Energy Systems Economics and Optimization - EEELE4220

Columbia Peak Shaving

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Motivation

Our main motivation for this project has been to evaluate possible alternatives to reduce Columbia's University electricity bill. In order to do that, we must first understand the main components of Columbia’s electricity bill, which can be split into two parts. The first part of the bill is given by Columbia’s electricity consumption times a fixed electricity rate of \$0.13/kWh, which is determined by its supply-demand contract with the utility company. The second, more significant part, consists of the peak demand charge. To calculate the peak demand charge, the utility identifies the two highest consecutive 15 minute intervals of demand and multiplies it by the respective on-peak/off-peak tariff.

Our goal is to reduce the peak demand charge by leveling out peaks in electricity use. In this case, we will use energy storage to shave off the peaks in consumption. We have the option of using a thermal or a lithium-ion battery, each with its own financial and operational characteristics.

Summary

We have been given Columbia's consumption data and different battery types to attempt to shave off the peak consumptions. In order to do this, we first have to decide which battery technology to use: lithium-ion or thermal energy storage. Secondly, we need to decide how to operate the battery, which means finding the best periods to charge and discharge our storage given the consumption profile. Also, we will present the total cost savings that Columbia can expect if it decides to invest in an energy storage solution.

Method 1

Analysis of peak demand period

We formulated Columbia University’s peak demand problem as a mixed-integer linear program using Python’s Gurobi and Cvxpy packages (details found in the Appendix).

The peak demand rate is on a three-level rachet for the summer months of June, July, August, and September and a two-level ratchet for all other months (Appendix).

Based on these ratchets, the most expensive peak demand rate is \$44.25/kW for the summer months and \$18.17/kW for all other months.

We analyzed the 2018 demand data to determine the distribution of peak period and peak day of week and found that for all months the peak period occurred between 10 AM – 6 PM on a weekday (Figure 1*)*. It would be unrealistic and prohibitively expensive to shift the peak demand from the period with the most expensive peak demand rate to the cheaper period through installing a super battery with an extremely high energy rating. As a result, we incorporated the peak demand charge (*B)* in our model as a static variable with a value of \$44.25/kW for the summer months and \$18.17/kW for all other months.

Lithium-ion battery or thermal energy storage

Next, we created a function that takes the monthly demand, battery power rating, battery type, month of the year, and current state-of-charge for the battery as inputs and runs the optimization procedure to return the optimal objective value and battery operations for that month. The specifications for each battery, shown in Table 1, were also taken into account in this function and the cost savings calculations. We created a for-loop that ran through all 12 months of 2018 and outputted the expected operational and battery costs for the entire year. Using this function, we experimented with different battery types and power/energy ratings to find the ideal battery specifications for cost savings.

In order to find the ideal battery specifications for cost savings, we design two optimization experiments. We perform optimization simulations by inputting different parameters, different power ratings of two kinds of technologies. The specific experimental parameters are detailed in the following Table 2. First one is aimed to find better storage technology between two candidates, the lithium-Ion battery or the thermal energy storage, and the approximate range of the optimal power rate. The other one is designed to find the optimal power rating of the better technology for 2018 peak shaving. We then calculated the NPV of the investment of each kind of storage system and compared NPVs to determine results.

NPV and IRR

The calculation and comparison in our project is based on a consensus that a future dollar is worth less than a dollar today, so we use net present value (NPV) to analyze the profitability of the projected investment. NPV is the difference between the present value of cash inflows and the present value of cash outflows over a period of time and is used to calculate the current value of a future stream of payments from a company, project, or investment. If the NPV of a project or investment is positive, it means its rate of return will be above the discount rate. After accounting for the time value of money, you will make money if you proceed with the investment.

The NPV calculation takes into account factors such as the investor's cost of capital, opportunity cost, and risk tolerance through the discount rate. In this project, we calculate the NPV of the investment of each battery for 10 years. To be specific, we estimate every year’s saving of peak shaving by one kind of battery with a certain power rating and discount every year’s saving into the present day, using a discount rate equal to the minimum acceptable rate of return(8%). The formula for calculating NPV is as follows.

$$\text{Net Present Value(NPV)} = -C_o + \frac{C_1}{(1+r)} + \frac{C_2}{(1+r)^2} + \ldots + \frac{C_T}{(1+r)^T}$$

$-C_0$ = Initial Investment
C = Cash Flow
r = Discount Rate
T = Time

The internal rate of return (IRR) is the annual rate of growth that an investment is expected to generate. It is numerically equal to the discount rate when the NPV equals zero. We calculate and analyze the IRR of our optimal investment to understand and compare potential rates of annual return over time.

Results

The results shown in Figure 2 indicate that the net present value for 10 years of the thermal energy storage with a certain power rating is always higher than the NPV for 10 years of the lithium-ion battery energy storage with the same power rating in the range of power ratings from 50kW to 500kW. Therefore, thermal energy storage is the better technology to shave off the peak consumption of Columbia University if only based on the data in 2018. Considering that Columbia University is a stable and continuously operating organization, the characteristics of electricity demand over time, like the peak demand and the approximate time of occurrence of the peak, do not change dramatically from year to year, especially between two consecutive years, so it is reasonable to assume that the thermal energy storage will be better investment choice in shaving off the peak consumption of Columbia University.

Since thermal energy storage has been chosen as the better investment option, our next step is to determine the best thermal energy storage with the optimal power rating. The blue curve represents the NPVs of the thermal energy storages with different power ratings. The highest point is around 350kW power rating. Then, we set a smaller increment, 10kW, and run the optimization program again to find the optimal point. According to the results shown by Table 3 and Figure 3, we got the highest NPV for 10 years, $273,046, and a good internal rate of return (IRR), 21.29%, when the thermal energy storage with 370 kW power rating is installed and assuming that the demand data in the next ten years is constant and is the same as that in 2018.

Forecasting

Once we selected the optimal battery type and power/energy ratings (370 kW thermal battery), we experimented with procedures to operate the battery in the most effective way. For this analysis, we assumed that the battery is bought at the end of 2018 and will be operated to shave the peak demand in 2019.

We first decided to forecast the 2019 demand using a model trained on the 2018 demand and use this forecast as an input in the optimization function to find the charge/discharge values for each timestep. We tried several different forecasting methods in R, including naïve, autoregressive integrated moving average (ARIMA), exponential smoothing (ETS), and seasonal trend decomposition loss function (stlf). The naïve, ARIMA, and ETS models had difficulty picking up on the seasonality of the demand and tended to predict a constant average value for demand at each time step. Although these models had a lower root mean-squared error (RMSE) and mean-absolute error (MAE) than the stlf model, their inability to identify daily trends made them undesirable (Table 4).

The stlf model, however, was able to incorporate the periodicity of the 15-minute interval data and generate a forecast that reflected the general demand trends. To make the stlf model more accurate, we adjusted the procedure so each month of demand was forecasted separately. In this way, we were able to feed more historical data into the stlf model and better pick up on the monthly trends in demand. Ultimately, the composite stlf model had the best performance with an RMSE of 126.2 kW and a MAE of 97.32 kW, which are, respectively, 15.35% and 11.84% of the mean demand (Figure 4).

We ran the forecasted demand through the optimization function to decide the schedule for the 370 kW thermal battery operation that would minimize the cost. Then, we used the battery charge/discharge schedule in tandem with the actual demand to discover the actual cost savings of operating the battery in this way. The results in Table 5 show that this method was ineffective because the 2019 forecasted operating cost savings were $710,616 yet in actuality the operating cost savings would actually be higher by $12,788. This mismatch in expectation versus reality is a result of the forecasting errors. While the forecasts are able to capture the long-term trends of the demand, they are not able to identify anomalies and individual spikes in demand each period that tend to be of a more stochastic nature.

Thus, we experimented with a new way to operate the battery.

Method 2

Because the demand tended to follow the same daily trends, we could assume that our day-ahead forecasts would be much more accurate at predicting spikes in demand. Therefore, we built a procedure that would aim to minimize the daily peak demand rather than the monthly peak. To implement this, we added a new input to the optimization function that was the current maximum peak for the month. We added a slack parameter to the objective function that penalized whenever the daily peak exceeded the current maximum peak. The new objective function is shown below:

$$min_{q_t, d_t} 2Bp \; + \; C\sum_t (D_t - d_t + q_t) \; + \; 10000 * (p - CurrentMaxPeak)$$

With this method, we re-evaluated the optimal battery using the 2018 demand data. We determined the optimal battery was a 290 kW lithium-ion battery (Figures 5 and 6 and Tables 6 and 7). With the 290 kW lithium-ion battery, we achieved an annual cost savings of $85,449.32 in 2019 (Table 8), the NPV for 10 years of $254,371.89 and the IRR of 23.56%. Figure 7 shows the demand without the battery and the demand with the scheduled charge/discharge of the 290 kW lithium-ion battery. The right plot shows the rolling demand, or demand for two consecutive periods. From this plot and Table 9, we see that the battery does reduce the peak demand below levels reached without the battery and the peak demand charge reduction was $41,437 (1,659 kW).

Cost of energy efficiency lost

Because of the lithium-ion energy storage's single-trip efficiency of 95%, not all electricity reaches the battery. Therefore, we need to account for the efficiency losses when charging and discharging the battery. The demand-supply contract's electricity price of $0.13/kWh is considered for this calculation. The annual efficiency lost when charging and discharging the battery equals 36.8 MWh, resulting in an annual cost of $4,791.

Conclusion

Through this study we can conclude that a significant reduction of Columbia's current electricity bill can be achieved with the use of a 290 kW lithium-ion energy storage.

Appendix

GitHub

Code and data results can be found on our team's GitHub here.

Problem Formulation

The parameters included in the formulation are listed below:

- Energy storage parameters
  - η: single-trip charge and discharge efficiency
    - Lithium-ion battery: 0.95
    - Thermal battery: 0.70
  - P: storage power rating
  - E: storage energy rating
- Campus demand profile
  - D_t: campus demand over time period t
- Decision variables
  - d_t: storage discharge power over time period t

- q_t: storage charge power over time period t
- e_t: energy stored or storage state-of-energy over time period t
- p: peak demand

- Peak demand and energy prices:
  - C: energy cost of electricity in $/kWh, $0.13/kWh in this case
  - B: peak demand charge of electricity converted to $/kWh

We structured these parameters in our optimization problem with the following constraints and objective function:

- Constraints
  - Discharge cannot be larger than the battery's power rating
    - $0 \leq d_t \leq P$
  - Charge cannot be larger than the battery's power rating
    - $0 \leq q_t \leq P$
  - Energy stored cannot be larger than the battery's energy storage rating
    - $0 \leq e_t \leq E$
  - The battery state-of-charge at the current time step minus the previous time step must be equal to the storage charge at time *t* times the battery efficiency minus the storage discharge at time *t* divided by the battery efficiency
    - $e_t - e_{t-1} = q_t\eta - d_t/\eta$
  - The peak demand over two consecutive demand periods must be greater than or equal to the demand minus discharge plus charge over each two consecutive periods
    - $p \geq D_t - d_t + q_t + D_{t+1} - d_{t+1} + q_{t+1}$
- Objective function:
  - $min_{q_t, d_t} 2Bp + C \sum_t (D_t - d_t + q_t)$

Peak Demand Ratchet

The peak demand rates is on a three-level rachet for the summer months of June, July, August, and September, with the following rates:

- 8 AM – 6 PM, Monday – Friday, $9.15/kW
- 8 AM – 10 PM, Monday – Friday, $18.44/kW
- All other times/days, $16.66/kW

The peak demand rate for other months is on a two-level ratchet shown below:

- 8 AM – 10 PM, Monday – Friday, $13.96/kW
- All other times/days, $4.21/kW

Figures

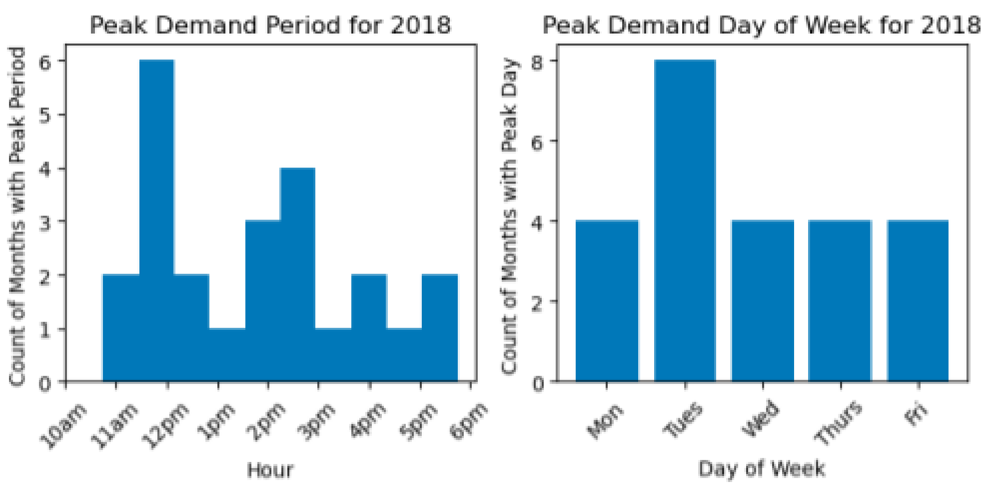

Figure 1. Analysis of 2018 peak demand Left: by hour; Right: by day of week

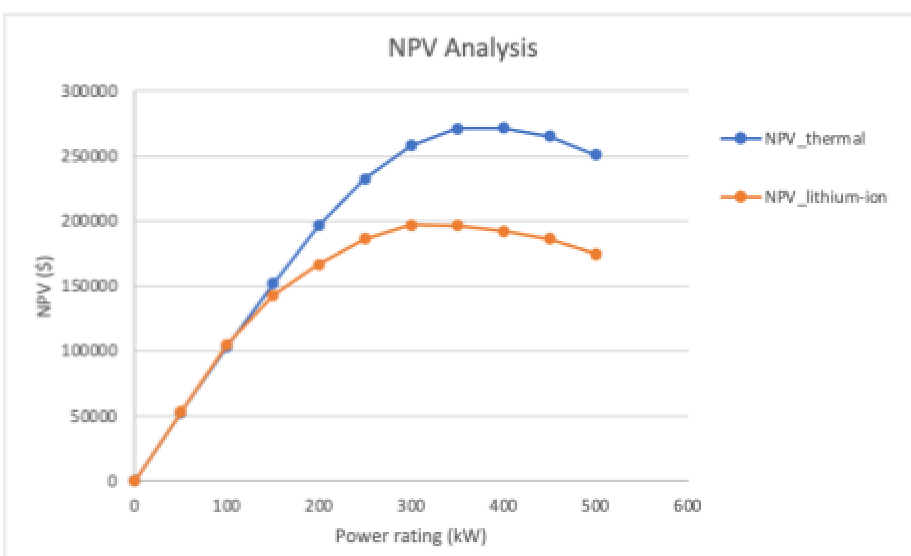

Figure 2. Method 1: NPV comparison of two storage technologies

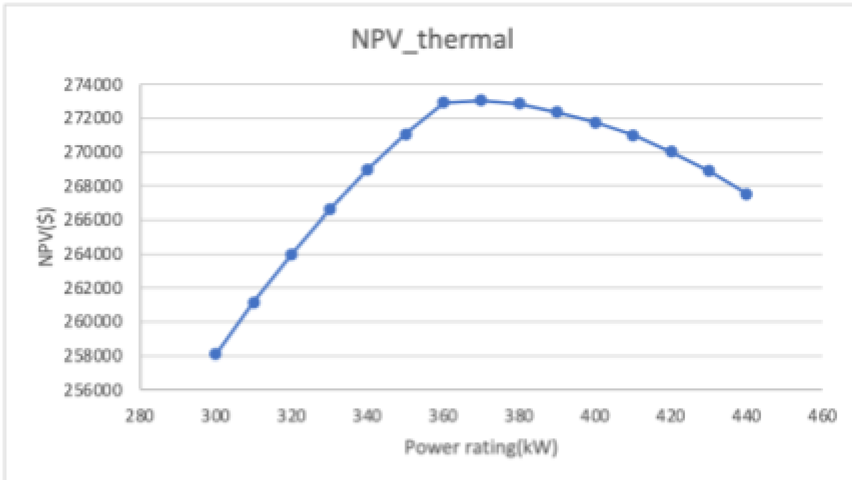

Figure 3. Method 1 :NPV comparison of the thermal energy storage with different power ratings.

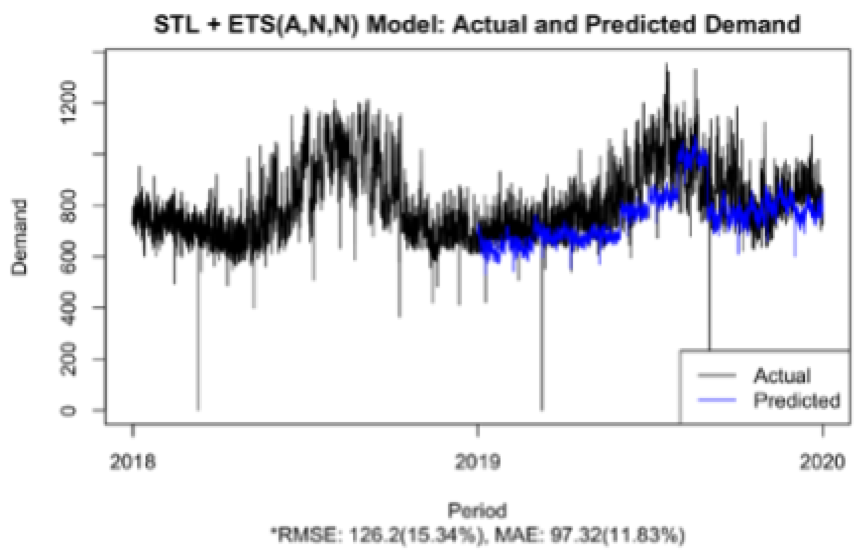

Figure 4. 2019 stlf composite demand forecast.

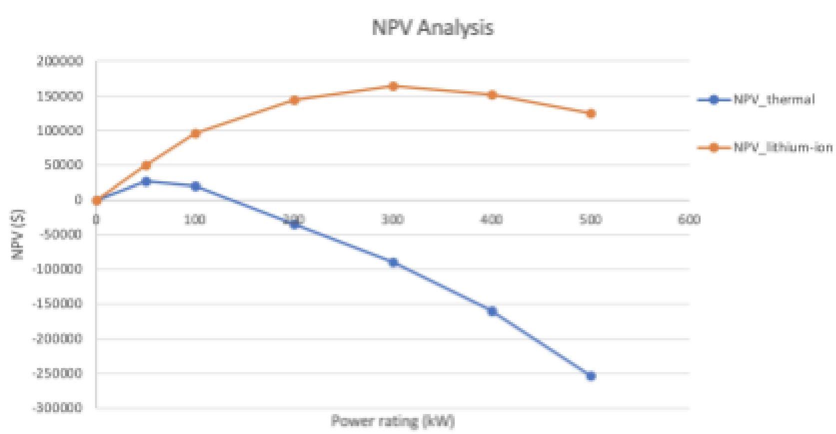

Figure 5. Method 2: NPV comparison of two storage technologies

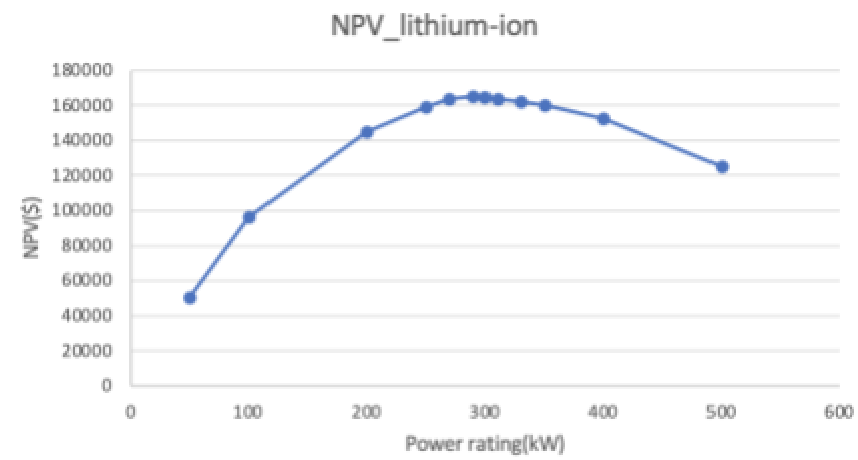

Figure 6. Method 2 :NPV comparison of the lithium-ion battery energy storage with different power ratings.

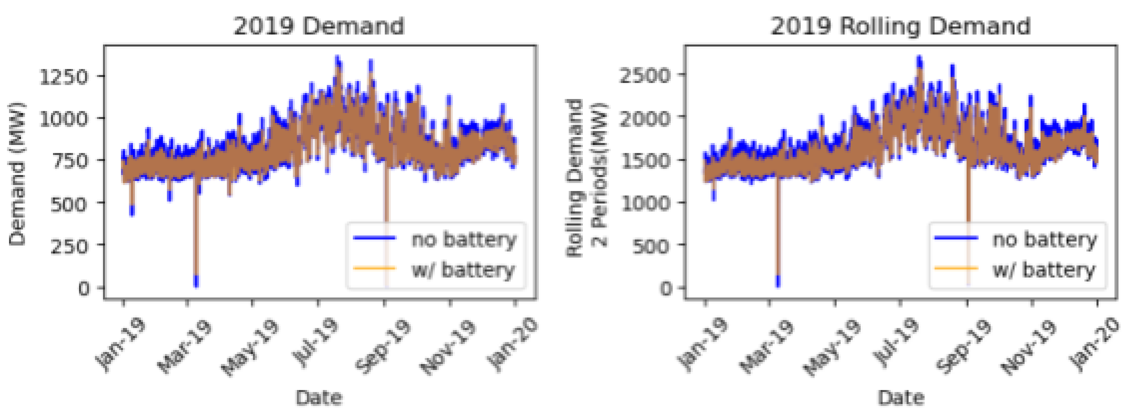

Figure 7. 2019 demand with and without 290 kW lithium-ion battery. Left: demand for each period; Right: Rolling demand.

Tables

	Lithium-Ion	Thermal
Power Rating Cost	\$300/kW	\$500/kW
Energy Rating Cost	\$200/kWh	\$50/kWh
Power Duration (Power:Energy Rating)	4 hours (1:4)	12 hours (1:12)

Table 1. Battery specifications.

		Lithium-Ion	Thermal
Experiment 1: Power ratings	Start at	50 kW	50 kW
	End in	550 kW	550 kW
	Increment	50 kW	50 kW
Experiment 2: Power ratings	Start at	\	300 kW
	End in	\	450 kW
	Increment	\	10 kW

Table 2. Method 1:Experiment to find optimal battery.

The thermal energy storage			
Power Rating (kW)	Battery Investment ($)	Expected Annual Savings ($)	10-year NPV ($)
300	330000	87642	258084.95
310	341000	89739	261155.99
320	352000	91801	263992.18
330	363000	93832	266620.36
340	374000	95822	268973.42
350	385000	97774	271071.50
360	396000	99689	272921.30
370	**407000**	**101347**	**273046.62**
380	418000	102958	272856.56
390	429000	104524	272364.55
400	440000	106072	271751.75
410	451000	107597	270984.63
420	462000	109094	270029.62
440	484000	111998	267515.70

Table 3. Method 1 :Optimization results for peak-shaving savings of the thermal energy storage with different power ratings

Model	RMSE (kW)	MAE (kW)
Naïve	197.41	155.89
ARIMA (0, 1, 5)	197.11	155.57
ETS	197.41	155.89
Stlf	225.45	186.34
Stlf (composite)	97.32	126.2

Table 4. Forecasting model evaluation metrics.

	Operating Costs			**Savings**	
Month	No Battery	Forecasted	Actual	Forecasted	Actual
1	$340,187	$299,097	$340,258	$41,090	-$71
2	$310,981	$276,779	$310,996	$34,202	-$14
3	$347,562	$319,008	$347,895	$28,555	-$333
4	$353,842	$305,236	$354,024	$48,606	-$182
5	$382,922	$316,093	$383,279	$66,829	-$357
6	$545,383	$431,813	$545,902	$113,570	-$519
7	$632,167	$472,999	$630,324	$159,168	$1,844
8	$596,645	$566,356	$601,033	$30,289	-$4,388
9	$528,734	$431,458	$534,063	$97,276	-$5,329
10	$395,900	$355,468	$398,525	$40,432	-$2,625
11	$369,616	$367,831	$370,106	$1,785	-$490
12	$407,547	$358,733	$407,872	$48,814	-$325
Total 2019	**$5,211,486**	**$4,500,869**	**$5,224,274**	**$710,616**	**-$12,788**

Table 5. Optimization results for 2019 forecasted vs. actual cost savings with 370 kW thermal battery.

		Lithium-Ion	Thermal
Experiment 1: Power ratings	Start at	50 kW	50 kW
	End in	500 kW	500 kW
	Increment	100 kW	100 kW
Experiment 2: Power ratings	Start at	250 kW	\
	End in	350 kW	\
	Increment	20 kW	\

Table 6. Method 2 :Experiment to find optimal battery.

The lithium-ion battery energy storage			
Power rating (kW)	Investment for battery ($)	Expected saving per year ($)	NPV for ten years ($)
50	55000	15720	50482.479
100	110000	30767	96449.074
200	220000	54405	145067.682
250	275000	64664	158900.703
270	297000	68666	163754.449
290	**319000**	**72188**	**165387.356**
300	330000	73721	164673.910
310	341000	75240	163866.524
330	363000	78269	162191.361
350	385000	81253	160214.243
400	440000	88292	152446.506
500	550000	100638	125289.171

Table 7. Method 2: Optimization results for peak-shaving savings of the lithium-ion energy storage with different power ratings

	Operating Cost		
Month	With Battery	No Battery	Cost Saved
1	$335,354.67	$340,186.78	$4,832.11
2	$306,888.84	$310,981.16	$4,092.32
3	$342,818.97	$347,562.36	$4,743.39
4	$348,988.94	$353,841.91	$4,852.98
5	$379,049.37	$382,922.08	$3,872.71
6	$532,946.16	$545,382.65	$12,436.49
7	$620,034.45	$632,167.39	$12,132.94
8	$584,226.69	$596,644.95	$12,418.26
9	$516,283.55	$528,734.07	$12,450.52
10	$391,832.50	$395,899.98	$4,067.48
11	$364,934.13	$369,615.69	$4,681.56
12	$402,677.95	$407,546.51	$4,868.56
Total 2019	**$5,126,036.21**	**$5,211,485.52**	**$85,449.32**

Table 8. Daily peak minimization results for 290 kW lithium-ion battery.

Month	Demand (kW)	Charge (kW)	Discharge (kW)	Peak Demand No Battery (kW)	 With Battery (kW)
1	2,097,953	34,433	31,070	1,856	1,711
2	1,914,353	31,876	28,753	1,709	1,585
3	2,160,324	34,358	31,005	1,836	1,693
4	2,160,324	32,837	29,634	2,009	1,864
5	2,355,035	31,725	28,630	2,112	1,995
6	2,571,862	31,222	28,175	2,385	2,240
7	3,025,729	34,739	31,351	2,699	2,556
8	2,822,082	32,666	29,480	2,596	2,451
9	2,504,575	29,919	26,980	2,295	2,150
10	2,382,811	33,377	30,115	2,370	2,247
11	2,296,152	28,720	25,918	1,957	1,818
12	2,536,403	31,606	28,524	2,141	1,996
Total 2019	**28,827,603**	**387,478**	**349,636**	**25,966**	**24,308**

Table 9. 290 kW lithium-ion battery schedule for 2019 and changes in peak demand

Contributions:

- Gabrielle: Coding of optimization function, forecasting, presentation visuals
- Rafael: cost of efficiency loss and peak demand charge reduction analysis, presentation, motivation and summary sections
- Yang: NPV, IRR, optimal battery operation based on NPV, presentation visuals