Economic Operation of Supercritical CO_2 Refrigeration Energy Storage Technology

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Abstract

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With increasing penetration of intermittent renewable energy resources, improved methods of energy storage are becoming a crucial stepping stone in the path toward a smarter, greener grid. SuperCritical Technologies is a company based in Bremerton, WA that is developing a storage technology that can operate entirely on waste heat, a resource that is otherwise dispelled into the environment. The following research models this storage technology in several electricity spot markets around the US to determine if it is economically viable. A modification to the storage dispatch scheme is then presented which allows the storage unit to increase its profit in real-time markets by taking advantage of extreme price fluctuations. Next, the technology is modeled in combination with an industrial load profile on two different utility rate schedules to determine potential cost savings. The forecast of facility load has a significant impact on savings from the storage dispatch, so an exploration into this relationship is then presented.

Table of Contents

Introduction

One of the main differences between the electricity market and most other economic markets has historically been the inability to store energy. Without a means to store power, generated power must be consumed instantaneously, which results in a constant balancing act of generation and demand and produces often unpredictable price fluctuations. Fortunately, the technology of bulk energy storage is becoming more advanced, allowing grid operators to more easily dispatch energy when and where it is needed.

With increasing penetration of intermittent renewable energy resources, improved methods of energy storage are becoming a crucial stepping stone in the path toward a smarter, greener grid. The benefits of bulk storage include smoother demand with lower peaks and higher troughs, decreased wind curtailment, and more flexibility in dispatch of resources whose availability is hard to predict. There are many energy storage technologies available from thermal to mechanical to chemical, all of which will play a significant role in the future of electricity delivery. The most prevalent form of energy storage is pumped hydropower, which has a global market share of 95%. However, the market for non-hydro forms of energy storage is rapidly expanding, with 284% growth in 2016. The main contributor to this growth is utility-scale lithium-ion batteries [1].

There are two basic categories of energy storage applications: power and energy. Power applications include frequency regulation, ramp rate control, and black-start capability for renewables. These all occur on short timescales, and while the technology analyzed in this paper may be able to provide these types of services, they are beyond the scope of this research. Some energy applications include peak shifting and economic arbitrage, which are the storage applications analyzed in this paper. These applications have storage cycles on the order of minutes to hours and even days.

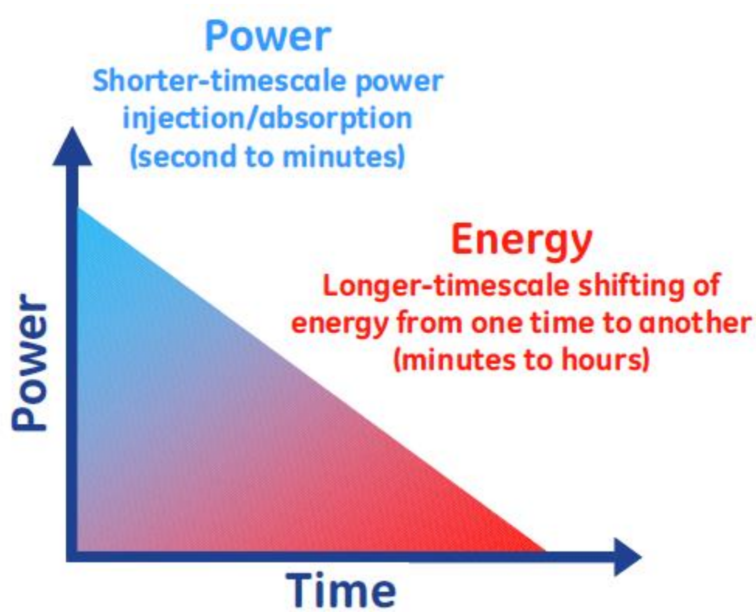

Figure 1: Two basic categories of energy storage applications are power and energy [2].

Energy storage can be very beneficial when used alongside intermittent energy sources such as wind energy. In many geographic areas, wind energy is more abundant at night, when demand is low.

Energy storage allows the extra wind energy during low cost periods to be used during the day when prices and demand are high. New York City and Los Angeles are two large urban centers which could see significant benefit from this storage application. Both cities are tied to numerous remote wind farms through transmission lines which become heavily loaded during the day. Energy storage units situated in the cities can charge at night while the wind is abundant and transmission lines are lightly loaded, and the energy can be used the following day during peak demand periods. Figure 2 shows an example of this peak shaving activity [3].

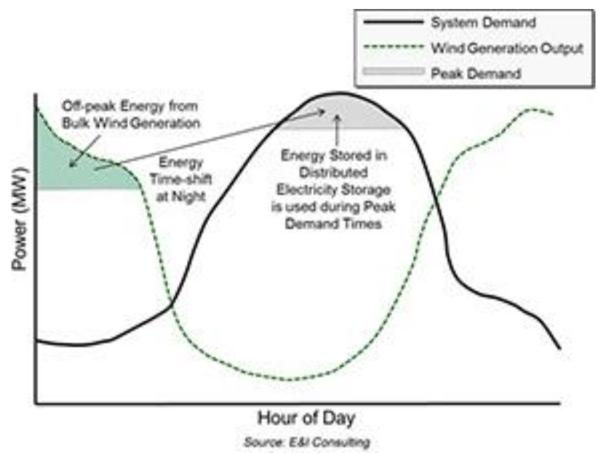

Figure 2: Example of peak shaving with wind energy [3].

While utility-scale solar installations made up most of the installed solar capacity in the past decade, projections show that distributed installations for commercial and residential customers will make up the majority in the coming years (Figure 3). With this trend from concentrated to distributed generation, it is possible that the same may occur with energy storage. One possible development is Community Energy Storage (CES) where small storage units are located within several hundred feet of a few utility customers. This proximity to the customer would improve reliability by allowing the battery to operate as a back-up generator in case of an outage. The batteries could also provide other ancillary support to improve overall grid performance. An example layout of CES is shown in Figure 4.

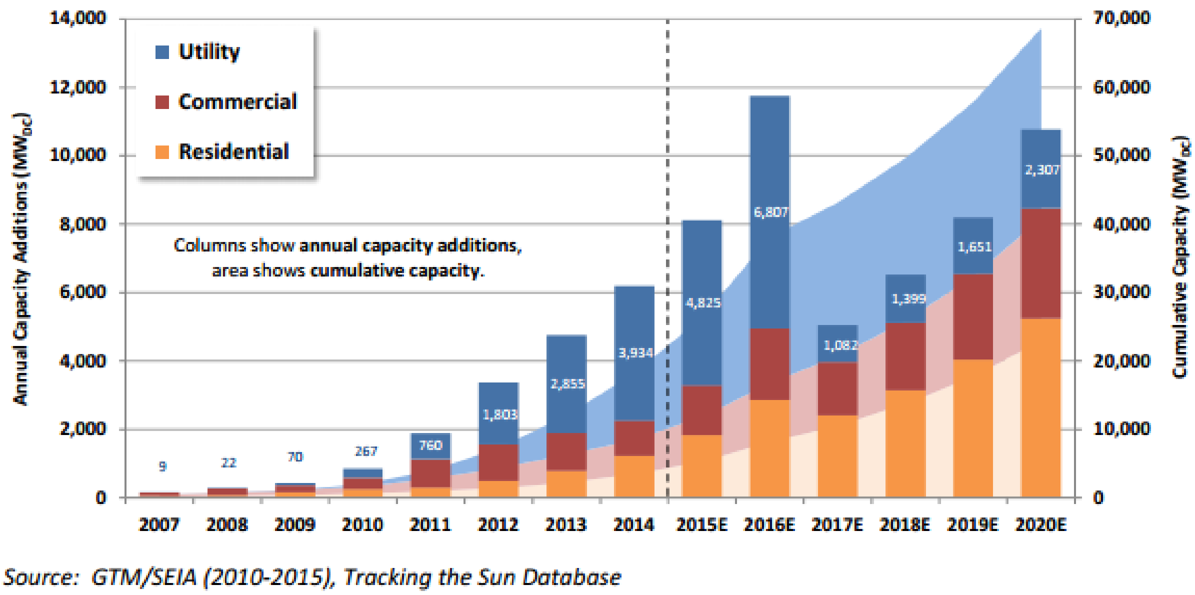

Figure 3: Historical and projected capacity of utility-scale, commercial, and residential solar installations in the United States [4].

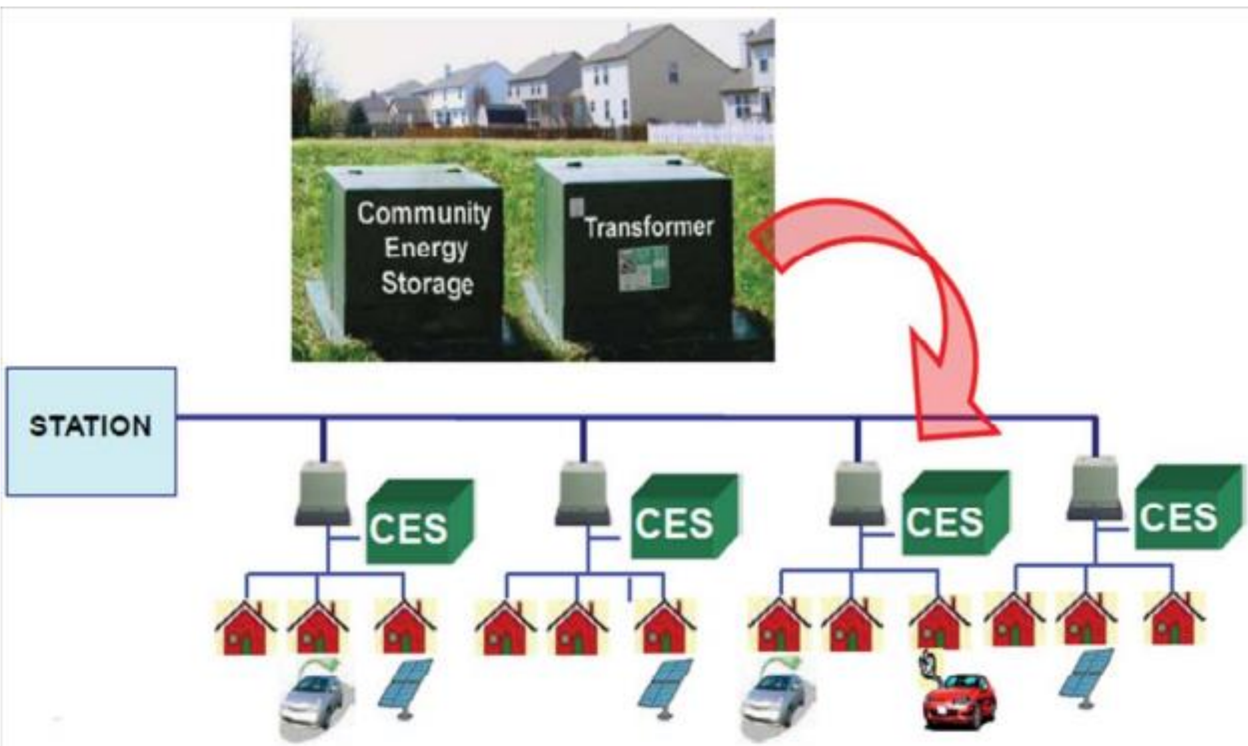

Figure 4: Possible layout of distribution system with Community Energy Storage (CES) [5].

Waste heat recovery (WHR) is the process of capturing excess heat from a separate process to turn into useful work. WHR can be used for a variety of applications including cooling, mechanical work, or power generation. The process of converting waste heat into power is formally called Waste Heat to Power (WHP). WHP requires medium to high temperatures (>120°C) which are typically only available at industrial facilities, so that is where most of the market potential exists. A report prepared for the US

Department of Energy determined in 2015 that the market for potential WHP rivals that of existing wind and solar installations in terms of electricity generated per year [6]. The details of this study are shown in Figure 5.

US Renewable Resource	US Installed Capacity	Average Capacity Factor	Electricity Generated per Year
Wind	69.47 GW	34.0%	207,000 GWh
Solar	22.7 GW	25.9%	51,500 GWh
WHP	15.265 GW (potential, US industrial sector only)	90.0%	120,300 GWh

Figure 5: Market potential of WHP compared to wind and solar in the United States [6].

Model Description

SuperCritical Technologies

SuperCritical Technologies is a company based in Bremerton, WA that is developing a family of modular power generation units called PowerCubes which use supercritical carbon-dioxide (SCO2) as a working fluid. One of the main applications of this technology is waste heat recovery combined with bulk energy storage with ice as the storage medium. The PowerCube uses a valve system to switch between an SCO2 Brayton cycle and an Ice-Rankine cycle. The SCO2 Brayton cycle is used to generate power while the storage unit charges or is idle. The storage is discharged by melting the ice, reconfiguring the unit to a Rankine cycle, which increases the efficiency of waste heat conversion and utilizes the previously stored energy. A conceptual process diagram for the unit is shown in Figure 6.

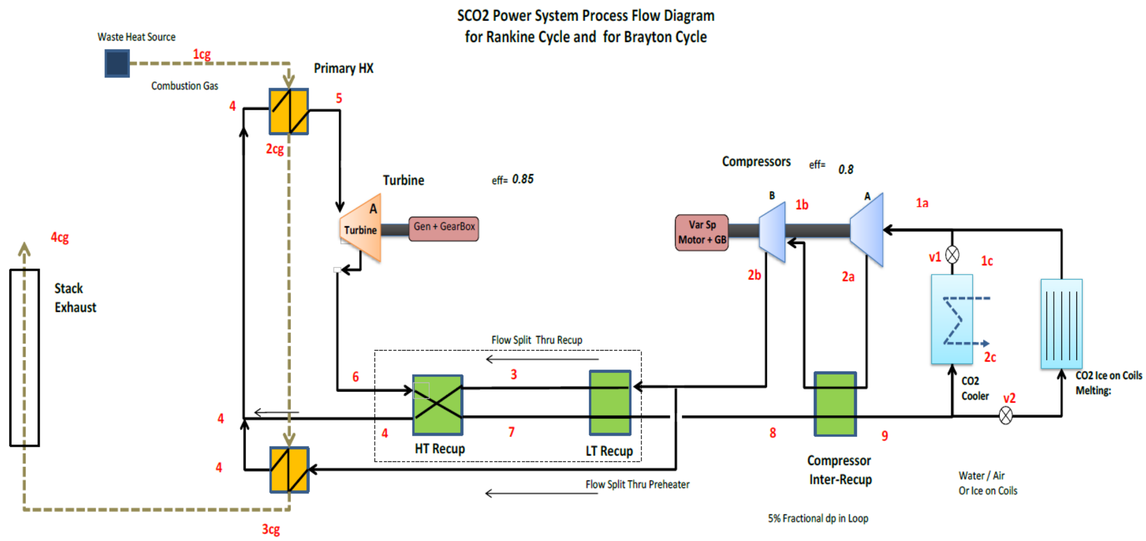

Figure 6: Process flow diagram of a PowerCube unit [7].

The PowerCube unit modeled in this report uses only waste heat that is assumed previously available and has no cost associated with it. Possible sources of this waste heat could be a high temperature manufacturing process such as smelting or the exhaust air from a 25MW gas turbine [7]. The unit has a nominal output of 5.6MW when it is not charging or discharging. The storage unit has a capacity of 20.2MWh, a maximum charge rate of 2.6MW, a maximum discharge rate of 5.2MW, and a round-trip storage efficiency of 71%. These values are extracted directly from [7]. The modeled unit can be in one of the following states during each hour: storing, charging, or discharging. When the unit is storing, its output is 5.6MW and the state of charge remains constant. When the unit is charging, its output is less than 5.6MW and the state of charge increases. When the unit is discharging, its output is greater than 5.6MW and the state of decreases.

An economic analysis was performed for two different PowerCube configurations: one with no storage unit, and one with a storage unit. The financial data used in this analysis was taken from a paper published by SuperCritical Technologies [8] and is summarized in Table 1. The prices are assumed costs and may not reflect actual prices today.

Table 1: Financial data for PowerCube units [8].

	PowerCube without Storage	**PowerCube with Storage**
Capital Cost	$12,700,000	$14,700,000
Loan Term	15 years	
Operating Costs	$500,000 per year	$600,000 per year
Overhaul Frequency	10 years	
Overhaul Cost	$635,000	$735,000
Escalation	3%	
Discount Rate	10%	

Spot Price Model – Profit Maximization

While most power consumers subscribe to a rate schedule set by their local utility, power producers in deregulated electricity markets commonly sell their power to the spot market. The following model was developed to maximize the profit that a PowerCube unit could earn participating on several different electricity spot markets around the United States. The model has hourly time resolution across the entire year of 2016. To simulate a full year, the optimization must be run once for every hour of the year. The model includes constraints on maximum storage capacity, maximum charge rate, and maximum discharge rate. The optimization problem is defined as follows:

$$\max obj = \sum_{t=0}^{tt} p_t^r * g_t^r + \sum_{t=tt+1}^{T} p_t^e * g_t^r + \sum_{t=0}^{T} (p_t^d * g_t^d - b_t^u - b_t^l)$$

$$if\ s_t \geq b^u\ then\ b_t^u = \varphi^u\ else\ b_t^u = 0$$

$$if\ s_t \leq b^l\ then\ b_t^l = \varphi^l\ else\ b_t^l = 0$$

$$\begin{aligned} s.t.\ \ g_t &= g_t^r + g_t^d \\ g_t &= g_t^d - s_t^i + s_t^o * \eta \\ s_t &\leq \bar{s} \\ s_t &= s_{t-1}^i - s_{t-1}^o + s_{t-1} \\ s_t^i &\leq \bar{s}^i * x_t \\ s_t^o &\leq \bar{s}^o * y_t \\ x_t + y_t &\leq 1 \end{aligned}$$

t	Time period.
tt	Dummy variable for iterating across all t.
T	Total number of time periods.
p_t^r	Real-time spot price in $/MWh during time t.
g_t^r	Energy bought or sold on the real-time market in MWh during time t.
p_t^e	Expected real-time spot price in $/MWh during time t.
p_t^d	Day-ahead price in $/MWh during time t.
g_t^d	Energy bought or sold on the day-ahead market in MWh during time t.
b_t^u	Objective function penalty for a state of charge above the upper buffer level in time t.
b_t^l	Objective function penalty for a state of charge below the lower buffer level in time t.
s_t	State of charge in MWh during time t.
b^u	Upper buffer level.

φ^u — Upper buffer penalty amount in $.

b^l — Lower buffer level.

φ^l — Lower buffer penalty amount in $.

g_t — Net output of the unit in MWh during time t.

s_t^i — Storage input in MWh during time t.

s_t^o — Storage output in MWh during time t.

η — Storage round-trip efficiency.

$\bar{s}$ — Storage capacity of the unit in MWh.

$\bar{s}^i$ — Maximum storage input in MWh during one time period.

x_t — Binary variable equal to 1 when the unit is charging and 0 when the unit is not charging.

$\bar{s}^o$ — Maximum storage output in MWh during one time period before efficiency is taken into account.

y_t — Binary variable equal to 1 when the unit is discharging and 0 when the unit is not discharging.

The forecast method used in this model is a simple five-day average of each hour of the day. All storage and output values in time periods before tt are constants set by previous optimizations. Storage and output values in time tt are determined by optimizing across the next 24 time periods using the expected prices for each hour. It is assumed that real-time prices are known at the start of each hour tt.

The PowerCube unit participates in the day-ahead market by committing its nominal capacity in every hour (5.6MW). The day-ahead commitment is constant so it only appears in the objective equation for total profit calculation and has no effect on the real-time market commitment of the unit's storage.

Buffer penalties in the objective function are used to modify how the unit dispatches its storage. The unit has both an upper and lower storage buffer level at which the objective function incurs a penalty. The magnitude of this penalty is determined by the upper and lower storage buffer penalties. Since large pricing variations tend to occur without warning at seemingly random times, imposing a storage buffer ensures that the unit will have a certain amount of storage available to take advantage of these large price swings. Figure 7 shows a visualization of the storage buffers and how the unit's state of charge affects the objective function.

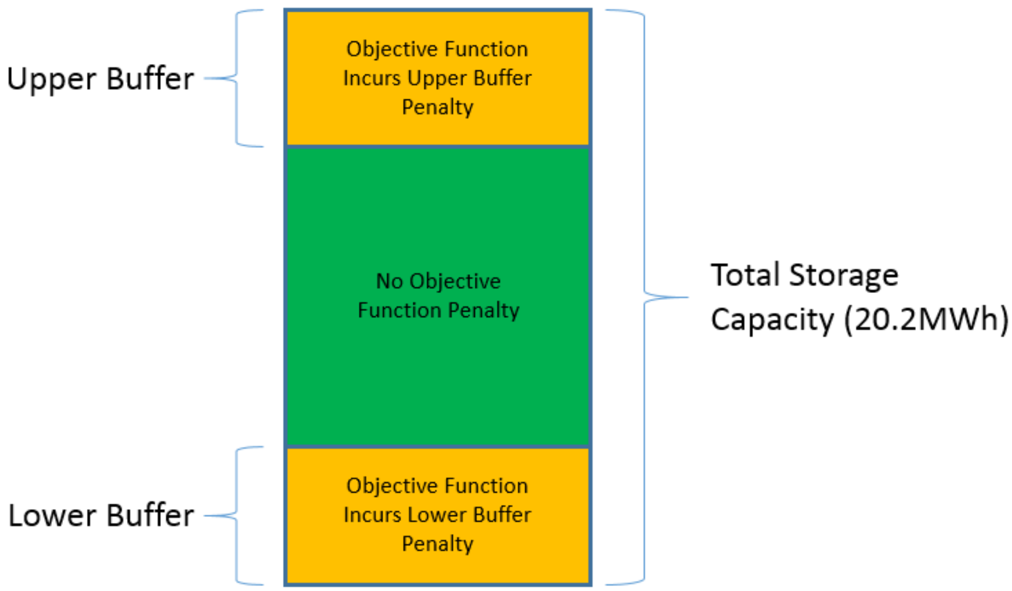

Figure 7: Visualization of the unit's storage capacity with storage buffers imposed.

Pricing data from each ISO was obtained from LCG Consulting's Energy Online database. Each ISO has real-time and day-ahead prices defined in different hubs and zones. The CAISO day-ahead prices were from zone PGAE and the CAISO real-time prices were from hub TH_NP15. ERCOT prices were from zone LZ_HOUSTON. MISO prices were from hub MINN.HUB. NYISO prices were from zone N.Y.C. Data from the year 2016 was used along with the final 120 hours of 2015 for forecasting purposes.

Economic dispatch of bulk storage units has been studied before in various research papers. For example, [9] analyzes the profitability of a compressed air storage unit on real-time prices of Ontario. The optimization problem presented in [9] is similar to the one in this paper, but several different forecast methods are analyzed and compared. It is determined that an adaptive parameter approach which tracks the forecast error and corrects the forecast accordingly is a good approach to capture as much profit from the unit as possible. [9] also analyzes a "back-casting" forecast method which simply uses the previous 24 hours of prices for its forecast, but does not perform as well as the adaptive method. This research uses a form of "back-casting" which is smoother because five previous days are used for the forecast. [9] does not use any form of storage buffers, which are presented in this research.

Another method of storage dispatch on real-time markets is presented in [10], wherein a set profile of charge and discharge levels is linked to specific prices. One of the conclusions presented in [10] is that it is beneficial to operate the battery only during extreme price fluctuations. The storage buffers in this research allow the storage unit to operate during those extreme price fluctuations while still extracting benefit from more modest price changes.

Rate Schedule Model – Cost Minimization

Most residential, commercial, and industrial electricity customers purchase their electricity through a local utility which defines the price of electricity for different customers in rate schedules. The most common charges included in utility rate schedules are energy charges and demand charges. Energy charges are the simplest form of billing for electricity because they are based on the amount of energy (usually measured in kWh) that a customer consumes during a billing period. However, with peak loading becoming a more prominent issue for the grid, utilities have started to put more weight on demand charges. Demand charges are based upon the maximum demand (usually in kW) that the customer reaches during a billing period. Both types of charges often have different components depending on the time of day or whether it is a weekday, holiday, or weekend. Rate schedules also often vary depending on the time of year.

The following model optimizes the dispatch of a PowerCube unit's storage capacity across a month on two different utility rate schedules by minimizing the total cost that the customer would pay at the end of the month. Two months out of the year are modeled, January and July, which are used to estimate the total electricity cost and savings of an industrial customer with a PowerCube unit.

$$\min obj = \bar{d} * \bar{\alpha} + \bar{\bar{d}} * \bar{\bar{\alpha}} + \tilde{d} * \tilde{\alpha} + \sum_t l_t^* * p_t$$

$$\begin{aligned} s.t.\ & l_t^* = l_t + s_t^i - s_t^o * \eta - \gamma \\ & s_t \leq \bar{s} \\ & s_t = s_{t-1}^i - s_{t-1}^o + s_{t-1} \\ & s_t^i \leq \bar{s}^i * x_t \\ & s_t^o \leq \bar{s}^o * y_t \\ & x_t + y_t \leq 1 \end{aligned}$$

$\bar{d}$	Maximum demand across the billing period in MW.
$\bar{\alpha}$	Maximum demand charge in \$/MW.
$\bar{\bar{d}}$	Peak demand across the billing period in MW.
$\bar{\bar{\alpha}}$	Peak demand charge in \$/MW.
$\tilde{d}$	Partial-peak demand across the billing period in MW.
$\tilde{\alpha}$	Partial-peak demand charge in \$/MW.
l_t^*	Facility load during time t after the PowerCube unit generation is subtracted in MWh.
p_t	Price of electricity during time t in \$/MWh.
l_t	Facility load during time t before the PowerCube unit generation is subtracted in MWh.
s_t^i	Storage input in MWh during time t.
s_t^o	Storage output in MWh during time t.
η	Storage round-trip efficiency.
γ	Nominal output of the PowerCube unit in MWh.
s_t	State of charge in MWh during time t.

$\bar{s}$	Storage capacity of the unit in MWh.
$\bar{s}^i$	Maximum storage input in MWh during one time period.
x_t	Binary variable equal to 1 when the unit is charging and 0 when the unit is not charging.
$\bar{s}^o$	Maximum storage output in MWh during one time period before efficiency is taken into account.
y_t	Binary variable equal to 1 when the unit is discharging and 0 when the unit is not discharging.

The load profile used in the rate schedule model was obtained from PG&E's Static Load Profile database. These Static Load Profiles were developed as estimated average consumptions of all customers on each of the PG&E rate schedules. Since the data is an average, it is presumably much less noisy than an actual industrial facility, so a normally distributed random number centered at 0 was added to every hour of load data. Additionally, the load data from PG&E is normalized, so for use in the model all consumptions were multiplied by 30MW, which results in a simulated load profile of a 30MW capacity industrial facility. The random number added to this profile was N(0,0.36) MW.

The performance of a PowerCube unit on utility rate schedules has been investigated before by SuperCritical Technologies in [8]. As expected, it was found that the unit achieves the highest savings when the rate schedule it is subscribed to contains large price fluctuations in peak and off-peak periods. The study in [8] did not consider demand charges, however, which can significantly contribute to a unit's savings.

Most of the other literature which analyzes energy storage dispatch on utility rates schedules is specific to battery technology when combined with either wind or solar. For example, [11] models a lithium-ion battery combined with a PV solar installation on a San Diego Gas & Electric rate schedule for industrial customers. [12] conducts two case studies of lithium-ion battery and PV solar installations on industrial facilities located in Knoxville, TN and Los Angeles, CA. The two methods of dispatch used in [12] are perfect day-ahead forecasting and manual dispatch where the user defines set time periods during which the battery should charge and discharge. The manual dispatch scheme was too simplistic to prove economically viable. In this research, it is found that optimizing dispatch over an accurate load forecast is crucial to minimizing electricity costs.

Rate Schedules

Pacific Gas & Electric - E-20

The first rate schedule modeled was Pacific Gas & Electric's (PG&E) E-20 schedule which provides service "to customers with maximum demands of 1000 kilowatts or more." This schedule includes different pricing for customers at secondary voltage, primary voltage, and transmission voltage. Prices used in the model were from the secondary voltage schedule, which is for customers receiving service from PG&E at voltages less than 2400V.

PG&E defines two different periods in the year as summer and winter. Prices and pricing structure changes between the two periods. Summer occurs between May 1 and October 31 while winter occurs between November 1 and April 30. Prices also vary between weekdays and "Holidays" which include weekends. Peak, partial-peak, and off-peak periods are defined in Table 2.

Table 2: PG&E's peak, partial-peak, and off-peak time periods.

		Peak	**Partial-Peak**	**Off-Peak**
Summer	**Weekday**	12pm to 6pm	8:30am to 12pm AND 6pm to 9:30pm	9:30pm to 8:30am
	Holiday	N/A	N/A	All day
Winter	**Weekday**	N/A	8:30am to 9:30pm	9:30pm to 8:30am
	Holiday	N/A	N/A	All day

The E-20 rate schedule includes standard energy rates which charge the customer per kWh consumed during peak, partial-peak, and off-peak time periods. Demand charges, which are based upon the maximum kW demand during a billing period (i.e. a month), are also included in the schedule. During the summer there are three demand charges: a max demand charge, a peak demand charge, and a partial-peak demand charge. The max demand is the overall maximum demand the customer experiences in the billing period. The peak demand is the maximum demand the customer experiences during peak time periods in the billing period. The partial-peak demand charge is the maximum demand the customer experiences during partial-peak time periods in the billing period.

Virginia Electric & Power - GS-3

The second rate schedule modeled was Virginia Electric & Power's (VE&P) GS-3 rate schedule which provides service to customers "whose peak measured demand has reached or exceeded 500 kW during at least the billing months within the current and previous 11 billing months" with service at secondary voltage. There are two periods defined by the schedule during which the peak hours are slightly different. The first period is June 1 through September 30 when the peak hours are 10am to 10pm. The second period is October 1 through May 31 when the peak hours are 7am to 10pm. Peak hours only occur Monday through Friday regardless of any observed holidays. All other hours are considered off-peak.

Energy and demand charges under the GS-3 rate schedule do not vary throughout the year. There are two energy rates: one for peak periods and one for off-peak periods. There is a max demand charge based on the overall maximum demand experienced by the customer during the billing period and a peak demand charge based on the maximum demand experienced by the customer during peak periods in the billing period.

A summary of the prices included in the two rate schedules is given in Table 3.

Table 3: Rate schedule prices.

Utility	Rate Schedule	Season	Max Demand Charge ($/MW)	Peak Demand Charge ($/MW)	Partial-Peak Demand Charge ($/MW)	Peak Energy Rate ($/MWh)	Off-Peak Energy Rate ($/MWh)	Partial-Peak Energy Rate ($/MWh)
PG&E	E-20	Summer	$15,670	$18,050	$5,010	$144.23	$82.10	$107.38
		Winter	$15,670	N/A	$50	N/A	$88.32	$102.03
VE&P	GS-3	Full Year	$2,760	$18,034	N/A	$25.52	$24.20	N/A

Results

Spot Price Model - Profit Maximization

The spot price model was used to determine an estimate for the annual profit of a PowerCube unit in four different pricing environments from around the US. These estimates are feasible because each hour's optimization used only pricing data from that current hour or previous hours. The annual profit described here only accounts for the net income of the PowerCube unit itself and neglects any capitol or operating costs. Figure 8 shows the total annual profit from both the waste heat recovery and storage. Figure 9 shows only the profit derived from the storage unit buying and selling energy on the real-time market.

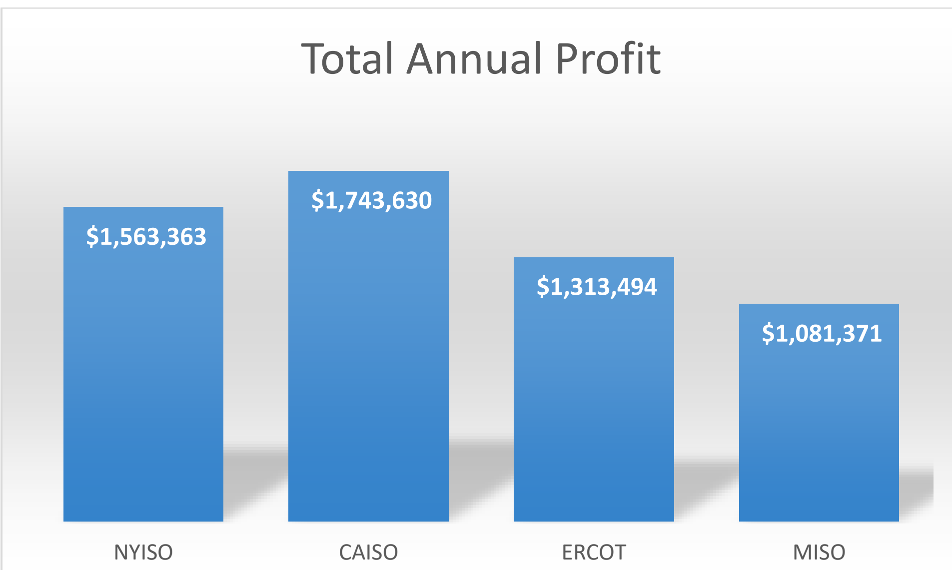

Figure 8: Total profit from PowerCube unit over a year in different ISO pricing environments.

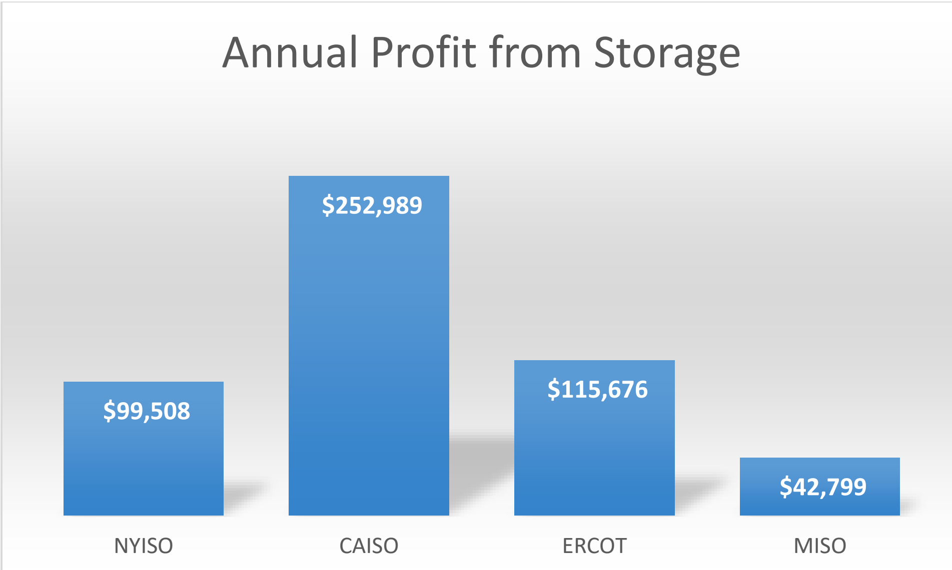

Figure 9: Profit from PowerCube storage over a year in different ISO pricing environments.

The total annual profit of the unit is highly dependent upon the mean price throughout the year. The CAISO data set has the highest mean and the highest total profit. The MISO data set has the lowest mean and the lowest profit. Profit from storage is highly dependent upon the variation in pricing throughout the year. The CAISO data set has a much higher standard deviation than the other sets, and it also has a much higher profit from storage than the other sets. The MISO data set has the lowest standard deviation and also the lowest profit from storage. This trend does not always hold, as the NYISO data set has a higher standard deviation than the ERCOT data set, but the ERCOT set resulted in a higher profit from storage than the NYISO set. Data statistics are shown in Table 4.

Table 4: Statistics of pricing data from each ISO (in $/MWh).

	NYISO	**CAISO**	**ERCOT**	**MISO**
Mean	$29.57	$31.35	$23.73	$20.64
Std. Deviation	$45.53	$77.11	$39.41	$13.21
Maximum	$1653.67	$1040.97	$1383.60	$267.63
Minimum	-$77.64	-$152.58	-$23.18	-$33.51

Using the resulting profits from the spot pricing model, an economic analysis was conducted to determine how long it would take to pay off the PowerCube unit considering loan payments, maintenance costs, and overhaul. Table 5 contains the results of this analysis. While the PowerCube eventually pays itself off in the NYISO and CAISO pricing scenarios, the payback period is at least 20 years. The unit does not achieve enough income to pay itself off for the ERCOT and MISO data sets over the entire 50-year economic analysis.

Table 5: Payback period for the PowerCube unit in each ISO pricing environment.

Data	Payback Period without Storage (years)	Payback Period with Storage (years)
NYISO	23	33
CAISO	22	20
ERCOT	N/A	N/A
MISO	N/A	N/A

Storage Buffers

The above analysis was conducted without storage buffers, which were previously described in the Model Descriptions section. Next, a sensitivity analysis of the buffer parameters for each pricing data set was performed. A set of parameters that approach ideal was extracted from each set of analyses. It was determined early on in the analysis that this problem is non-convex, so determining the optimal parameters must be done iteratively and heuristically, and any maximum found may only be a local maximum. Even without finding the absolute maximum point, the additional profit derived from including the storage buffers makes them an advantageous inclusion in the storage dispatch scheme.

The method used to find a set of parameters approaching the maximum profit was to sweep across each parameter with a wide resolution then sweep across what appeared to be the peak with a higher resolution, if necessary. When sweeping the lower and upper buffer penalties, the penalty not being swept was set to $0 and the buffer levels were set to 2MWh lower and 18.2MWh upper. For the sweep across lower buffer levels, the previously-found best penalty values were used along with 18.2MWh as the upper buffer level. Finally, for the sweep across upper buffer levels, all previously-found best values were used for the penalties and the lower buffer level. If this process were continued, a local maximum might eventually be found. However, since the optimization problem is very large for each individual data point, only one sweep across each parameter was performed in this study.

A summary of results for this analysis of storage buffers is included in Table 6 with detailed results in Appendix 2. It is somewhat counterintuitive that the NYISO data set achieves the highest profit gain when buffers are used since CAISO has a higher standard deviation in pricing. However, it is likely the NYISO data set's high maximum price of $1653.67 that makes the lower buffer so profitable. Alternatively, the MISO data set with its low mean, standard deviation, and maximum predictably achieves the lowest profit increase.

Table 6: Summary of results for including buffers in the storage dispatch scheme.

ISO	Profit from Storage without Buffers	Profit from Storage with Buffers	% Increase
NYISO	$99,508	$132,107	33%
CAISO	$252,989	$291,604	15%
ERCOT	$115,676	$130,454	13%
MISO	$42,799	$47,602	11%

Unfortunately, to achieve the profit increase of Table 6, full knowledge of 2016 prices is required. In order to test the predictability of the buffer parameters, the model was tested for the first three months of 2017 using the CAISO data set and the best buffer parameters from 2016 (b^l = 9MWh, φ^l = \$40, b^u = 19.5MWh, φ^u = \$3). The resulting profit from storage using these parameters was \$80,248, whereas the profit from storage when no buffers were used was \$83,381. This is a 3.8% decrease. This suggests that the ideal buffer parameters can change drastically over time.

To get a sense for how much the ideal buffer parameters change from month to month, each parameter was swept in January and February of 2017 using the CAISO data set. The sweep process was the same as described earlier and was performed only once for each month. In January, the best parameters were b^l = 0MWh, φ^l = \$0, b^u = 18.2MWh, and φ^u = \$10. The resulting profit from storage with these parameters was \$24,365, which is only a 0.2% increase from the resulting profit of storage with no buffers used. Parameter sweeps for the month of January are shown in Figure 10, Figure 11, and Figure 12. The results show that any deviation from the best parameters found would likely result in a decrease of profit from storage relative to the case when no buffers are used.

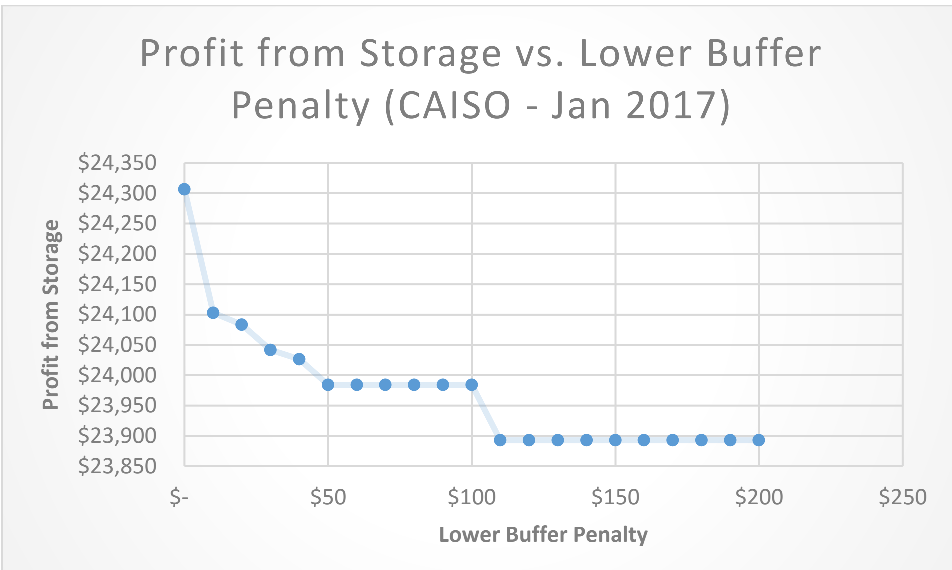

Figure 10: Profit from storage vs. lower buffer penalty with CAISO pricing in January 2017. (b^l = 2MWh, b^u = 18.2MWh, φ^u = \$0)

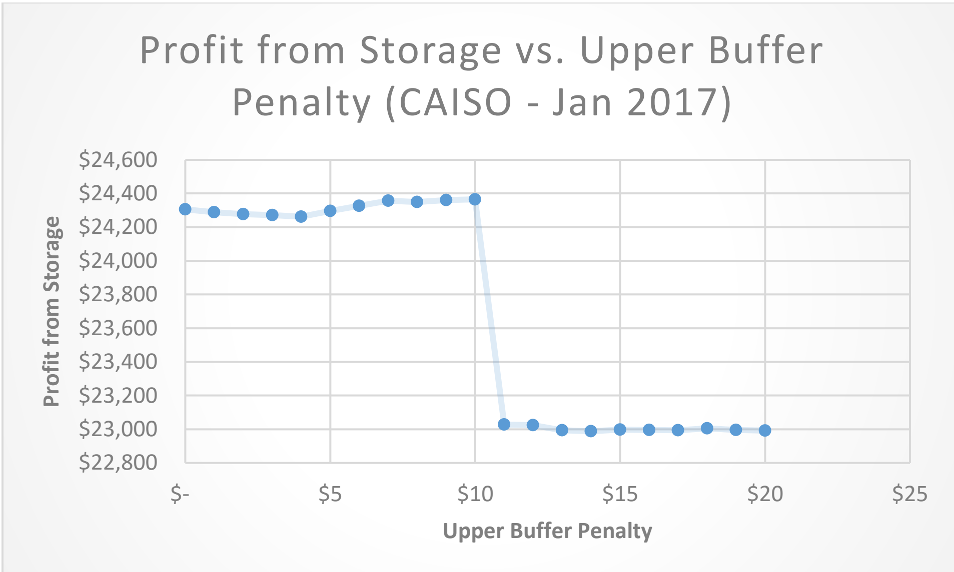

Figure 11: Profit from storage vs. upper buffer penalty with CAISO pricing in January 2017. (b^l = 2MWh, φ^l = $0, b^u = 18.2MWh)

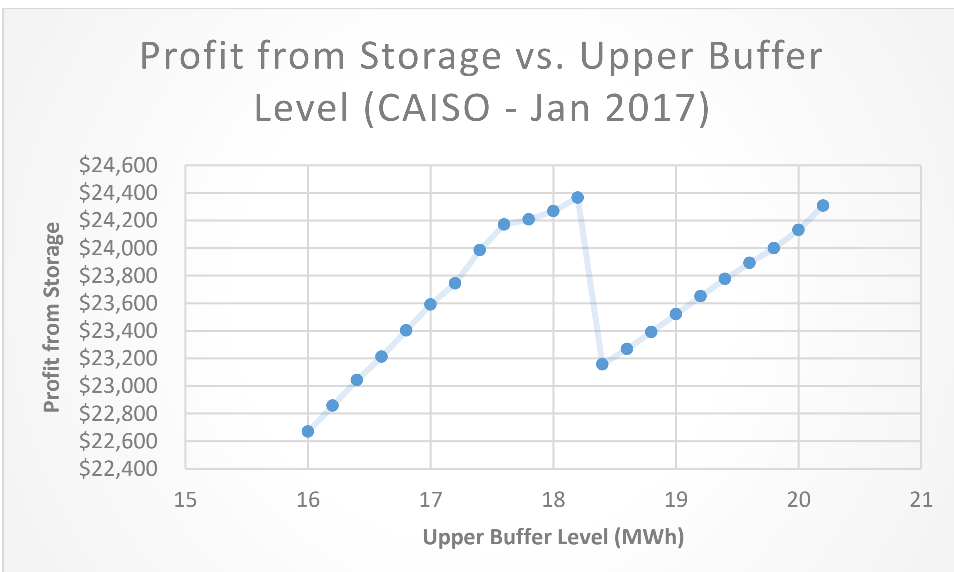

Figure 12: Profit from storage vs. upper buffer level with CAISO pricing in January 2017. (b^l = 0MWh, φ^l = $0, φ^u = $10)

In February, the best parameters were b^l = 2MWh, φ^l = $60, b^u = 16.8MWh, and φ^u = $8. The resulting profit from storage with these parameters was $33,303, which is a 4.6% increase from the resulting profit of storage with no buffers used. Parameter sweeps for the month of February are shown in Figure 13, Figure 14, Figure 15, and Figure 16.

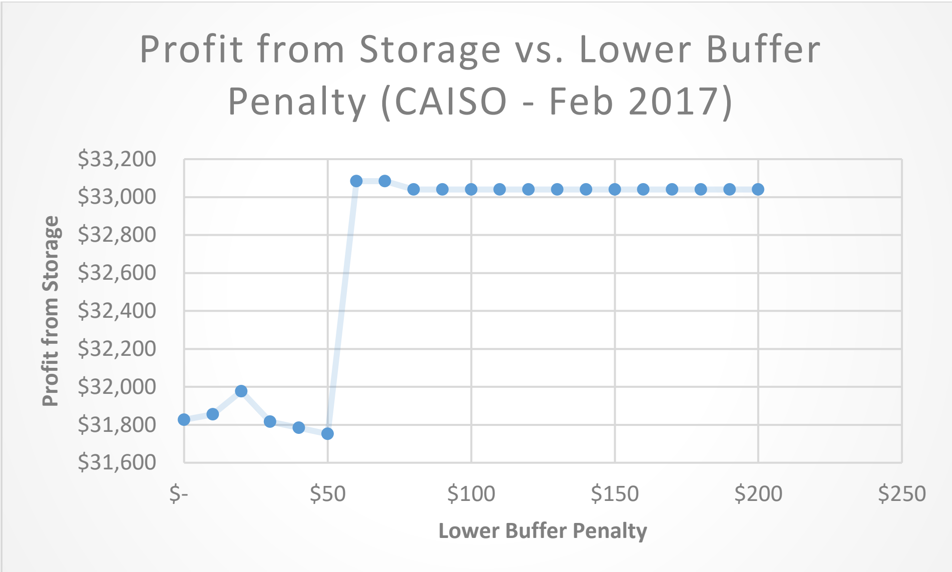

Figure 13: Profit from storage vs. lower buffer penalty with CAISO pricing in February 2017. (b^l = 2MWh, b^u = 18.2MWh, φ^u = $0)

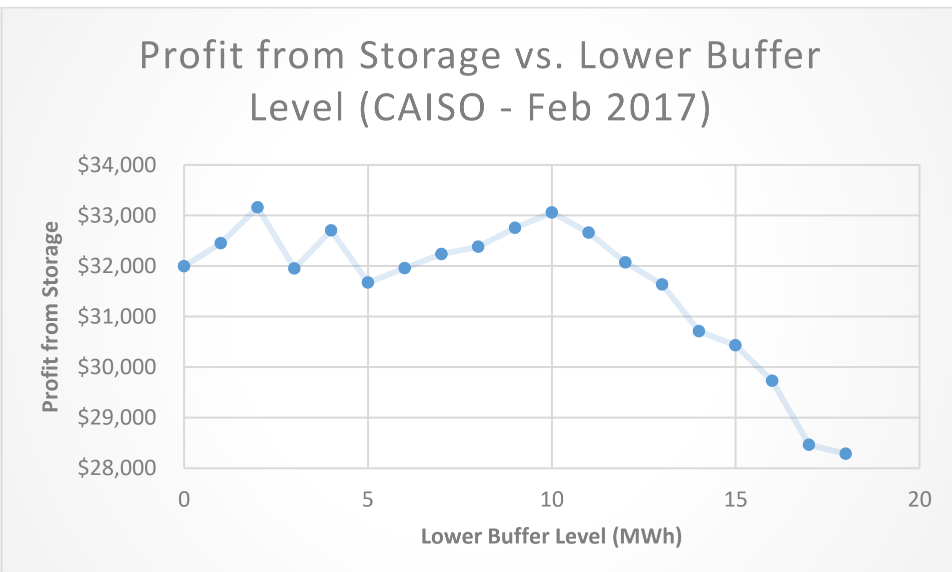

Figure 14: Profit from storage vs. lower buffer level with CAISO pricing in February 2017. (φ^l = $60, b^u = 18.2MWh, φ^u = $8)

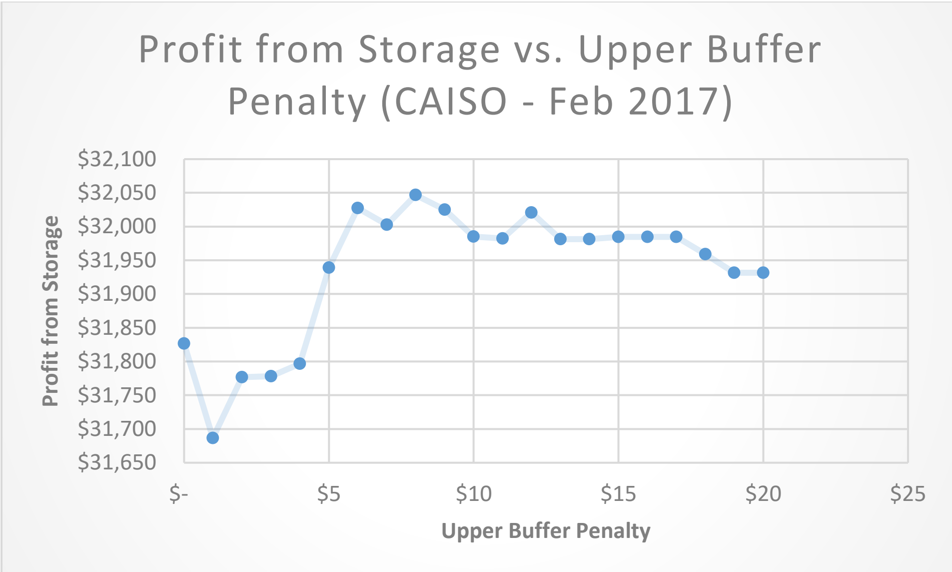

Figure 15: Profit from storage vs. upper buffer penalty with CAISO pricing in February 2017. (b^l = 2MWh, φ^l = \$0, b^u = 18.2MWh)

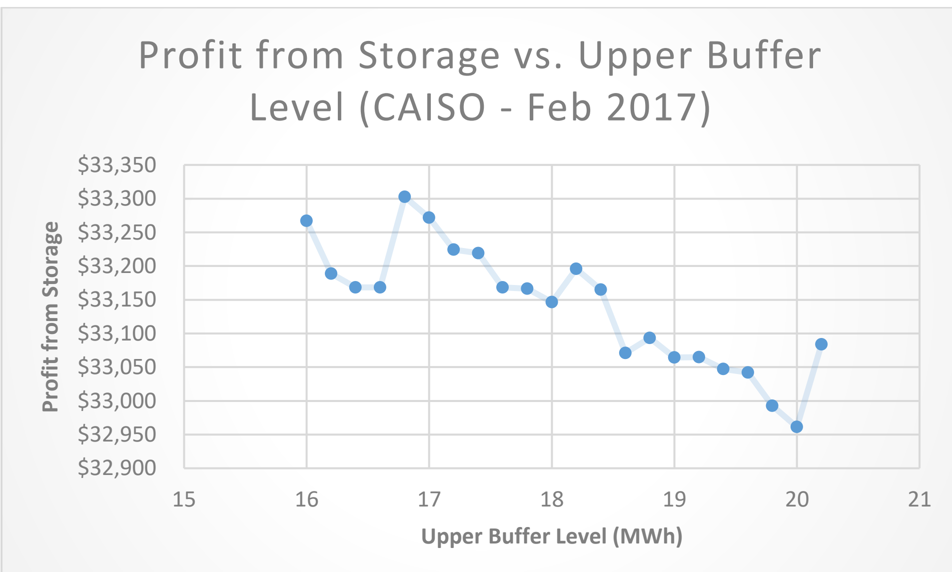

Figure 16: Profit from storage vs. upper buffer level with CAISO pricing in February 2017. (b^l = 2MWh, φ^l = \$60, φ^u = \$8)

Based on the results above, it is unlikely that the buffer parameters can be predicted over short time periods. This raises the question of whether the ideal parameters might be more consistent over longer time periods. To test this, the best buffer parameters from 2016 on the CAISO data set were used in all of 2015. The profit from storage with those buffer parameters was then compared to the profit from storage in 2015 when no buffers were used. The profit from storage increased by 3% when the 2016 buffer parameters were used. While this is a relatively minor benefit, it suggests that there may be a set of buffer parameters that almost guarantees an increased profit from year to year.

To fully visualize the changing benefit of storage buffers in separate years, surface plots of the lower buffer parameters were constructed for 2015 and 2016 on the CAISO data set. These plots are shown in Figure 17 and Figure 18. While the maximum potential benefit of the storage buffers in 2015 is considerably lower than in 2016, the ideal parameters appear to lie around the same values. This is further evidence that it may be possible to predict a good parameter set for the year ahead.

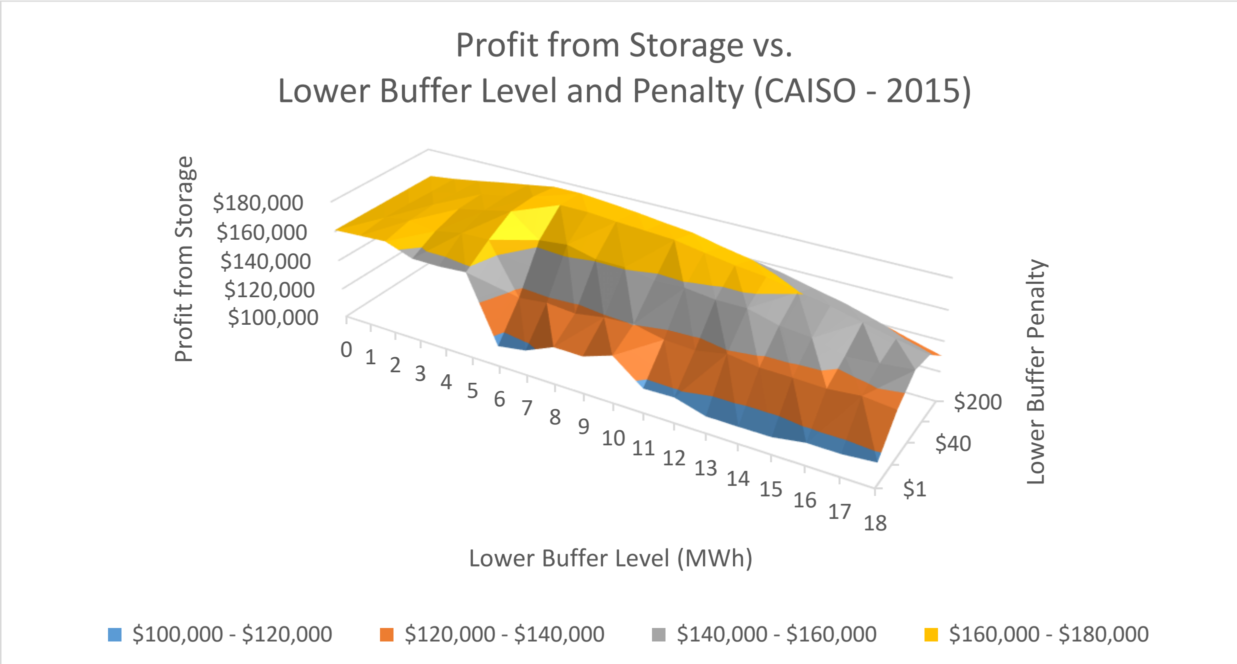

Figure 17: Profit from storage vs. lower buffer level and penalty on the CAISO data set in 2015. (b^u = 18.2MWh, φ^u = $3)

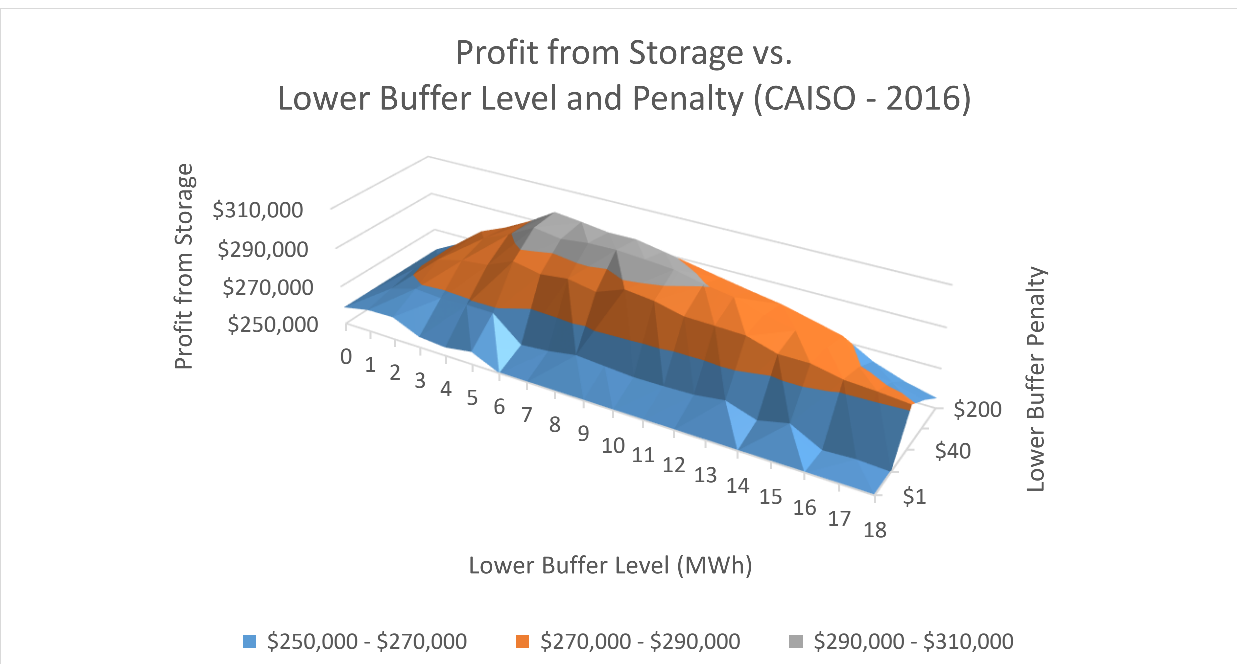

Figure 18: Profit from storage vs. lower buffer level and penalty on the CAISO data set in 2016. (b^u = 18.2MWh, φ^u = $3)

Rate Schedule Model – Cost Minimization

The rate schedule model was used to determine the savings that the PowerCube unit could achieve on two different utility rate schedules. The two rate schedules analyzed were PG&E's E-20, and VE&P's GS-3. Both of these schedules are for large industrial customers. The main challenge of dispatching energy storage on a utility rate schedule is balancing the losses associated with charging and discharging the storage element and ensuring that the storage element has enough energy available to shave the peak load, minimizing demand charges.

The economic results from this analysis are shown in Table 7. The savings achieved on both rate schedules were high enough to offset all annual expenses within the first year. On PG&E's E-20 rate schedule, the unit saved a substantial amount more than on VE&P's GS-3 rate schedule because of the high difference between peak and off-peak energy pricing and the numerous demand charges.

Table 7: Annual savings from the PowerCube unit on two different rate schedules.

Data	Savings without Storage ($)	Savings with Storage ($)	Savings from Storage Only ($)
PG&E E-20	$6,635,761	$7,072,520	$436,759
VE&P GS-3	$2,634,972	$2,822,332	$187,371

An interesting effect is observed when optimizing the storage dispatch on a rate schedule. If the difference between peak and off-peak prices is high enough to offset the round-trip storage efficiency, the unit will almost always fully charge before the peak period of the day in order to maximize its savings on energy arbitrage. This also allows the unit to maximally shave the load peak, which typically occurs within the peak rate period, lowering monthly demand charges as much as possible. Figure 19 is an example of this effect in July on PG&E's E-20 rate schedule.

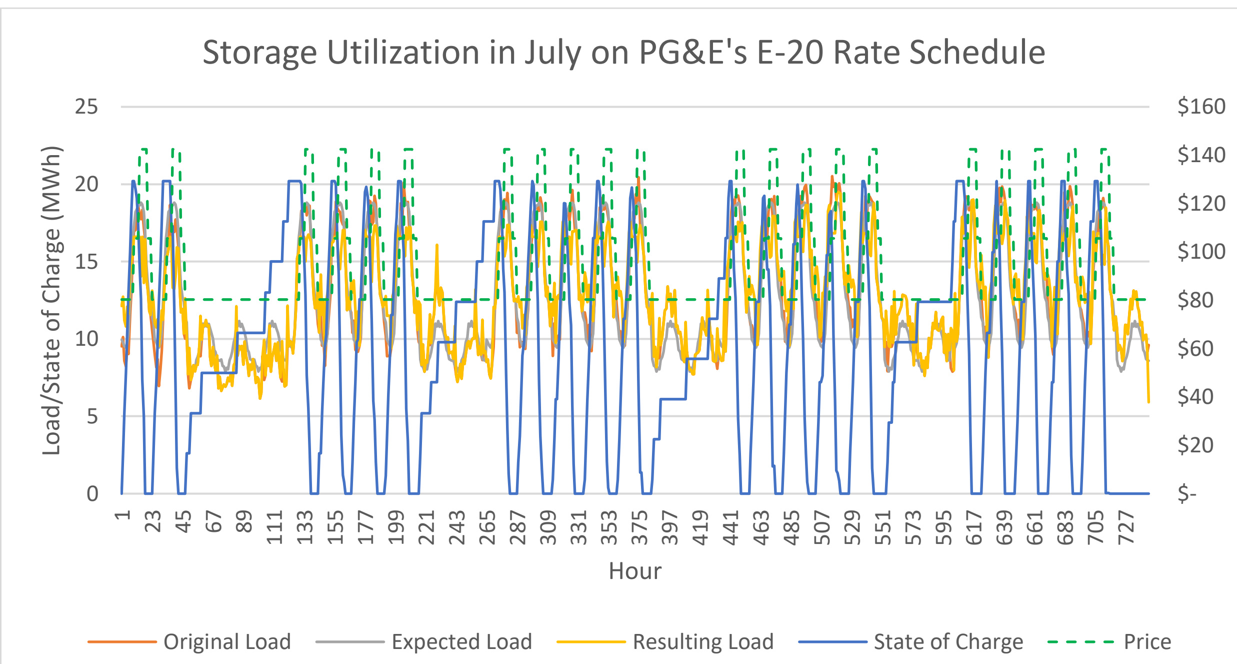

Figure 19: Results of optimal storage dispatch on PG&E's E-20 rate schedule in July.

Alternatively, when the difference between peak and off-peak energy prices is not large enough to make up for the round-trip efficiency of storage, the unit must determine whether the amount of possible peak shaving will make up for the loss incurred from energy arbitrage. An example of how this can negatively affect the monthly savings from storage is shown in Figure 20. At the beginning of the month the unit determines that even though it will lose money on energy arbitrage, it is possible to shave the peak load and decrease the monthly demand charge. On the third peak load day of the month (around hour 133), the unit underestimates a spike in load and the peak demand increases. Since the demand charge is based on the highest peak demand in the entire month, it is only worth it for the unit to shave the remaining peaks to the level of that unexpected spike. The unit proceeds to charge to just over half its storage capacity before the fourth peak day of the month, leaving little energy to shave any unexpected spikes in load. The load does spike during the fourth peak day and the maximum demand jumps even higher than before. This results in the unit only charging up to about 2.5MWh for the next peak period which is hardly enough to do any peak shaving at all. By the middle of the second week of the month, the maximum demand is higher than the forecast so the unit determines that it is not even worth charging.

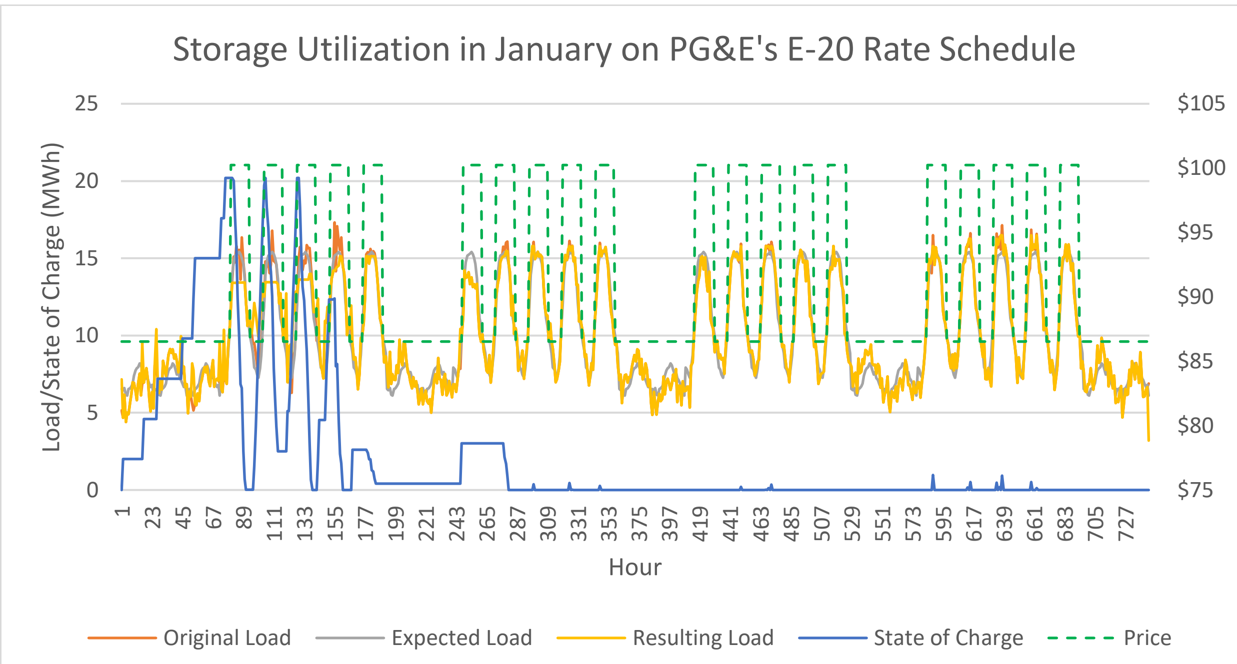

Figure 20: Results of optimal storage dispatch on PG&E's E-20 rate schedule in January.

While PG&E's E-20 rate schedule only causes this debilitating effect during the winter months when energy prices do not vary much, VE&P's GS-3 rate schedule causes it year-round. Figure 21 and Figure 22 show the results of storage dispatch on VE&P's GS-3 rate schedule for July and January, respectively. Both graphs show the unit failing to shave the peak load because of its decision to only partially charge before a peak period.

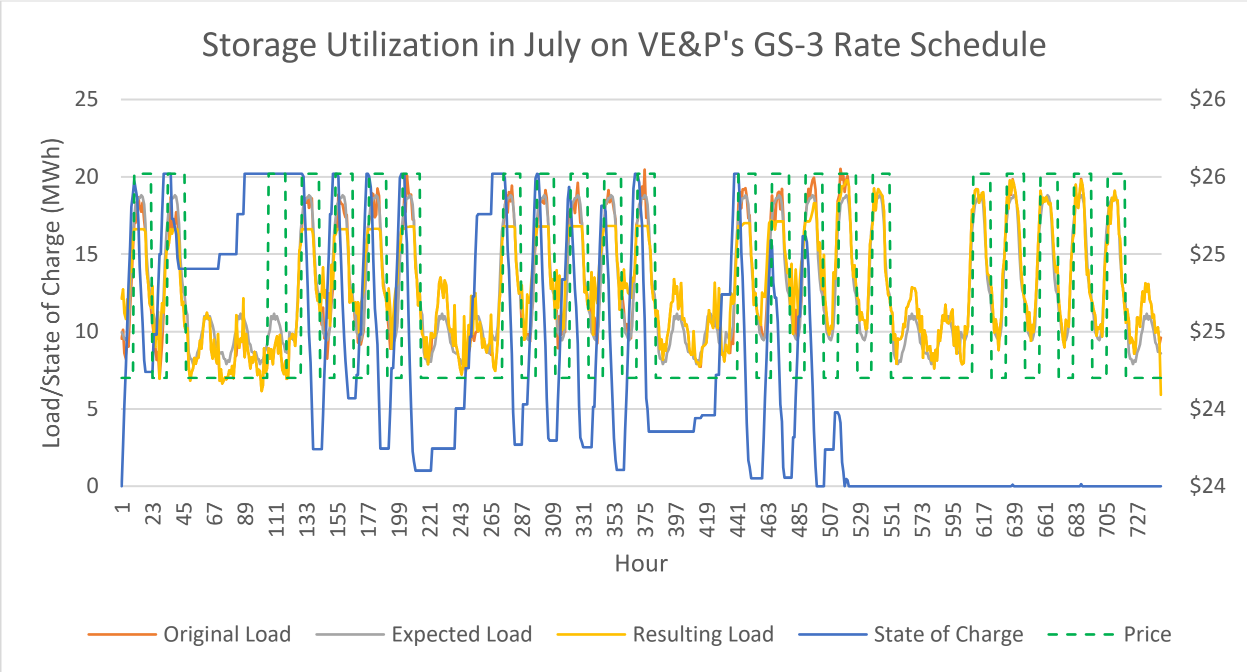

Figure 21: Results of optimal storage dispatch on VE&P's GS-3 rate schedule in July.

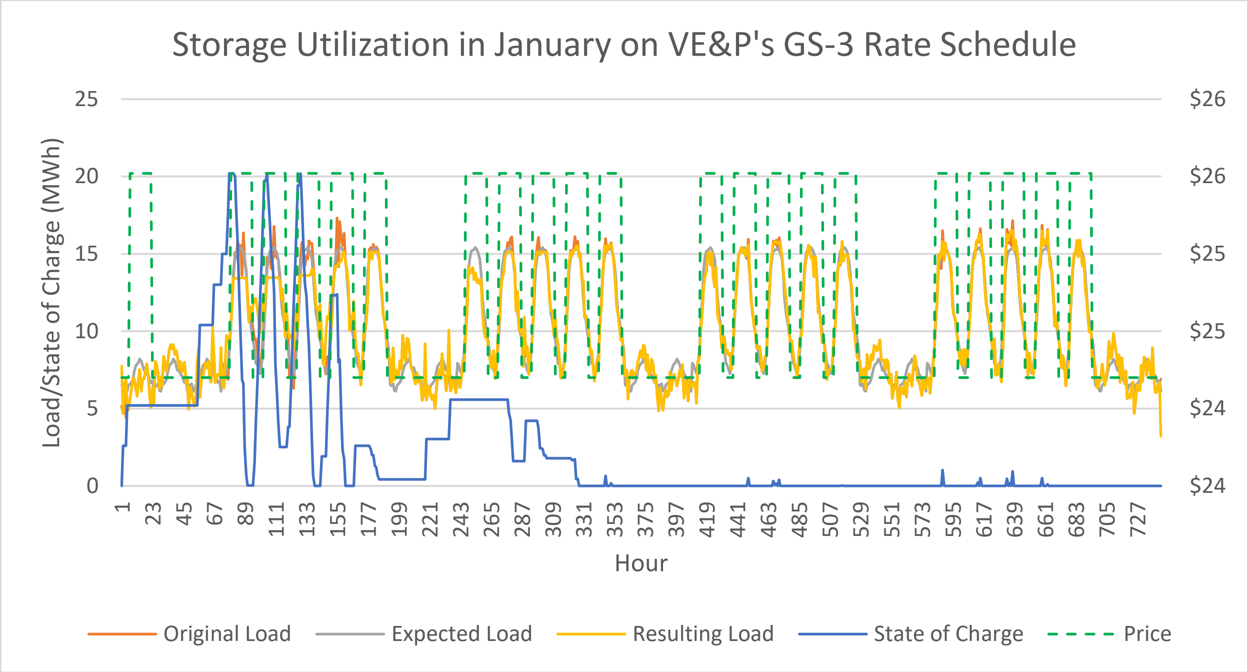

Figure 22: Results of optimal storage dispatch on VE&P's GS-3 rate schedule in January.

The unit's failure to shave the peak demand throughout the month is directly affected by the load forecast. With a perfect load forecast, every peak in the month will be shaved to the same minimized level. The load in this model includes random noise, however, so a perfect forecast is impossible. Instead of attempting to predict random load spikes, the effect of increasing the load forecast on weekdays was analyzed. Figure 23 shows the results of increasing the weekday load forecast by various MWh amounts. When the weekday load forecast is increased by just under 1MWh above average, the savings from storage increase by 255% for the month. If the load forecast is too high, the savings begin to diminish.

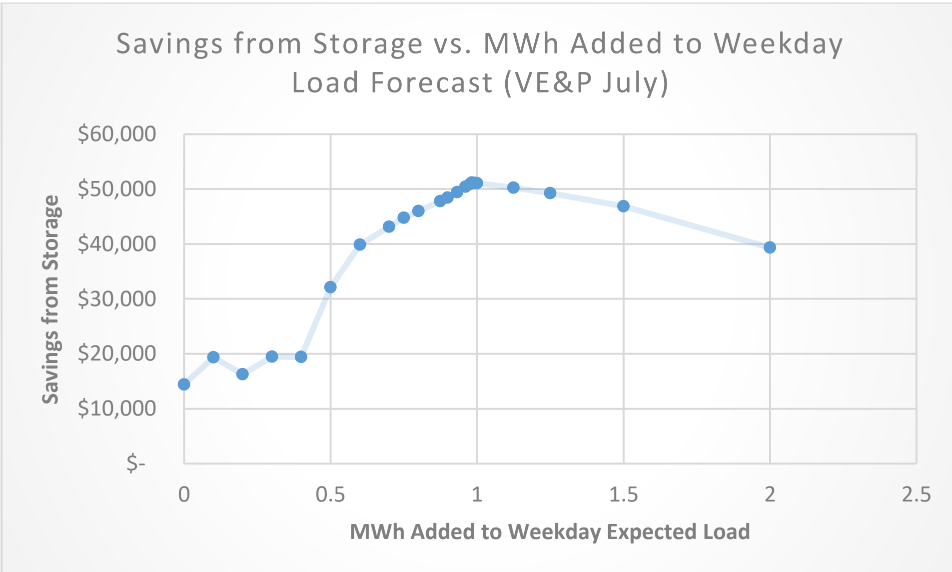

Figure 23: Savings from storage on VE&P's GS-3 rate schedule in July for increased weekday load forecasts.

The same analysis was conducted on VE&P's GS-3 rate schedule in January and on PG&E's E-20 rate schedule in January. Results from this analysis are shown in Figure 24 and Figure 25, respectively. For all three of the analyzed cases, the optimal forecast was between 0.9 and 1 MWh above average. The savings on VE&P's GS-3 rate schedule in January reached 253% above the base case and on PG&E's E-20 rate schedule in January savings reached 256% above the base case. If the weekday forecast for the VE&P rate schedule is increased by 0.9MWh for both January and July, the total estimated annual savings are $2,634,972 without storage and $3,281,616 with storage.

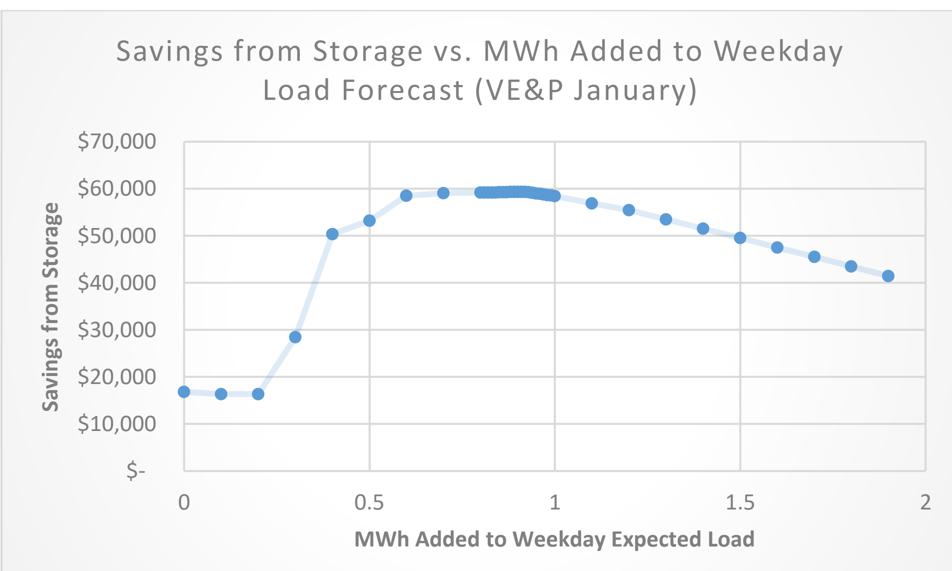

Figure 24: Savings from storage on VE&P's GS-3 rate schedule in January for increased weekday load forecasts.

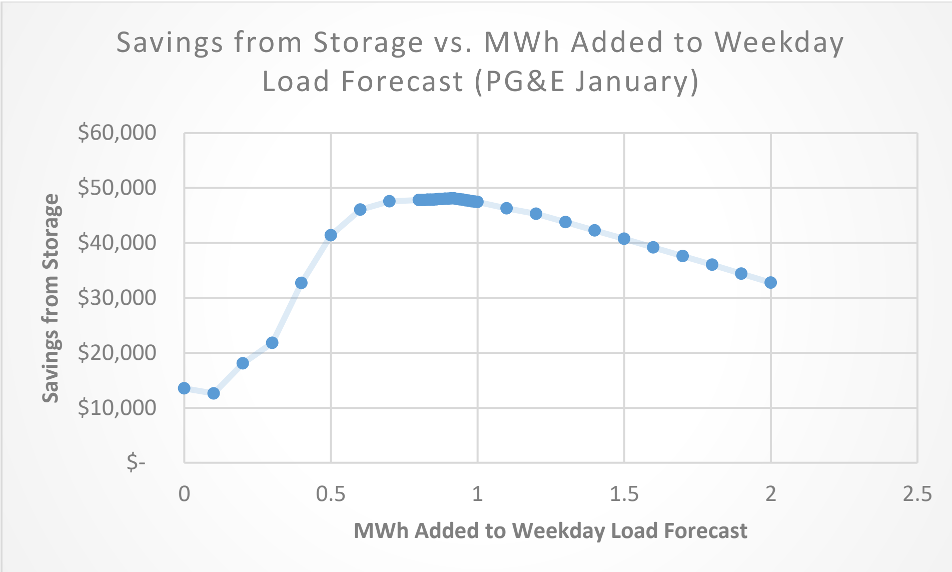

Figure 25: Savings from storage on PG&E's E-20 rate schedule in January for increased weekday load forecasts.

Figure 26 shows the storage dispatch profile for an increased weekday forecast in January on PG&E's E-20 rate schedule. Because the unit expects a higher peak demand each day, it almost always charges fully before the peak period so it is successful in shaving every peak to a consistent level.

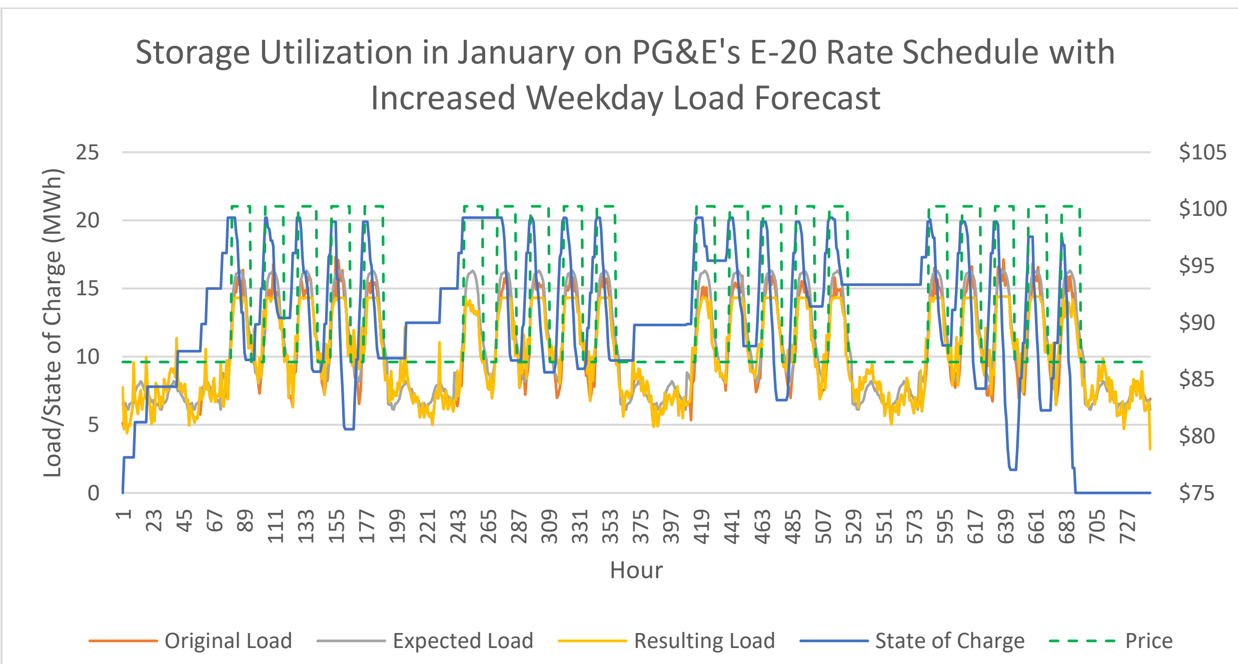

Figure 26: Results of optimal storage dispatch on PG&E's E-20 rate schedule in January with an increased weekday load forecast.

The result of the optimal weekday forecast addition being just under 1MWh for the above three cases is a curious one considering the load is different in January and July, and two different rate schedules are being used. One of the only consistencies between the three cases is the noise level added to the base load curve. To test whether this had an effect on the optimal forecast level, different levels of noise were tested along with multiple instances of each noise level. This analysis was conducted on the VE&P rate schedule in July.

First, the load profile with no noise added was tested and the optimal forecast addition was just above 1MWh. The resulting curve for this case is shown in Figure 27.

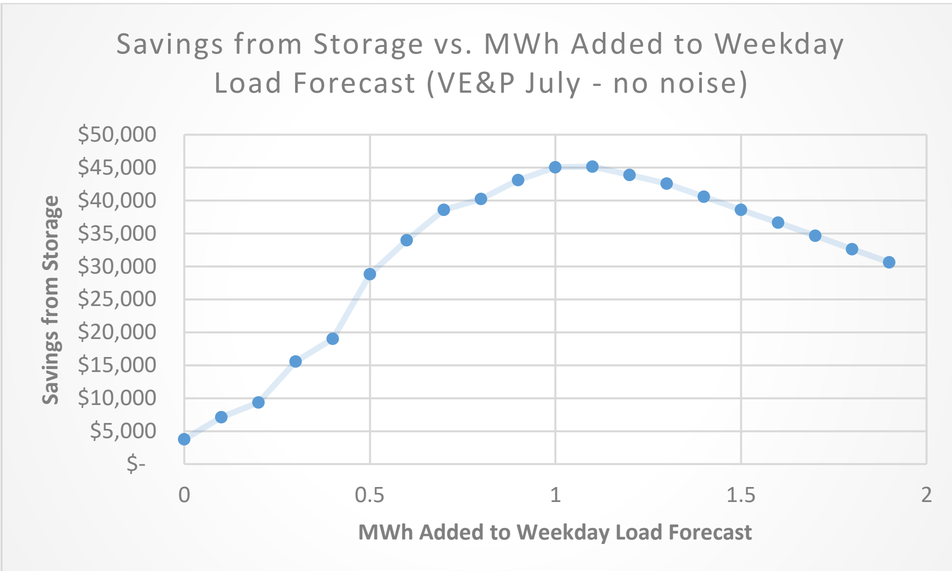

Figure 27: Savings from storage vs. MWh added to weekday load forecast on the VE&P rate schedule in July with no noise added.

Next, a small amount of noise, N(0,0.13) MWh, was added to the load profile. Figure 28 shows the result of this analysis under three different instances of noise. In two of the instances the result was similar to the "no noise" case. However, in one instance the optimal addition to the forecast was around 0.75MWh. In all instances, using a weekday forecast addition of 1MWh would result in a large profit increase compared to an average weekday load forecast.

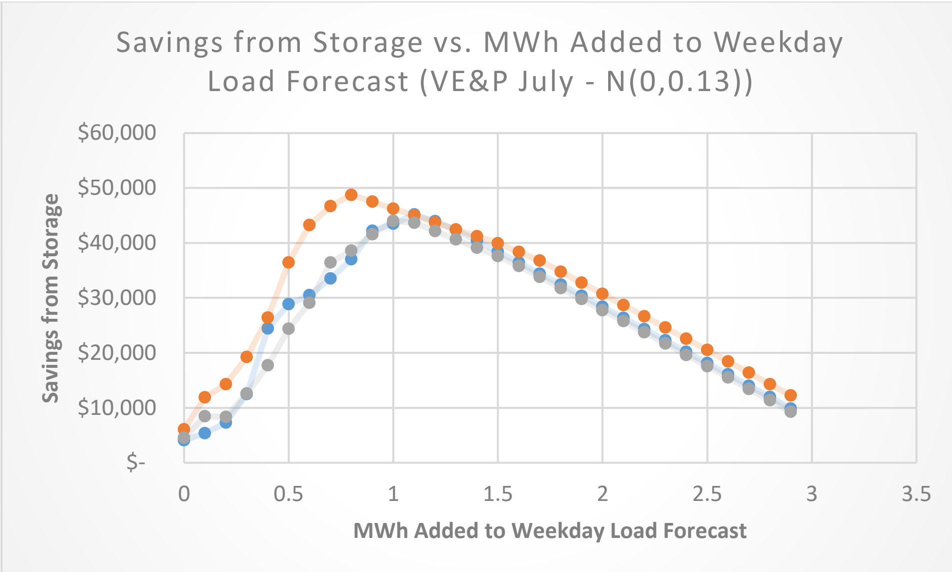

Figure 28: Savings from storage vs. MWh added to weekday load forecast on the VE&P rate schedule in July with N(0,0.13) noise.

Figure 29 shows the result of using a much higher noise level, N(0,1.44) MWh. In the three instances of noise tested, the optimal level of weekday load forecast and the maximum possible savings varied greatly. In general, higher noise increased the possible savings and also increased the optimal forecast. If a weekday forecast addition of 1.7MWh were used, in all three instances the unit would achieve a high profit increase over an average weekday forecast. As long as an electricity customer is able to approximately characterize the noise present on their load profile, it should be possible to make a reasonable estimate of the optimal forecast to allow a storage unit to shave peak loads and decrease demand charges.

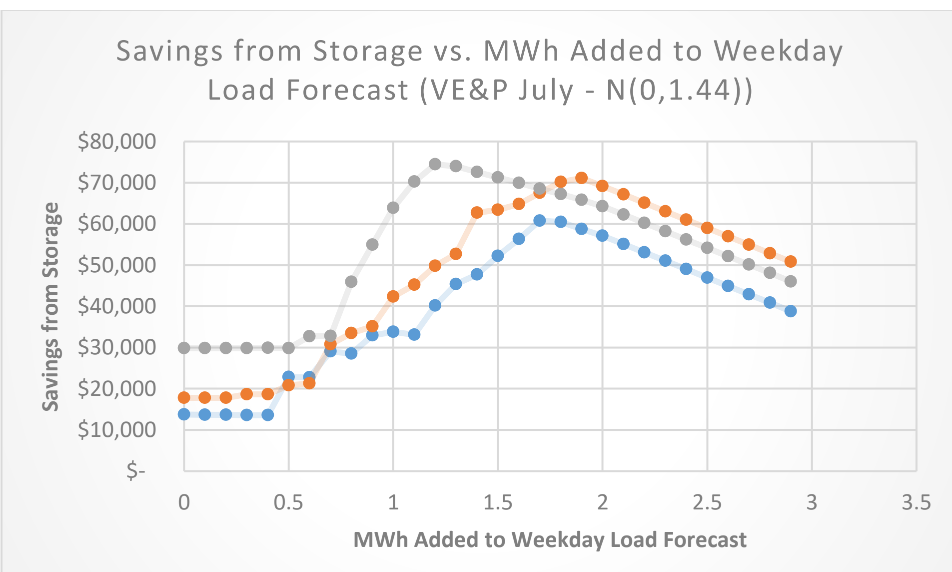

Figure 29: Savings from storage vs. MWh added to weekday load forecast on the VE&P rate schedule in July with N(0,1.44) noise.

Conclusion

In this study, the economic dispatch of an energy storage technology developed by SuperCritical Technologies called the PowerCube was analyzed under different pricing conditions. First, the PowerCube unit was dispatched in the real-time markets of four geographically distant ISOs in the US. While the storage unit achieved much higher profits in pricing scenarios with large price fluctuations like CAISO and NYISO, none of the resulting annual profits were high enough to pay off the PowerCube in less than 20 years.

A method of improving the real-time dispatch of energy storage in the form of storage buffers was then presented. By modifying the objective function of the storage dispatch optimization problem, it was shown that a storage unit can capitalize on very large price spikes and achieve a higher annual profit. The main issue with using storage buffers is determining the optimal upper and lower buffer levels along with their associated objective function penalties. Optimal parameters varied widely between different ISO pricing sets and were also inconsistent month to month. However, the best set of buffer parameters for the CAISO data set in 2016 did achieve an increase in profit in 2015, suggesting that the parameters may be more consistent over longer time periods.

Next, the PowerCube unit was modeled on two different utility rate schedules: PG&E's E-20 and VE&P's GS-3, both of which are for large industrial customers. The rate schedules introduced demand charges, which are based upon the highest level of facility consumption in a billing period and incentivize peak shaving. When using an average load forecast, the PowerCube unit achieved enough savings on both rate schedules to offset all annual costs within the first year.

A debilitating effect on storage dispatch was observed when the difference between peak and off-peak energy prices was not large enough to make up for the round-trip efficiency of the storage. It was found that by increasing the weekday forecast, the PowerCube unit would more successfully shave all the peaks throughout the month and achieve much higher savings. The relationship between load noise level and the optimal weekday forecast addition was then explored, with the determination that as long as the noise can be approximately characterized, a suitable forecast level can be found.

Future Work

The potential applications of energy storage in an electricity market are abundant, with energy arbitrage and peak shaving being two of the most basic. In order to understand the full extent of the PowerCube's capabilities, further study into how the unit could provide frequency regulation, ramp rate control, and black-start capability is required. Additionally, consumers may not have a free waste heat source available which would add fuel costs to the optimal dispatch function. Determining which fuels would be economical on which rate schedules could open the market to many additional consumers.

Further study on storage buffers is required to determine whether it is possible to predict parameters that will consistently yield increased profit from storage in a pricing environment. By determining the ideal parameters in multiple years on many other ISO pricing data sets, a pattern may be revealed which would either confirm or deny their usefulness in the dispatch scheme. Combining the storage buffers with more complex methods of price forecasting could also yield interesting results.

Appendix 1: Model Parameter Definitions

t	Time period.
tt	Dummy variable for iterating across all t.
T	Total number of time periods.
p_t^r	Real-time spot price in \$/MWh during time t.
g_t^r	Energy bought or sold on the real-time market in MWh during time t.
p_t^e	Expected real-time spot price in \$/MWh during time t.
p_t^d	Day-ahead price in \$/MWh during time t.
g_t^d	Energy bought or sold on the day-ahead market in MWh during time t.
b_t^u	Objective function penalty for a state of charge above the upper buffer level in time t.
b_t^l	Objective function penalty for a state of charge below the lower buffer level in time t.
s_t	State of charge in MWh during time t.
b^u	Upper buffer level.
φ^u	Upper buffer penalty amount in \$.
b^l	Lower buffer level.
φ^l	Lower buffer penalty amount in \$.
g_t	Net output of the unit in MWh during time t.
s_t^i	Storage input in MWh during time t.
s_t^o	Storage output in MWh during time t.
η	Storage round-trip efficiency.
$\bar{s}$	Storage capacity of the unit in MWh.
$\bar{s}^i$	Maximum storage input in MWh during one time period.
x_t	Binary variable equal to 1 when the unit is charging and 0 when the unit is not charging.
$\bar{s}^o$	Maximum storage output in MWh during one time period before efficiency is taken into account.
y_t	Binary variable equal to 1 when the unit is discharging and 0 when the unit is not discharging.

$\bar{d}$	Maximum demand across the billing period in MW.
$\bar{\alpha}$	Maximum demand charge in \$/MW.
$\bar{\bar{d}}$	Peak demand across the billing period in MW.
$\bar{\bar{\alpha}}$	Peak demand charge in \$/MW.
$\tilde{d}$	Partial-peak demand across the billing period in MW.
$\tilde{\alpha}$	Partial-peak demand charge in \$/MW.
l_t^*	Facility load during time t after the PowerCube unit generation is subtracted in MWh.
p_t	Price of electricity during time t in \$/MWh.
l_t	Facility load during time t before the PowerCube unit generation is subtracted in MWh.
γ	Nominal output of the PowerCube unit in MWh.

Appendix 2: Buffer Parameter Sensitivity Analysis Graphs

NYISO

Figure 30, Figure 31, Figure 32, and Figure 33 show results of the sensitivity analysis of buffer parameters under the NYISO pricing set. The best lower buffer penalty was roughly $100 with a lower buffer level of 12MWh. The best upper buffer penalty was roughly $0.6 with an upper buffer level of 17.4MWh. With the best set of parameters, the annual profit from storage increased by 33% over the base case when no storage buffers were used.

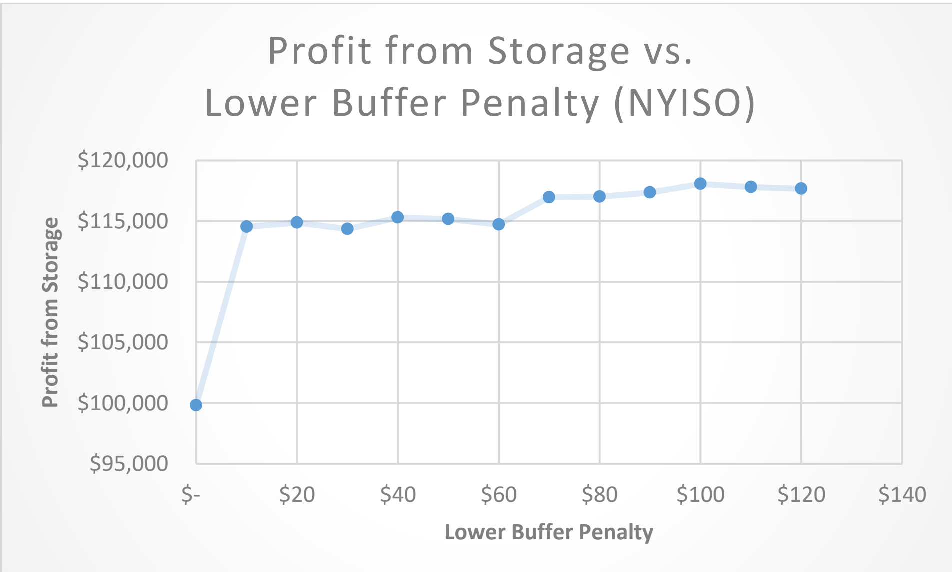

Figure 30: Profit from storage vs. lower buffer penalty with NYISO pricing. (b^l = 2MWh, b^u = 18.2MWh, φ^u = $0)

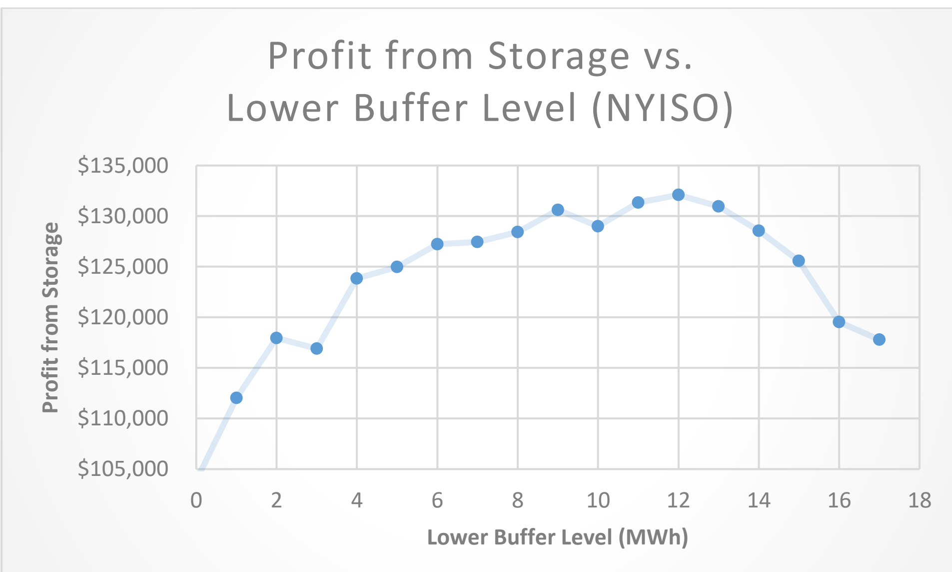

Figure 31: Profit from storage vs. lower buffer level with NYISO pricing. (φ^l = $100, b^u = 17.4MWh, φ^u = $0.6)

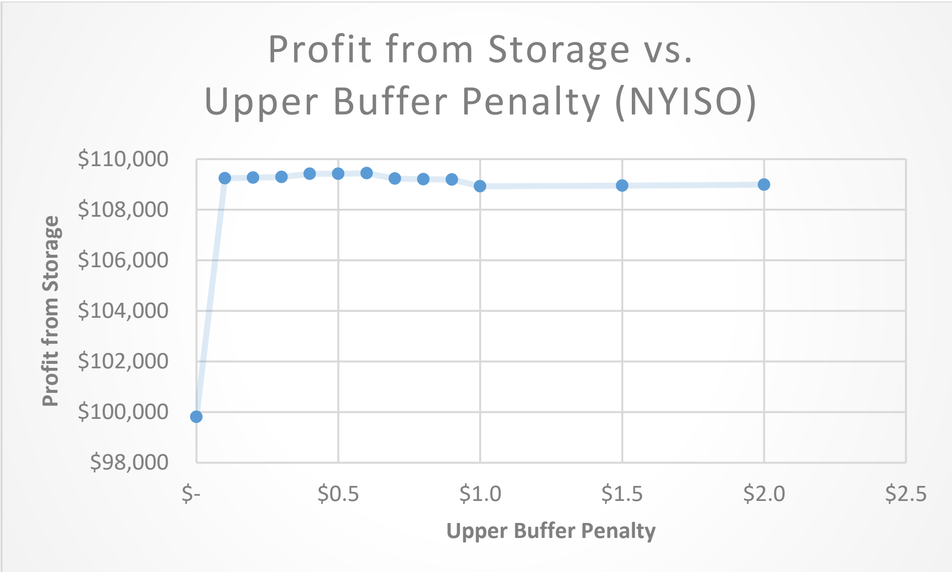

Figure 32: Profit from storage vs. upper buffer penalty with NYISO pricing. (b^l = 2MWh, φ^l = \$0, b^u = 18.2MWh)

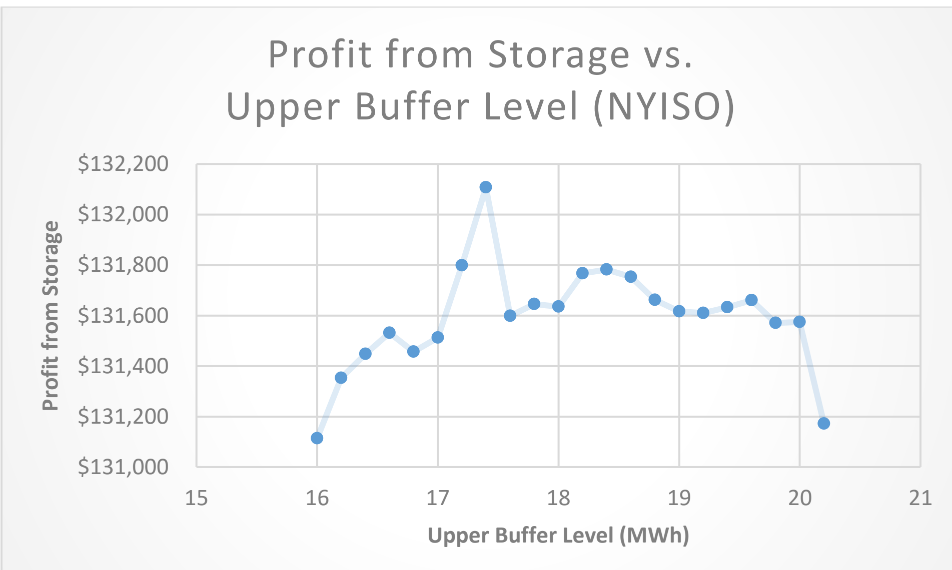

Figure 33: Profit from storage vs. upper buffer level with NYISO pricing. (b^l = 11MWh, φ^l = \$100, φ^u = \$0.6)

CAISO

Figure 34, Figure 35, Figure 36, and Figure 37 show results of the sensitivity analysis of buffer parameters under the CAISO pricing set. The best lower buffer penalty was roughly $40 with a lower buffer level of 9MWh. The best upper buffer penalty was roughly $3 with an upper buffer level of 19.5MWh. With the best set of parameters, the annual profit from storage increased by 15% over the base case when no storage buffers were used.

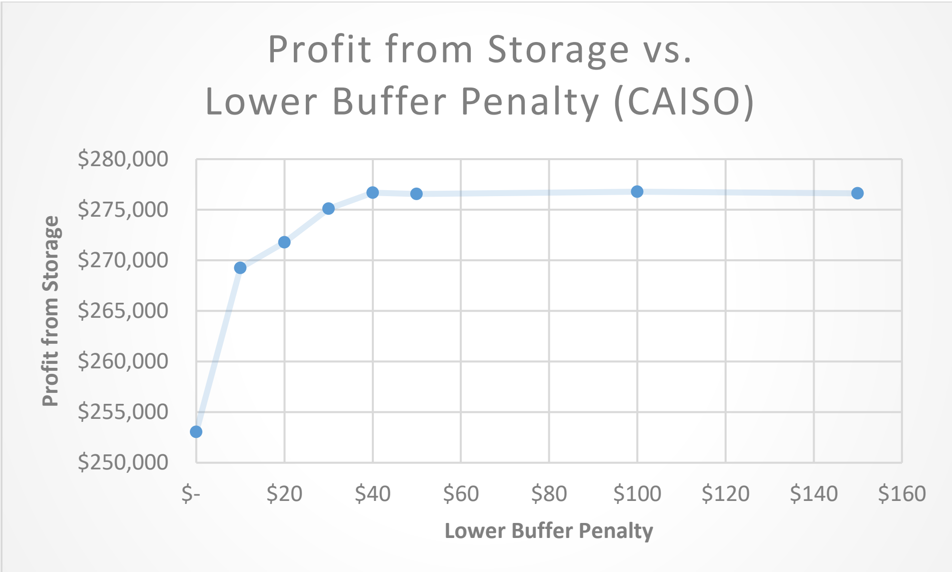

Figure 34: Profit from storage vs. lower buffer penalty with CAISO pricing. (b^l = 2MWh, b^u = 18.2MWh, φ^u = $0)

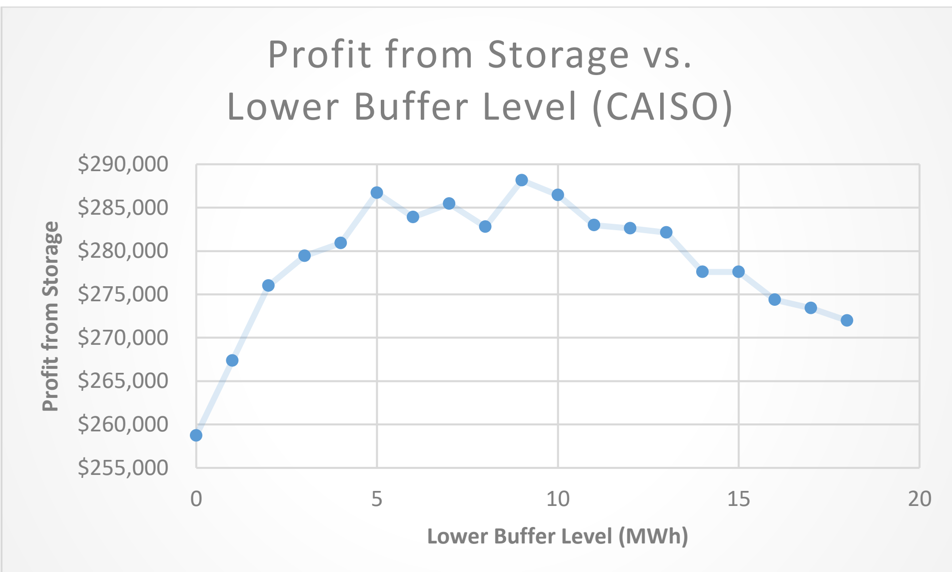

Figure 35: Profit from storage vs. lower buffer level with CAISO pricing. (φ^l = $40, b^u = 18.2MWh, φ^u = $3)

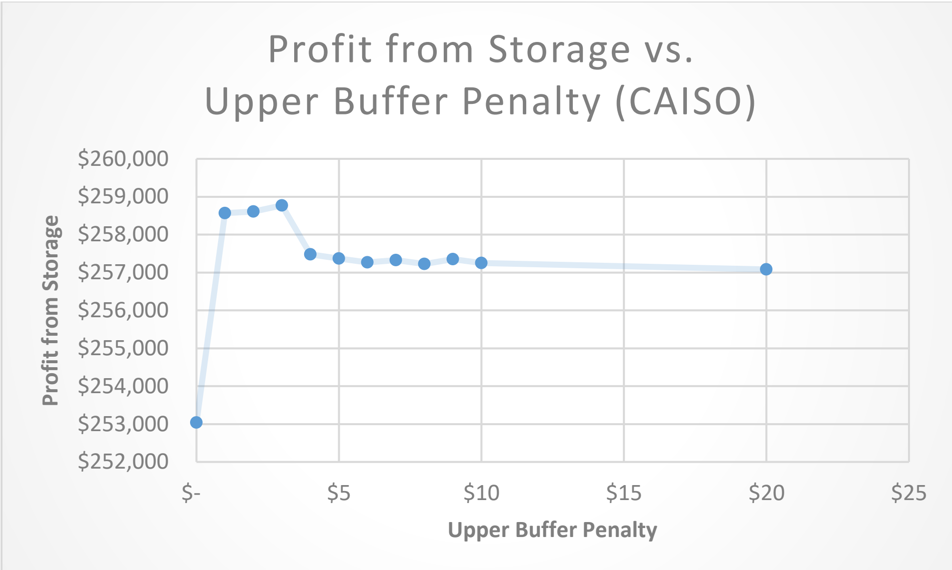

Figure 36: Profit from storage vs. upper buffer penalty with CAISO pricing. (b^l = 2MWh, φ^l = $0, b^u = 18.2MWh)

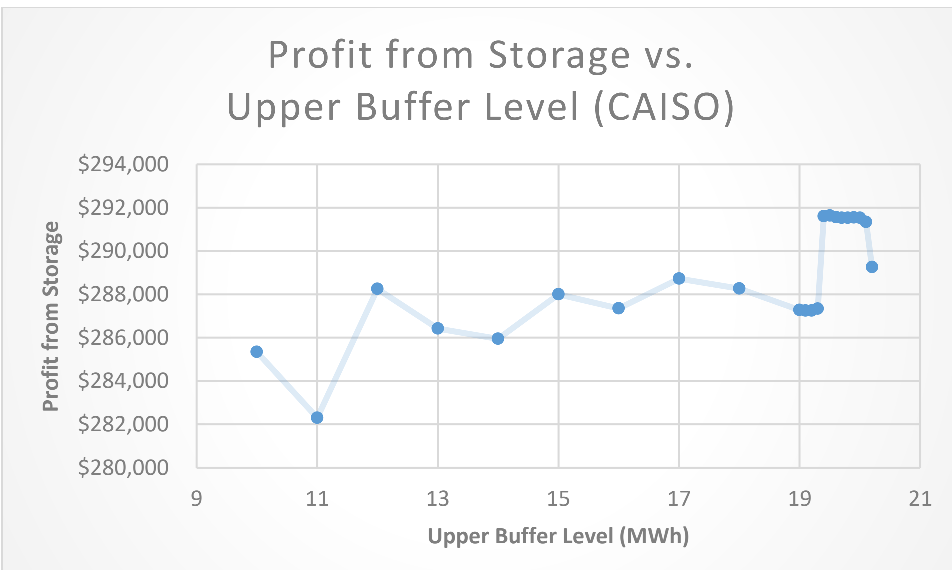

Figure 37: Profit from storage vs. upper buffer level with CAISO pricing. (b^l = 9MWh, φ^l = $40, φ^u = $3)

ERCOT

Figure 38, Figure 39, Figure 40, and Figure 41 show results of the sensitivity analysis of buffer parameters under the ERCOT pricing set. The best lower buffer penalty was roughly $10 with a lower buffer level of 5MWh. The best upper buffer penalty was roughly $0.1 with an upper buffer level of 20.1MWh. With the best set of parameters, the annual profit from storage increased by 13% over the base case when no storage buffers were used.

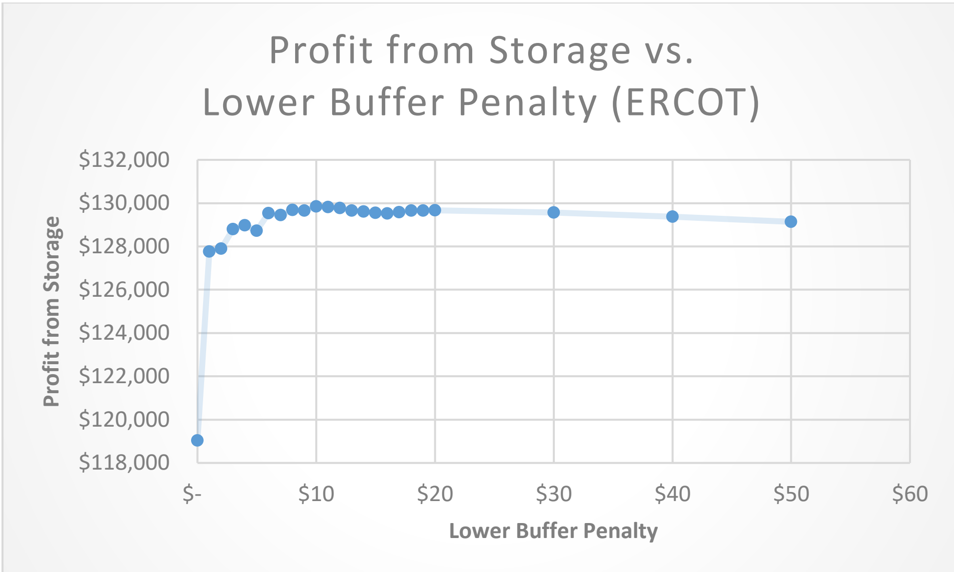

Figure 38: Profit from storage vs. lower buffer penalty with ERCOT pricing. (b^l = 2MWh, b^u = 18.2MWh, φ^u = \$0)

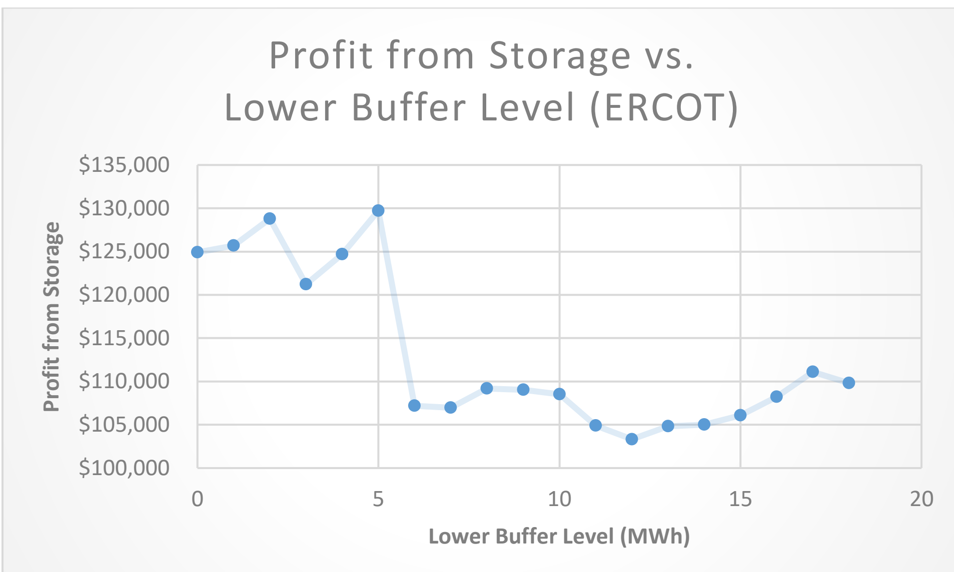

Figure 39: Profit from storage vs. lower buffer level with ERCOT pricing. (φ^l = \$10, b^u = 18.2MWh, φ^u = \$0.1)

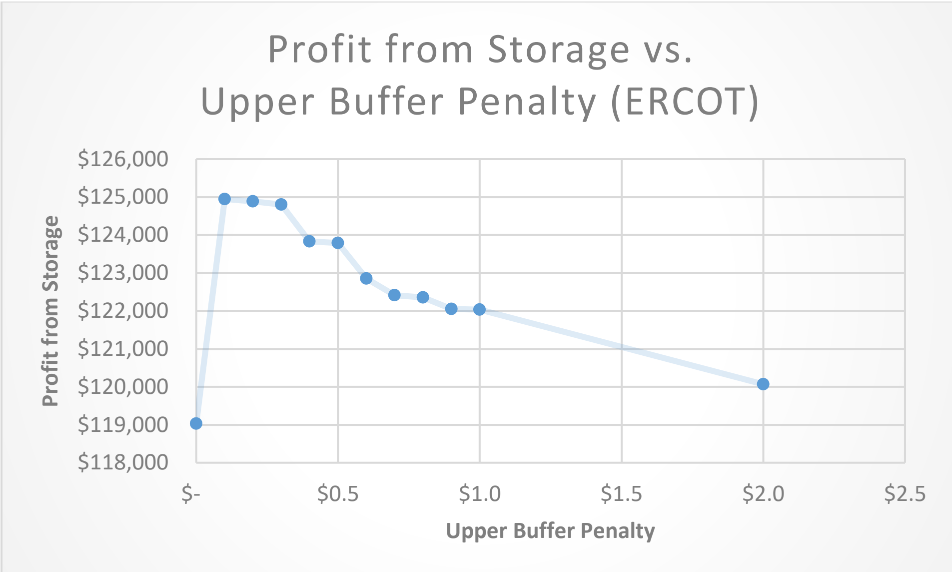

Figure 40: Profit from storage vs. upper buffer penalty with ERCOT pricing. (b^l = 2MWh, φ^l = \$0, b^u = 18.2MWh)

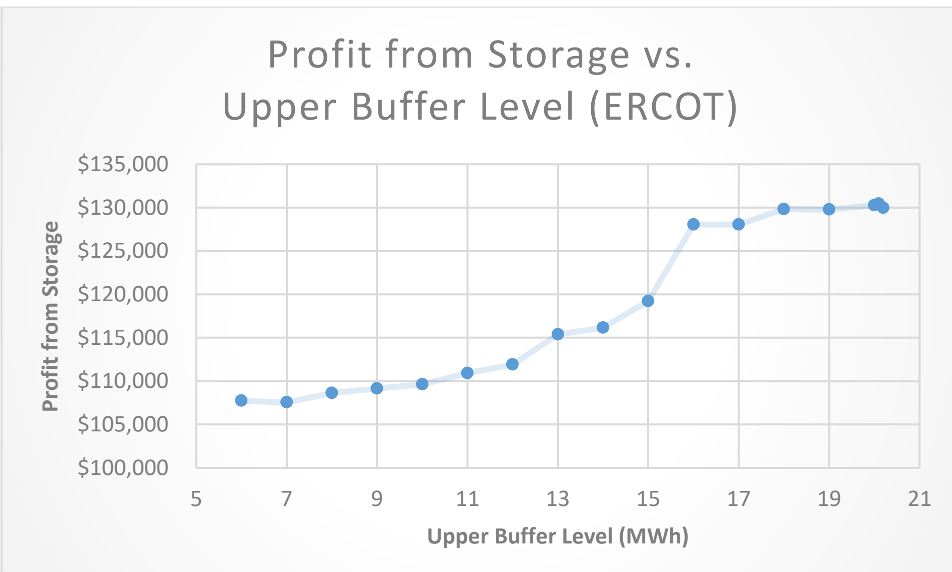

Figure 41: Profit from storage vs. upper buffer level with ERCOT pricing. (b^l = 5MWh, φ^l = \$10, φ^u = \$0.1)

MISO

Figure 42, Figure 43, Figure 44, and Figure 45 show results of the sensitivity analysis of buffer parameters under the ERCOT pricing set. The best lower buffer penalty was roughly $5 with a lower buffer level of 2MWh. The best upper buffer penalty was roughly $0.1 with an upper buffer level of 18.4MWh. With the best set of parameters, the annual profit from storage increased by 11% over the base case when no storage buffers were used.

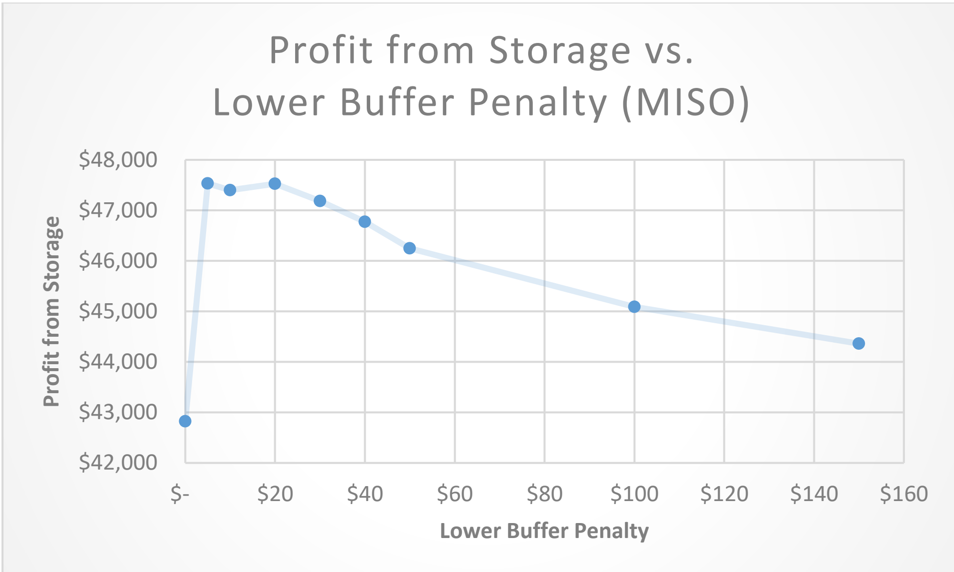

Figure 42: Profit from storage vs. lower buffer penalty with MISO pricing. (b^l = 2MWh, b^u = 18.2MWh, φ^u = $0)

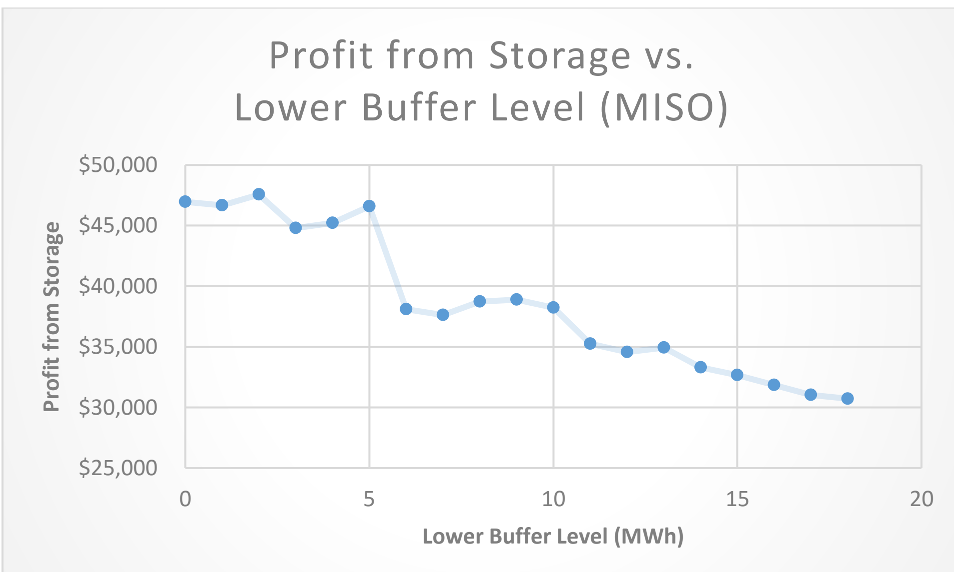

Figure 43: Profit from storage vs. lower buffer level with MISO pricing. (φ^l = $20, b^u = 18.2MWh, φ^u = $0.1)

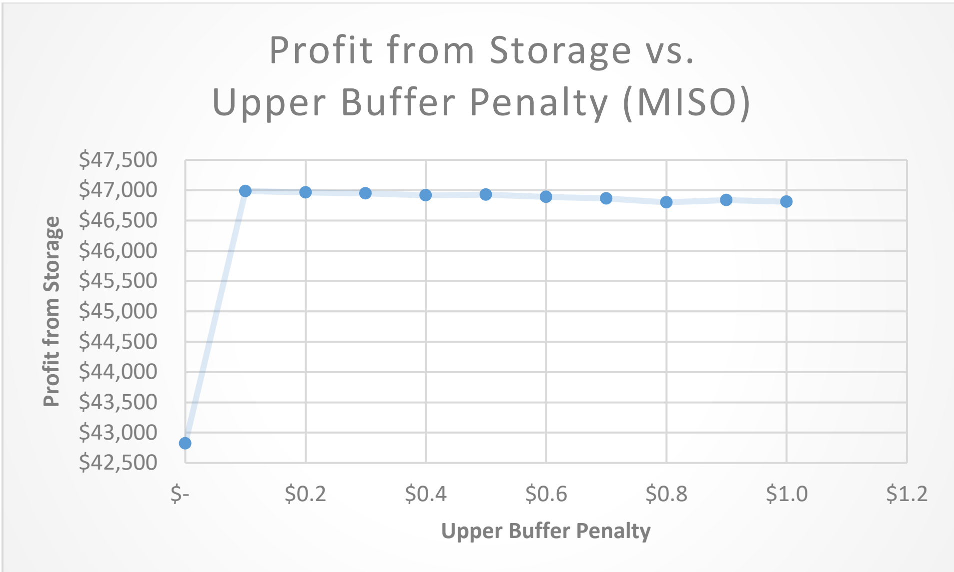

Figure 44: Profit from storage vs. upper buffer penalty with MISO pricing. (b^l = 2MWh, φ^l = $0, b^u = 18.2MWh)

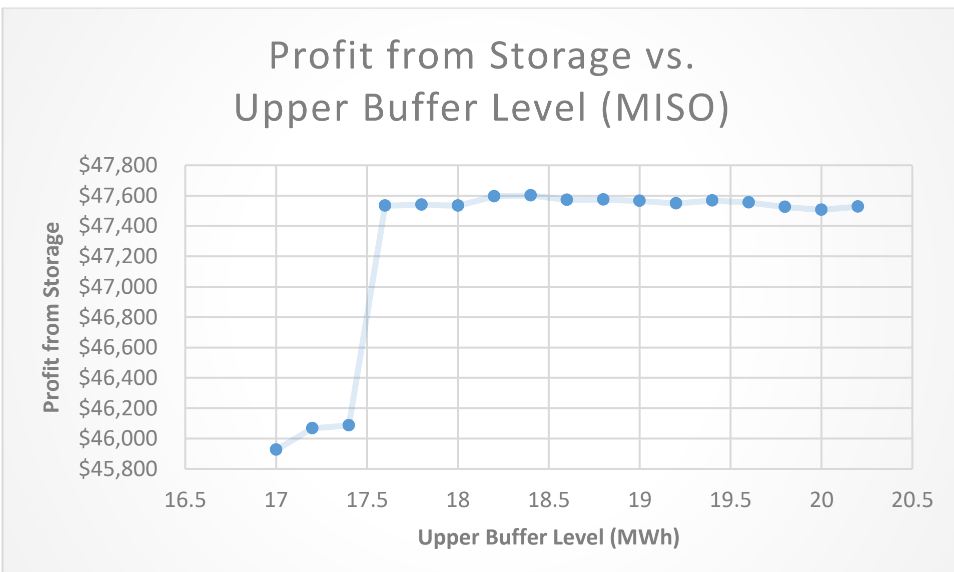

Figure 45: Profit from storage vs. upper buffer level with MISO pricing. (b^l = 2MWh, φ^l = $20, φ^u = $0.1)

Works Cited

[1] W. Steel, "Energy Storage Market Outlook 2017: State of Play," Renewable Energy World, 2 February 2017. [Online]. Available: http://www.renewableenergyworld.com/articles/print/volume-20/issue-1/features/storage/energy-storage-market-outlook-2017-state-of-play.html. [Accessed 4 April 2017].

[2] D. Manz, J. Keller and N. Miller, "Value Propositions for Utility-Scale Energy Storage," IEEE, Schenectady, NY, 2011.

[3] Energy Storage Association, "Applications of Energy Storage Technology," 2017. [Online]. Available: http://energystorage.org/energy-storage/applications-energy-storage-technology. [Accessed 4 April 2017].

[4] M. Bolinger and J. Seel, "Utility-Scale Solar 2014: An Empirical Analysis of Project Cost, Performance, and Pricing Trends in the United States," Lawrence Berkeley National Laboratory, Berkeley, California, 2015.

[5] R. Fioravanti and A. Nourai, "Community Energy Storage for Reliability," EEWeb, 22 April 2013. [Online]. Available: https://www.eeweb.com/blog/nicholas_abisamra/community-energy-storage-for-reliability. [Accessed 4 April 2017].

[6] Alphabet Energy, "Waste Heat to Power: The Hottest New Clean Energy Solution; Possibly Even Hotter than Solar," 3 December 2015. [Online]. Available: https://www.alphabetenergy.com/waste-heat-to-power-the-hottest-new-clean-energy-solution-possibly-even-hotter-than-solar/. [Accessed 4 April 2017].

[7] S. A. Wright, C. S. Davidson and W. O. Scammell, "Bulk Energy Storage using a Supercritical CO2 Waste Heat Recovery Plant," in *The 4th International Symposium - Supercritical CO2 Power Cycles*, Pittsburg, 2014.

[8] W. Scammell, C. Davidson and S. Wright, "Economic Issues For Waste Heat Recovery & Bulk Energy Storage," in *The 4th International Symposium - Supercritical CO2 Power Cycles*, Pittsburg, 2014.

[9] H. Khani and M. Zadeh, "Online Adaptive Real-Time Optimal Dispatch of Privately Owned Energy Storage Systems Using Public-Domain Electricity Market Prices," *IEEE Transactions on Power Systems,* vol. 30, no. 2, pp. 930-938, 2015.

[10] S. Tewari and N. Mohan, "Optimal Strategy to Dispatch Storage in Real-Time Markets," GCMS, Minneapolis, 2011.

[11] A. Nottrott, J. Kleissl and B. Washom, "Energy dispatch schedule optimization and cost benefit analysis for grid-connected, photovoltaic-battery storage systems," Elsevier, La Jolla, CA, 2012.

[12] N. DiOrio, A. Dobos and S. Janzou, "Economic Analysis Case Studies of Battery Energy Storage with SAM," National Renewable Energy Laboratory, Golden, CO, 2015.