Optimization of Battery Storage Profitability with Wind Energy

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Abstract

As wind energy production rises, energy storage methods are needed to decrease intermittency and allow better control of the grid. This study considers the effect of a control system optimizing battery charging and discharging to maximize profitability. Different locations, dates, and constraints were considered. An analysis of different objective functions and solver capability is implemented. A battery storage system with an optimized charging and discharged schedule can improve profitability of a wind farm, if capital costs are neglected.

Introduction and Background

As concerns about global warming mount, renewable energy sources are increasingly being called on to replace fossil-fuel power plants. However, renewable energy sources have issues with intermittency that cause problems with grid management and result in energy waste. Energy storage systems have been suggested as a way to reduce the strain on the grid and reduce grounded electricity. Many types of energy storage have been suggested, but battery technology is currently considered the best option.

Large scale battery storage has been used in several high profile energy shortage situations in the last year, as evidenced by Tesla's installation of 100 MW of storage in southern Australia in 2017.[1] Despite the hype, battery technology is still expensive and has a potentially high environmental cost.[2] This study seeks to solve the problem of intermittency and battery cost by optimizing when power is discharged from battery storage to maximize profits from a 100 MW wind energy scheme with a 2400 megawatt hour (MWh) battery capacity over a 24 hour period. Due to high capital costs, this study only considers the degradation costs to the battery and efficiency losses in considering profitability of the wind farm. Wind and power data from several locations along with hourly energy pricing data were used to optimize. Changes in the price of batteries, bounds of the manipulated variables, and the initial guesses of the variables were also considered in this paper.

Modeling Framework

Software

The optimization was written in GEKKO, a python library that allows solving in the APMonitor Modeling Language. APMonitor converts Differential and Algebraic Equations (DAEs) to Nonlinear Programming (NLP) by using orthogonal collocation on finite elements to discretize the model. Derivative values are related to non-derivative values by creating a matrix of coefficients that is used to produce algebraic expressions; gradients are determined by automatic differentiation. An Interior Point Solver (IPOPT) then solves the system of equations.[3]

Model Overview

In this model, wind farm power and time-of-day pricing were used to control battery charging and discharging, shown in Figure 1 as valves. By manipulating the flow of electricity from the windmill to either battery storage or to the grid, an optimum schedule can be found for dispersal of energy for maximum profit. The equations representing this system and a discussion of their meaning is found in the next section.

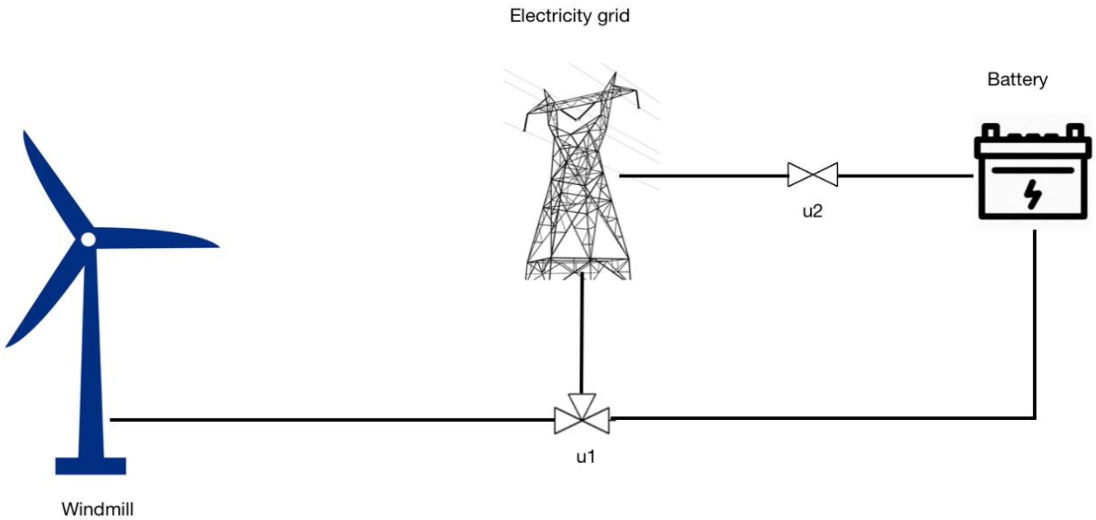

Figure 1: System Schematic

Model Assumptions

A key component of the model was accounting of battery degradation costs. Hoke et al. developed a model of battery degradation as a function of temperature, state of charge, and depth of discharge.[4]

$$C_{bd} = \max\left(\left(c_{Q,T} + C_{Q,SOC} + C_{Q,DOD}\right), \left(c_{P,T} + C_{P,SOC} + C_{P,DOD}\right)\right) \quad (1)$$

C_{bd} is the cost of battery degradation, T is temperature, SOC is state of charge, and DOD is depth of discharge. The equation says there is a cost due to power fade and a cost due to capacity fade; whichever cost is greater is the true degradation cost. To simplify the optimization, in this study only capacity fade was considered.

Batteries degrade due to temperature. This effect is seen most readily during charging due to the resistance of the battery. The cost of degradation due to temperature effects is

$$C_{x,T} = \mathrm{C_{bat}} * \left(\int \frac{1}{8760 * L_x\big(T_{amb} + R_{th} * P(t)\big)} dt + \frac{t_{max} - t_{ch}}{8760 * L_x(T_{amb})} - \frac{t_{max}}{8760 * L_x(P_{min} * R_{th} + T\_amb} \right) \tag{2}$$

where T_{amb} is ambient temperature, R_{th} is thermal resistance of the battery pack, $P(t)$ is time-dependent power fade, t_{ch} charging time, t_{max} is maximum charging time, P_{min} is minimum power required to fully charge the battery, and L_x(T) is an Arrhenius function. Because of the size of the battery and the 24 hour window of optimization, temperature related degradation wasn't considered in our model.

The cost of degradation per hour due to state of charge is

$$C_{SOC} = C_{bat} * \frac{m * SOC_{ave} - d}{CF_{max} \ * 15 * 8760} \tag{3}$$

where C_{bat} is the cost of the battery array, SOC_{ave} is the average state of charge of the battery, CF_{max} is the amount of fade until battery death, and m and d are curve fitting parameters. Variables m and d were fit to capacity fade data.[5]

The cost of the battery was related to the cost per kilowatt hour times the size of the battery array ($Batt_{max}$).

$$C_{bat} = \frac{cost}{kWh} * Batt_{max} \tag{4}$$

The battery array considered has a capacity of 2400 MWh. This size was chosen because it has the capacity to supply a full day's energy. The battery array was fixed rather than optimized because the optimizer set the battery size to zero, reflecting the high cost of the battery. The size of the wind farm was chosen to reflect the median size of modern wind farm capacity.

The cost of degradation due to depth of discharge is related to the change in SOC and the number of cycles at which it occurs.

$$N = \left(\frac{\Delta SOC}{145.71}\right)^{-\frac{1}{.6844}} \tag{5}$$

To create this simplified model, Hoke et al. assumed that N cycles at a given SOC was the same as N cycles with an average ΔSOC change. There is no data to confirm this assumption, but simplicity in the battery model was preferred. In this study, a constant ΔSOC of 25% was assumed, but it was found that the simulation wasn't sensitive to this value. Because of this assumption, the cost of degradation due to depth of discharge simplified to a constant.

$$C_{bat} = C_{dod} * N \tag{6}$$

The current energy in the battery (batt) is represented by the following differential equation

$$\frac{d(batt)}{dt} = U_1 * power * \eta - U_2 * batt \tag{7}$$

where U_1 is the portion of the power from the windmill going into the battery, U_2 is the portion of power discharged from the battery, $power$ is the power produced by the windmill, and η is the efficiency of the charging and discharging process. The efficiency was set at 95% to account for losses due to both charging and discharging.[6] This equation is an energy balance of the battery.

To calculate the profit of the wind farm, we must first account for the transfer of energy to the grid. The balance on the energy in the system and sold to the grid is

$$grid = (1 - U_1) * power + U_2 * batt \tag{8}$$

where $grid$ is the power sold at each time step. The energy sent to the grid is a function of the power from the windmill and power discharged from the battery.

Calculating profit requires the amount of energy provided to the grid and the hourly price of electricity; this gives the revenue. In this study, only the cost of state of charge and depth of discharge are taken into account. Subtracting the costs of degradation from the revenue gives the profit.

$$profit = grid * TOD - C_{SOC} - \frac{C_{dod}}{24} \tag{9}$$

In Equation 9, $profit$ is the profit made by the system at every time step and TOD is the time step price of electricity per MWh. Because C_{dod} is the total cost of depth of discharge in a day, this value was divided by 24 to get the cost of an hour.

Input Data

Wind and power data from various areas and time of day prices from several days were used. Wind speed data from Austin, Texas,[7] power data from the Sotavento Experimental Wind farm in Galacia, Spain,[8] and power data reported from BMRS with data from Great Britain's electricity market. [9] Data for each location was collected on July 20 and December 20, 2017. These sources were chosen to give a better idea of the changes in energy production at different locations and seasons. The different types of wind and power data will allow interesting comparisons for power providers. The Austin, TX wind data is an average of the hourly winds over a year, the power data from BMRS in the UK is the total wind production across the UK at each hour, and the data from the Sotavento Experimental Wind farm is from a single wind farm. All power data have been normalized by making the highest power value equal to 100 MW to make comparison of different locations and dates easier.

This equation converts the wind data to power data.

$$P = \frac{1}{2} * \rho * A * v^3 \tag{10}$$

In Equation 10, P is the power generated by the windmill, ρ is the density of the air, A is the cross-sectional area of the windmill, and v is the wind speed.[10]

Hourly pricing data for July 20, 2017 and December 20, 2017 was sourced from real time energy price data in the central US.[11] The same pricing scheme was used for all of the location optimizations. This allowed a better comparison of the different locations than if location specific pricing had been used. This was especially crucial due to differences in energy subsidization in the different markets considered.

Manipulated Variables

The manipulated variables are U1 and U2, which are shown as valves in Figure 1. The manipulated variable U1 aims at controlling the percentage of power currently produced going into the battery or the electricity grid. If U1 is 100%, then all of the power being generated goes into the battery. Conversely, if U1 is 0%, all of the power produced is sold directly to the grid. U2 is also a percentage, capped at 20%. It represents the percentage of the battery that can be discharged to the grid at any time step. The 20% cap is reflective of the limits of safe battery discharge for long term battery life.[12] This cap can be adjusted as safer battery discharging methods are available. Several other bounds are considered in this paper and can be seen in the results section.

Objective and Constraints

Our model objective was to maximize profits. We do this by optimizing over the entire time horizon and setting our objective as maximizing profit at every time step. With this approach, we can then sum the total of the profit time steps to get a total profit for the day.

Modern battery life management limits how deeply batteries discharge.[12] Equation 5 shows that the depth of discharge is a large factor in determining battery life. To avoid shortening battery life, batteries are prevented from dropping below a certain percentage. In keeping with this practice, the variable representing the battery charge (batt) was limited to 30% of the maximum battery capacity.

To maximize profits, the model would likely want to sell all power in the battery by the end of the day, leaving the battery at the lower bound. This does not reflect the reality of power production, where needs are cyclical. To reflect this, a cyclical constraint was added to the battery as a second objective. This constraint forces the battery to have the same charge at the beginning of the cycle as it does at the end of the optimization. This ensures that there is still a power reserve left in the battery to begin the next day.

Results and Discussion

Comparison of Locations

The results of the optimization for the different locations and dates are presented in this section. It can easily be seen from the power charts that the averaged wind data from Austin, Texas returns positive profits overall. This is intuitive, since averaging over a year allows most of the variability of the wind data to be smoothed out. A similar result can be observed in the data from BRMS. Though the data is from two 24-hour periods, because the data represents all of the wind farms in the UK and was normalized to 100 MW, some of the variability of wind power was removed, although not as much as the data from Austin, TX. The Sotavento data is the hourly data from one wind farm, and thus all of the variability of wind power is visible. This explains the positive profits from Texas and the UK, while the Sotavento profits are negative for one of the days optimized over. The daily profit data is summarized in Table 1. The optimization shows that by manipulating the charging and discharging of the battery, profits can be maximized (or at least losses minimized) over the time period. This shows that if wind conditions can be known at least 24 hours in advance to some accuracy, a wind farm with battery storage can optimize how power is dispersed to maximize profits.

Table 1: Daily Profit from Each Location and Date

Location and Data Date	Daily Profit
UK July 20, 2017	$35,198.06
UK Dec 20, 2017	$8,126.53
Spain July 20, 2017	-$21,564.68
Spain Dec 20, 2017	$13,939.53
Austin Average Data, July 20, 2017	$16,926.25
Austin Average Data, Dec 20, 2017	$6,494.47

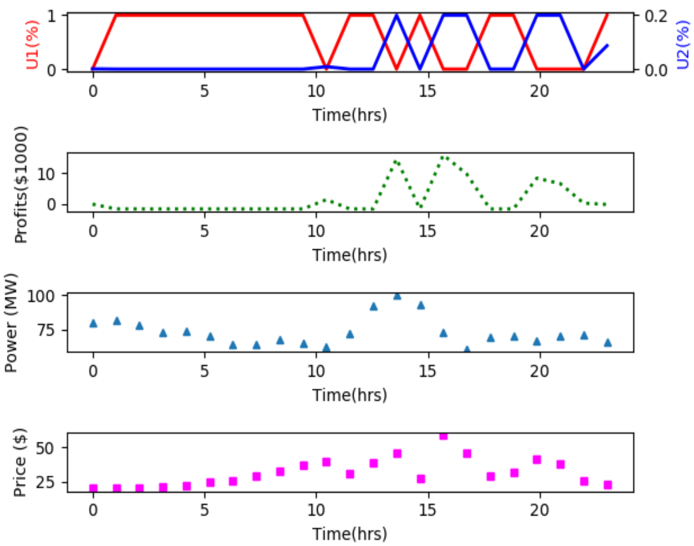

Figure 2: UK July Plots

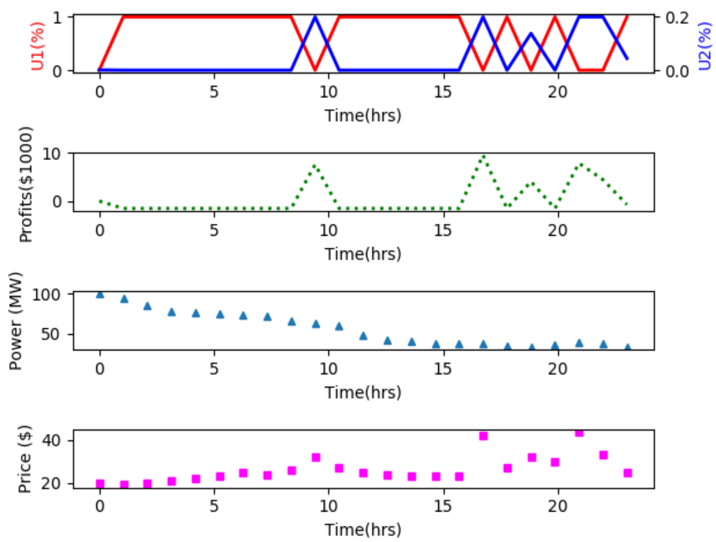

Figure 3: UK December Plots

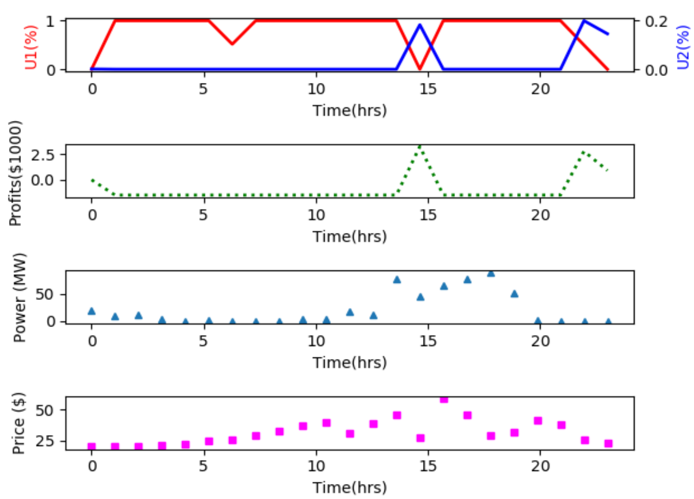

Figure 4: Sotavento July Plots

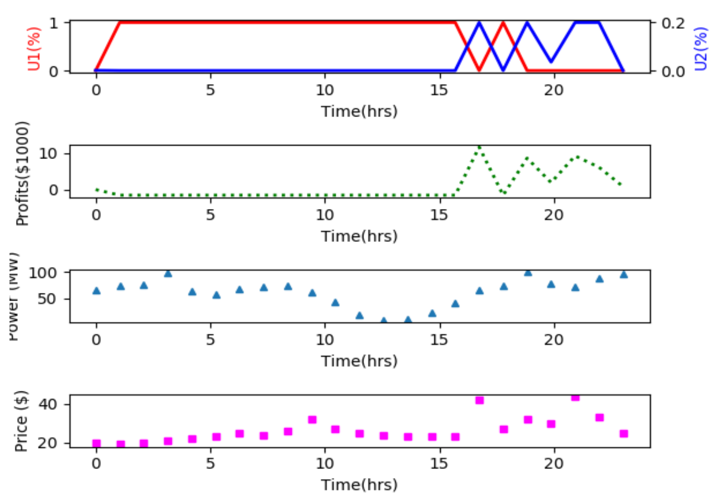

Figure 5: Sotavento December Plots

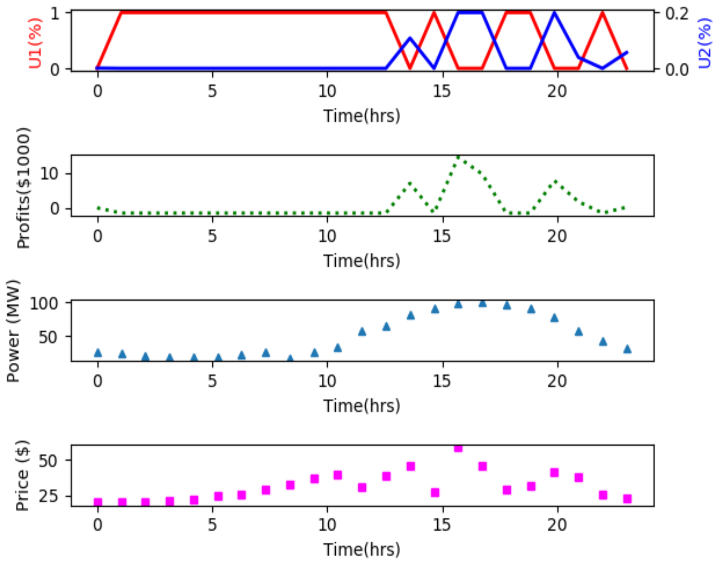

Figure 7: Austin July Plots

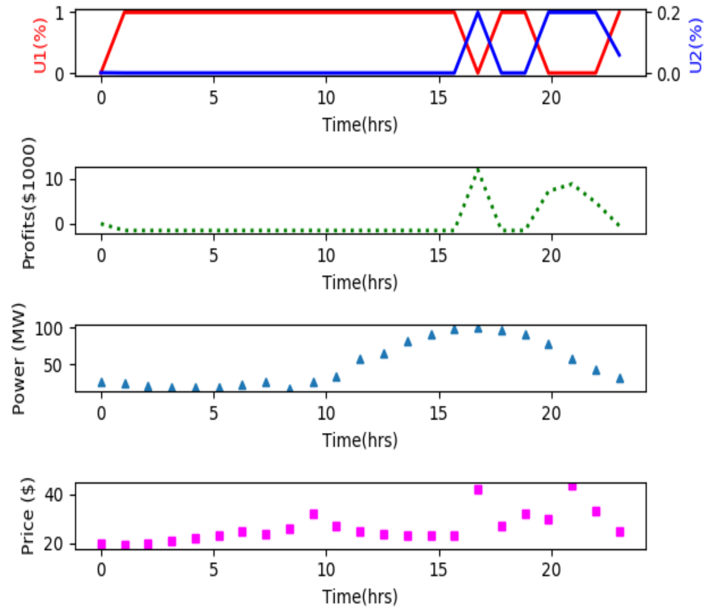

Figure 6: Austin December Plots

Discussion of Cost Changes

The optimization results were highly dependent on the cost of the battery. Several different costs were considered, from current costs to predicted future costs.[13]

These values were tested on the Austin, TX power data with time of day pricing from July 20, 2017. As would be expected, the lower the battery cost is, the more profitable the windmill is. It is important to remember that our optimization only considers the operating costs of the wind farm, and none of these figures consider the capital costs of the venture.

Table 2: Battery Cost and Daily Profit

Cost of Battery ($/MWh)	Profit
30	$43,461.09
80	$31,823.06
145	$16,926.25
200	$4,283.62

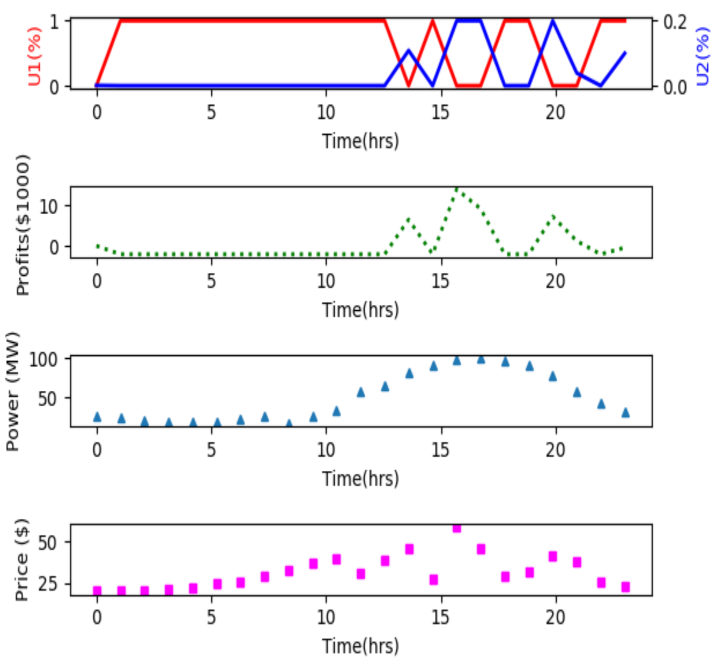

Figure 8: Battery Cost $200/MWh

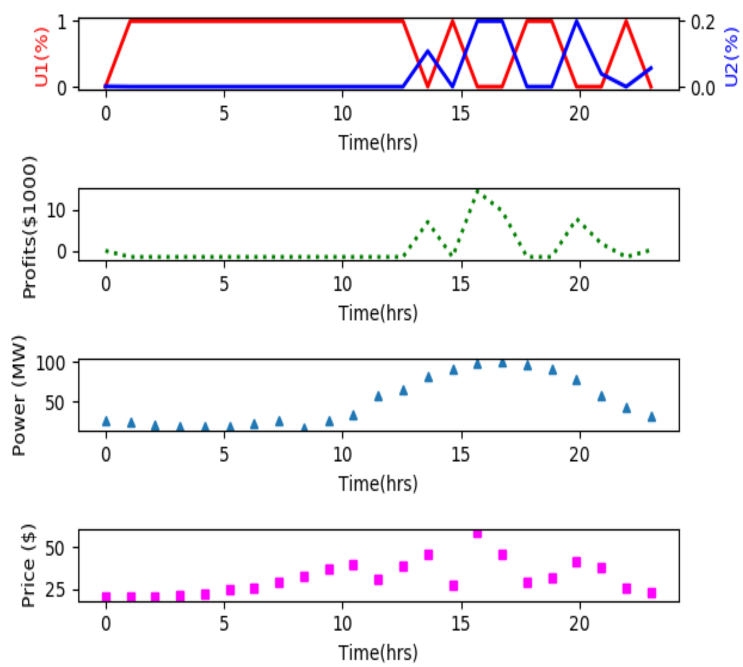

Figure 9: Battery Cost $145/MWh

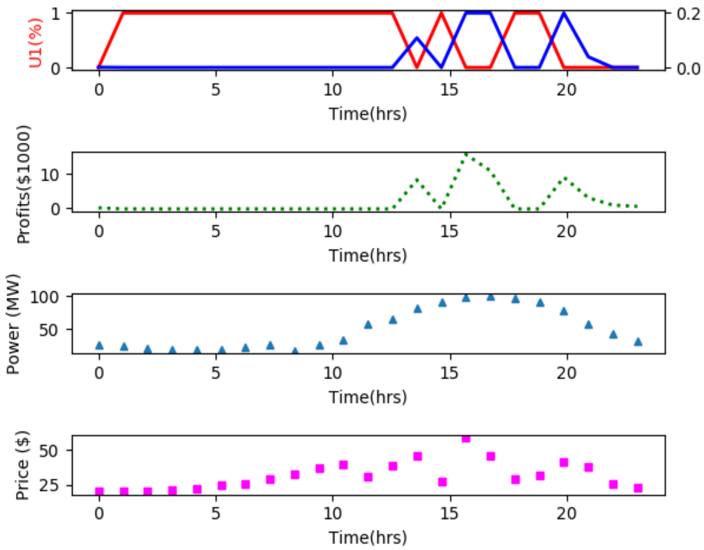

Figure 10: Battery Cost $30/MWh

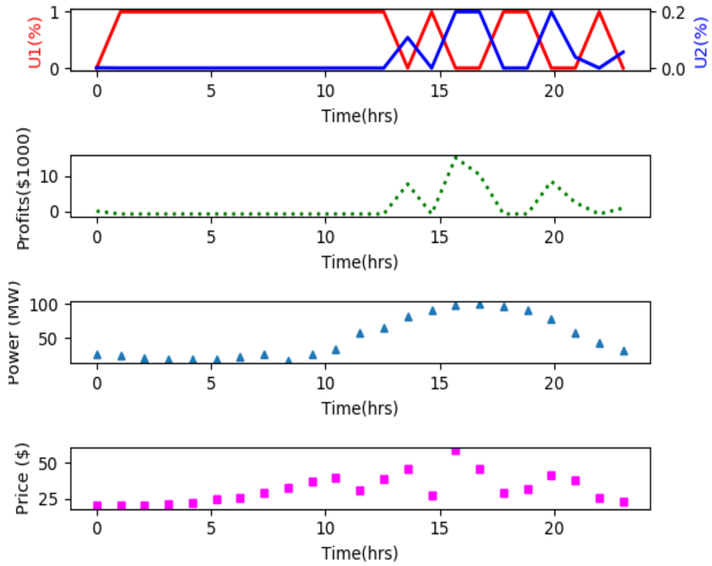

Figure 11: Battery Cost $80/MWh

Discussion of Battery Initial Charge

Due to safe battery charging practices, the lower bound of the battery was set at 30%. When the variable was initialized, the lower bound was taken as the initial value. To determine whether that was significant due to the periodic constraint, other initial values of the battery were tested on the Austin, TX power data with time of day pricing from July 20, 2017. It was observed that there was an optimum initial condition, somewhere between 30% and 75%. This would make an excellent area for future optimization work. This result shows that our model is very sensitive to the initial condition of the battery, and a better model would likely be able to optimize the initial value as well.

Table 3: Initial Charge and Daily Profit

Initial Charge	Daily Profit
30% Initial Charge	$16,926.25
50% Initial Charge	$19,421.83
75% Initial Charge	$618.11
100% Initial Charge	-$13,090.97

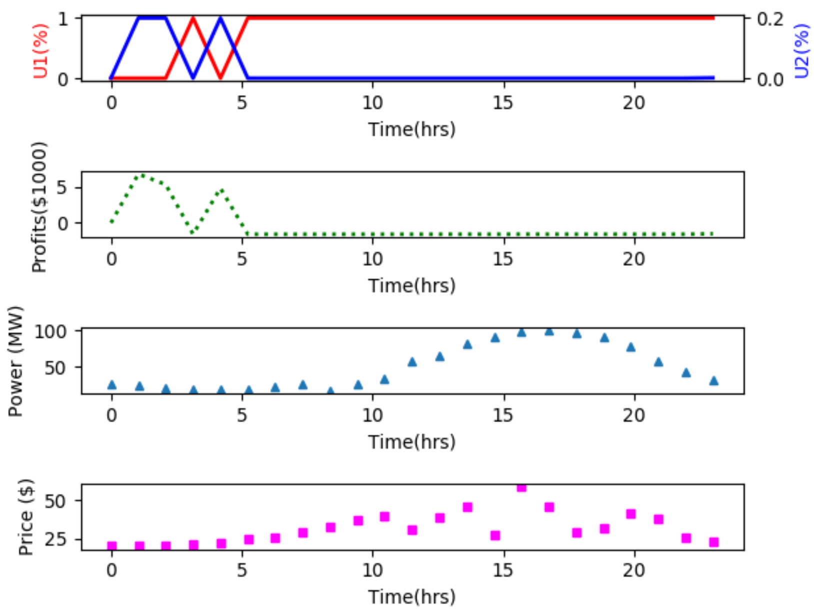

Figure 12: 100% Initial Charge

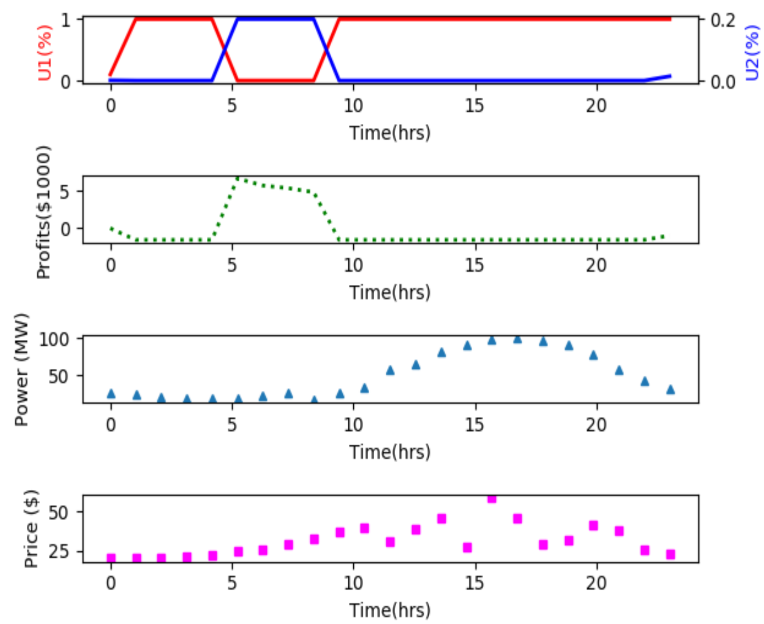

Figure 13: 75% Initial Charge

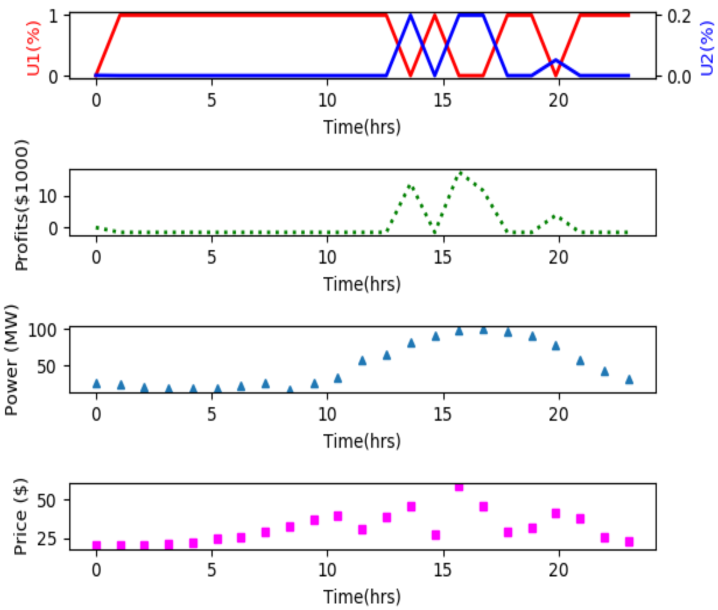

Figure 14: 50% Initial Charge

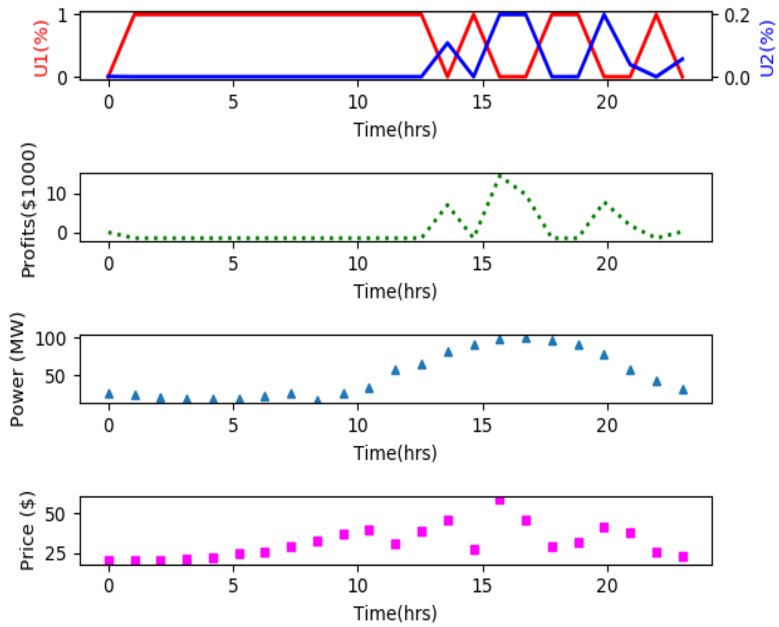

Figure 15: 30% Initial Charge

Discussion of Upper Bounds of U_2

Current battery technology places limits on how fast batteries can be charged and discharged. The rate of charge and discharge has a large effect on the number of cycles in a battery's life. In this study, it was assumed that the limit for the battery was 20% per time step in the battery model in keeping with charging practices. As battery technology progresses, faster charging and discharging may become a reality. [12,14]

To reflect this, several upper bounds were considered on U_2, the variable representing the percentage of the battery discharged per time step. These values were tested on the Austin, TX power data with time of day pricing from July 20, 2017. It was found that the higher the U_2 upper bound was, the more profitable the venture was. This make sense, considering that the optimizer was allowed to sell all of the electricity at the most profitable time step. It was surprising that degradation costs did not increase more than the profitability. It could be that neglecting the degradation due to the large temperature change associated with rapid discharging didn't allow the cost of degradation to increase as quickly as profitability. It is also possible that degradation of the battery isn't as significant a factor as was expected.

Table 4: U2 Upper Bound and Profit

U2 Upper Bound	Profit
U2 = 1	$21,039.48
U2 = .5	$19,836.27
U2 = .3	$16,926.25
U2 = .1	$13,650.00

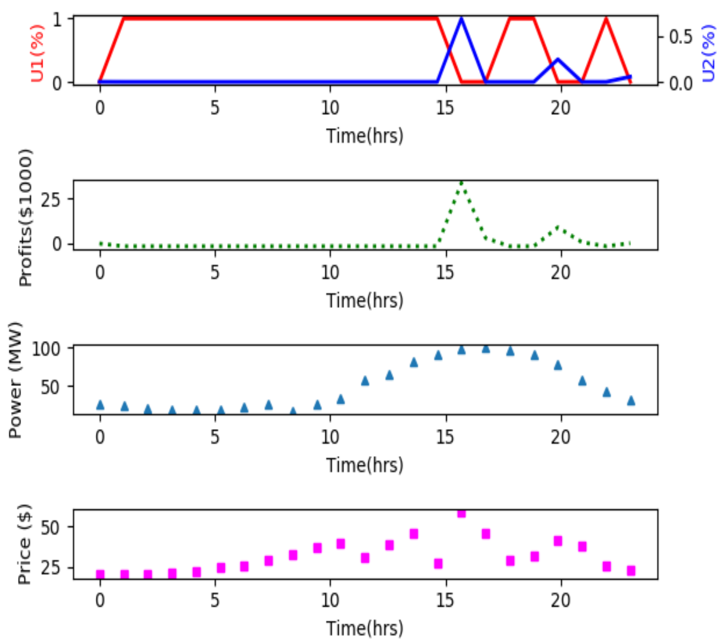

Figure 16: U2 Upper Bound of 1

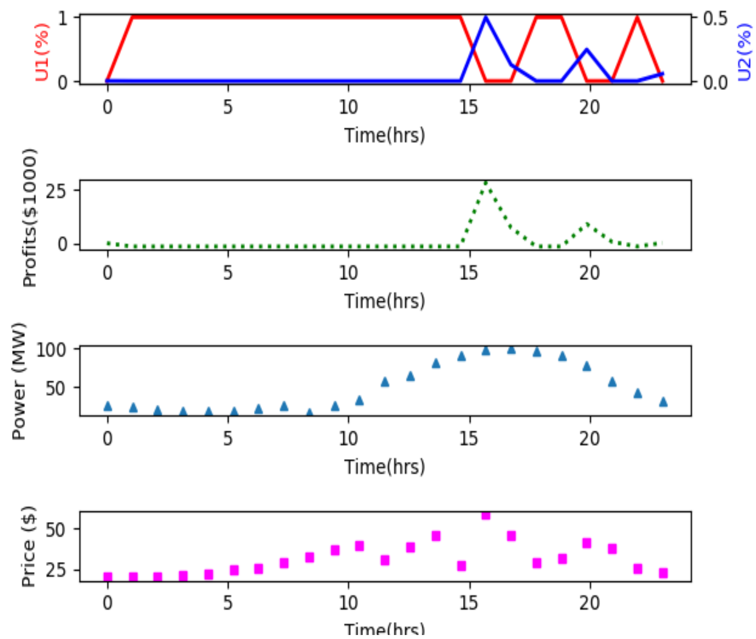

Figure 17: U2 Upper bound of .5

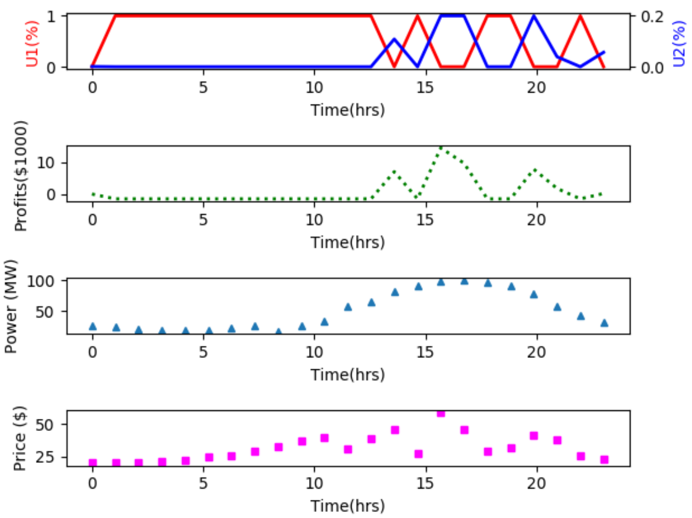

Figure 18: U2 Upper Bound of .3

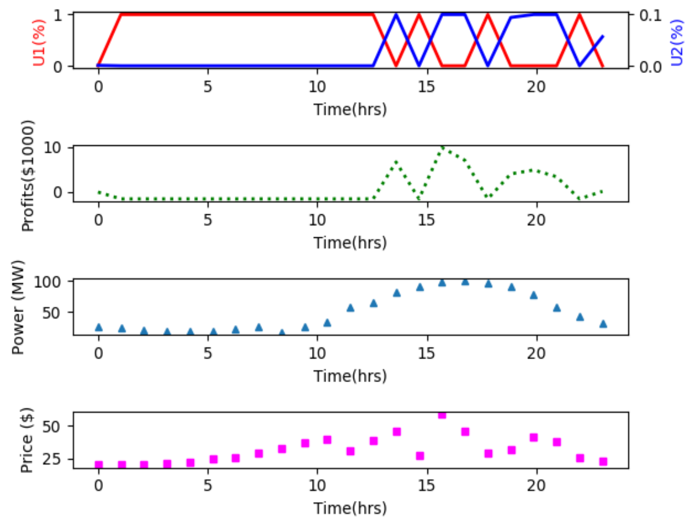

Figure 19: U2 Upper Bound of .1

Discussion of Objective Function Choice

While examining some initial results, it was discovered that the optimizer was finding local maxima rather than the best value for profitability. Our initial objective function was

$$objective = \text{maximize}(profit^2) \tag{11}$$

By changing the objective function to

$$objective = \text{maximize}(\sqrt{profit}^2) \tag{11}$$

the best result is achieved. It is suspected that the initial objective function led to a scaling issue. With the original expression, the objective function reached a magnitude of 10^8. At this high value, when the optimizer found a local maximum, the tolerances of APMonitor were reached and the solution was accepted. APMonitor is designed for tolerances in the range of 0-100. By changing our objective function, the objective function was reduced and the solver had reason to continue looking for the best solution.

These plots compare the results with the two different objective functions on wind data from Austin and time of day pricing from July 20. The updated objective function returns a higher profit by $17,000.

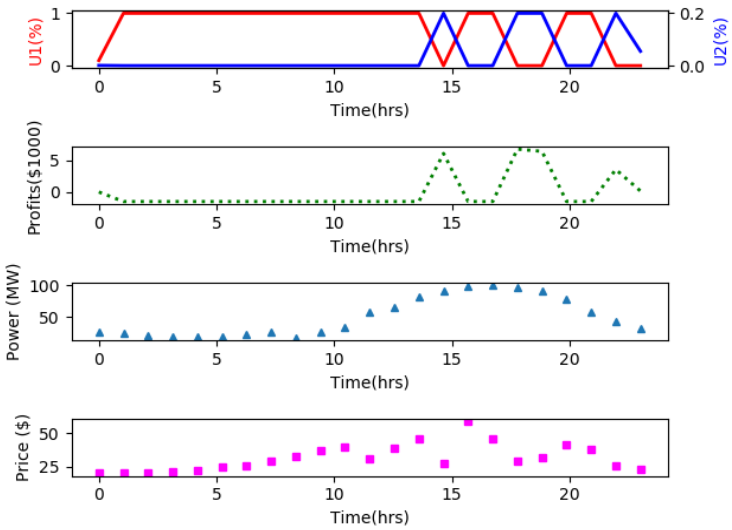

Figure 20: Original Objective Function

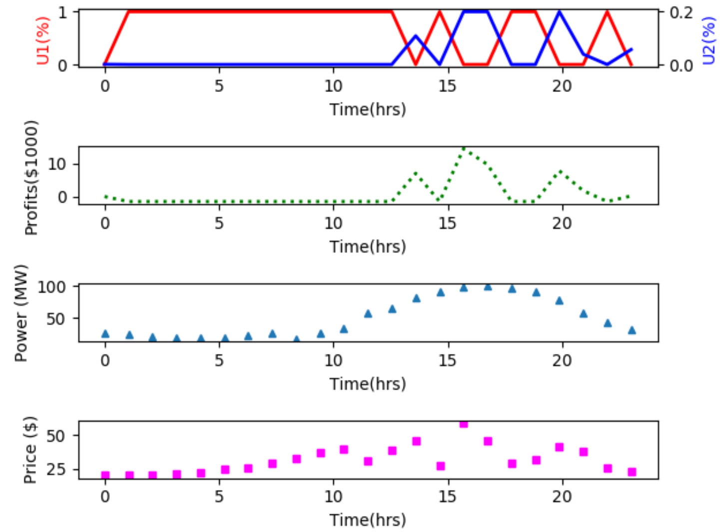

Figure 21: Updated Objective Function

Conclusions

Our results show that wind energy with optimized battery usage can increase profitability of wind farms. These results can be seen even when including the costs of battery degradation and has been proven for several locations and dates.

The cost of the battery is the major expense in the energy system. Thus, enhancing battery life is key to increasing profits. As battery costs drop and battery technology is improved, battery storage will become more profitable.

Acknowledgements

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