid and campus buildings are not in fact subject to PG&E's E-19S tariff, hindering our conclusive net savings results.

Another limitation is that energy losses due to the storage were neglected, i.e. the battery round trip efficiency was considered to be 100%, which does not accurately reflect the reality. Furthermore, no cost penalty for battery cycling, battery degradation and maintenance, or a minimum arbitrage opportunity was implemented in the model.

Finally, we considered offline optimization on historical data, whereas the load profile of a building is usually uncertain. The optimization could be online if we could predict the load. The prediction could be achieved using regression on weather data and historical load profile, or using a Markov Decision Process. Considerations can also include incorporating stochastic load forecasting with dynamic programming to eliminate the assumption of perfect foresight tied to the offline model.

Summary

We developed a linear program cost-optimization of battery sizing and operation to observe minimal costs, otherwise thought of as maximum savings, of electricity bills based on time-varying tariffs. Our model was applied to various buildings on the UC Berkeley campus using PG&E's E-19S time-varying tariff and market-based battery pricing interpolated from Tesla Powerpack costs. Results show that significant positive net monthly savings are achieved for all six evaluated buildings. This underscores a significant revenue stream to justify the high capital costs of batteries. Future model development can include other revenue streams in the cost-optimization, such as wholesale market pricing and resource adequacy.

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A Electricity Tariffs

Table 2: PG&E E-19S time varying tariff

	All Time ($)	Peak ($)	Part-Peak ($)	Off-Peak ($)
Energy rate - Summer	-	0.14726	0.10714	0.08057
Energy rate - Winter	-	-	0.10165	0.08717
Demand rate - Summer	17.33	18.74	5.23	-
Demand rate - Winter	17.33	-	0.13	-

Table 3: PG&E E-19S time varying tariff

Season	Definition	Peak	Part-Peak	Off-Peak
Summer	May 1 to Oct 31	12:00 noon to 6:00 p.m. Mon through Fri	8:30 am to 12:00 noon and 6:00 pm to 9:30 pm Mon through Fri	All other hours
Winter	Rest of the year	-	8:30 am to 9:30 pm Mon through Fri	All other hours

B Additional Results for UC Berkeley Buildings

Table 4: Optimal battery sizing and cost specifications for six UC Berkeley campus buildings.

Building	Total Energy Consumption (kWh)	Battery Capacity Size (kWh)	Inverter Size (kW)	Duration (hours)	Normalized Monthly Battery Cost ($)
Haas School of Business	263508	2676	442	6.1	11216
Doe	48621	444	66	6.7	1845
McLaughlin	20111	139	24	5.8	585
RSF	76451	411	97	4.2	1786
Memorial Stadium	120169	1596	412	3.9	7011
Wheeler	53213	486	116	4.2	2114

Table 5: Cost-optimized results for Energy, Demand, Total, and Net Savings

Building	Pre-opt. Energy Cost ($)	Pre-opt. Demand Cost ($)	Pre-opt. Total Cost ($)	Energy Savings Savings ($)	Demand Savings ($)	Total (w/ Batt cost) ($)	Net Savings ($)
Haas School of Business	28179	27048	55227	3768 13%	11438 42%	15206 28%	399 7%
Doe	5352	6051	11403	512 10%	2615 43%	3127 27%	1282 11%
McLaughlin	2166	2462	4628	167 8%	970 39%	1137 25%	553 12%
RSF	7773	6728	14501	588 8%	2691 40%	3279 23%	1494 10%
Memorial Stadium	12007	24451	36457	1845 15%	14814 61%	1666 46%	9649 26%
Wheeler	5714	7149	12862	679 12%	3649 51%	4328 34%	2214 17%

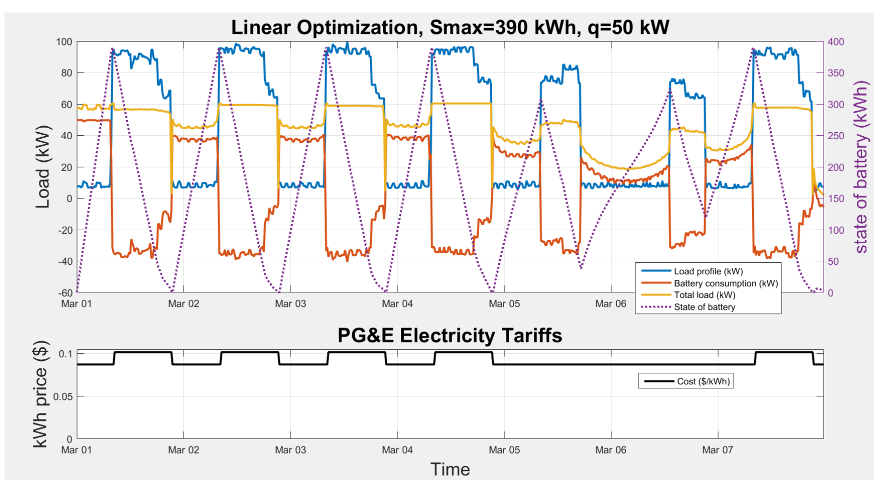

Figure 7: Cost without battery: $1153.53. Cost with battery: $891.52. Savings: $262.01 i.e. 22.7%.

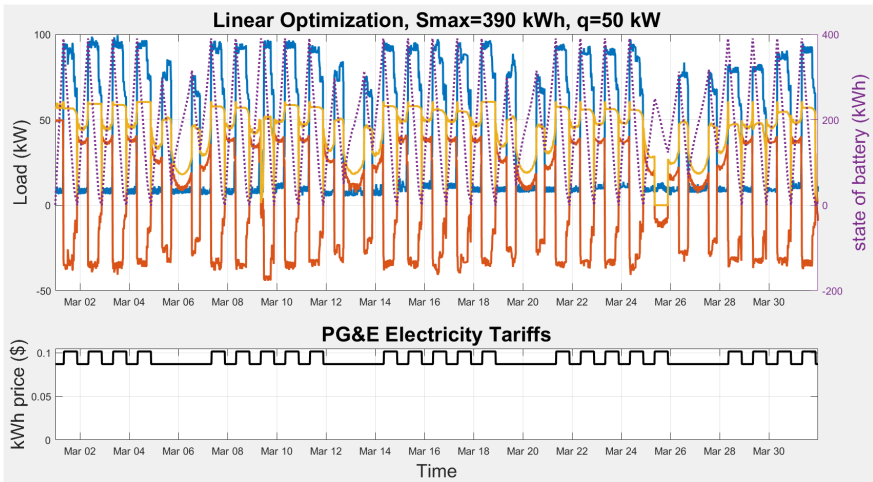

Figure 8: Cost without battery: $4991. Cost with battery: $4188. Savings: $803 i.e. 16.1%.

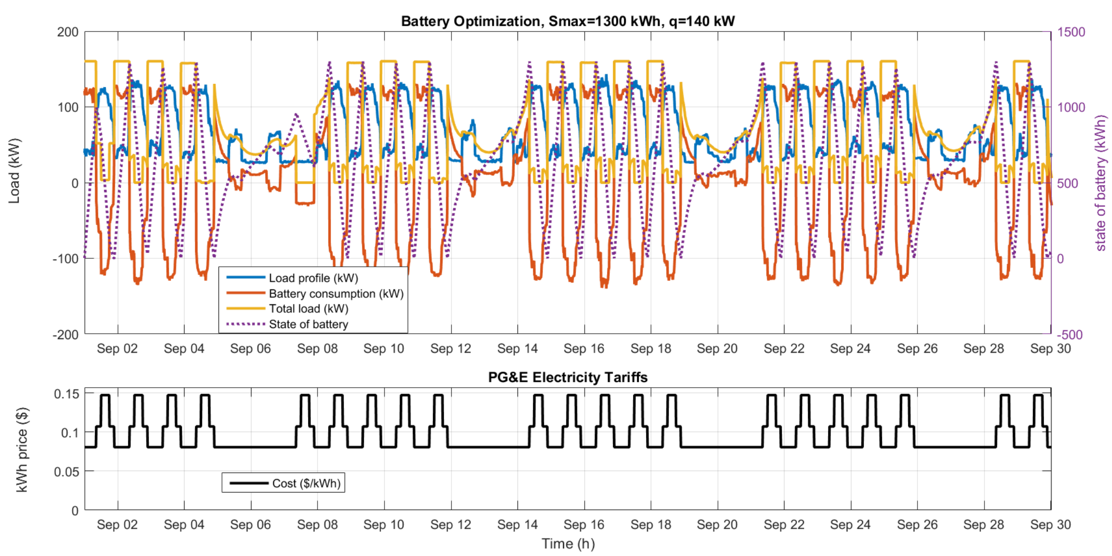

Figure 9: Cost without battery: $26373.38. Cost with battery: $18485.33. You save $7888.05 i.e. 29.9%.

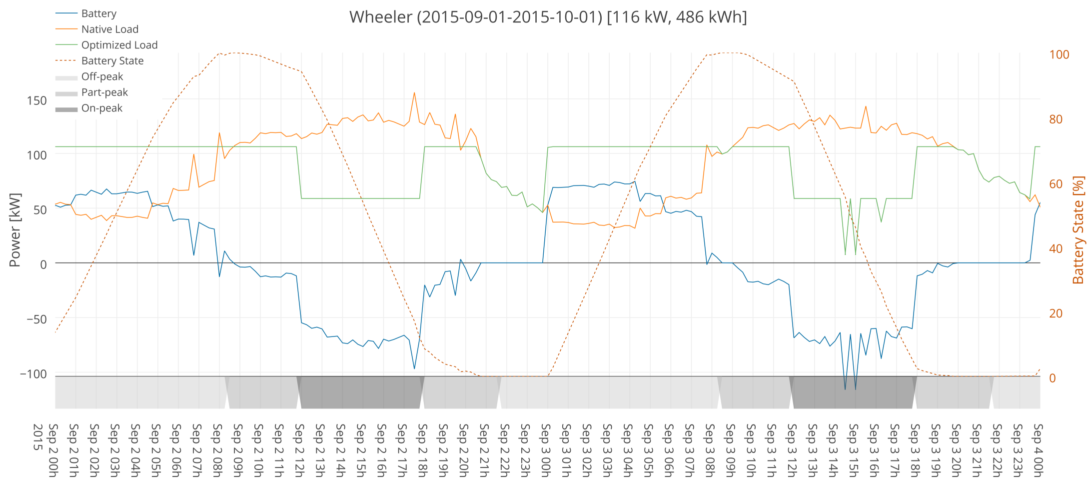

Figure 10: Wheeler with optimal battery size of 116 kW, 486 kWh for September 2015 achieving 17% net savings ($2214) including battery costs.

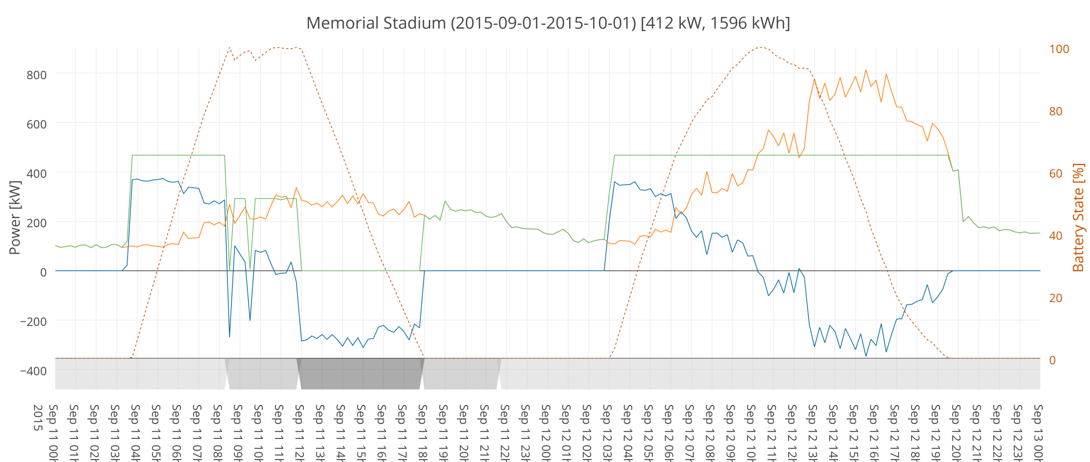

Figure 11: Memorial Stadium with optimal battery size of 412 kW, 1596 kWh for September 2015 achieving 26% net savings ($9649) including battery costs. The massive weekend peak is likely to be a football game.

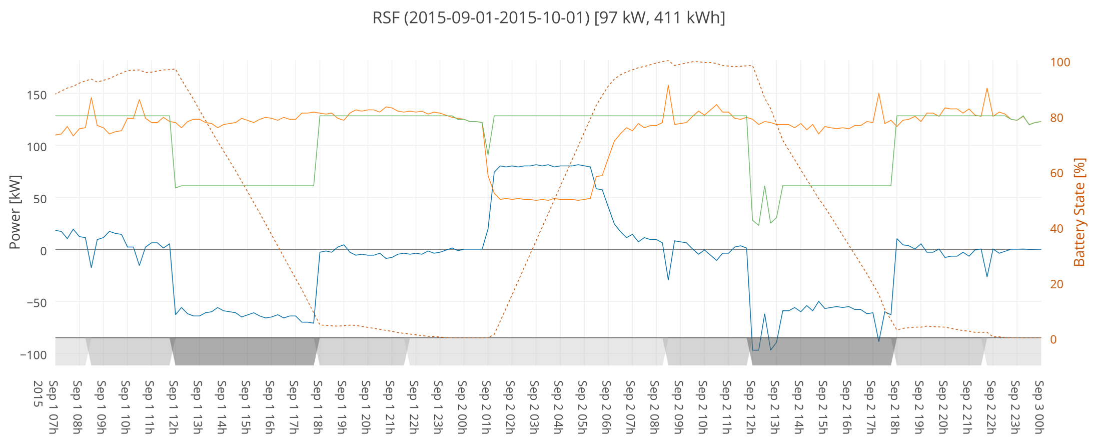

Figure 12: RSF with optimal battery size of 97 kW, 411 kWh for September 2015 achieving 10% net savings ($1494) including battery costs.

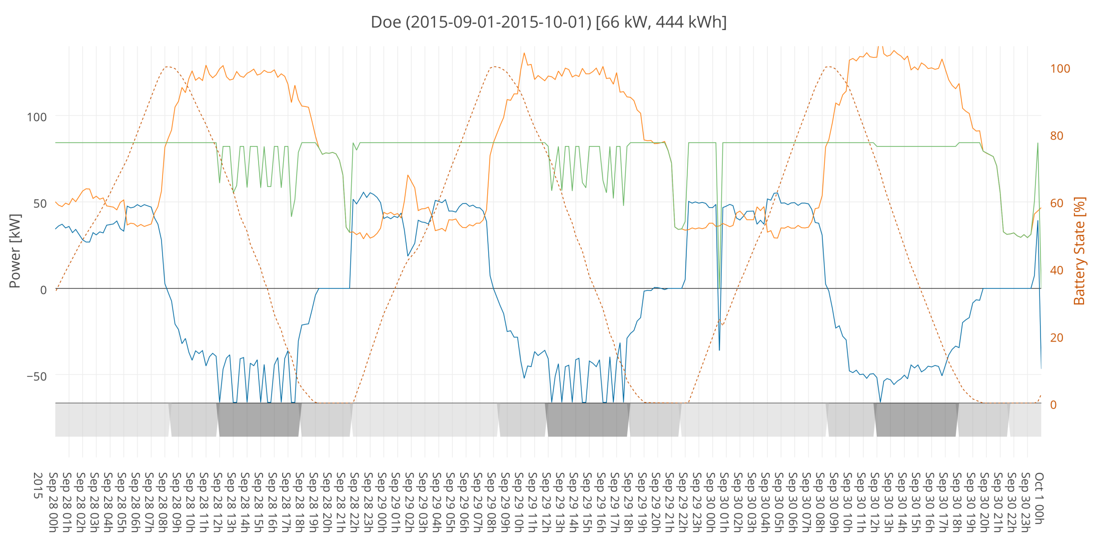

Figure 13: Doe Library with optimal battery size of 66 kW, 444 kWh for September 2015 achieving 11% net savings ($1282) including battery costs.

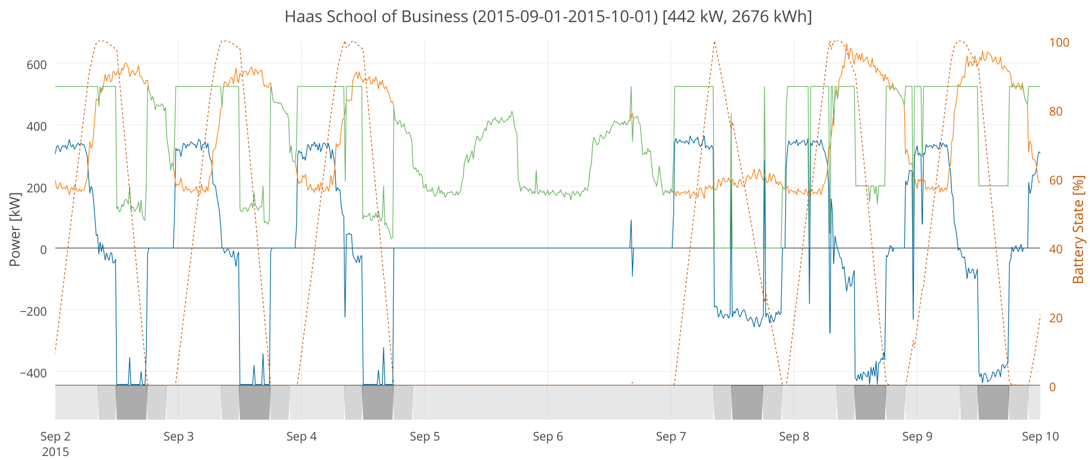

Figure 14: Haas School of Business with optimal battery size of 442 kW, 2676 kWh for September 2015 achieving 7% net savings ($3990) including battery costs.

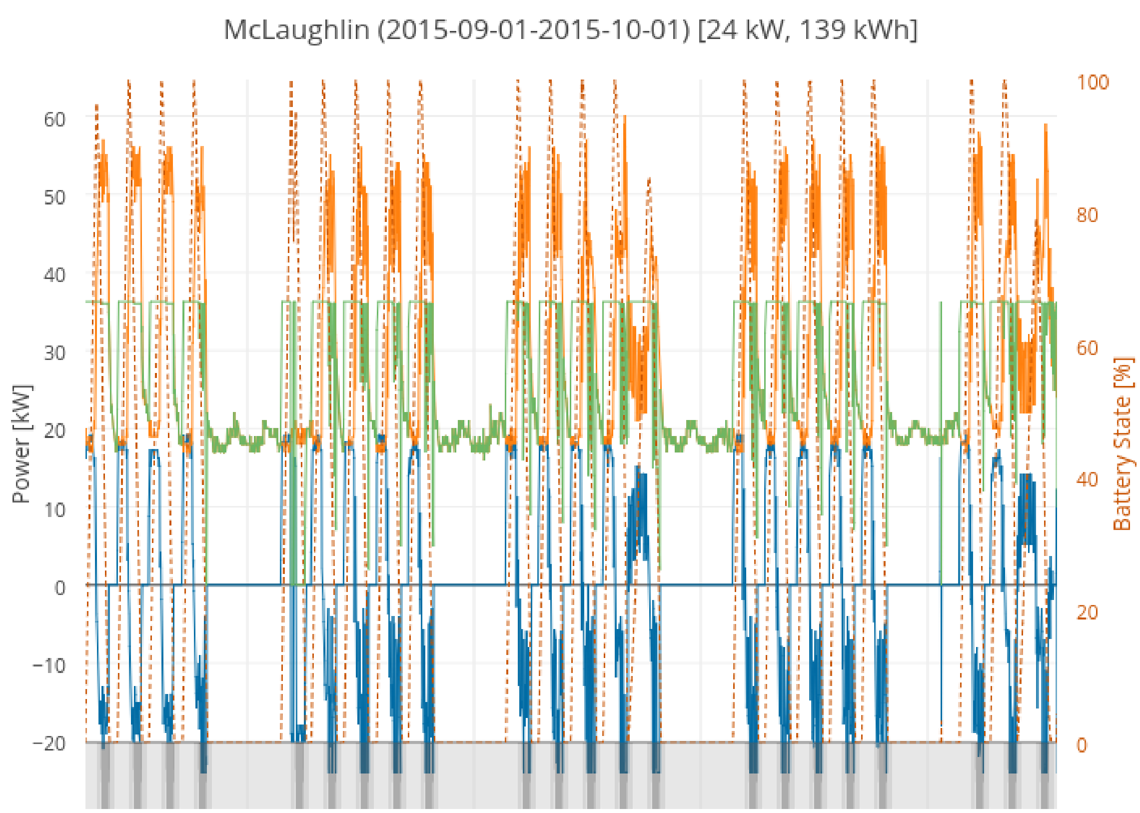

Figure 15: McLaughlin with optimal battery size of 24 kW, 139 kWh for September 2015.