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Modeling And Sizing Of Energy Storage Devices For Wind Power Generation

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Abstract

Variability in wind power generation prevents the electric grid from relying on this source of energy. Coal, natural gas, and hydropower companies all schedule generators in advance. Wind turbines, however, are not predictable, making it difficult to follow a scheduling plan. Storing electricity can serve to mitigate wind fluctuations, enabling the absorption of energy during peak production and supplying energy to the grid during troughs. A pair of storage devices, which maximizes profit based on fluctuating electricity prices, has been modeled. Optimization of control actions of the storage devices to maximize profit was achieved with CVX. The simulations resulting from this study show that installing a large-rate, relatively low-storage capacity device, and a large-storage, relatively low-rate capacity device interconnected can smooth variations in wind power production much more economically than a single storage device with both large storage and rate capacities. Furthermore, this study shows that the device's efficiencies do not have a high impact on the profit obtained with a particular device pair. Finally, these results can be used to choose a combination of storage technologies with the appropriate set of characteristics that will mitigate wind fluctuations and maximize profit.

Keywords: Wind power, energy storage, optimization

1. Introduction

The increasing efforts to replace fossil fuel-based electricity production with renewable generation make wind an attractive source of energy. Climate change, energy security, and fossil fuel availability are encouraging governments to incorporate wind generators at large scale. For example, the European Union has set a goal of 20% electricity generation to be served by renewable sources by 2020, and approximately one third of this electricity is expected to come from wind[1]. The United States has also set a goal for electricity to come from renewable sources; by 2030, it is expected that 30% of the United States' electricity will come from wind[1]. In spite of the benefits that wind power generation offers, its unpredictable nature makes it difficult to control. Unlike coal plants and gas turbines, wind generators cannot be adjusted to produce a certain amount of electricity at a given time. High electricity generation will occur when there is a lot of wind. However, when wind availability is low, other generators in the grid will have to respond, ramping from low to high production or vice versa, in order to meet the demand. These sudden changes in generation can deteriorate power plants' hardware, reducing their lifetime, and causing more CO_2 emissions[1]. Current electricity generators were not designed to interact with the unpredictability of wind. As a result, large-scale penetration of wind will require the electric grid to adjust to sudden changes in wind availability. Plants that are able to cycle their power output quickly enough to meet system requirements will have to replace current generation technologies. Managing electricity production with large amounts of wind in the grid will face increased costs because different unit commitment decisions must be made to schedule generators[2]. Generators are typically scheduled in advance of their production. Wind generators, however, cannot be scheduled too far in advance due to the inherent variability of wind. Gas turbines have fast-ramping capabilities and could be installed jointly with wind generators to meet their generation schedule. However, unlike wind turbines, gas turbines require fuel, which means that incorporating wind into the grid would be more costly than not incorporating it at all. This would increase the price of electricity even if the power from wind were effectively free[2].

Studies have shown a couple methods to control wind variability in addition to fast-ramping generators: wind curtailment and energy storage. Wind curtailment consists of absorbing less than available wind power. Curtailment smoothens the wind's output to the electric grid during high availability. During low wind availability, however, curtailment cannot compensate for the power shortage to meet the demands of the grid[3]. On the other hand, electricity storage has the capability to absorb and supply power to the electric grid during high and low wind availability respectively. Different energy storage technologies are available. For example, energy can be stored in the rotation of a flywheel, the potential energy of a hydro-pumped storage or a compressed gas, chemical processes of batteries and fuel cells, and in the electric field of a capacitor[2]. Each of these technologies has different characteristics and choosing the appropriate combination of properties to compensate for wind fluctuations will allow storage devices to be sized and incorporate wind into the electric grid[4]. Various studies using storage devices to reduce the variability of wind and decrease operational costs have been published. However, scant attention has been paid to including a portfolio of storage devices not only to mitigate wind fluctuations, but also to maximize profit based on fluctuating electricity prices. The price of electricity fluctuates throughout the day, and it is roughly proportional to its demand. That is, during peak consumption hours, the price of electricity is high, and during low consumption, electricity price decreases[5]. Electricity storage can be used to absorb power during high wind availability, store the excess power, and sell it to the electric grid when the price of electricity is high.

2. Research Objective

The goal of this investigation is to determine the characteristics of a pair of energy storage devices that minimize wind fluctuations and maximize profit based on time variable electricity prices. Control actions of the storage devices was achieved with an optimization package called CVX[6]. An analysis of the effects of storage properties allows choosing the appropriate storage technology to meet the needs of a particular system, minimizing fluctuations and maximizing profit.

3. Model Development

This model assumes an aggregate of wind turbines as the source of power. The variability of wind decreases as the number of turbines and wind power plants distributed over and area increase; variability also decreases with spatial aggregation[1]. This study uses wind generation data from the Bonneville Power Administration located in the state of Oregon[7]. Yearly data sets with five-minute resolution are available at the BPA's website corresponding to the aggregate generation of all wind farms in the BPA's area. This particular study uses data corresponding to one week of generation in the months of June and July 2013. Furthermore, the time varying electricity prices used in this investigation were taken from the National Grid's website and are presented in one-hour resolution intervals[8].

3.1. Power Flow Model

The BPA's wind power data is the input to this power flow model. The aggregate of turbines is connected to a pair of storage devices of different characteristics, which deliver power to the electric grid. This model assumes that the grid operator makes decisions on when to charge or discharge the storage devices. This indicates that the operator either stores energy when too much wind is available or supplies power when wind is not sufficient to keep a commitment[2]. The model also allows power transfer between the two storage devices and curtailment. Curtailment allows removing peaks in generation without using storage. Moreover, electrical connections between the turbines, storage system, and electrical grid are not modeled. Instead, it is assumed that the grid operator will be able to adjust the power flow as needed to properly charge, discharge, curtail, and transfer power in the storage system. Figure 1 shows a schematic representation of the power flow model.

Furthermore, the model proposes a scheme that optimizes charging, discharging, transfer, and curtailment decisions using CVX's optimization capabilities to find a sequence of control actions. This sequence minimizes the penalties assigned to the system when it does not meet a generation schedule, and maximizes profit based on time dependent electricity prices. This approach provides the best control scheme to meet the proposed objective. The system includes a discrete time step model of power flow. The power delivered to the grid at a certain time step is the power available from the wind minus the amount of power used to charge the storage system and wasted in curtailment plus the amount of power delivered to the grid from storage as shown in equation (1).

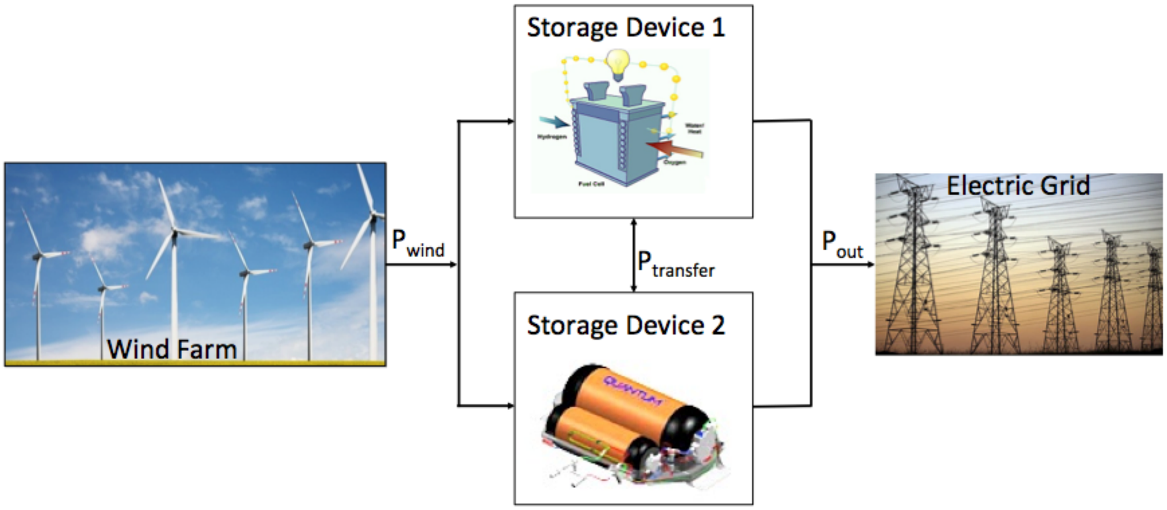

Figure 1: Wind farm and 2-storage device system

$$P_{del}(t) = P_{wind}(t) + \eta_1 P_{d_1}(t) + \eta_2 P_{d_2}(t) - P_{c_1}(t) - P_{c_2}(t) - P_l(t) \tag{1}$$

where η is the charging efficiency of the each individual storage device and represents how well the storage can convert the electrical power from wind into electrical stored energy. In this model, power is expressed in megawatts (MW). In addition, the energy in storage device 1 is modeled as the initial storage state plus the energy charge and minus the energy discharge and transfer to storage device 2:

$$E_1(t+1) = E_1(t) + \left[\eta_1 P_{c_1}(t) - P_{d_1}(t) - P_t(t)\right]\Delta T \tag{2}$$

Also, the energy in storage device 2 is modeled as the initial storage state plus the energy charge and transfer from device 1 minus the energy discharge:

$$E_2(t+1) = E_2(t) + \left\{\eta_2\left[P_{c_2}(t) + P_t(t)\right] - P_{d_2}(t)\right\}\Delta T \tag{3}$$

where ΔT is the time step in minutes and energy is expressed in megawatt-hour (MWh). Power is lost entirely when the storage system is discharged to the grid or when it is curtailed. In each optimization problem, constraints are imposed on the system to avoid trivial solutions such as that where all power is curtailed, giving a perfectly smooth delivery, but no delivery to the grid[2].

One of the key aspects of this investigation is determining how wind generation can adhere to a schedule of generation. In a real power grid system, generators are scheduled in advance of their operation. Wind generators must also adhere to this system if wind is to be incorporated into the grid. Therefore, it is necessary that wind generators forecast their future energy production and maintain commitments to schedules the same way traditional generation does: generators must maintain a constant output during delivery[2]. The natural variability, and under or over-predicting wind generation can incur penalties on the storage system. Therefore, this model is attempting to minimize the mismatch between the scheduled and delivered power to reduce penalties. Also, it is assumed that the grid operator schedules wind generation based on a particular generator's forecast. To simplify the calculations, this model assumes a perfect forecast. That is, the available wind power is exactly the same as the forecasted power. For this system to meet load demands, the market scheduling is accounted for by introducing the following timescales: t_{LA}, the look-ahead time gives the amount of time ahead of generation a schedule is made; t_C, the commitment time is length of time a constant commitment must be kept; and t_D, the delivery time gives the timescale on which power is delivered to the grid. Figure 2 shows a timeline of a typical generator's schedule.

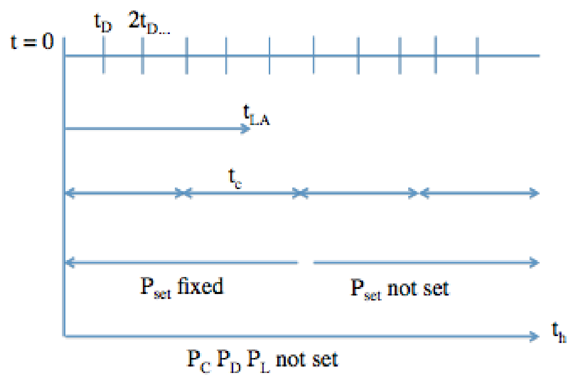

Figure 2: Timeline of scheduling power for delivery[2]

A look-ahead time length away, the power generation for that interval is scheduled. The system is forced to keep a constant power, P_{set}, during a commitment interval. Generation is often scheduled in blocks of t_C length; this commitment can be adjusted anytime except when it is t_{LA} away from generation. Therefore, to make up for over or under-predictions of wind availability, the storage system must charge or discharge its power. Simultaneously, the system must recognize the price of electricity for a future delivery interval, t_D, and assure that deviations of delivered power, P_{del}, from schedule power, P_{set}, are small in order to maximize profit. This model tested look-ahead time and commitment intervals of 60 minutes, and deliveries were always made on 15-minute intervals. The time horizon T_h, the time on which a forecast of future generation was available, was set to 360 minutes as in reference[2].

3.2. Optimization

The sequence of control actions that minimize penalties and maximize profit was found with CVX, which is a Matlab-based system for convex optimization[9]. In this scheme, the scheduled power, and the system's charging, discharging, curtailment and transfer decisions were determined at each optimization interval. The optimization was carried over the time horizon T_h and was redone every t_D minutes. The objective function of the optimization problem was expressed as shown by equation (4)

$$\max_{P_c,P_d,P_t,P_l,P_{set},P_{del}} \sum_{t=1}^{T_h} \left\{ \left[Price_{Ele}(t) \times P_{del}(t) \right] - \sqrt{ \sum_{t=1}^{T_h} \left\{ Pen \times Price_{Ele}(t) \times \left[P_{set}(t) - P_{del}(t) \right] \right\}^2 } \right\} \tag{4}$$

where the variables available for optimization are P_c, P_d, the charging and discharging rate of the system; P_t is the transfer power between the storage devices; P_l is the curtailed power; and P_{set} and P_{del} are the scheduled and delivered power respectively. The mismatch between the scheduled and delivered power is penalized by introducing a penalty term, Pen. The electrical grid operator assigns a penalty to the system (1 was used in this study). The penalty is multiplied by the price of electricity, $Price_{Ele}$, and the square of the mismatch of schedule and delivery. Missing the schedule by greater amounts will incur greater penalties and minimize profit. Similarly, a really high price of electricity can incur losses in the system. Therefore, a combination of small deviations in delivery and a reasonably high price of electricity will yield the highest profit. Furthermore, the net profit achieved with a particular combination of storage characteristics was defined as the sum of the profits at each delivery interval. The profit at each delivery interval and the net profit for a particular set of electricity prices and storage system characteristics were calculated with equations (5) and (6) respectively.

$$Pro_{int}(t) = \left[Price_{Ele}(t) \times P_{del}(t)\right] - \sqrt{\sum_{t=1}^{T_D} \left\{Pen \times Price_{Ele}(t) \times \left[P_{set}(t) - P_{del}(t)\right]\right\}^2} \tag{5}$$

$$Profit_{Net} = \sum_{t=1}^{T_h} Pro_{int}(t) \tag{6}$$

The performance of the system was also evaluated by observing the effect of penalties on the net profit and storage parameters. That is, the profit as a function of penalty was determined for each delivery interval, and the net penalty is the sum of all such penalties. The penalty at a particular delivery interval and the net penalty were determined with equations (7) and (8) respectively.

$$Pen_{int}(t) = \sqrt{\sum_{t=1}^{T_D} \left\{Pen \times Price_{Ele}(t) \times \left[P_{set}(t) - P_{del}(t)\right]\right\}^2} \tag{7}$$

$$Pen_{Net} = \sum_{t=1}^{T_h} Pen_{int}(t) \tag{8}$$

3.3. Optimization Constraints

Constraining the amount of energy in storage, charging/discharging rate, and power transfer at a given time represents real device limits. To model storage capacity, the total amount of storage in the system was constrained to be less than a chosen maximum. That is:

$$0 \le E_1(t) \le E_{cap_1} \tag{9}$$

$$0 \le E_2(t) \le E_{cap_2} \tag{10}$$

where E_{cap} represents a particular device's maximum capacity and it is expressed in megawatts-hour (MWh). Charging, discharging, and curtailment rates were constrained to be non-negative and less than the maximum charging rating of a particular storage device. The maximum charging and discharging rates were assumed to be equal as shown in equations (11) and (12).

$$0 \le P_{c_1}(t), P_{d_1}(t), P_l(t) \le P_{cap_1} \tag{11}$$

$$0 \le P_{c_2}(t), P_{d_2}(t), P_l(t) \le P_{cap_2} \tag{12}$$

where P_{cap} represents a particular device's charging/discharging capacity and it is expressed in megawatts (MW). Finally, the scheduled power is never larger than the available power from wind. Negative delivery or curtailments are trivial decisions as indicated by equations (13) and (14) respectively.

$$0 \leq P_{set}(t) \leq P_{wind_{\max}} \tag{13}$$

$$0 \leq P_{del}(t), P_l(t) \tag{14}$$

The storage system for optimization consists of an infinite rate capacity, 0.8 efficiency device (storage 1), and an infinite storage capacity, 0.1 efficiency device (storage 2). In other words, the rate capacity of device 1 was left unconstrained during optimization while storage capacity was varied according to equation (9). Furthermore, the storage capacity of device 2 was left unconstrained during optimization, whereas its rate capacity was allowed to vary according to equation (12).

4. Results

The optimization resulted in a delivery schedule where the promised power, P_{set}, is equal to the forecasted wind power. The addition of the 2-storage device system allows P_c and P_d, the charging and discharging rates, to compensate for the difference between the scheduled and delivered power. The performance of the 2-device system is shown in figures 3 and 4.

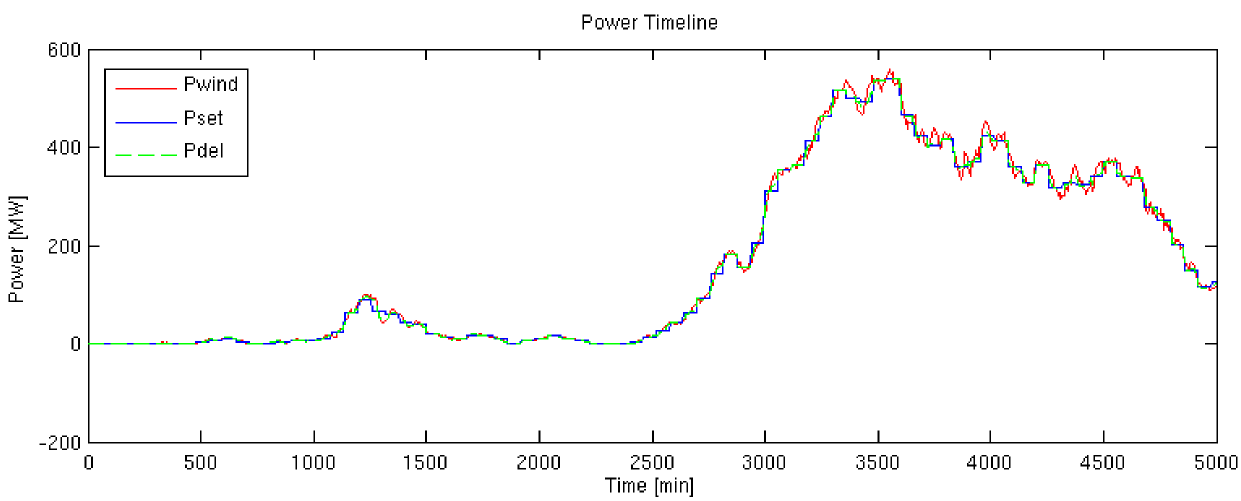

Figure 3: Wind, scheduled, and deliver power

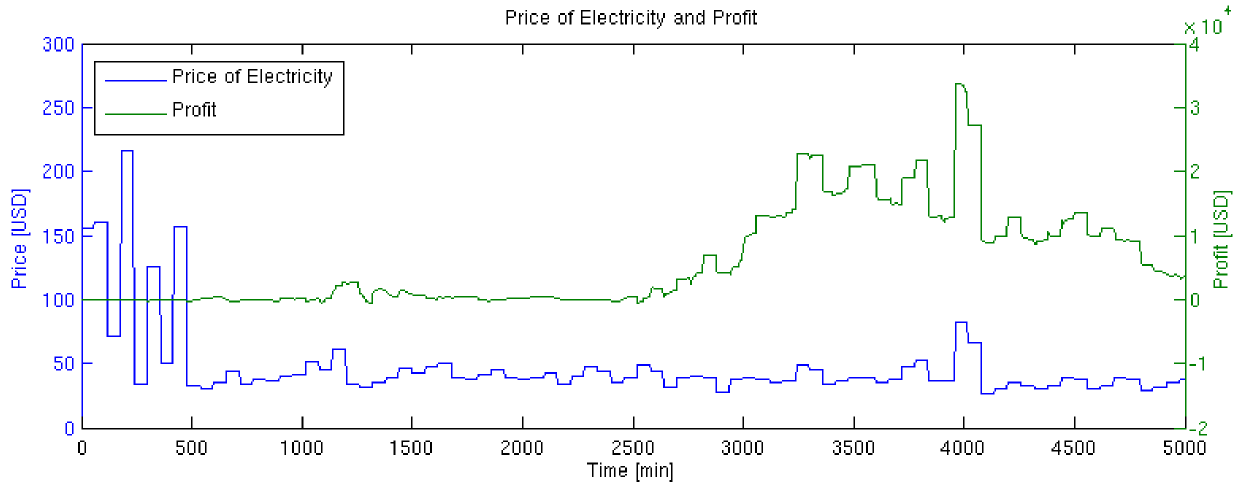

Figure 4: Wind, scheduled, and deliver power (top). Electricity prices and profit (bottom)

Figure 3 shows BPA's wind data (red), scheduled (blue), and delivery power (green). The scheduled and delivered power are the output of the optimization performed with CVX. Moreover, figure 4 shows profit and time dependent electricity prices where profit was computed with equation (5). Although one week of wind power data was used in this study, figure 3 shows only a portion of these data for clarity purposes. In addition, the characteristics of the 2-device storage device system that resulted from optimization are presented in figure 5. This plot shows profit as a function of device characteristics. The x-axis shows the storage capacity of device 1, whereas the y-axis shows the rate capacity of device 2.

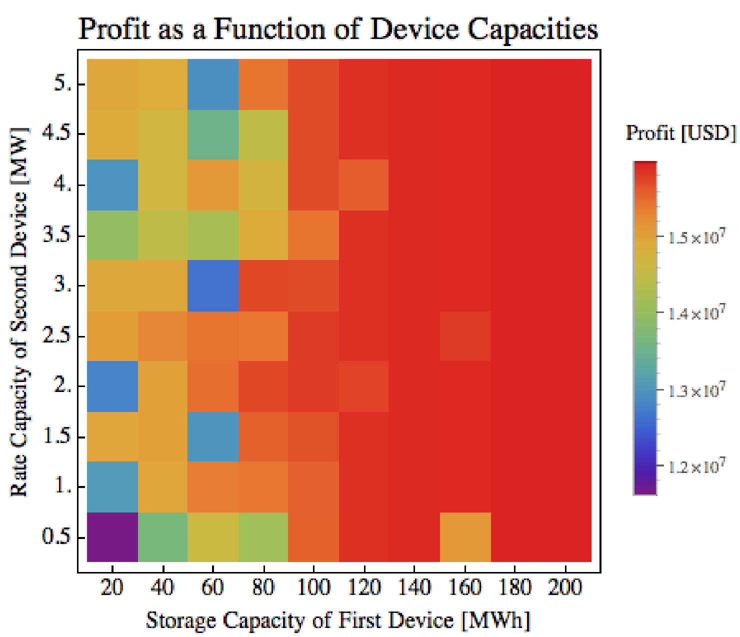

Figure 5: Plot of profit as a function of 2-device system characteristics

The performance of a single device system was also determined to confirm if the addition of a pair of storage devices to the wind generator-grid system improves its performance. Figure 6 shows a plot of profit as a function of single-device system characteristics. The efficiency of the presented storage device is 0.8.

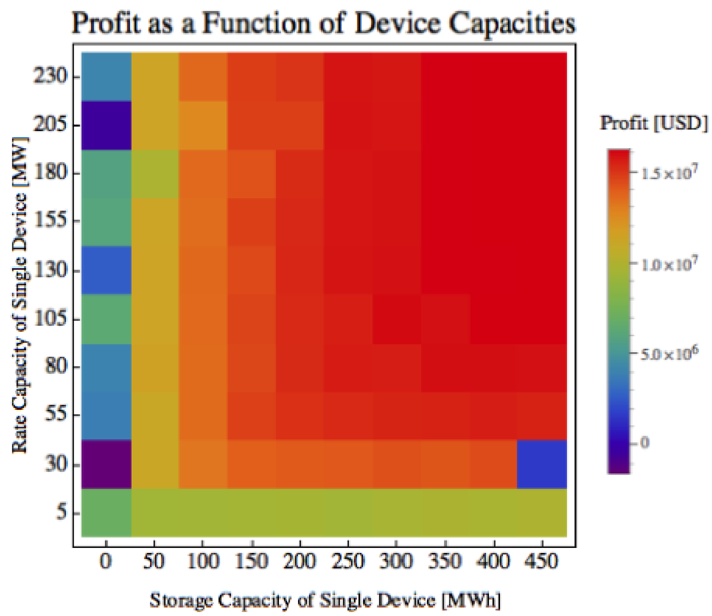

Figure 6: Profit as a function of single device characteristics

The efficiencies of the 2-storage device system are presented in figure 7. This plot also shows the effect of storage efficiencies on profit. Profit in figures 5, 6, and 7 were computed with equation (6).

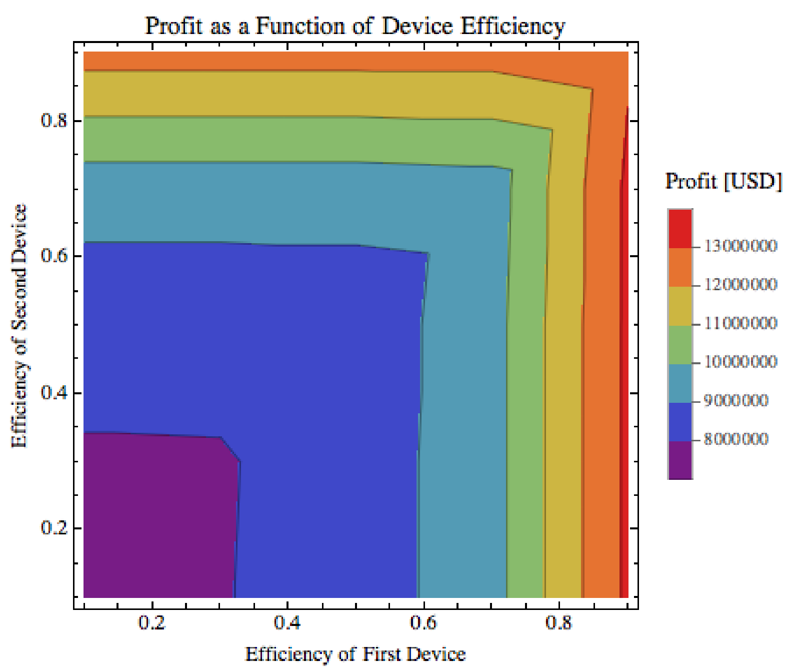

Figure 7: Profit as a function of device efficiencies

This study also includes the effect of penalties on the performance of the 2-device system. Penalties for missing a schedule are assigned by the grid operator, and they are not published. Therefore, this study uses equation (7) to model such penalties where the constant *Pen* was set equal to 1. Figure 8 shows a plot of profit as a function of penalty and storage capacity. Profit values were computed with storage capacities of 10, 120, 250 and 500 MWh. Profit and penalties were computed with equation (6) and equation (8) respectively.

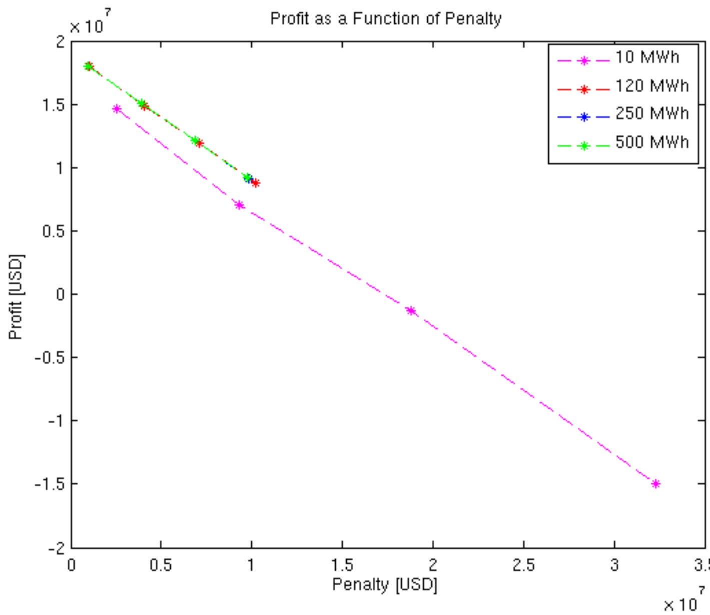

Figure 8: Profit as a function of penalty and storage capacity

In addition, Figure 9 shows a plot of profit as a function of penalty and rate capacity. Rate capacities of 0.5, 10, and 100 MW are presented. Profit was also computed with equation (6).

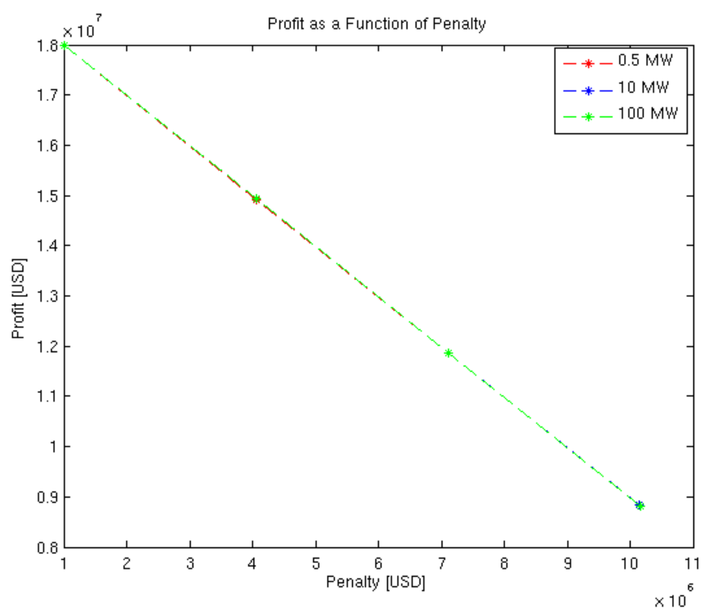

Figure 9: Profit as a function of penalty and rate capacity

5. Discussion and Conclusions

From the results of this investigation, it is clear that the large-scale penetration of wind into the electric grid is possible with the addition of storage. The proposed 2-storage device system smoothens the wind power output of an aggregate of turbines as shown in figure 3. The system appears to absorb power during high wind availability and supplies power during wind troughs. This means that the system is absorbing power, P_c, during peaks of generation to charge the storage devices, and is delivering power, P_{del}, during low wind availability by discharging the storage devices. This behavior is observed in figure 3. During stages of high wind availability, the system closely matches the available power's profile. On the other hand, during times where the power available does not meet the scheduled profile, the system releases power from storage and meets the scheduled profile. Furthermore, the system is scheduling an approximately constant power, P_{set}, to be supplied over its delivery interval, t_D. The delivered power, P_{del}, is closely following the schedule; however, there are instances where the system has over or under-predicted its delivery. These mismatches result in penalties and no profit is achieved as observed in the time interval between 1000 and 2500 minutes.

Similarly, evidence that the 2-storage device system is maximizing profit by minimizing scheduled and delivered power mismatches appears in figures 3 and 4 in the interval between 0 and 500 minutes. In spite of high electricity prices, the system is not making any profit during this interval because the system is assigning penalties to the delivery mismatch, and high electricity prices amplify such penalties [equation (7)]. On the other hand, in the vicinity of 4000 minutes, the system makes a profit of approximately 30,000 dollars because the delivered power follows the scheduled power very closely, and the price of electricity is relatively high. Profits increase when the system is able to stick to its generation schedule, and prices of electricity do not magnify penalties. Evidently, the addition of storage allows wind generators to adapt to the scheduling system of the electricity market. Generally, meeting a delivery schedule to avoid penalties increases profits. The role of storage in meeting such a schedule is to discharge when the system under-predicted generation, or to absorb power when the system over-predicted generation. If the system has a large storage capacity, it will be able to store more electricity and discharge to meet its schedule. However, more storage capacity requirements make the system more expensive.

Moreover, the variable nature of wind forces the storage system to charge and discharge very rapidly to meet its schedule. So, a high rate capacity allows the system to charge or discharge as needed, but induces higher costs. Therefore, the lower storage and rate capacities the system requires to maximize profit, the better. Figure 5 shows that large storage and rate capacities do increase the profit the system makes; however, the system saturates, and no further improvement is achieved. The 2-storage device system's saturation point occurs at approximately 130 MWh of storage capacity and 0.5 MW of rate capacity. An example of a two-storage device system with these characteristics is a battery and a high-power flywheel[10]. The axes of figure 5 were selected so that they show what combination of storage and rate capacities yields the largest profits.

Similarly, a single-storage device system also saturates. However, such saturation occurs at around 300 MWh of storage capacity and 100 MW of rate capacity. A hydro-pumped storage system is an example of a storage device with such large storage characteristics. Notice that installing a 2-storage device system with only 0.5% rate capacity and 43% storage capacity of a large device such as a hydro-pump yields the same profit. Installing a battery and a high-power flywheel is cheaper and requires considerably less geographic space that a hydro-pumped storage. As a result, a system with a large-rate, relatively low-storage capacity device, and a large-storage, relatively low-rate capacity device interconnected can smooth variations in wind power generation much more economically than a single storage device with both large storage and rate capacities.

Another conclusion from this study is that the efficiencies of the storage devices do not play an important role in meeting a schedule and maximizing profit. Figure 7 shows that profit does not significantly increase by adding more efficient storage. After the efficiency of a storage device has been set, the second device's efficiency is somewhat arbitrary. Ideally, a 2-device system will have an efficient, and a moderately efficient storage device pair. Having two highly efficient storage devices is more expensive and does not guarantee higher profits. Therefore, in this study, storage device 1's efficiency was set equal to 1, and device 2's efficiency was set equal to 0.1.

In addition, notice that figures 8 and 9 also show that the addition of storage capacity to the 2-device system counteracts the effect of penalties and improves its performance. However, when the system reaches its saturation point, no further profit is achieved and penalties take over. Similarly, adding extra rate capacity to the system does not improve its performance. Although real electricity cost data were used in this optimization, the main purpose of this study is to demonstrate that significant savings can be achieved by installing a 2-device storage system rather than a single-device storage system. Therefore, selecting the technologies that would best adapt to the demands of the grid using the results of this study can be included in future studies where more precise electricity prices are included. Finally, multiple storage systems can also be investigated to observe their interaction with the grid. Although it is expected that a multiple device system will perform similarly, the cost of installation may be higher and therefore not as feasible.

6. Acknowledgements

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