Optimizing Battery Sizing and Dispatching To Maximize Economic Return

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Abstract

Battery energy storage is poised for rapid growth in both behind-the-meter and utility-scale installations due in large part to significant reductions in installed costs of this technology. Such energy storage systems can derive revenue by serving a variety of applications which include, among others, demand charge management, energy arbitrage, ancillary services, and resiliency. In many cases, however, the value of the benefits from any one of these applications are still less than the cost of the system. As a result, there is strong interest in stacking revenue streams, or serving multiple applications at different times over the course of a year. The challenge then is to determine which applications to serve and when to serve them, to assure that the economic return of the battery system is maximized over its lifespan. In this paper, we describe a mathematical optimization model that we have developed to determine the optimal sizing and dispatching of energy storage. We then demonstrate our model by analyzing the techno-economic potential for a battery at an office complex in California where we also show how suboptimal battery sizing can negatively impact the economics of the project.

Introduction

There is growing consensus among analysts that energy storage is on the cusp of becoming technically and economically viable for a broad range of energy applications. Continued innovation by the battery industry combined with a sustained effort on cost reduction is helping the energy storage industry close in on market viability. Costs are falling; by 2020 pricing for energy storage is expected at $200 per kilowatt-hour (half of today's price), and is further expected to be $160 per kw-hour by 2025. Another way to look at it is to note that energy storage is today where PV was in 2005.

Perhaps the biggest barrier to mainstream adoption of energy storage technology is the lack of upfront analytics and models to determine the technical and economic feasibility of energy storage projects. A recent McKinsey report noted the irony of a market where some entities that have access to grid data on electricity have an incomplete understanding of how to evaluate the economics of storage, while those entities that understand these economic metrics have very limited access to real-world data on electricity use. This inability to utilize a more comprehensive model incorporating detailed customer electrical data and battery performance data makes it difficult at this time to identify and capture viable opportunities.

Current practice often involves an evaluation of the economics of storage systems using 'averaged' data when doing analysis. Aggregating data is not useful in that it does not provide the precision required to identify which customers and applications would be most profitable to focus on. What is sorely needed is a proprietary energy-dispatch model that can incorporate a wide variety and range of real world data.

In the remainder of this paper, we will first review the various revenue streams available to battery energy storage. We'll then describe a mathematical optimization model capable of determining the optimal sizing and dispatching of battery energy storage. We'll then demonstrate the use of this model to analyze a battery energy storage project in California.

Finally, we should note that the objective of this case study, and moreover this paper, is not to show where battery energy storage does or does not work economically, but rather to show how differences in battery sizing and dispatching can lead to significantly different economic returns at the same site. Therefore, we recommend not focusing on the specific parameters and battery costs assumed – which will surely change rapidly –but rather the approach to the techno-economic modeling, analytics, and optimization.

Battery Energy Storage Revenue Streams

Batteries are able to derive revenue from multiple applications in both behind-the-meter and utility-scale installations. Some of these value streams are due to the structure of the rate tariff, and are therefore generally available to commercial, industrial, and in some cases residential, customers in regions with such tariffs. Others rely on participating in energy markets and as such are only available in places where markets are available.

Demand Charge Management

Also known as “peak shaving”, demand charge management involves strategically discharging the battery to clip the peaks of the site’s electrical load profile, and thus lower their peak demand charges. Demand charge management is perhaps the most common application for commercial and industrial customers in a behind-the-meter setting. Any savings from demand charge management appear as savings in demand charges on the monthly utility.

Energy Arbitrage

Batteries can be used to shift consumption from periods when electricity is expensive to a period when it is cheap. Or batteries can be used to shift solar production from midday to evening hours. In any case, the general idea is to charge the battery when the value of the electricity – either purchased from the grid or produced locally – is low to a period when it is worth more. Energy arbitrage can often be stacked with other applications. Savings from energy arbitrage appear as savings in energy costs directly on the monthly utility bill.

Demand Response

Some utilities offer demand response programs whereby they will pay customers to temporarily reduce their demand upon request. The way these programs work is that a customer enrolls in the program and then if they respond to a request to temporarily reduce their demand, they receive a payment. They can, of course, reduce demand any way they wish – including simply shutting down equipment – but the strategic discharge of a battery during these periods can allow the customer to respond to the request without impacting their site. It’s worth noting that demand response requests from the utility may or may not perfectly align with when the site would have normally chosen to discharge the battery to mitigate their own peak demand. Revenue from participating in a demand response program appears on the utility bill or other statement depending on the contract.

Ancillary Services / Frequent Regulation

Batteries can be used to stabilize the voltage and frequency of the utility grid. In some markets, private entities can participate in the ancillary service market by bidding to provide services such as frequency regulation to the independent system operator. Then if their bid is accepted and they are called upon to provide support, they receive a payment based upon successfully responding. The rules surrounding participation in ancillary services markets are complex and vary regionally as the market is continually evolving, but this can be a significant revenue stream for batteries, particularly those in utility-scale systems.

Transmission and Distribution Feeder Upgrade Deferral
Utilities spend significant funds upgrading substations and distribution lines to insure that they are able to meet the peak demand for electricity. Interestingly, this peak demand may only exist for a few hours per year. Strategically located batteries may be able to actually reduce this peak demand, thus saving the utility money by allowing them to defer upgrading substations or lines. Furthermore, the batteries may only be needed for this utility-sided peak load reduction a few hours per year, allowing them to be used for other applications during the remainder of the time. As should be expected, this revenue stream is typically only available to clients in specific locations and requires significant cooperation with the utility.

Resiliency / Energy Security / Backup Power
Perhaps the most traditional use of battery energy storage has been to provide backup power to critical loads during short or extended grid outages. In this application, batteries help the site avoid losses, perhaps from missed sales or from the spoilage of product, that would have otherwise occurred. Calculating the value of these avoided losses can be challenging and requires stochastic analysis to quantify the probability of a grid outage and its duration, as well as the critical load and the state of charge of the battery at the time of the outage, particularly if the battery system is also serving other applications throughout the year. For these reasons, assigning a monetary value to the resiliency benefit is difficult and often omitted in techno-economic analysis of battery energy storage systems.

Revenue Stream Stacking
Many of these applications do not utilize the battery continuously, but rather for short periods every day, or in some cases, for a few periods throughout the year. This underutilization of the battery can be a hindrance to developing economically viable projects. As a result, there is considerable interest in serving secondary applications during periods where the battery would otherwise sit idle. Drawing revenue from such stacked revenue streams can then push a potential project into the realm of viability.

The Revenue Stacking Challenge
Batteries can derive revenue by serving several applications over the course of a year. The challenge then is to determine which ones the battery should serve, when it should serve them, and how large the battery should be, all such that the net present value of the project are maximized. This is a difficult problem.

During the planning phase of a project, it is generally necessary to model at least one year of operation such that all of the seasonal and diurnal effects can be appropriately represented. Since it is common for utilities to measure peak demand on 15-minute increments, it is generally necessary for models considering demand charge reduction as a possible revenue stream to also use 15-minute timesteps, of which there are 35,040 in a year. Even the simplest battery dispatch model needs to decide whether to charge or discharge the battery (or do nothing) during every time period. Implicitly, this results in a problem with over 70,000 decision variables.

We believe that problems of this type are well suited to formal mathematical optimization models, either in the form of linear programs or mixed-integer linear programs and there are a number of these in the literature [1,2,3]. The model that we discuss is unique in that it focuses specifically on optimizing the sizing and dispatching of battery energy storage.

Model Description
Determining the sizing, configuration, and dispatching of a battery project that maximizes the economic return of a project is a challenging task. Not only does the power and energy rating of the battery need to be determined, but the dispatch strategy, e.g. how the battery will be used, needs to be projected. A formal mathematical optimization model is well suited to this task due to the sheer number of decision variables.

Our techno-economic model discussed here is comprised of a series of equations and constraints that represent how a site uses electricity. The fundamental constraint for behind-the-meter applications is that the electrical load must be met during every timestep of the analysis period from some combination of purchases from the grid or discharges from battery energy storage.

The objective of the model is to maximize the net present value (NPV) of the project by considering all potential revenue streams, as well as capital and operating costs of the battery storage systems over the life cycle of the project. Revenues may include avoided utility costs, avoided losses due to grid outages, or payments received from providing services to the grid operator. In the end, the expectation is that every cost or revenue related to energy at the site is included.

Advanced Grid Module

For behind-the-meter applications such as demand charge reduction, energy arbitrage, and demand response, interaction with the utility grid is essential. Therefore, the model needs to have a detailed representation of the true costs of obtaining electricity from the grid in order to accurately value the costs that are displaced by installing batteries.

The electrical grid in our model is generally assumed to be an ideal source of electricity, which is to say the model can, by default, choose to buy as much power from the grid during each time period as it wants. There is no capital or O&M costs associated with the grid while the operating costs are dictated by the prevailing tariff structure of the local utility. These tariff structures can be quite complex, and are one of the key drivers for the adoption of battery energy storage. Therefore, it is critical to model them with as high of fidelity as possible.

The two key components of most utility bills are volumetric energy charges (per kilowatt-hour) and demand charges (per kilowatt) and both are included in the model. The cost of electricity may vary over the course of a day (or year) in the case of time-of-use energy rates or may be tiered indicating that a customer pays a given rate for the first block of energy but then bumps up (or down) for the next block.

The more common demand charges are simple monthly, time-of-use, or a combination of the two, and can all be included in the model. We also include lookback ratchets if they exist, again with the goal of capturing all of the features of the tariff so that the model has an accurate depiction of how electricity is billed at the site.

We generally assume that the grid is 100% reliable by default, meaning that it can supply an infinite amount of electricity in any time period. For resiliency analysis, however, we can inject random grid “failures” into the model to evaluate the battery’s ability to sustain outages, though that type of analysis is beyond the scope of this paper.

Battery Storage Module

Battery storage in our model can be thought of as a bucket that moves energy from one time period to another. The task of the model then is to determine the size of the bucket, as well as when to fill and empty the bucket to maximize the economic return of the project.

In our model, the battery is sized along two dimensions, power and energy, with the power limiting the rate at which it can charge and discharge, and the energy determining its capacity. The round-trip efficiency can be specified representing the loss of energy through the charge / discharge process.

Our bucket model of battery energy storage is mostly technology and chemistry agnostic and instead focused on the bulk energy transfer from one time period to another; the details of how the battery performs are beyond the scope of a techno-economic model such as this, and, in our experience, the effects are not particularly significant when performing an analysis at 15-minute intervals. That said, we attempt to capture the main characteristic of types of batteries as much as possible. For example, we may set a 25% minimum state of charge when modeling Lithium Ion batteries, while a flow battery may be allowed to completely discharge without concern for damaging the battery.

The power and energy aspects of the battery can be sized (and costed) independently, allowing the model to determine the optimal configuration given the characteristics of the load profile and the tariff structure. This requires a cost per kilowatt-hour for the energy and a cost per kilowatt for the power electronics which allows the model to analytically determine the best mix of power and energy, given the load profile and prevailing tariff structure at the site. Put another way, this allows the model to only buy the components it needs, rather than being forced to purchase capabilities that will not be used.

This independent sizing feature is particularly applicable for flow batteries where the energy capacity can be scaled almost limitlessly by increasing the size of the tank and the amount of solution. For solid state batteries, there may be more discrete energy-to-power ratios, but since these can vary among vendors, it can still be illustrative to understand the design space when considering a battery project. We can, of course, also fix the energy-to-power ratio when analyzing the viability of specific products.

The capital cost of the battery, including both capacity and power, represents the installed cost of the system, and should reflect the total price that the customer would pay including equipment, engineering, and permitting. If the power and energy are sized independently, a unit cost for each characteristic is necessary. If, for example, a 3-hour battery is being considered, then the energy-to-power ratio is fixed and a simple cost per kilowatt-hour of the battery is sufficient.

Modeling battery degradation can be challenging and is often assumed to be driven by a combination of two factors, age and use. Depending on the technology, throughput and cycling characteristics of the battery can lead to capacity fade. Depth of discharge also plays a role. Even when batteries are not used at all, they may still suffer capacity fade as they age.

For behind-the-meter applications, we generally start by assuming that battery fade will be dominated by calendar life degradation which is often specified by the manufacturer. We then verify that this assumption is valid by examining the dispatch strategy recommended by the model. For pure frequency regulation applications, a cycling-based model of degradation may be more appropriate.

Battery Dispatch Strategy

A key benefit of using a mathematical optimization model as compared to a simulation based approach is that we do not need to explicitly program any particular dispatch strategy a priori. Instead, we can let the model determine the optimal dispatch for each time period that maximizes the NPV of the project. This means that the operation of the battery and even the application being served can vary from day-to-day or even hour-to-hour to maximize the economic return, subject to any operating constraints and / or rules governing the various energy markets.

Mathematical optimization models such as this are basically omniscient, meaning they have perfect knowledge of the past and fewer electrical loads at the site. This means that they can see, with perfect accuracy, when a load spike is coming such that it can have the batteries properly charged to mitigate it. Similarly, the model can know with complete confidence when the load will tail off at the end of the day such that it can achieve the maximum amount of demand reduction given the capacity of the battery.

Clearly real-time controllers do not have perfect prediction of future electrical loads and weather patterns as there will always be a degree of randomness to even the best forecast. That said, we think using a perfect prediction model during the planning and design phase is appropriate for it gives a best bound scenario around which to evaluate the project. If the project is not viable under a perfect dispatching scenario, then it clearly will not be viable under real world conditions. There are also ways to make the model less aggressive with its dispatching by, for example, setting a slightly higher than required minimum state-of-charge on the battery such that it has a reserve should the load not drop as fast as predicted late in the day.

Case Study: An Office Complex in Southern California

In this section, we will use the model to analyze the techno-economic potential for battery energy storage at an office complex in greater Los Angeles. There are two applications available to the battery at this site, demand charge management and energy arbitrage. We therefore are using the model to simultaneously

- Optimize the size of the battery in both energy and power
- Optimize dispatching of the battery by deciding when to peak shave and when to arbitrage
- Optimize the target demand level for each demand period

Site Overview

The office is served by Southern California Edison (SCE). With permission from the owner, we obtained the 15-minute electrical load profile for the preceding twelve months from the utility. Figure 1 shows the load profile for a week in July. The site has significantly lower peaks on the weekends than during the week.

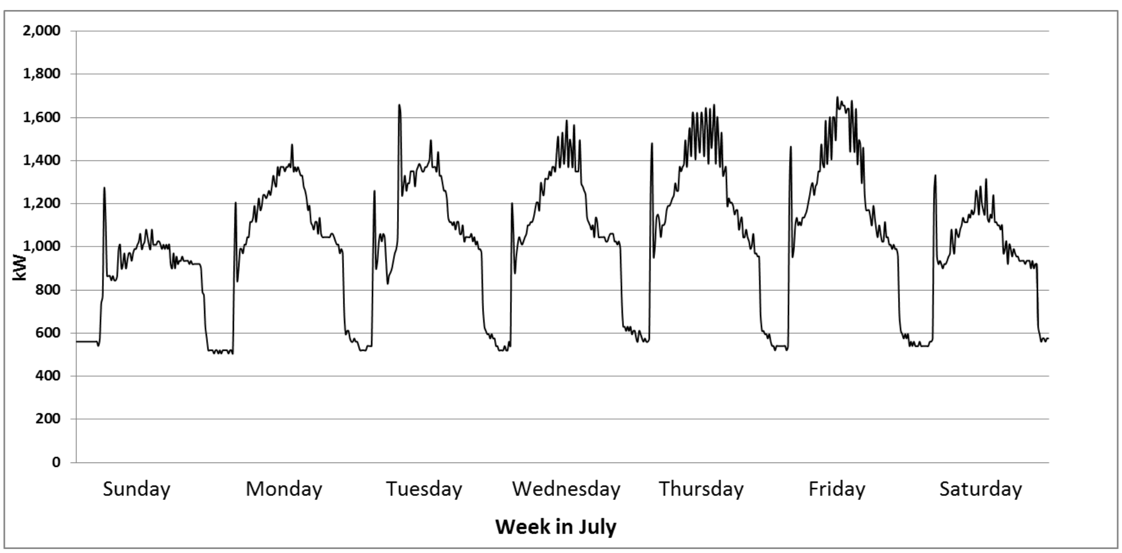

Figure 1. Office complex electrical load profile for one week in July.

The office building is on the SCE Time-of-use General Service 3 (TOU GS 3) Option B tariff which is a very complex rate structure that includes both variable energy charges and complex demand charges [4]. The primary demand charge is a simple monthly demand, which SCE refers to as a facilities demand charge, that applies to the peak demand for each month. Then during the summer months (June-September), there are TOU demand charges layered on top of this monthly demand charge, specifically a peak demand charge that applies during the afternoon and a part-peak demand charge that applies during the morning and evening hours. Each period also has a different TOU energy rate, such that nighttime consumption of electricity costs about half what it does during the afternoon hours. Table 1 summarizes the rate tariff.

Table 1. Summary of Rate Tariff for Southern California Edison Time-Of-Use General Service 3

Months	Period	Hours	Demand Charge	Energy Charge
Summer (June-Sept)	Peak	12 PM – 6 PM	$17.43	$0.12
	Mid-peak	8 AM – 12 PM, 6 PM – 9 PM	$3.43	$0.08
	Off-peak	All other hours		$0.06
Winter	Peak	8 AM – 9 PM		$0.07
	Off-peak	All other hours		$0.06
All months			$17.81	

Scenario 1: Optimal Sizing

We used our battery optimization model to determine whether a battery would be cost effective at this site, and if so, what size would maximize the NPV of the project. We used an analysis period of 10 years to effectively correspond to the anticipated lifespan of the battery. We chose to err on the conservative side by assuming electricity rates would remain at their current level for the duration of the analysis period, which is to say the inflation rate was set to 0%.

To start, we allowed the model to independently size the power and energy of the battery. We did this so as to get a feel for the optimal duration of the battery given the characteristics of the load profile and the tariff. This required us to assume an installed cost for both power and energy aspects of the battery. We chose $800 / kW and $300 / kWh – meaning, for example, that a 1 MWh : 250 kW battery would cost $500,000 – based on rough estimates in the space, rather than a quote from a specific vendor. Since tax credits for batteries vary from location to location (and possibly even by the target application), we again chose to be conservative by omitting them from our analysis. We did assume that the owner of the battery was a taxable entity and would be able to depreciate the capital cost of the battery.

For the battery, we assumed a round-trip efficiency of 85% and that only 75% of the energy capacity was usable. We expect this might be representative of a typical lithium ion battery.

The model found that a 473 kWh:310 kW battery would maximize the NPV of the project and would therefore be economically optimal. This is approximately a 1.5-hour battery.

This battery system would be expected to cost $284,000 to install, and then be expected to save $77,000 in utility charges the first year. These savings come largely from reducing the peak demand charges but there are also some minor energy charge savings due to arbitrage opportunities. This results in an NPV of $187,789 or about a 24% internal rate of return. Table 2 summarizes the projected financial performance of the system.

Table 2. Summary of Results	
Battery Size	473 kWh:310 kW
First Year Savings	$76,843
Demand Savings	$75,502
Energy Savings	$1,341
Capital Cost	$284,000
Net Present Value	$187,789
Internal rate of return (IRR)	24%

The vast majority of the utility bill savings from the battery come from demand charge reduction. Figure 2 shows the demand reduction each month. It is worth noting that since the power rating of the battery is 310 kW, that is also the maximum demand reduction that can be achieved for any given demand period. Therefore, any period that achieves a 310 kW demand reduction is maximizing the demand reduction capabilities of the battery. Also note that the peak demand period only exists during the four summer months.

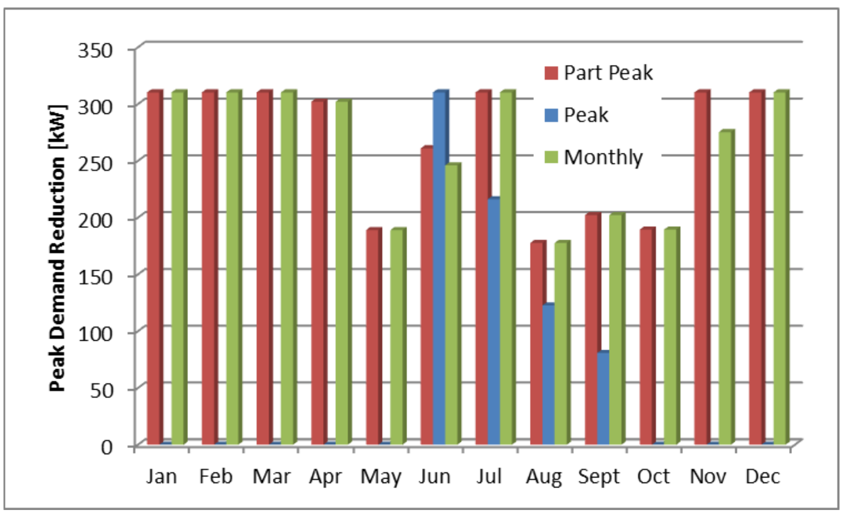

Figure 2. Peak demand reduction for each month and period for the optimal case.

We can translate the demand charge reduction into actual utility bill savings by multiplying the demand reduction from Figure 2 by the peak demand charges from Table 1. These are shown in Figure 3.

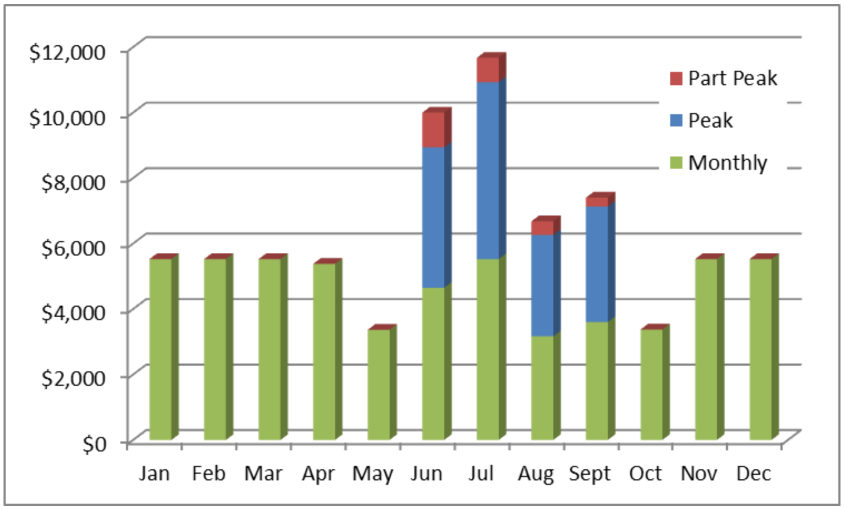

Figure 3. Demand charge savings by month and demand period for the optimal case.

Although peak demand charge savings comprise the vast majority of the battery's revenue, there are also some consumption charge savings. The site actually saves $1,341 in consumption charges despite the fact that it uses more units of electricity than it did before due to the round-trip efficiency of the battery being less than 100%.

We can gain understanding into how the battery is achieving the demand reduction by examining the dispatch of the battery. Figure 4 shows the battery dispatch for July 11, which is a representative weekday for the month. The battery strategically discharges to reduce demand in both the part-peak and peak periods. The horizontal dashed lines show the optimal demand targets for each of the periods which were determined by the model.

A close examination of the dispatch shows that the battery is able to briefly recharge during the part-peak period as the electrical load drops below the demand target. Even though the cost of electricity is higher than during the off-peak period, it is still economically advantageous to do this since the models knows it will be able to use this energy to reduce demand charges later in the day. The battery is then recharged at the start of the off-peak period, which occurs at 11 PM during the summer months.

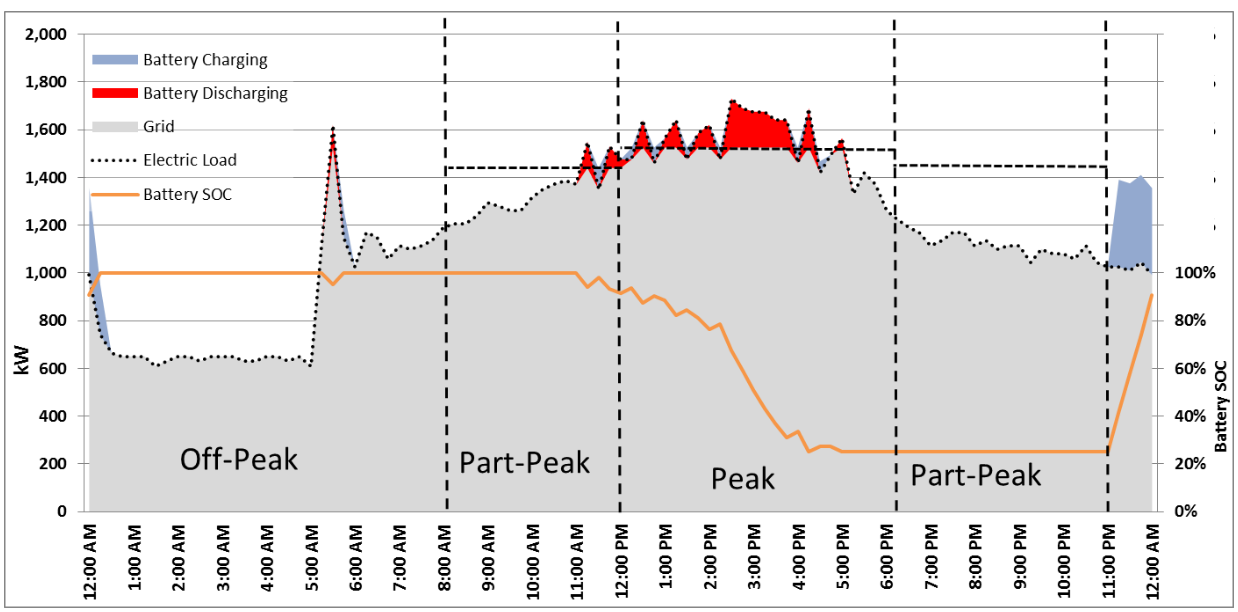

Figure 4. Optimal battery dispatch strategy for Tuesday July 11.

The battery was only serving one application on July 11, as it needed the entire capacity to achieve the demand target level, and that was a more lucrative revenue stream than energy arbitrage. Other days can have different characteristics which cause the model to dispatch differently.

Figure 5 shows the battery dispatch for the following day, July 12. The electrical load on this day has a lower peak compared to the prior day, so the battery is able to meet the demand targets without expending as much energy and does not discharge at all during the part-peak period. As a result, the battery has excess energy at the end of the day which it then discharges to displace expensive electricity during the peak period. This is an example of energy arbitrage since the battery was charged at the cheap off-peak rate and then discharged during the high peak period. The model has therefore determined that on this day it can stack demand charge reduction and energy arbitrage and thus serve two applications.

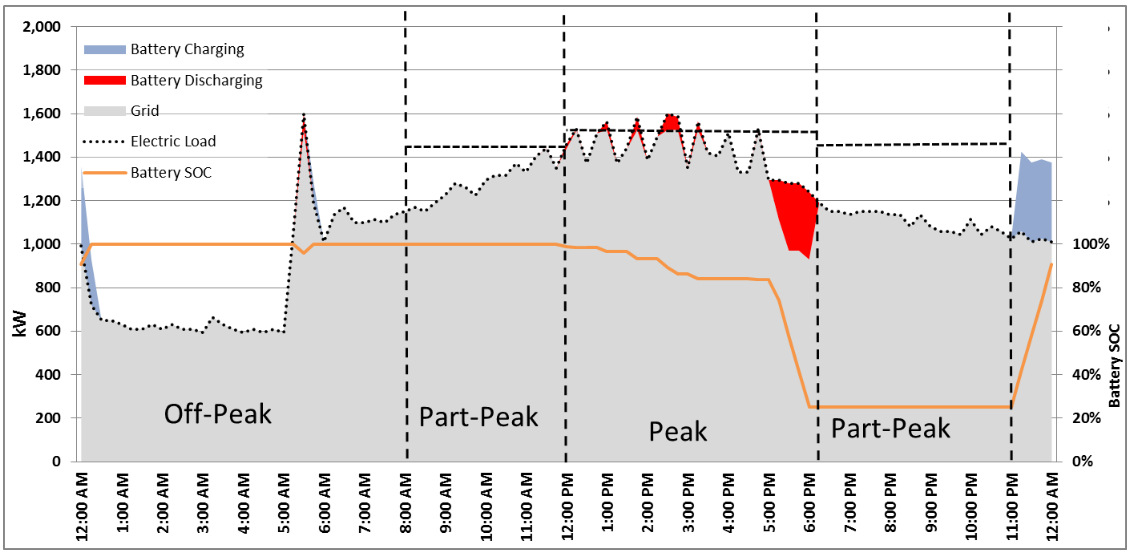

Figure 5. Optimal battery dispatch strategy for Wednesday July 12.

Now that we determined the theoretically optimal battery size, we decided to look at how various suboptimal sizes would impact the economics of the project.

Scenario 2: Restricting The Battery To Have A 4-Hour Duration

Although the model found that a 1.5-hour battery was optimal for the site given the prevailing tariff and load profile, we wanted to examine how the economics changed if we were to instead specify a 4-hour battery given the proliferation of these in the marketplace. We repeated the same analysis, except this time we constrained the model such that it could only choose a 4-hour battery – it would still find the optimal energy capacity, but the energy-to-power ratio would be fixed such that it would always specify a 4-hour battery.

When constrained to choosing a 4-hour battery, the model increased both the power and energy ratings of the system. The NPV naturally is lower – if it was higher, than this would have been the optimal result in the first scenario – and the IRR is also lower. For ease of comparison with the optimal case, the economics of the 4-hour scenario are summarized in the second column of the Table 3.

Table 3. Results for both the optimal and 4-hour battery scenarios		
	Optimal	**4-Hour**
Battery Size	473 kWh:310 kW	1527 kWh:381 kW
First Year Savings	$76,843	$109,724
Demand Savings	$75,502	$105,562
Energy Savings	$1,341	$4,162
Capital Cost	$284,000	$557,011
NPV	$187,789	$117,196
IRR	24%	15%

Although this is the optimal solution when the model is forced to specify a 4-hour battery, it is clearly suboptimal compared to the previous solution. This is because the capital costs of the battery have grown by nearly 100% while the annual savings have grown by only 50%.

We can examine the same set of figures with the new configuration. In Figure 6 we see that in most months, the battery is able to achieve demand reduction equivalent to full rated power of the battery. This is a direct result of the energy-to-power ratio being higher since having more energy available means that it can sustain the power output for a longer period of time.

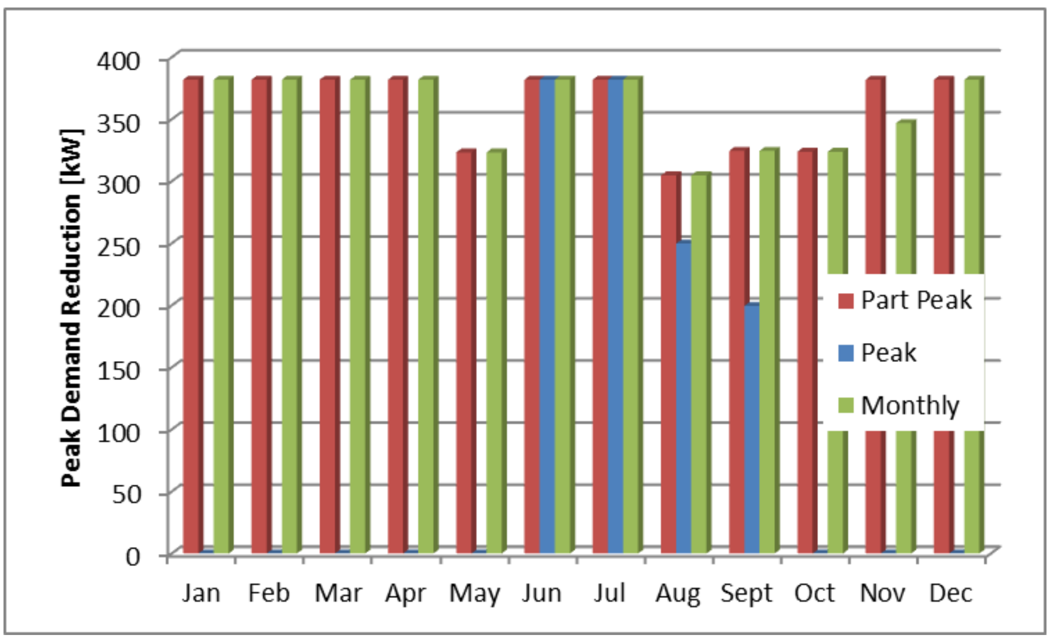

Figure 6. Peak demand reduction for each month and period for the optimal case.

This translates into higher monthly demand charge savings as shown in Figure 7.

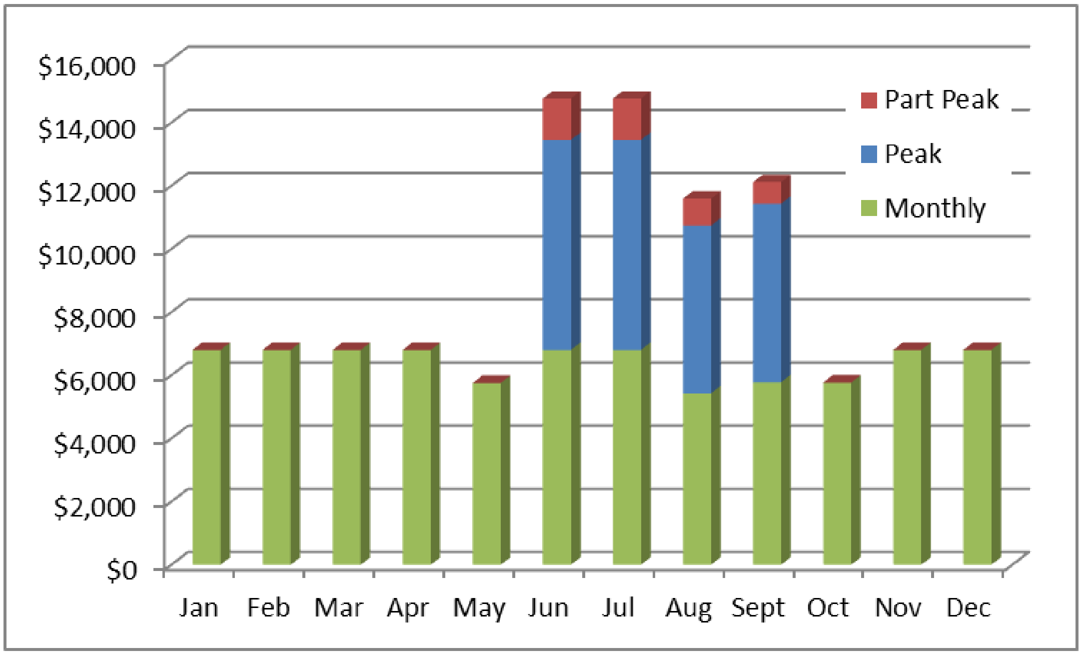

Figure 7. Demand charge savings by month and demand period for the 4-hour case.

The analytics show that the 4-hour battery will achieve greater demand reduction benefits than the 1.5-hour solution. But the benefits are not sufficient to justify the higher cost which leads to a lower overall NPV and rate of return.

The dispatch strategy for the 4-hour scenario is shown in Figures 8 and 9, which depict the same days as Figures 4 and 5 for the 1.5-hour solution. As can be seen, somewhat more demand reduction is achieved with the 4-hour battery, but it requires more and more energy to accomplish it. This is because the period of time that the demand must be shaved becomes longer as more demand reduction is achieved.

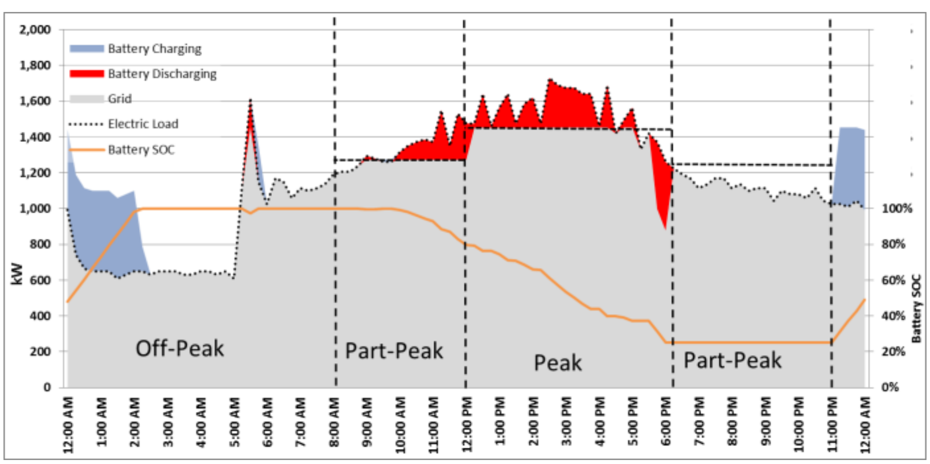

Figure 8. Optimal battery dispatch strategy for Tuesday July 11 (4-hour battery)

On the second day, the battery is able to perform even more energy arbitrage.

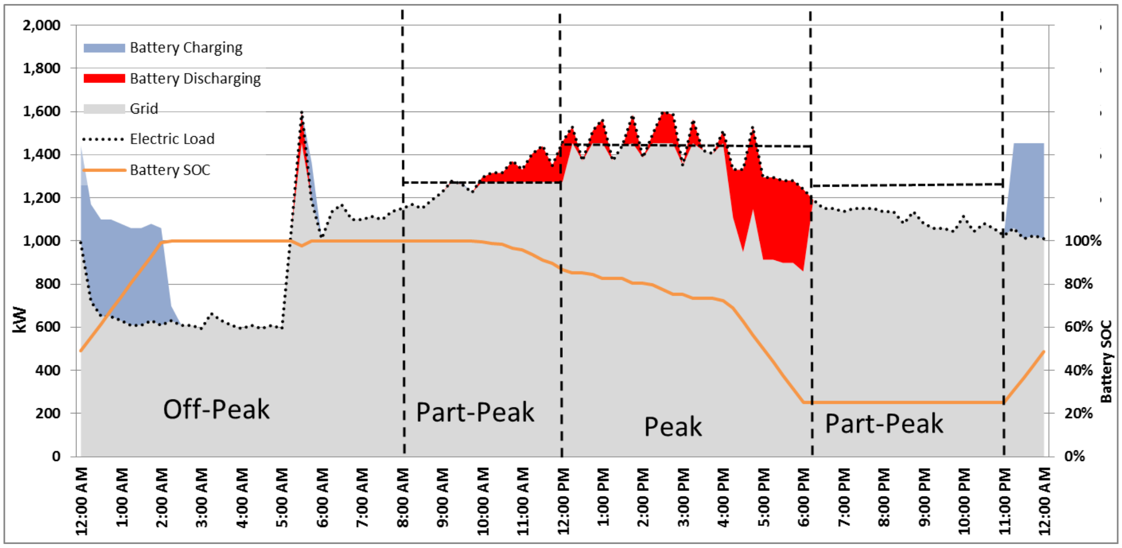

Figure 9. Optimal battery dispatch strategy for Wednesday July 12 (4-hour battery)

As an analogy, imagine using a bulldozer to level the top of a mountain. It is relatively easy to clear a small flat space at the top because not much dirt needs to be moved. But as the summit is excavated further, the flat space gets wider and wider, and more and more dirt needs to be scraped aside. Soon even lowering the height of the hill by a small amount requires a large effort. This is the same effect that batteries face when used for demand charge management – the first few kilowatts of demand reduction come relatively cheaply and have a high economic return, but as the peak gets flatter and flatter, a bigger (e.g. higher energy) battery is required to achieve the same amount of demand reduction.

Discussion

The two scenarios result in two very different energy capacities (473 kWh vs. 1527 kWh). The power ratings of the batteries in the solutions, however, are relatively similar (310 kW vs. 373 kW) and this is the key to understanding the design space of the project.

With this load profile and this prevailing tariff, the model would optimally like to build a battery capable of shaving 300-400 kW of demand and it does so in both scenarios. The nature of the load profile, however, is such that it only requires a modest amount of energy to accomplish this amount of demand reduction. This is because the load profile is "peaky" meaning that it has demand spikes of relatively short duration. The battery then needs the power to mitigate the spike, but since the spike is not all that wide, it does not need to apply the power for a long interval, which is to say it does not need that much energy.

In the first scenario, the model finds that the optimal solution only requires a 1.5-hour battery. In the second scenario, however, the model is constrained to only specifying 4-hour batteries. In this case, the model "reluctantly" adds a lot of energy capacity that it would not otherwise need. In some ways, it is still building a battery with a very similar power rating, it just now has to buy a lot of energy capacity that it does not really want. But since it has to take that energy, it might as well use it as best it can, and to do that, it slightly upsizes the power rating as well. In the end, it is able to perform more demand charge reduction, just not enough to truly justify the added energy capacity, at least as compared to the optimal case in the first scenario.

Again, this result is specific to the electrical load profile, the applications available, the prevailing tariff structure at the site, and the assumed costs of the battery. A less peaky load profile as would likely be found in a hospital may better utilize a longer duration battery. A tariff structure with just a simply monthly demand charge may favor a battery with yet a different energy-to-power ratio. And the existence of a demand response program or allowing the battery to capture value by performing outage mitigation could also drastically change the optimal sizing and dispatching of the battery. The theme, of course, is that optimal battery sizing and dispatching is highly sensitive to the characteristics of the site and that techno-economic modeling is necessary to optimize the system and ensure a favorable economic return.

Summary

Our intent for this paper was to demonstrate the viability of approaching energy storage applications with a mathematical model for providing accurate techno-economic modeling, analytics, and optimization strategies using real world utility and battery data. This capability is critical to the widespread adoption of energy storage systems, and mathematical modeling offers significant advantages compared to just providing specific parameters and assumed battery costs, which has been the typical method up to this point. The case study presented and discussed clearly shows how differences in battery sizing and dispatching can create significantly different economic returns at the same site, and our techno economic model facilitated a clear analysis for improved justification and decision making.

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