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Abstract

Wind generation presents variability on every time scale, which must be accommodated by the electric grid. Limited quantities of wind power can be successfully integrated by the current generation and demand-side response mix but, as deployment of variable resources increases, the resulting variability becomes increasingly difficult and costly to mitigate. In Chapter 2, we model a co-located power generation/energy storage block composed of wind generation, a gas turbine, and fast-ramping energy storage. A scenario analysis identifies system configurations that can generate power with 30% of energy from wind, a variability of less than 0.5% of the desired power level, and an average cost around $70/MWh.

While energy storage technologies have existed for decades, fast-ramping grid-level storage is still an immature industry and is experiencing relatively rapid improvements in performance and cost across a variety of technologies. Decreased capital cost, increased power capability, and increased efficiency all would improve the value of an energy storage technology and each has cost implications that vary by application, but there has not yet been an investigation of the marginal rate of technical substitution between storage properties. The analysis in chapter 3 uses engineering-economic models of four emerging fast-ramping energy storage technologies to determine which storage properties have the greatest effect on cost-of-service. We find that capital cost of storage is consistently important, and identify applications for which power/energy limitations are important.

In some systems with a large amount of wind power, the costs of wind integration have become significant and market rules have been slowly changing in order to internalize or control the variability of wind generation. Chapter 4 examines several potential market strategies for mitigating the effects of wind variability and estimate the effect that each strategy would have on the operation and profitability of wind farms. We find that market scenarios using existing

price signals to motivate wind to reduce variability allow wind generators to participate in variability reduction when the market conditions are favorable, and can reduce short-term (30-minute) fluctuations while having little effect on wind farm revenue.

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Chapter 1: Introduction

1.1 Background and Motivation

The rapid deployment of energy storage and the increasingly significant amount of variability introduced by new wind generation will be two of the most important and interesting changes to electricity grids over the next few decades. Energy storage is frequently described as the solution for the variability of wind power (as well as a host of other issues), but the relationship between storage and variable generation is subtle and complex. Variability is not new to the electricity grid, well-established methods for mitigating its effects already exist, and energy storage technologies are both novel and costly. Thus, while energy storage is able to eliminate the negative effects of wind variability, it should not be assumed that storage is the ideal compliment to increasing quantities of wind generation. Only through prudent comparison of potential wind integration techniques will we identify the best options and determine how energy storage contributes to the solution.

Wind power is the renewable electricity source of choice, due to its relatively low cost and established technology. As a result, wind power is the most important contributor to Renewable Portfolio Standards (RPS) adopted by most states and, given the economic and political difficulties with nuclear power and carbon capture and sequestration, a critical part of any effort to reduce US greenhouse gas emissions in the next few decades. The total quantity of installed wind generation has been rapidly increasing in the US (Figure 1.1), and wind power represents a large fraction of new generation (44% in 2008, 39% in 2009, by nameplate capacity) (Wiser & Bolinger, 2010).

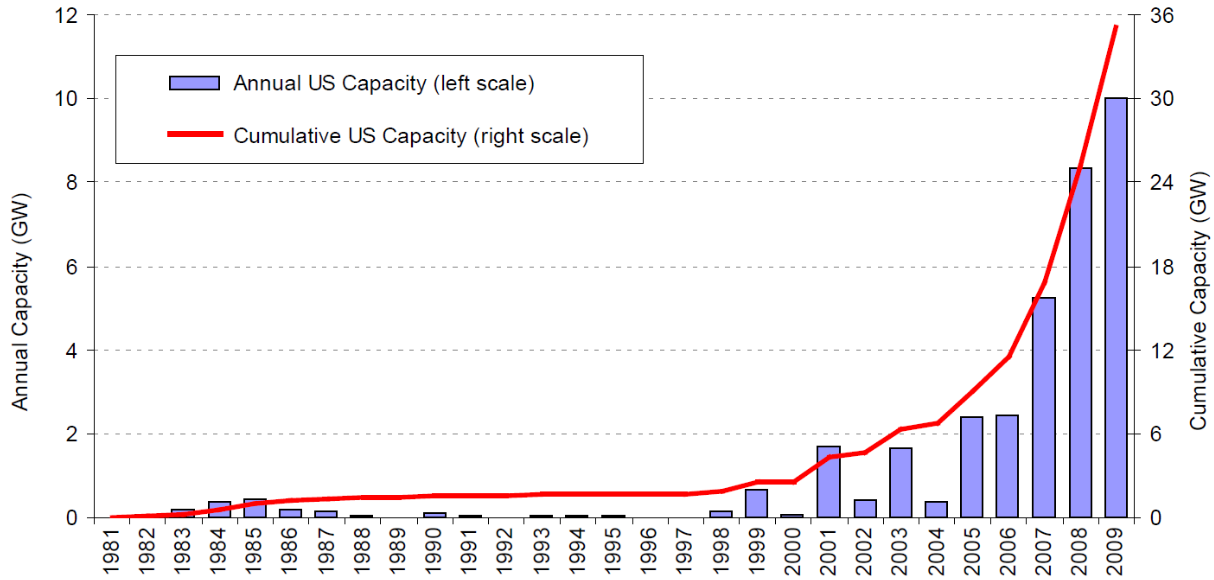

Figure 1.1: New and cumulative wind (nameplate) capacity in the US. (From US DOE, *2009 Wind Technologies Market Report*)

But wind power output is variable on every time scale, and rapid increases in variable generation are an important concern for the traditionally risk-averse electricity industry. There is no doubt that wind generation and its fluctuating power output can be successfully integrated into the electricity grid, but there is uncertainty regarding the costs, methods, and scale of that integration. Given the size of the electricity industry, small percentage improvements in wind integration costs can have very large effects and are worth investigating. In 2010, wind accounted for 2.3% (95,000 GWh) of US electricity generation (US Energy Information Administration, 2011). At a wind integration cost of $3/MWh (see Figure 1.2), accommodating this amount of wind energy costs roughly $300M per year. If we were to meet the goal of attaining 20% of US electricity from wind, as proposed and described in the US Department of Energy (DOE) study "20% Wind Energy by 2030", the wind integration costs alone may be around $7B annually (assuming a wind integration cost of $6/MWh), or about 2% of the operating costs of the entire US electricity industry (US DOE, 2008). And, importantly, these wind integration costs are generally borne by entities other than the wind producers, who may be best able to mitigate that variability. The rapidly increasing deployment of wind generation offers an opportunity to implement appropriate policies and technologies immediately, before the bulk of future wind generation has been constructed and the system becomes difficult to change.

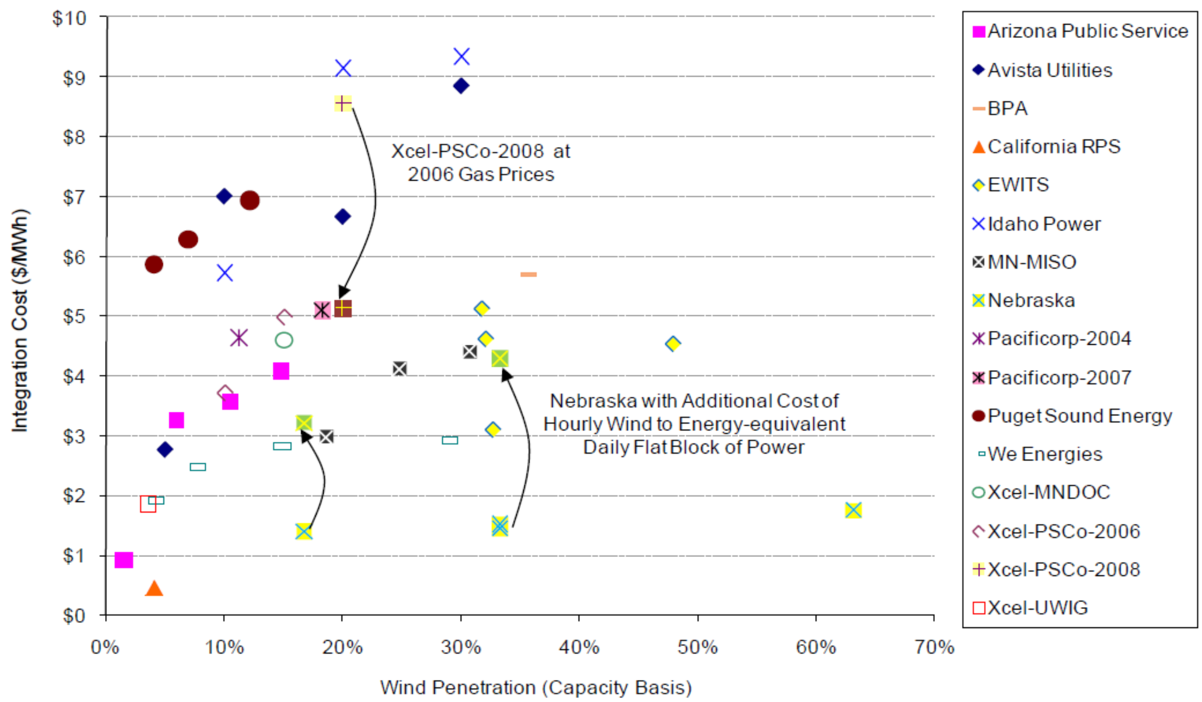

Figure 1.2: Estimated wind integration costs from various studies versus wind penetration. (From US DOE, *2009 Wind Technologies Market Report*)

There has been significant interest in grid-level energy storage technology over the past five years, though actual implementation has been limited. Partly, this is due to the fact that energy storage is currently quite expensive, limiting use to critical applications where traditional technologies are unable to provide the required services at an affordable cost. But the fact that most energy storage technologies are new and unproven is also important, resulting in an understandably measured uptake of the novel technologies and prompting researchers to question how energy storage should be used. Many current applications use energy storage to simulate services provided by traditional generators under operational and market rules defined and refined for a traditional generation fleet over the last hundred years. Though the design of electricity grids and markets cannot be faulted for historically focusing on traditional assets, it seems unlikely that the value of novel technologies, such as energy storage, can be fully captured if they are forced to imitate traditional resources. By examining applications and market structures that take advantage of the strengths of energy storage, we can suggest alternative market rules and structures that can extract more value from the new technologies than would otherwise be possible.

1.2 Overview of Thesis

This thesis aims to answer several questions relating to the short-term variability of wind generation, energy storage technologies, and their potential relationship:

1. Given the strengths of energy storage and the weaknesses of traditional generators, what type(s) of novel energy services is it most suited to? In particular, how can energy storage be used to reduce the short-term variability of wind power?

2. How can the currently rapid development of energy storage technologies best be channeled towards producing future value for electricity grids? How should current energy storage technologies be improved to meet near-term electrical grid needs?

3. How would different market rules affect the deployment and operation of wind farms and related technologies? How can the costs due to variability of wind be internalized to wind generators?

It is important to note that this thesis focuses mainly on short-term (10s of seconds to sub-hourly) variability, as this part of the frequency spectrum represents an area where traditional generators are weak, energy storage is strong, and prior research is incomplete.

The larger question that this thesis attempts to address is this: *What is the most efficient and cost-effective method of integrating large quantities of wind power, and what role (if any) does energy storage play in that solution?* This is a critical question, and the answers developed over the next decade have the potential to reshape electrical grids in the US and around the world. While a complete answer is beyond the scope of a single author, this thesis contributes important insights to the ongoing dialogue. This work contributes several new results and analyses to the existing science. In an analysis of fast-ramping energy storage used to locally smooth wind fluctuations, a new potential application for emerging energy storage technologies is identified. In the first quantitative analysis of the value of energy storage properties that looks at different technologies and applications, several consistently valuable properties are identified. Finally, a new way of internalizing wind variability that can reduce wind integration costs is proposed and analyzed.

The thesis is divided into five chapters. This chapter provides a brief background of the larger issues surrounding wind variability and energy storage. Chapter 2 examines an system where energy storage is used to eliminate sharp fluctuations in a co-located wind/natural gas turbine/energy storage system. Chapter 3 investigates which properties of energy storage technologies are most valuable to improve, as a guide to future development. Chapter 4 examines electricity market rules that partially internalize the negative effects of wind variability, and the expected response from wind generators is determined. Chapter 5 summarizes the conclusions of the thesis and discusses further work that could be done to improve and expand upon the results presented herein.

1.3 References

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Chapter 2: Compensating for Wind Variability Using Co-Located Natural Gas Generation and Energy Storage

2.1 Abstract

Wind generation presents variability on every time scale, which must be accommodated by the electric grid. Limited quantities of wind power can be successfully integrated by the current generation and demand-side response mix but, as deployment of variable resources increases, the resulting variability becomes increasingly difficult and costly to mitigate. We model a co-located power generation/energy storage block which contains wind generation, a gas turbine, and fast-ramping energy storage. Conceptually, the system is designed with the goal of producing near-constant "baseload" power at a reasonable cost while still delivering a significant and environmentally meaningful fraction of that power from wind. The model is executed in 10 second time increments in order to correctly reflect the operational limitations of the natural gas turbine. A scenario analysis identifies system configurations that can generate power with 30% of energy from wind, a variability of less than 0.5% of the desired power level, and an average cost around \$70/MWh. The systems described have the most utility for isolated grids, such as Hawaii or Ireland, but the study has implications for all electrical systems seeking to integrate wind energy and informs potential incentive policies.

2.2 Introduction

Wind power output is variable on every time scale (Apt, 2007). Wind power variation on the scale of hours or days can be smoothed by traditional generators or by compressed air energy storage (CAES). Natural gas turbines in particular are able to quickly change their power output and are important for the integration of wind power, but are unable to respond in seconds to minutes, especially from a cold start. For example, the GE 7FA gas turbine, a common unit, has a fast start-up option which allows the turbine to dispatch in 10 minutes after a start signal (GE Energy, 2009) (Kim, Song, Kim, & Ro, 2002). In addition to non-zero startup time, these generators have low operating limits, limited ramp rates, inefficiency at low output, and other characteristics that are sometimes neglected when they are modeled as wind-smoothing devices. For this reason, if a wind farm is coupled with a gas generator (or gas-fired CAES), the power output can be smooth on an hourly scale, but can still become quite noisy on shorter time scales. In most contemporary electrical systems, this high frequency variation is mitigated by distributing the response over a large number of traditional generation resources or hydropower resources providing regulation service (Castronuovo & Lopes, 2004) (Greenblatt, Succar, Denkenberger, Williams, & Socolow, 2007). At higher wind penetration levels significant ancillary services, in the form of quick-ramping regulation, are likely to be required. This can lead to increased emissions, as it has been shown that fast and frequent ramping of gas generators decreases their average efficiency, increases their average CO_2 emissions, and greatly increases their NO_x emissions for some types of gas generators (Katzenstein & Apt, 2009). Energy storage may mitigate variability in renewable generation, but most energy storage technologies are still prohibitively expensive for bulk storage applications and typically have limited round-trip efficiencies (Ummels, Pelgrum, & Kling, 2007) (Black & Strbac, 2007) (McDowall, 2006).

The goal of this work is to determine whether adding a small amount of fast-ramping energy storage to wind+natural gas turbine systems can reduce the costs and emissions of smoothing the output from wind generators by providing a small amount of short time scale smoothing. Conceptually, gas generators and storage are used complementarily to smooth wind – energy storage is expensive but is able to ramp extremely quickly and handle high power levels while gas turbines are able to provide large quantities of fill-in power at a reasonable cost but have important operational limitations. We investigate a hybrid (gas turbine and energy storage) compensation system by modeling both wind power and the gas+storage system at a 10-second time resolution.

Three results are presented. First, we show that modeling wind and compensating resources using shorter time scales produces results notably different than modeling them in 1-hour blocks. Studies frequently use 1-hour blocks of time, both because of the availability of such data and because the largest amplitude wind fluctuations occur over longer time scales (Wan & Bucaneg, 2002). However, all of the time-based operational limitations of natural gas generators occur sub-hourly and, by modeling in 1-hour increments, gas turbines unrealistically appear to be "perfect" generators capable of fulfilling any power requirements. Thus, the need for finer time resolution is not due to wind fluctuations, but mainly required for the accurate modeling of the response to these fluctuations. Second, we demonstrate that a small amount of energy storage co-located with the wind and natural gas turbines can significantly reduce high-frequency power fluctuations. As mentioned above, energy storage devices can buffer the power spikes and dips from wind fluctuations. The inclusion of energy storage decreases the quantity and size of power fluctuations externalized to the grid, which then requires less regulation service. Third, we demonstrate a wind/natural gas/energy storage hybrid generation block that is capable of delivering a large fraction of wind energy, smoothed to a power variability of less than 0.5%, at a reasonable cost.

2.3 Methodology

We model the wind power/natural gas turbine/energy storage system using a time-series operational framework which takes as an input actual wind generation, measured with 10-second time resolution, and a number of operational constraints, including natural gas ramp rate and system target power output. The model determines the operation of the generation and storage resources required to meet the defined system power requirements. This operational model is used in a scenario analysis which investigates different system combinations and determines their average cost of electricity and the wind energy content of their power output (Figure 2.1). The objective of the scenario analysis is to identify the systems that can produce power with a particular renewable energy content at the lowest cost.

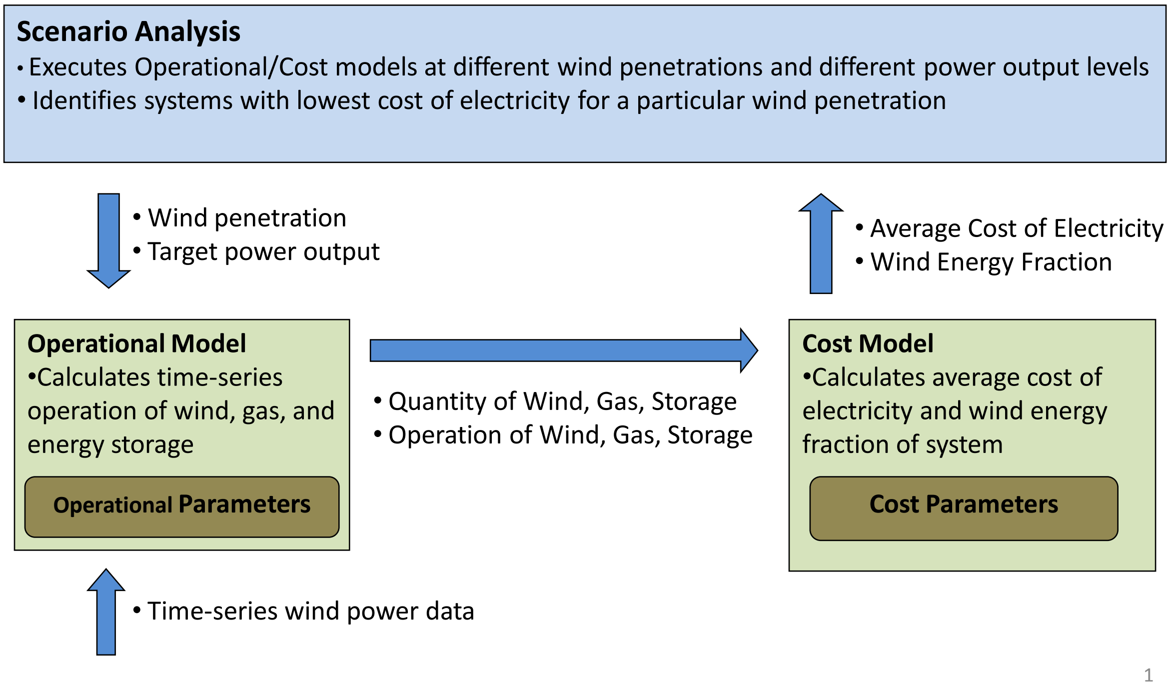

Figure 2.1: System block diagram showing structure of scenario analysis used. The higher level scenario analysis runs the operational and cost models under various conditions. The goal of the scenario analysis is to identify systems with the lowest average cost of electricity given a particular wind penetration. Appendix A (Section 2.8) contains a more detailed description of the scenario analysis structure and the underlying operational and cost models.

2.3.1 Model Description

For each combination of wind generation, natural gas generation, and power output, the model determines the quantity of fast-ramping energy storage (industrial-scale Sodium Sulfur (NaS) batteries, flywheels, or supercapacitors) required to produce a fixed power output with constrained variability.

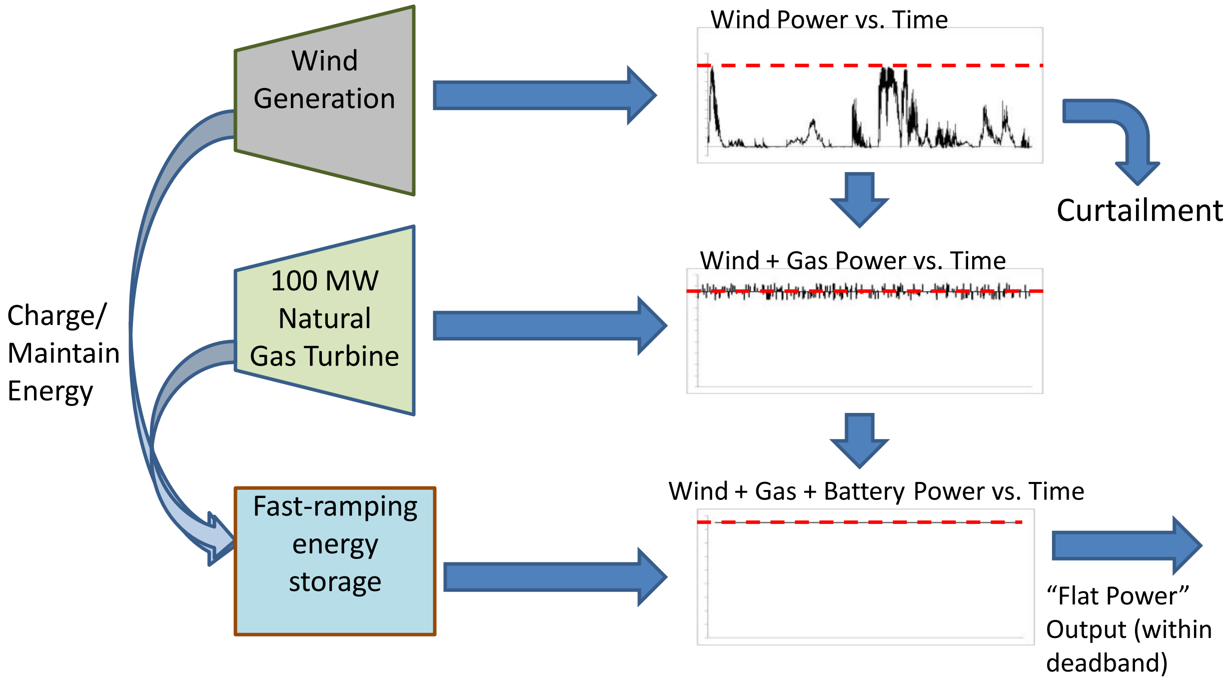

Figure 2.2: Model concept of wind/natural gas/energy storage generation block. The scale of wind generation and the wind generation profile are fixed for each run of the model. The 100 MW natural gas turbine attempts to smooth the wind power to the target power output level (red dashed line). Due to the operational constraints of the gas turbine, there may be some residual power transients which are eliminated by a fast-ramping energy storage device, which is sized to the minimum scale required to mitigate the remaining fluctuations.

For each system examined, the gas generator is modeled to operate such that it provides maximum fill-in power for the varying wind resource in an effort to bring the combined wind+gas power output to the target power output. If the gas turbine is unable to provide all of the required fill-in power due to insufficient ramping capability or cold-start limitations, the residual power is provided by an energy storage device. This residual power includes both positive and negative power requirements from the energy storage, which represent both the discharge energy from the device as well as the required charge energy. Actual 10 second time resolution wind data is used to model the wind generation (Southern Great Plains United States wind farm, sum of 7 turbines, 15 days, 10 second resolution, 46% capacity factor during this period[1]). When necessary, the model allows for curtailment of wind energy (if the storage is fully charged but the combined wind+gas output is higher than the target) by assuming a communications link between the system control and the wind farm control station.

[1] This unrepresentatively high capacity factor is discussed and analyzed in the Sensitivity Analysis section.

The gas turbine is modeled with finite start-up time, maximum ramp rate, low operating limit, and minimum run time. Performing a time series simulation of a gas turbine with these characteristics more accurately demonstrates the issues involved with traditional generators providing fill-in power for wind variability, and allows a better estimation of costs and emissions due to that power.

Once the gas turbine has provided all of the smoothing allowable by its operational constraints, the minimum size of the required energy storage device can be directly determined. Given the wind+gas generation, the residual power that must be handled by an energy storage device is calculated, including both charge and discharge energy. From this residual power profile, the power and energy capacity capabilities required from the energy storage can be calculated. When sizing the energy storage, the power requirement is equal to the maximum power required to/from the energy storage during the operational period. The energy capacity requirement is derived from the maximum energy span (difference between highest and lowest energy state) required from the energy storage. This is equivalent to assuming a battery with infinite capacity, then observing the maximum energy span (which is also the minimum possible storage capacity) and using that value for the required storage capacity. The power requirement of the energy storage is used as determined directly from the model, but the energy capacity requirement is doubled from what the model determines as the minimum possible energy capacity. This reflects the understanding that the 15 days of wind data used might not present the worst case energy cycle to the storage device, as well as a conservative design stance towards this relatively unproven technology.

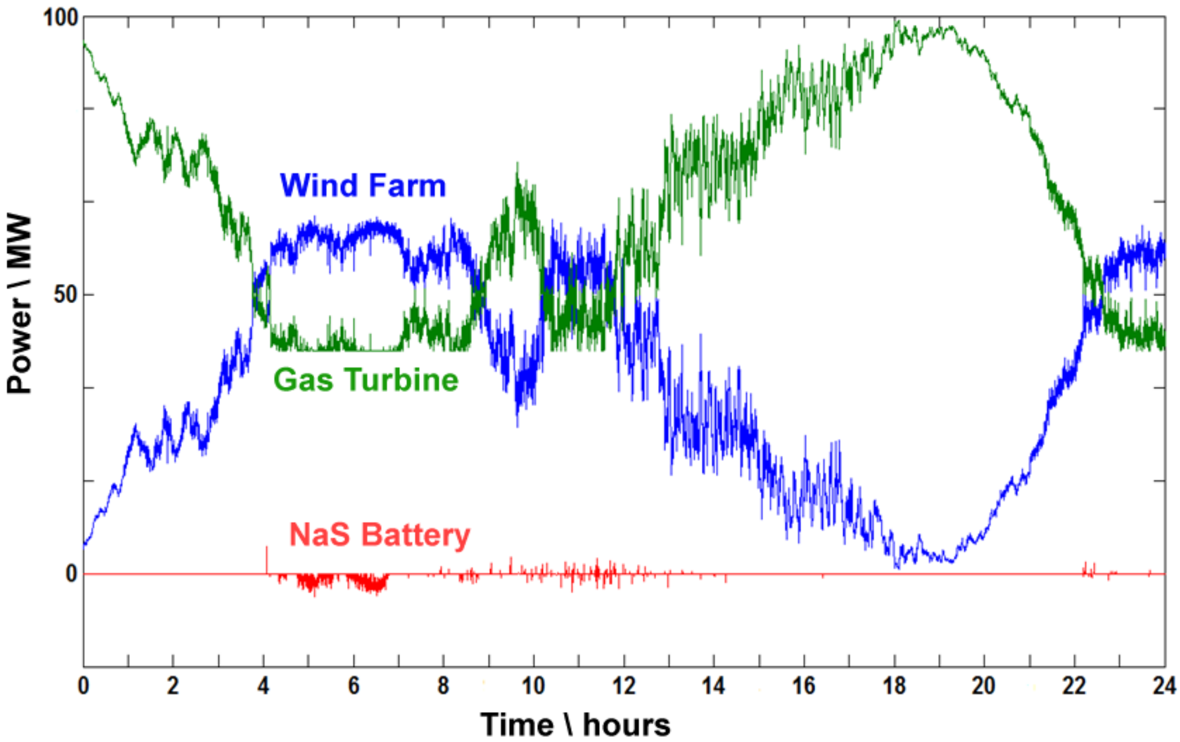

Figure 2.3: A sample of the operational output from the Wind/Natural Gas/NaS Battery model. This shows a 24 hour period of operation of a system with 100 MW of natural gas capacity, 66 MW of wind capacity, and a target power output of 100 MW. Positive values for the battery power indicate discharge while negative values are charging events. The battery is required infrequently and generally for short, sharp charges/discharges. As the wind power increases in hours 4 – 7, the natural gas turbine ramps down to its low operating limit of 40 MW and the excess energy is used to charge the battery. The wind generation profile comes from actual 10-sec time resolution data.

We examined three different types of storage: Sodium Sulfur (NaS) batteries, flywheels, and supercapacitors. This paper focuses on NaS Batteries because that technology was found to be the least expensive at all points in this study. Energy storage is modeled using the most realistic operational and cost data available: efficiency, power/energy ratio, maintenance energy, and a cost model dependent upon both power and energy requirements are all utilized. For consistency, most of the data for operational and cost modeling of energy storage are taken from EPRI's Handbook of Energy Storage (EPRI-DOE, 2002). Where additional data is available from the manufacturer, such as the pulse power limitations on Sodium Sulfur batteries, those limitations have also been used (NGK Insulators, 2005).

The energy storage device is constrained to have a net energy balance equal to or greater than zero over the studied period. If the energy balance through the device is found to be negative, then the operation of the gas generator is adjusted to produce more charging energy during periods of low gas turbine output. Additionally, wind and gas power are used to provide the maintenance energy for certain types of storage devices, such as flywheels or Sodium Sulfur batteries. We make the assumption that only one type of fast-ramping energy storage will be used in the system, and each of the three investigated technologies are studied in separate runs of the model, allowing comparison between technologies.

In order to keep the study simple and general, the model is constrained to produce power with a small "deadband", allowing for the system output power to vary within 0.5% of the target power output. This is intended as a realistic simulation of the small allowable variation in real power systems (if the allowable deadband is set to zero, then the system is constrained to produce perfectly "flat" power).

The objective function of a single run of the model is to meet the target power output (within the deadband) while minimizing the Power (P_{batt}) and Energy (E_{batt}) requirements of the energy storage device (Equations 2.1 and 2.2), in order to prevent over-sizing of this expensive resource.

$$\textit{Minimize } \mathrm{E_{batt}} = \mathrm{E_{batt,max}} - \mathrm{E_{batt,min}} \tag{2.1}$$

and

$$\textit{Minimize } \mathrm{P_{batt,max}} \tag{2.2}$$

such that, at all points in time (t), the sum of wind, gas, and battery power minus curtailment and battery maintenance energy is within the deadband around the target power level (Equation 2.3). The gas generator has a ramp rate limitation (Equation 2.4), high and low operating limits (Equations 2.5 and 2.6), and a minimum run time (Equation 2.7). The power out of the energy storage device comes at an efficiency penalty (Equation 2.8), and round trip efficiency of the energy storage device is divided geometrically between the charge and discharge portions of the cycle (Equation 2.9).

$$P_{target} \pm P_{db} = P_{wind}(t) + P_{gas}(t) + P_{batt}(t) - P_{maint}(t) - P_{curt}(t) \quad (2.3)$$

$$\left|P_{gas}(t) - P_{gas}(t-1)\right| \leq \dot{P}_{gas,max} * T_{step} \quad (2.4)$$

$$P_{gas}(t) \leq P_{gas,max} \quad (2.5)$$

$$P_{gas}(t) \geq P_{gas,max} * C_{lol} \quad (2.6)$$

$$P_{gas}(t) > 0 \ \text{ if } \exists x \text{ s.t. } \ t - T_{mr} < x < t-1, \ P_{gas}(x) = 0 \quad (2.7)$$

$$E_{batt}(t) = P_{batt,out}(t) * T_{step} * \sqrt{\eta_{batt}} - P_{batt,in}(t) * T_{step} / \sqrt{\eta_{batt}} \quad (2.8)$$

$$E_{batt}(t) = E_{batt}(t-1) - E_{batt,out}(t) * \sqrt{\eta_{batt}} + E_{batt,in}(t) / \sqrt{\eta_{batt}} \quad (2.9)$$

where P_{target} is the target power output, P_{db} is the deadband power, P_{wind} , P_{gas} , P_{batt} and are the power outputs of wind, gas, and energy storage, P_{maint} is the maintenance power for the energy storage device, P_{curt} is the curtailed power, T_{step} is the step time (10 sec in this study), $P_{gas,max}$ is the maximum power output of the gas turbine, C_{lol} is the low operating limit constant, T_{mr} is the minimum run time of the gas turbine, $E_{batt,out}$ is the energy discharged from the energy storage device, η_{batt} is the round-trip efficiency of the energy storage device, and $E_{batt,in}$ is the charge energy put into the energy storage device.

Once the operation of the wind generation, natural gas turbine, and energy storage device has been determined, the emissions and costs of the system over the studied timeframe can be calculated. The emissions calculation uses results from Katzenstein and Apt (Katzenstein & Apt, 2009) showing the effect of partial load conditions on efficiency and CO_2 and NO_x emissions of a Siemens-Westinghouse 501FD gas turbine. Capital, variable, and average costs of electricity are also calculated for each potential composite system, including amortized capital costs, other fixed costs, and variable costs of the wind generation, the gas turbine, and the energy storage device. NO_x and CO_2 prices are included in the cost calculation. Emissions allowance prices are applied directly to the emissions, and do not account for seasonal or regional variation, and thus present an upper bound on the cost of emissions. Appendix A (Section 2.8) contains a more thorough and systematic description of the model structure, describing both the operational and cost calculations and the sources for the base-case values.

Table 2.1: Base-Case Operational and Cost Inputs to the generation block model

Operational Inputs	Base-Case Value
Natural Gas (NG) Low Operating Limit	40% of nameplate capacity
NG Start-up Time	10 min
NG Ramp Rate Limit	25%/min
NG Minimum Run Time	60 min
NG Lifetime	30 years
Wind Lifetime	20 years
NaS Round-trip Efficiency (RTE)	75%
NaS Maintenance Energy	2.2 kW/ module
NaS module Power Limit[a]	250 kW
NaS module Energy Capacity	360 kWh
NaS module Lifetime	20 years
Supercapacitor RTE[b]	70%
Supercapacitor Lifetime	20 years
Flywheel RTE	90%
Flywheel Friction Losses	3% of max. power output
Flywheel module Power Limit	1500 kW
Flywheel module Energy Capacity	5 kWh
Flywheel module Lifetime	20 years

[a] NaS battery model also uses pulse limitations defined by manufacturer

[b] Supercapacitors are modeled with no power limitation

Cost Inputs	Base-Case Value
Blended Cost of Capital	8%
NG Capital Cost	\$620 / kW
NG Price	\$5/MMBTU
NG Variable Cost	\$0.0014 / MWh
NG Fixed Operating Cost	\$10 / kW-year
Wind Capital Cost	\$1500 / kW
Wind Variable Cost	\$0.015 / kWh
CO_2 Price	\$25 / tonne
NO_x Price	\$750 / tonne
NaS Capital Cost	\$240,000 / module
NaS Fixed Operating Cost	\$8,000 / module - year
Supercapacitor Capital Cost due to Power	\$60 / kW
Supercapacitor Capital Cost due to Capacity	\$143,000 / kWh
Supercapacitor Fixed Operating Cost	\$13 / kW - year
Flywheel Capital Cost	\$720,000 / module
Flywheel Fixed Operating Cost	\$78,000 / module - year

2.3.2 *Computational Scenario Analysis*

The model described above is executed at a variety of conditions in a scenario analysis. A particular run of the scenario analysis examines different ratios of wind/natural gas capacity in order to determine how the average price of electricity changes with increased wind penetration. Within each wind penetration level, the model is executed at various power output levels in order to determine the power output that allows for the lowest average cost of power, given the particular wind penetration. Every run of the model assumes a 100 MW natural gas turbine, and the quantity of wind generation is varied so that the percent of capacity due to wind varies from 0% to 90%. Once the model has been executed at these 10 wind penetration levels and at 10 different power output levels for each wind penetration (100 runs total), the model is executed another 10 times around the points that demonstrated the lowest average cost of power at each wind penetration. This allows for a more detailed analysis around the most relevant areas and results in a total of 200 runs of the model for each scenario analysis. When a scenario analysis is executed, the program calculates the average cost of electricity, capital costs, variable cost of operation, maximum battery charge/discharge rate, CO_2 and NO_x emissions, and delivered wind energy as a percent of total delivered energy for each run of the model.

The model and scenario analysis programs were written in MATLAB. A quad-core PC was used, which could execute a single run of the operational/cost models in approximately 5 minutes, so that a single scenario analysis required 15 hours of processing time.

The goal of the scenario analysis is to use the model described above to study the relationship between wind penetration and the cost of producing power with little or no fluctuations. In particular, this structure can be used to determine which system produces smoothed power at the lowest price, given a desired set of constraints. Furthermore, by applying different conditions to the scenario analysis, the effect of factors, such as varying natural gas price, can be examined.

2.4 Results

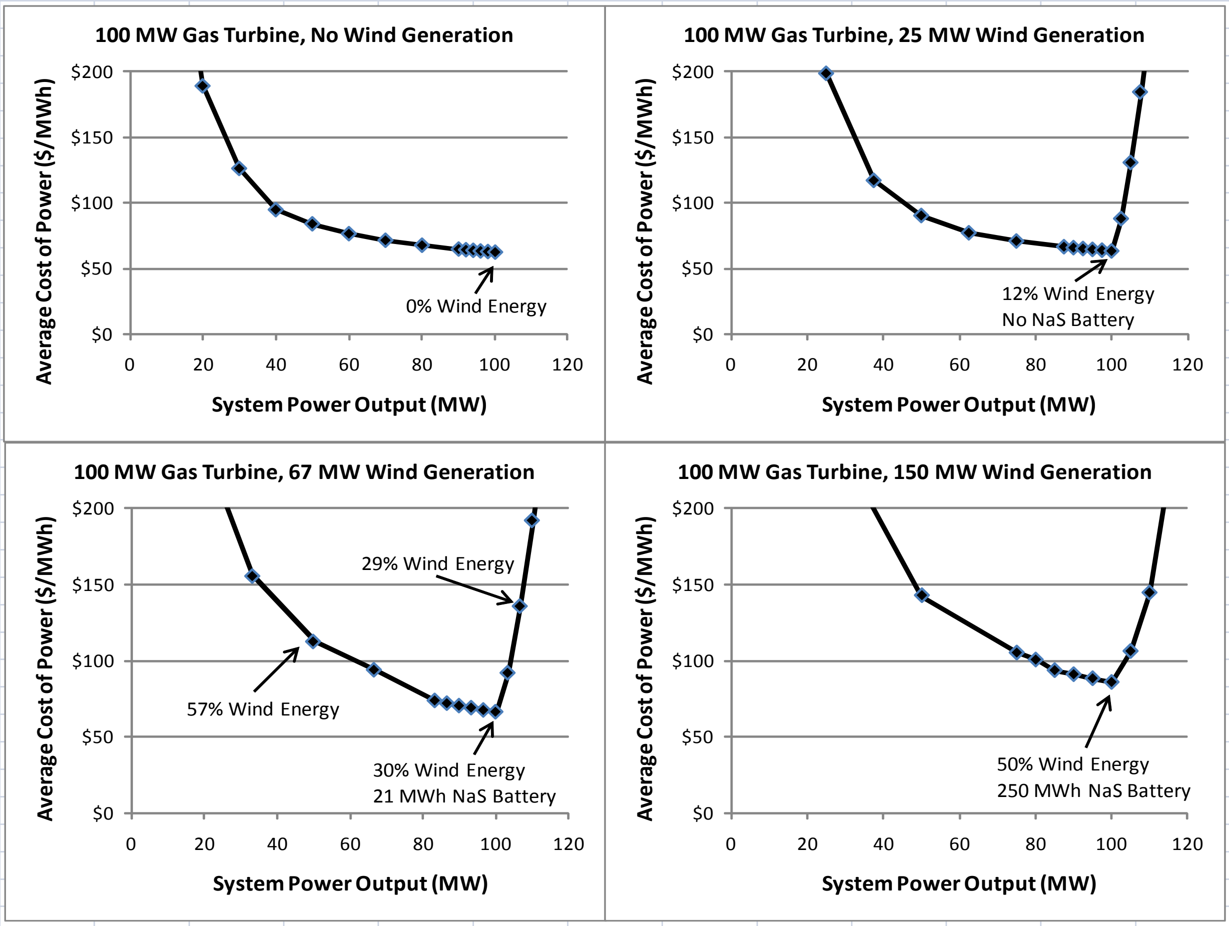

Figure 2.4: Average Cost of Power under a variety of wind penetrations. Each chart shows the model output at different power output levels for the Wind/Gas/NaS Battery generation block at a particular wind penetration. The model constraints, including power deadband, are met for all points shown. Each curve has a lowest cost of power point which reflects a balance between inefficient use of capital resources (at low power output levels) and increased need for NaS Batteries (at higher power output levels). In all scenarios examined, the power output with the lowest average cost occurred at or near the firm generation power (100 MW). The increase in cost after the low point is attributable almost entirely to a rapidly increasing energy storage requirement. The sizing and operation of the NaS batteries is discussed in greater detail in Appendix B (Section 2.9).

We first discuss the results for NaS batteries, using the base case assumptions (Table 2.1). Figure 2.4 displays the average cost of power under different wind penetrations and power output levels. For all scenarios except the case with only a gas generator, the average cost of power has a minimum because of the balance between efficient use of the capital-intensive generation resources (the gas and wind turbines) and avoiding large-scale deployment of the relatively expensive energy storage systems. This minimum point, representing the system with the lowest average cost of power, is always very close to 100 MW, equal to the firm power provided by the gas turbine. While it is possible to have a relatively flat power output higher than the firm power, the cost of the storage then required to ensure power constrained within the deadband (+/- 0.5%) is so high that it drives the average price of electricity up. Or, to state it an alternate way, the lost value of the curtailed wind energy is less than the cost of the storage required to deliver it within the deadband. This is due entirely to the properties of the energy storage device – if the costs were to decrease or the efficiency were to increase, the lowest cost of electricity point would tend to shift to higher power output levels.

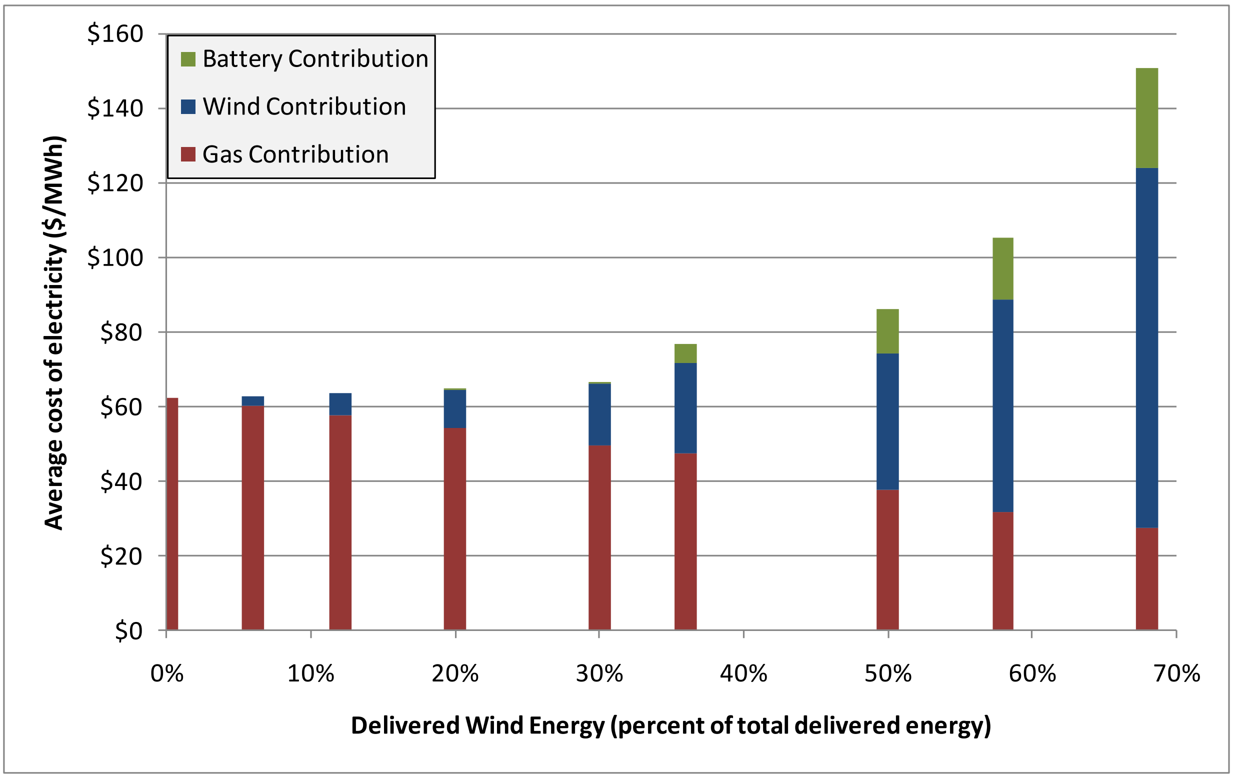

Figure 2.5: Average cost of power in the Wind/Gas/NaS Battery system as a function of delivered wind energy and divided according to system component. Each bar represents a system with 100MW of gas generation and corresponds to the lowest cost of power for a particular wind/gas ratio. Due to the 0.5% deadband allowance, NaS Batteries are not required until after 12% delivered energy from wind. There is a slight discontinuity after 30% wind energy, corresponding to the point at which wind power fluctuations are so great that they force the gas turbine to shut down at times to prevent the generation of excess power. Costs due to emissions are attributed to the gas turbine. Costs are for generation only, and exclude transmission costs.

The wind/gas/NaS Battery systems with the lowest average cost of electricity from each wind/gas capacity ratio are plotted in Figure 2.5, which demonstrates that the contribution to electricity cost due to the required NaS batteries is negligible over a wide range of wind penetrations. This result also shows that the average price of electricity stays fairly constant as wind penetration increases up to 30%. This result is in part due to the unrepresentatively high wind capacity factor of 46% (2008 US average wind capacity factor was 34%) which, given the base assumptions, results in a cost of $55/MWh for unsmoothed wind energy (Wiser & Bolinger, 2008). The effect of more typical capacity factor is discussed in Section 2.5. These results also demonstrate a noticeable transition around 30% wind energy. This change is due to a change in the operation of the gas turbine: while the turbine is ramped up and down in all scenarios, it is occasionally forced to shut down entirely with systems that have greater than 30% wind energy. The need to startup and shutdown the turbine produces notably lower efficiencies and requires more energy storage.

The average cost of power from the system increases rapidly at higher wind penetrations due to three factors: the need for increased quantities of energy storage, the inefficient fuel utilization of the gas turbine at partial power, and the reduced capacity factor of the gas turbine as a capital resource. If the variability of generation was irrelevant, energy costs of a wind/natural gas system would be a linear interpolation of the energy costs of the two technologies, which would be less expensive. Figure 2.6 shows the cost of smoothing services by comparing the energy costs of naturally variable wind/gas combinations (no smoothing) with the flattened "baseload" power produced by the described systems (smoothed to within 0.5% deadband). These results are comparable with the wind integration costs determined in other studies (DeCesaro, Porter, & Milligan, 2009).

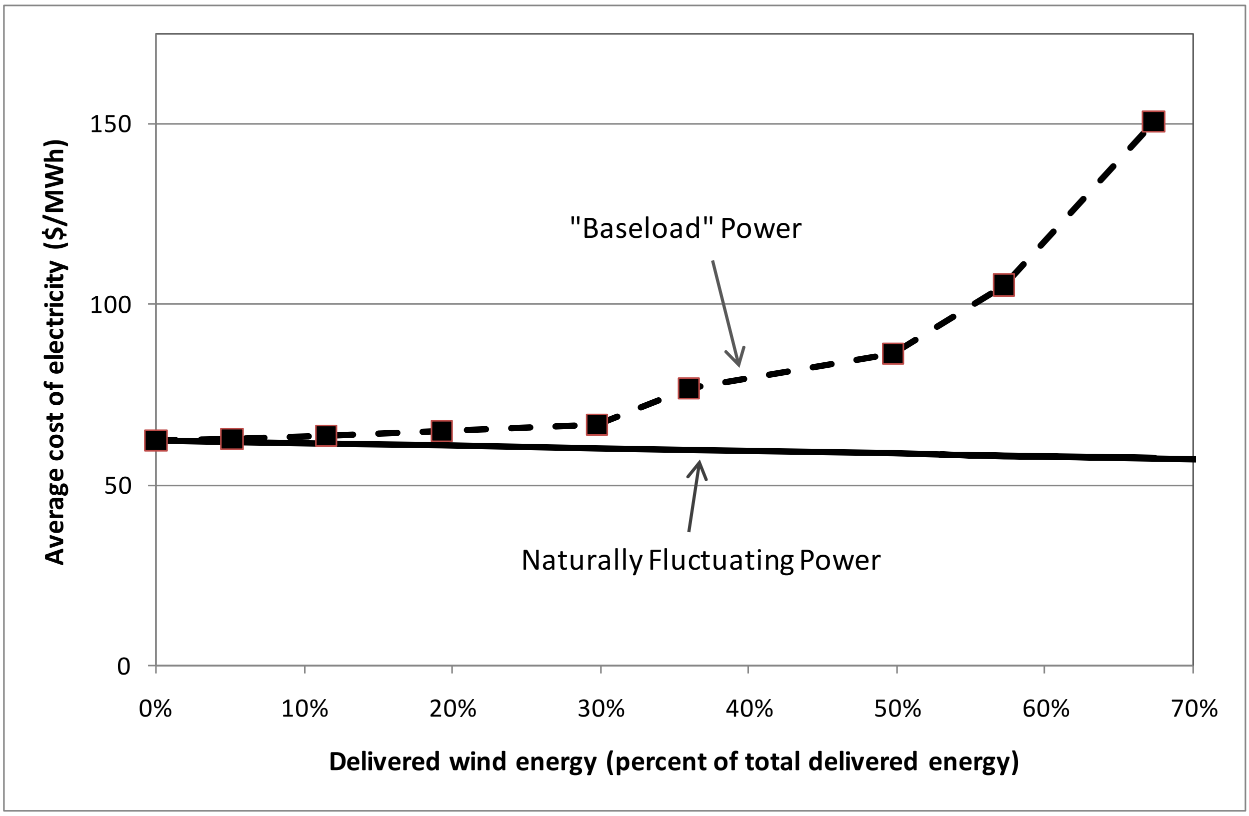

Figure 2.6: Average cost of energy for the described "baseload" systems, which regulate power output to 100 +/- 0.5 MW, and a mix of gas generation and unsmoothed wind energy. The naturally fluctuating wind/gas line is a linear interpolation of natural gas power, at a cost of $62/MWh, and wind power, calculated at $55/MWh using the base-case inputs. The difference between the two lines is the cost of reducing power fluctuations to +/- 0.5%, attributable to inefficient utilization of the gas turbine and the requirement for energy storage.

We found NaS batteries to be more cost effective than flywheels or supercapacitors for this application, although the other technologies are still viable options at low wind penetration levels. Flywheels were found to be expensive for this application due to the constant and sizable losses due to friction. Despite their excellent performance, supercapacitors currently have very high capital cost (per kWh) approximately 200 times greater than that of NaS batteries. Figure 2.7 compares the three energy storage technologies and their effect on average cost.

As discussed earlier, the operation of the system is engineered to minimize the energy services from the energy storage devices. The energy throughput for each case has been calculated and normalized to the full storage capacity of the device. For the scenarios calculated, the energy throughput varies between 14 and 240 complete charge/discharge cycles (equivalent) per year, though it should be noted that they are never fully cycled in the model. This amount of energy throughput is well within specifications for any of the three storage technologies examined.

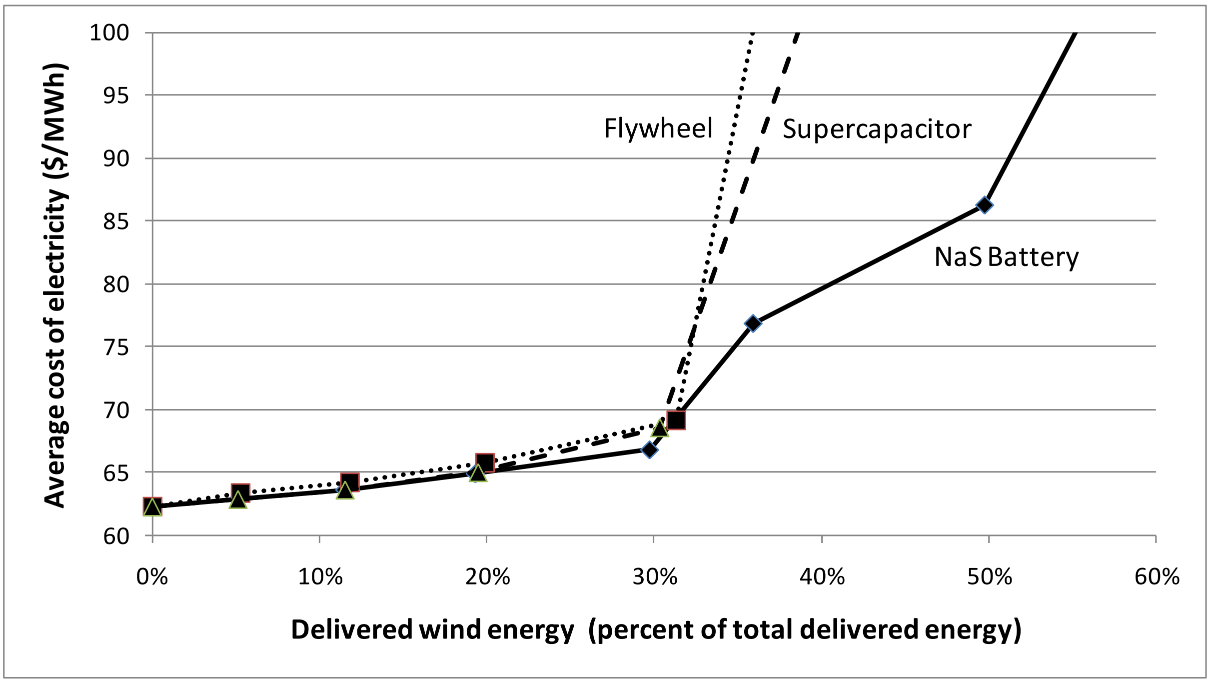

Figure 2.7: Average cost of power in the Wind/Gas/Energy Storage system for three different energy storage technologies. At lower wind penetrations, the cost contribution of energy storage is negligible and the chosen technology has little effect on the average cost of power. At higher wind penetrations, when storage cost becomes important, NaS Batteries dominate the other options.

The CO_2 and NO_x emissions from operation of the natural gas turbine were calculated using a time-series analysis that determines the emissions for each ten second step of operation. The turbine is modeled as a Siemens Westinghouse 501FD, using published emissions data (Katzenstein & Apt, 2009). The emissions of the systems producing the lowest average cost of power can be seen in Table 2.2. These results re-affirm the conclusion of Katzenstein and Apt that a single gas turbine, when providing fill-in power for variable renewable generation, does not result in proportional decreases in CO_2 emission and can cause increases in NO_x emission as renewable penetration increases (these authors also considered systems with multiple turbines supplying regulation). It is further demonstrated that the addition of an energy storage device does not substantially alter the finding.

Table 2.2: Cost, Emissions, and NaS Battery Capacity for Wind/Gas/NaS Battery Systems

Wind Nameplate Capacity (MW)[a]	0	25	43	67
Delivered Wind Energy	0%	12%	19%	30%
Average Cost of Electricity ($/MWh)[b]	62	64	65	67
Contribution of NaS Battery to Average Cost of Electricity (percent)	0%	0%	0.5%	1%
Average CO_2 Emissions (tonnes/MWh)	0.34	0.31	0.29	0.26
Average NO_x Emissions (g/MWh)	50	44	40	164
NaS Battery Capacity (MWh)	0	0	10	21

[a] *All systems include a 100MW gas turbine.*

[b] *The average cost of electricity includes emissions prices of $25/tonne for CO_2 and $750/tonne for NO_x.*

We summarize the important results from the base-case scenario analysis in Table 2.2. These systems all produce electricity with very little variation (100 +/- 0.5 MW at all times) and show that a large quantity of wind energy can be integrated into the electrical grid at a reasonable cost, if the compensating resources are chosen and operated appropriately.

While the results above are presented in the abstract, we now turn to a more concrete example. Texas, the US state which currently has the most wind power, also gets a large fraction of electrical generation from natural gas. The Integrated Environmental Control Model (IECM)[2] was used to calculate that, in west Texas (elevation: 3000 ft), the power output of a GE 7FA gas turbine would be 108 MW, though this value can vary slightly due to environmental conditions. This turbine is modeled as co-located with a wind farm consisting of 48 1.5 MW turbines experiencing a capacity factor of 30%, and 60 NGK Insulators PQ NaS Battery Modules. Using the base-case assumptions from Table 2.1, this co-located wind/natural gas/NaS battery system can produce a continual 108

[2] The Integrated Environmental Control Model is a tool designed to calculate the performance, emissions, and cost of a fossil-fueled power plant and was developed at Carnegie Mellon University. More information about the IECM can be found at http://www.cmu.edu/epp/iecm/

MW of power (within a 0.5% deadband) at an average cost of \$69/MWh, getting 20% of the delivered energy from wind power[3]. With a Production Tax Credit of \$21/MWh for the wind energy, the average cost of power for this system would drop to \$65/MWh. This is only \$3/MWh (5%) greater than the calculated cost for a gas turbine-only system.

2.5 Sensitivity Analysis

We performed sensitivity analysis for natural gas price, blended cost of capital, wind capacity factor, and deadband range. In each sensitivity analysis, only the target parameter is varied and each data point represents a complete re-run of the scenario analysis under that varied parameter.

Since 2001, the price of natural gas as delivered to industrial customers has varied between \$3.5 and \$13 per MMBTU, with an average value around \$6.50/MMBTU (EIA, 2009). The base-case natural gas price used in the cost model is \$5/MMBTU, and that figure is varied from \$4/MMBTU to \$10/MMBTU in the sensitivity analysis. As seen in Figure 2.8, the sensitivity of average electricity price in the wind/gas/NaS Battery system to natural gas price is a function of the percent of energy from natural gas generation. As the wind penetration increases, the system becomes less sensitive to natural gas price. At higher natural gas prices, the average cost of electricity decreases with increased wind penetration, up to 30% wind by energy.

[3] The figure of 20% energy from wind accounts for all of the wind energy produced. At 30% capacity factor, the wind farm produces an average power of 21.6 MW, which is 20% of the target power output of 108 MW.

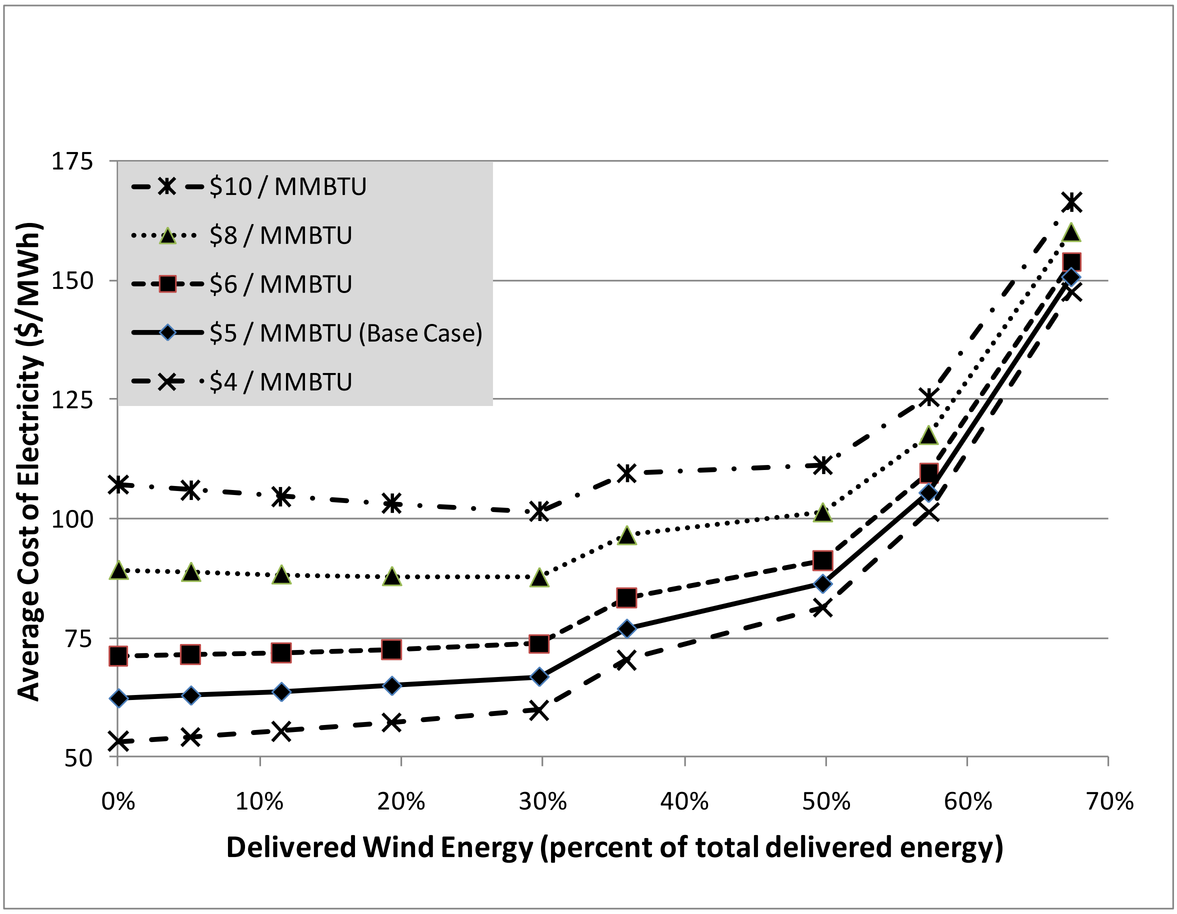

Figure 2.8: Sensitivity of Scenario Analysis output to natural gas prices between $4 and $10 per MMBTU. The Wind/Gas/NaS Battery systems are most sensitive to natural gas price at low wind penetrations. At higher natural gas prices ($8 and $10 per MMBTU), the average cost of electricity decreases as wind generation is added, up to 30% of energy from wind.

The base-case blended cost of capital used in the model is 8%. This rate is varied between 6% and 12%. Figure 2.9 shows that the sensitivity to interest rate is low for the case where only a natural gas turbine is used and increases with wind penetration. Gas generation requires a low capital investment relative to its total cost, while wind turbines and energy storage devices have almost all of their lifetime costs up front in the form of capital investment.

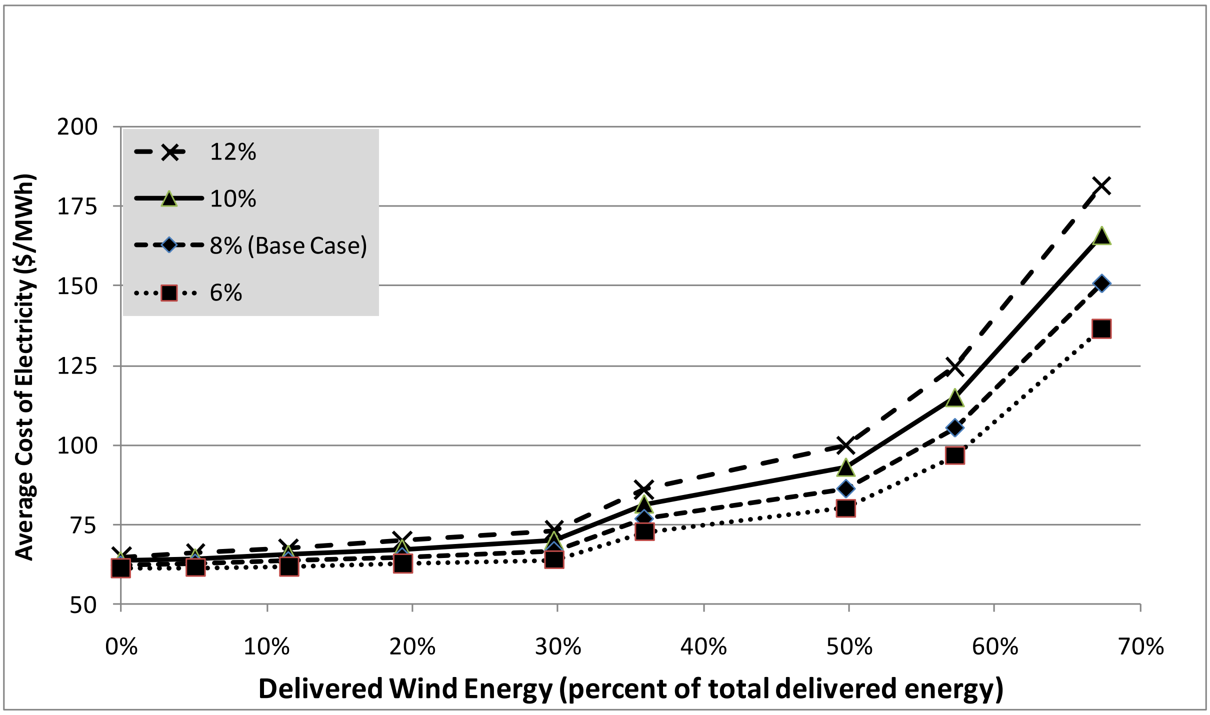

Figure 2.9: Sensitivity of Scenario Analysis output to Cost of Capital Rates between 6% and 12%. The Wind/Gas/NaS Battery systems are most sensitive to interest rate at high wind penetrations due to the capital-intensive nature of wind generation and energy storage.

The wind capacity factor of the wind data used in this study is 46%, unrepresentatively high for onshore wind generation (Wiser & Bolinger, 2008). As a result, it is important to investigate the effect that a lower wind capacity factor would have on the average price of electricity from the wind/gas/NaS Battery systems studied. Lower capacity factors are modeled by using smaller portions of the wind data set that have lower capacity factors. These contiguous subsets (of the original 15 days of wind data) are extracted and represent between 5 and 9 days of operation. The wind capacity factor is varied from the 46% base case down to 20% and demonstrates that varying the wind capacity factor has the largest effect on average cost of electricity at higher wind penetration levels (Figure 2.10).

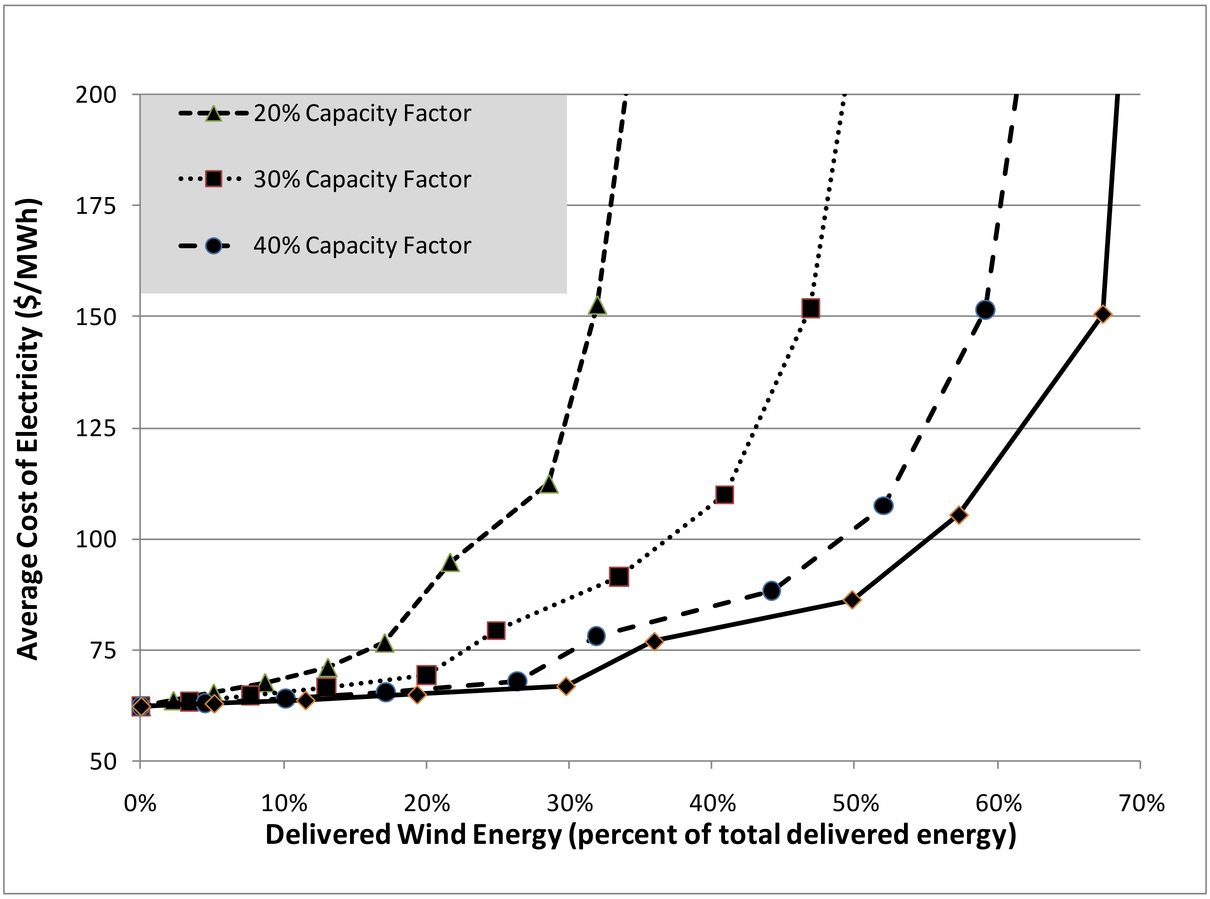

Figure 2.10: Sensitivity of Scenario Analysis output to wind capacity factor between 20% and the base-case value of 46%. Wind capacity factor has a very large effect on average cost of electricity for systems requiring a large fraction of delivered energy from wind.

The allowed deadband range is a function of the power quality required from a given generator. In a small grid, where there are insufficient compensating resources, generators would be more constrained in their unrequested fluctuations, while in large grids with significant compensating resources, power deviations are less burdensome. The base case deadband range is 0.5%, and this figure is varied in sensitivity analysis from 0% to 10% (Figure 2.11). The change in deadband range has very little effect at low wind penetrations, as the gas turbine can easily compensate for the wind variability and any energy storage required has a negligible cost. At higher wind penetrations, a larger deadband displaces the need for costly batteries and effectively increases the operating range of the gas turbine, lowering the average cost of electricity. Furthermore, a larger deadband enables the acceptance of wind energy that would otherwise be curtailed and thus results in a larger fraction of delivered wind energy. With no deadband allowed, all wind penetration levels require some amount of energy storage, while increasing the deadband to the base-case of 0.5% allows systems up to 12% energy from wind to operate without any storage.

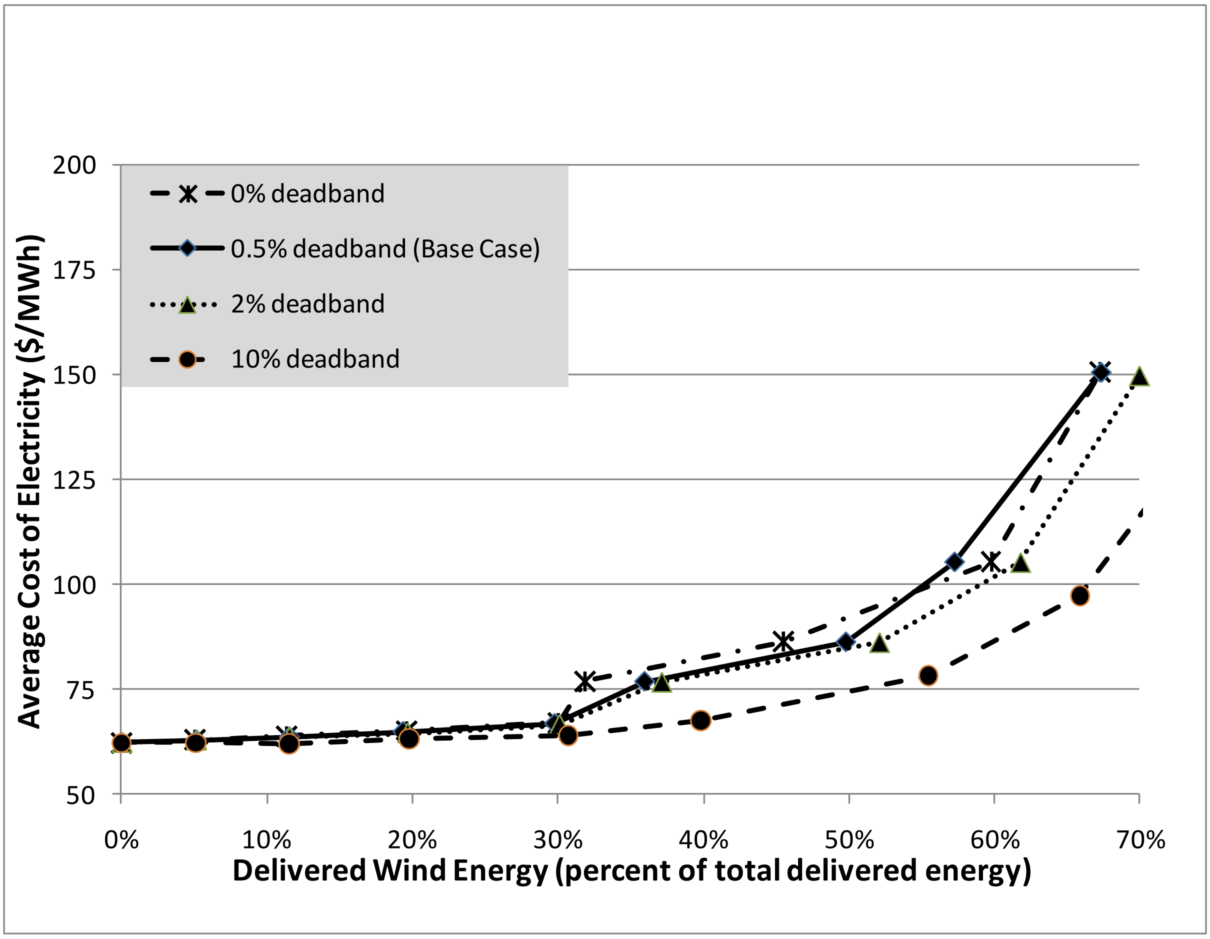

Figure 2.11: Sensitivity of Scenario Analysis output to deadband range between 0% and 10%. Higher deadband allowance results in the need for less energy storage, which is fairly negligible at lower wind penetrations but becomes important at higher wind penetrations.

Table 2.3 summarizes the sensitivity analysis results at three wind penetration levels.

Table 2.3: Sensitivity analysis summary of wind/gas/NaS battery systems

Parameter	Range of Values	Effect on Price at 0% Wind Energy	Effect on Price at 30% Wind Energy	Effect on Price at 60% Wind Energy
Natural Gas Price	$4 to $10 per MMBTU	-17% to +72%	-11% to +52%	-4% to +19%
Blended Cost of Capital Rate	6% to 12%	-2% to +4%	-5% to +9%	-9% to +15%
Wind Capacity Factor	20% to 46%	No effect	+209% to 0%	Unfeasible* to 0%
Deadband Range	0% to 10%	No effect	+0.3% to -4%	+4% to -13%

*The system with 20% wind capacity factor is unable to deliver 60% wind energy due to NaS battery maintenance energy.

2.6 Discussion

The systems described above utilize a hybrid compensating system to produce fill-in power for wind, smoothing the power output. Unsurprisingly, the cost of the smoothing service comes at a premium, and is greater than the linear combination of natural gas energy cost and wind energy cost. It is important to determine what circumstances make this premium for smoothed power worthwhile.

In most electric markets, policies encourage the deployment of wind generation. As part of this encouragement, coupled with the limited deployment of wind resources, there are currently few restrictions on the variability of the power produced by wind farms. But, as the penetration of wind power increases, particularly in the attempt to achieve the renewable portfolio standards that have been adopted by 29 US states, the variability of wind power will become an increasingly important issue. Already, electrical systems that utilize a relatively large fraction of wind energy, such as ERCOT and Nord Pool, are considering enacting or have enacted limitations on the ramp rate of wind power (ERCOT, 2010) (Morthorst, 2003). Determining who bears the responsibility for dealing with the variability of wind will become an important policy decision in the coming decades. But regardless of who is responsible, compensating for large-scale penetrations of wind energy requires careful planning.

In the near term, there are other applications for the described systems, such as small electrical grids that are unable to rely on a large base of traditional generators to provide compensation. Ireland plans to generate 13.2% of its electricity needs from renewable power in 2010, with wind power supplying the vast majority (Department of Communications, Marine and Natural Resources, 2004). Ireland currently has a maximum demand of around 6.5 GW with an installed wind capacity of almost 1.5 GW. At times, almost 40% of the island's power comes from wind power and this fraction will only increase as more wind generation is constructed (Kanter, 2009). Hawaii has a peak firm power capacity of approximately 2 GW and already has a 10% wind penetration on the Big Island (HECO, 2009). Additionally, motivated by the high electricity prices in Hawaii, the governor has announced a goal of 70% of energy from "efficiency and renewable resources" by 2030 (State of Hawaii, 2008). A higher price of electricity, a desire for increased renewable penetration, and a smaller generator base in these electric grids makes them candidates for systems similar to those described herein. The costs for integrating wind are shown to be reasonable and the required technology can be co-located with the wind generation, avoiding the need to rely on a large base of traditional generation resources that is non-existent in small electrical grids such as Hawaii and Ireland.

Our results suggest a different policy guideline for large electrical systems attempting to integrate wind generation, especially those with flexible traditional generators such as ERCOT. While the hybrid wind/gas/storage systems are shown to be a financially viable option, the scenario analysis results also show that a small deadband (0.5%) allowance and the availability of compensating generation permits wind energy fractions of up to 12% before any storage is required, while a deadband of 0% requires some energy storage at all wind penetration levels. This suggests that energy storage may not be needed, on a system level, until approximately 10% of energy is produced by wind. Despite this, large electricity markets may still find a use for fast-ramping energy storage as a substitute for the close coordination required to provide fill-in power through the market. We have shown that the use of energy storage to smooth the sharpest fluctuations, allowing a gas turbine to provide the remaining fill-in energy, is a cost-effective application. As a result, complex electricity markets might consider enacting lightly binding limitations on the bus-bar ramp rate of wind generators, which could then motivate the deployment of small energy storage systems co-located with wind generation.

This model of wind/gas/energy storage generation systems demonstrates a potential method for integrating significant quantities of wind energy while reducing power fluctuations to a small deadband and maintaining a reasonable cost of electricity. Furthermore, over a wide range of wind penetrations relatively little energy storage is needed and this energy storage acts to mitigate potentially harmful transient pulses. By studying these wind/gas/energy storage systems, we are better able to understand the issues associated with wind integration and the value that traditional generation and energy storage can provide, especially when working in concert with one another to mitigate undesired variability.

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2.8 Appendix A: Model and Scenario Analysis Description

The critical tools in this study are the scenario analysis structure used to investigate different wind/gas/storage systems and the underlying operational and cost models. This appendix describes each of these components in detail.

2.8.1 Scenario Analysis

The scenario analysis is the highest level of the program and utilizes repeated runs of the operational and cost models with the goal of surveying a wide variety of wind/gas/storage systems. A scenario analysis consists of two cycles of 100 runs each, where the second cycle investigates the "areas of interest" from the first cycle in greater detail. The objective of the scenario analysis is to identify the systems with the lowest average cost of power, given a particular fraction of delivered energy from wind.

At the start of a scenario analysis, the operational and cost parameters are set to the base-case values or, for sensitivity analysis, a single parameter is changed from the base-case value. The operational and cost parameters are then held constant for the duration of the sensitivity analysis.

The first cycle of the scenario analysis consists of 100 runs of the operational and cost models. The scenario analysis varies two parameters: the system wind penetration and the target power output. Wind penetration is varied from 0% to 90% system wind capacity in 10% increments (10 levels) while the system power output is varied from 10% of total system generation capacity (gas capacity plus wind capacity) to 100% of total system generation capacity in 10% increments (10 levels). The scenario analysis runs every combination of these two parameters, giving the total of 100 runs. The scenario analysis collects data on each run of the model including average cost of power, energy from wind, energy from gas, CO_2 and NOx emissions, and magnitude of required energy storage.

In the second cycle of the scenario analysis, the target power output that resulted in the lowest average cost of electricity is identified for each wind penetration level. These "areas of interest" are then investigated in finer detail in the second cycle. At each wind penetration level, the system power output is varied +/- 10% around the lowest average cost point in 2% increments (10 levels). The wind penetration levels used are the same as in the first cycle of the scenario analysis. This results in another 100 runs of the operational and cost models. The relevant data are again extracted from each run and saved for later analysis.

2.8.2 Operational Model

The operational model is the most complex part of this study. This model takes as inputs the pre-defined operational parameters, the wind penetration and system power output values from the scenario analysis, and a file representing a time-series wind data set. The wind data used in this study is actual 10-sec resolution data taken from a southern Great Plains wind farm (sum of 7 turbines), though the model is configured to accept any time-series data with equally spaced samples. The wind power used for the model is proportionally scaled directly from the input wind data.

The model assumes a single gas turbine, which operates to provide fill-in power for the wind generation within its operational limitations and within the defined deadband. The gas turbine limitations are a high operating limit, a low operating limit, a ramp rate limit, a must-run time, and a start-up time. The turbine is forbidden to operate above the high operating limit or below the low operating limit. The ramp rate limitation is applied by converting the ramp rate constant (in percent per minute) to a maximum power change per step, and restricting the power output change per step to that value. The must-run time defines the minimum amount of time that the gas turbine must operate before it can shut down. If the gas turbine has been running for the required period and gets a signal to provide a power output of zero, then it immediately shuts down and ceases to deliver any power. Thus, as the power required from the gas turbine decreases, the gas turbine ramps down to the low operating limit then holds at that point until it is prompted to turn off completely. If the gas turbine is off and gets a signal to deliver any amount of power, then it begins the start-up process. This process is modeled as delivering no power for the duration of the start-up time and then immediately jumping to the low operating limit. The start-up process is not cancelled if the gas turbine ceases to receive a signal to produce power. The start-up and shut down processes are the only exceptions to the ramp rate limitation.

The gas turbine attempts to bring the total wind plus gas power output to the target power output level at every point in time. Thus, the deadband range becomes important only for the determination of the energy storage operation. Once the power output of the wind and the gas turbine are defined, the power requirement to/from the energy storage device (the "residual power") is calculated. This residual power is equal to the target power output minus the power outputs of the wind and gas generation. The magnitude of the residual power is then reduced at each point by the deadband power, reducing the power requirement levied on the energy storage device. Importantly, the residual power has both positive and negative values, corresponding to discharge and charge power.

The model next calculates the quantity of energy storage that would be required to provide the residual power defined above. For NaS batteries and flywheels, the systems come in modules with fixed power limitation and energy capacity. Thus, for these technologies, the amount of storage needed is the maximum of the amount required to provide the capacity needs and the amount required to provide the power needs. Because supercapacitors have essentially no power limitation, the power and energy capacity requirements are considered separately. NaS batteries and flywheels both require a fixed maintenance power which is unrelated to their round-trip efficiency. This power requirement is then added to the output of the gas turbine which, in effect, acts to slightly scale up the size of the gas turbine so that it provides all of its previous services as well as providing a fixed power output to the energy storage devices. The round-trip efficiency (RTE) for the energy storage devices is defined as the ratio of AC energy in to AC energy out.

The model requires that the energy storage charge state at the end of the studied period be equal to or greater than its initial state. To do this, the model determines whether the defined residual power, given the round-trip efficiency of the energy storage, is sufficient to achieve a concluding charge state greater than the initial charge state. If the concluding state is determined to be lower, than the gas generation is adjusted to provide more charge energy.

If it is required that the gas turbine produce more power, this is done in a non-forward looking way that attempts to maximize the efficient use of the turbine. As long as more charge energy is required, the model first increases any local minima in the gas turbine power output. If there are no local minima, then it increases the lowest global point. If the gas turbine is at maximum power output at all points when it is operational, then the model extends the periods of operation. The energy output of the gas turbine is increased in this manner until there is sufficient energy through the energy storage device to meet the described constraints. If the gas turbine is operational at all points in time and is at the high operating limit the entire time, then the system is declared “insufficient”, model execution is ceased, and no data is returned to the scenario analysis for that system.

2.8.3 Cost Model

The cost model uses the data regarding quantity and operation of the wind, natural gas, and energy storage resources to calculate the cost of the system. Additionally, it contains a set of pre-defined cost parameters, such as cost of capital rate and natural gas price.

The cost model calculates the amortized capital cost of each technology using the lifetime of that resource and the global cost of capital rate. It then calculates the other fixed costs of each resource using the pre-defined cost parameters. The variable cost of the natural gas generator is separated into the cost due to fuel and emissions and other variable costs. The cost model uses the emissions and efficiency data for a Siemens-Westinghouse 501FD from Katzenstein and Apt (Katzenstein & Apt, 2009). Fuel consumption, CO_2 emissions, and NOx emissions are calculated for each operational step and summed. These values are used to determine the cost of natural gas and the costs due to emissions. The cost module uses all of the data described above to calculate the average cost of electricity, the capital cost of the resources, and the variable cost of operation of the system.

2.8.4 Sources for Operational and Cost Parameters

The base-case parameters used in the model come from a variety of sources. The operational and cost data associated with energy storage technologies is taken, with little modification, from the EPRI-DOE Handbook of Energy Storage (EPRI-DOE, 2002). For NaS batteries and flywheels, the Handbook of Energy Storage has cost information that regards power and energy as independent costs, while the system is forced to purchase an actual production module with a fixed performance. Costs for the natural gas turbine and wind generators were adapted from the DOE/NETL Cost and Performance Baseline for Fossil Energy Plants (DOE/NETL, 2007) and the Levelized Cost of Energy Analysis from Lazard, Ltd (Lazard, 2008). The natural gas price of $5/MMBTU was chosen to approximately reflect the current price. All prices were brought to 2010 dollars by applying a 2%/year inflation rate.

2.9 Appendix B: Battery Energy Statistics and Value

When wind variability is smoothed exclusively by a gas turbine, there are fast transient pulses that the gas generator is unable to accommodate due to operational limitations. This results in short-duration power spikes and drops that would be externalized to the grid without an energy storage device to act as a buffer. In order to determine what services the energy storage device is providing in the wind/gas/storage generation block, it is critical to characterize the nature of the power spikes and drops that would result in the absence of such a device.

A brief statistical characterization was performed over the power fluctuations resulting from a wind/gas system to investigate the time between power fluctuations and the total energy deviation of those fluctuations. Firstly, power fluctuations within the deadband are considered complete acceptable and are not factored into the calculations. Power spikes/drops that persist over multiple time steps are considered a single event rather than a series of smaller events, as the most important factor of an event is the total energy lost or gained during that event. For simplicity, and due to the fact that the positive and negative energy deviations appear to be approximately equal in size and frequency, they are treated as equivalent and the absolute value of the energy deviation is used. Given these definitions, there are three factors that are relevant to the analysis of this data set: the time between events, the length of events, and the energy of events. Of these, the time between events and the total energy delta of the events are the more important factors.

The analyzed scenarios are those demonstrating the lowest average cost of electricity, given the base-case parameters, for wind penetrations of up to 50% energy from wind. Because of the base-case deadband of 0.5%, the first three scenarios (0%, 5%, and 12% energy from wind) do not have any power fluctuations outside of the deadband and thus do not require any energy storage at all. Higher wind penetrations have fluctuations with greater energy deviations, but these events are not necessarily greater in quantity. A summary of the descriptive statistics for these cases is contained in Table 2.4. The contribution to the average electricity price due to the NaS battery system, scaled to eliminate the described fluctuations, is also included for reference.

Table 2.4: Summary of power fluctuations without energy storage.

Wind Nameplate Capacity (MW)[a] Delivered Wind Energy (percent)	43 19%	67 30%	100 36%	150 50%
Average Time Between Fluctuation Events (sec)	7130	176	397	553
Average Length of Fluctuation Events (sec)	10	23	177	320
Average Total Energy Deviation of Fluctuation Events (kWh)	0.79	0.72	4.8	92
Maximum Energy Deviation of Fluctuation Events (kWh)	9.7	23	1900	9500
Maximum Power Deviation (MW)	1.5	4.9	13	80
Contribution of Mitigating NaS Battery to Electricity Price ($/MWh)[b]	$0.31	$0.73	$5.13	$11.84

[a] *All systems have a 100 MW natural gas turbine.*

[b] *The last row shows the cost of the NaS Battery which is able to mitigate the described power fluctuations to within the base-case deadband level of +/- 0.5% of target power output.*

The value of the energy storage device in these systems is a function of both the perceived value of power quality and the cost and performance of other mitigation options. Without a thorough review of power quality requirements and smoothing alternatives, which is beyond the scope of this study, a definitive statement about the value of the energy storage system cannot be made. Regardless, it is clear that the value proposition of the co-located energy storage device is not unreasonable, and should be considered as a potential option for mitigation of these short time-scale fluctuations.

Chapter 3: What Properties of Grid Energy Storage are Most Valuable?

3.1 Abstract

While energy storage technologies have existed for decades, fast-ramping grid-level storage is still an immature industry and is experiencing relatively rapid improvements in performance and cost across a variety of technologies. In this innovation cycle, it is important to determine which properties of emerging energy storage technologies are most valuable. Decreased capital cost, increased power capability, and increased efficiency all would improve the value of an energy storage technology and each has cost implications that vary by application, but there has not yet been an investigation of the marginal rate of technical substitution between storage properties. We use engineering-economic models of four emerging fast-ramping energy storage technologies and examine their cost-effectiveness for four realistic current applications. We determine which properties have the greatest effect on cost-of-service by performing an extended sensitivity analysis on the storage properties for combinations of application and storage type. We find that capital cost of storage is consistently important, and identify applications for which power/energy limitations are important. Each combination is different and blanket statements are not always appropriate.

3.2 Introduction

There has been significant interest in fast-ramping[1] grid-tied energy storage in recent years. The costs of storage have been decreasing for many technologies while the performance has been improving (Eyer & Corey, Energy Storage for the Electricity Grid: Benefits and Market Potential Assessment Guide,

[1] "Fast-ramping energy storage" refers to technologies that are able to shift their power output from full charge to full discharge (or vice versa) in seconds or less.

2010) (Baker, 2008). These trends suggest that a substantial quantity of energy storage is likely to be installed on the grid in the next few decades. But energy storage technologies are not interchangeable, due to the differing limitations, operations, and capabilities. The applications served by energy storage are not equivalent to one another due to the different types of charge/discharge profiles required from the storage. Thus, in order to properly evaluate energy storage technology for current electrical grid applications, it is necessary to examine particular technologies being used for particular applications.

Previous work has compared the properties of different energy storage technologies and matched them to the most appropriate applications, and that work is not reproduced here (Butler, Miller, & Taylor, 2002) (Eyer, Iannucci, & Corey, Energy Storage Benefits and Market Analysis Handbook, 2004) (Hadjipaschalis, Poullikkas, & Efthimiou, 2009) (Ibrahim, Ilinca, & Perron, 2008) (Kondoh, et al., 2000) (Schoenung S. , 2001). Instead, we examine the effects that improving the attributes of energy storage will have on the cost of providing different energy services, and compare the results across different technologies and applications.

We developed engineering-economic models of four energy storage technologies and examined their cost-effectiveness for different applications. We then performed extended sensitivity analysis on the "cost-of-service" for each energy storage technology in each realistic application, where cost-of-service is defined as the annual cost of delivering an energy service from a storage technology[2]. From this, we calculate the marginal rate of technical substitution[3] between storage properties and determine which energy storage properties are the most limiting and thus the most important to improve, using the cost of delivering a realistic energy service as the objective criteria. We focus on the class of scalable fast-ramping energy storage technologies that are currently being developed and beginning to be deployed, as these emerging technologies have the potential for cost and performance improvements in

[2] The cost-of-service includes fixed costs, variable costs, and amortized capital costs.
[3] If output is held constant, the decrease in one production input factor that is reduced when another input is increased is the marginal rate of technical substitution.

the coming years. This work examines realistic current technologies and applications, and is intended as a near-term analysis of emerging grid-level energy storage.

The paper is organized as follows: first, we describe the modeling methodology for the storage technologies and applications and the method used to determine which storage properties are most limiting. Second, we present the results and examine how these results are affected by changes to the storage parameters. Third, we discuss how these results can be used to inform decision-making over future energy storage research and development.

3.3 Methodology

We examine four storage technologies as applied in four applications: sodium sulfur (NaS) batteries, lithium ion batteries, flywheels, and supercapacitors. The applications are frequency regulation, wind smoothing in a generation block producing baseload power, wind smoothing in a generation block producing load-following power, and peak shaving. We determine the effect that changes in storage parameters have on the cost of providing a specific service. Each energy storage technology was modeled separately, since energy storage technologies differ in more than just operational parameters. A model was developed individually for each of the four applications. The result is a matrix of sixteen different models, for the four storage technologies applied to the four different applications. The more important aspects of the storage and applications modeling are described below and greater detail can be found in the Appendix (Section 3.8).

3.3.1 Energy Storage Modeling

The four energy storage types represent an operationally diverse set of fast-ramping storage technologies that have potential for significant market share in the coming decades (Eyer & Corey, Energy Storage for the Electricity Grid: Benefits and Market Potential Assessment Guide, 2010) (Butler, Miller, & Taylor, 2002) (Eyer, Iannucci, & Corey, Energy Storage Benefits and Market Analysis Handbook, 2004). Currently, the vast majority of energy storage on the grid is provided by pumped hydro, with a very small amount of compressed air energy storage (CAES) (EPRI, 2010). These technologies are not considered because this analysis is focused on scalable and emerging fast-ramping energy storage. Pumped hydro and CAES are more mature and less likely to experience technical innovation, are less scalable, and are more geographically constrained (EPRI, 2010).

We developed an engineering-economic model for each of the four energy storage technologies; each is modeled with its own set of operational and cost parameters, including round trip efficiency, energy capacity, fixed operating cost, capital cost, and expected duration of capital investment. While the core storage model is the same for all four technologies, slight changes to the model are required for each, due to functional differences in the four technologies. Energy storage is modeled using the most realistic operational and cost data available. For consistency, most of the data for operational and cost modeling of energy storage are taken from the EPRI-DOE Handbook of Energy Storage (EPRI-DOE, 2002). Where additional data are available from the manufacturer, such as the pulse power limitations on Sodium Sulfur batteries (NGK Insulators, 2005) or the properties of commercially produced flywheels (Beacon Power, 2011), these have been used. Two of the technologies (NaS batteries and flywheels) are modeled as modular, meaning that they come in pre-defined modules with fixed properties. In both cases, this storage technology is available commercially only in modular form, due to fundamental constraints of the technology (the need to maintain NaS batteries at elevated temperature and the economies of scale for flywheel design and construction). While the module size can be adjusted in theory, we have chosen to model the modules as available in the marketplace. We note later the implications of modularization for our results.

The NaS battery is modeled after the currently-available PQ modules produced by NGK Insulators, currently the only supplier for this technology (NGK Insulators, 2005). Because NaS batteries are commercially available only in a pre-defined modular form as noted above, their power-to-energy ratio is fixed. NaS batteries require a temperature of ~ 325 degrees Celsius to operate and thus require a continual "maintenance power" to maintain that temperature (accounted for in this model). NaS batteries have a continuous power rating of 0.05 MW, and have a manufacturer-defined pulse power capability (also accounted for in the model) under which they can provide up to five times the normal power rating for 30 seconds, making their maximum power output 0.25 MW.

Table 3.1: NaS battery properties examined and their base-case values.

NaS Battery Parameter	Base-Case Value
Round-trip Efficiency	80%
Module Energy Capacity	0.36 MWh
Module Power Limit	0.25 MW
Module Maintenance (Heating) Power	2.2 kW
Module Capital Cost	\$240K (\$670K / MWh)
Module Fixed Operating Cost	\$8K / module - year (\$22K / MWh-year)
Length of Capital Investment	20 years

Li-ion batteries are modeled without modularization and we make the assumption that a system could be created with a wide range of power-to-energy ratios, as required for each application. A generic Li-ion battery is modeled, with parameters close to existing units but not taken from any particular product.

Table 3.2: Li-ion battery properties examined and their base-case values.

Li-ion Battery Parameter	Base-Case Value
Round-trip Efficiency	80%
Capital Cost of Batteries	\$500K / MWh
Capital Cost of Power Electronics	\$300K / MW
Fixed Operating Cost	\$8K / MW - year
Length of Capital Investment	10 years

Flywheel energy storage, like NaS batteries, is assumed to come in discrete modules with pre-defined properties and is based on Beacon Power's Smart Energy 25 flywheel (Beacon Power, 2011). In addition to round trip efficiency limitations, the flywheel model accounts for friction losses which reduce the stored energy over time.

Table 3.3: Flywheel energy storage properties examined and their base-case values.

Flywheel Energy Storage Parameters	Base-Case Value
Round-trip Efficiency	90%
Module Energy Capacity	0.025 MWh
Module Power Limit	0.1 MW
Flywheel Friction Losses	3% of max power (3 kW)
Module Capital Cost	$200K
Fixed Operating Cost	$5K / module - year
Length of Capital Investment	20 years

Supercapacitors are modeled with no power limitation and are not modularized, allowing the model to choose the quantities of power electronics and energy capacity independently (EPRI-DOE, 2002).

Table 3.4: Supercapacitor properties examined and their base-case values.

Supercapacitor Parameters	Base-Case Values
Round-trip Efficiency	70%
Capital Cost of Supercapacitors	$143M / MWh
Capital Cost of Power Electronics	$60K / MW
Fixed Operating Cost	$13K / MW - year
Length of Capital Investment	20 years

3.3.2 Applications Modeling

Four applications were chosen as representative of the types of energy services that are currently being used with or considered for the storage technologies we examine (Eyer & Corey, Energy

Storage for the Electricity Grid: Benefits and Market Potential Assessment Guide, 2010). Both energy-intensive (peak shaving) and power-intensive (frequency regulation and wind integration) applications are represented. The applications examined have been identified as some of the most beneficial (in a $/kW basis) and represent a subset of the services energy storage may provide on the grid (Eyer & Corey, Energy Storage for the Electricity Grid: Benefits and Market Potential Assessment Guide, 2010). These four applications are not exhaustive of the many potential energy storage applications, but were selected because they represent some of the more promising current applications. All four applications require only a small deployment of storage, which is appropriate for the relatively new and expensive technologies studied. Importantly, grid code will change over time and affect the way that storage is used - one example is a 2011 FERC Notice of Proposed Rulemaking that proposes to change the way fast-ramping storage is compensated for frequency regulation service (Federal Energy Regulatory Commission, 2011). This analysis is focused on realistic current and near-term deployments of energy storage, but the charge/discharge profiles required of grid-tied energy storage will likely remain similar to the applications examined herein.

Each application was modeled using a time-series analysis, as shown schematically in Figure 3.1. This block diagram describes the general method used to calculate annualized cost-of-service. The application model determines the time-series charge/discharge profile that energy storage must satisfy in order to meet the pre-defined requirements of that application. The storage model determines the quantity of energy storage needed to fulfill the requirement of the application and also tracks the charging energy required by the energy storage. The output of the cost model is the annualized cost of providing the required energy service. Input parameters for the applications are described in Tables 3.5-3.8, though it is important to note that we create a unique model for each application that differ in more than just input parameters. A discount rate of 8% is used throughout. For the sake of brevity, the critical features of each application are described below while greater detail about the application models can be found in the Appendix (Section 3.8).

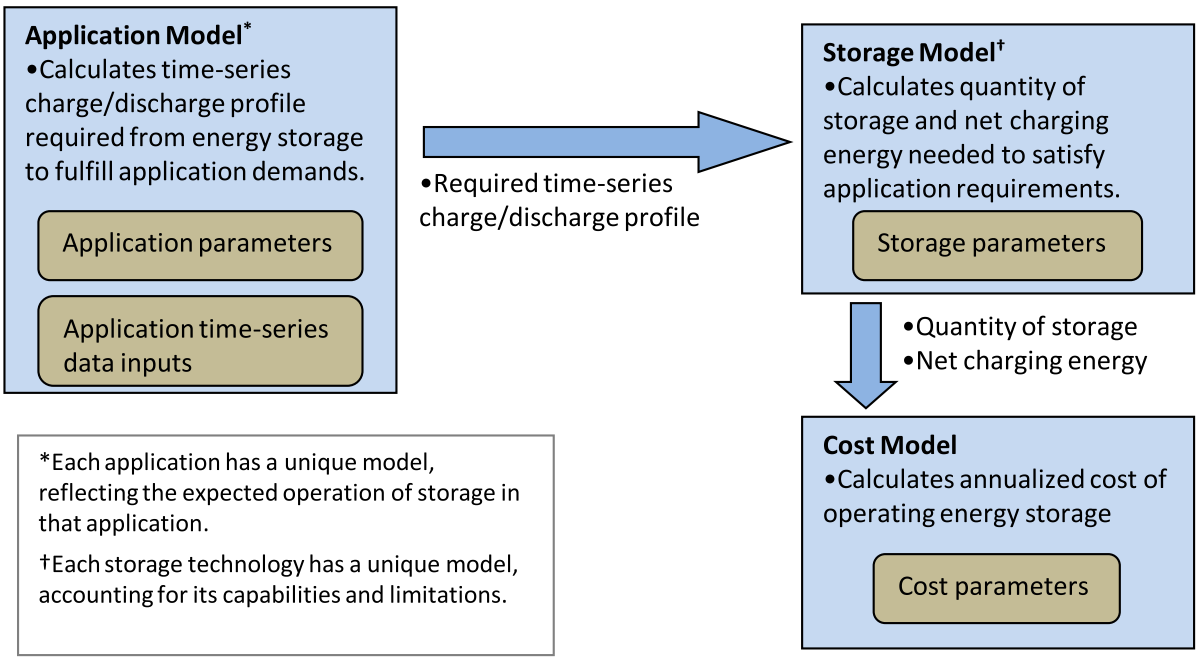

Figure 3.1: Method used to calculate average cost-of-service.

The frequency regulation application calculates the cost of providing a year of frequency regulation service using a particular energy storage technology. Frequency regulation is an ancillary service that follows a signal from the system operator and normally requires rapid changes in power output from a generation asset. For storage, this is implemented by scaling each energy storage device to the minimum size at which it can successfully follow the regulation signal for the entire period. The frequency regulation data set consists of five days of 2-second resolution signal made available by the PJM Interconnection (PJM, 2009). Because the storage provides frequency regulation service continuously, resulting in a roughly constant energy demand, an average electricity cost of $50/MWh is used for the net electricity consumed. During the period covered by the signal released by PJM, the dispatched regulation power up/down went to the contracted maximum power several times, but it is not safe to assume that the maximum possible 15-minute energy deviation was experienced in the five days of data PJM released. Thus, the power requirement of the energy storage is used as determined directly from the model, but the energy capacity requirement is doubled from what the model determines as the minimum possible energy capacity. The model calculates the total cost of providing a year of 100 MW frequency regulation service, and forces the storage to pay for energy lost to inefficiency. This internalizes the cost of the charging energy and allows a fair comparison between storage technologies with differing round-trip efficiencies and losses.

Table 3.5: Key frequency regulation parameters.

Frequency Regulation Parameter	Value
Modeled Period	5 days
Modeled Time Increment	2 seconds
Balancing Energy Bid Interval	15 minutes
Balancing Energy Cost	$50 / MWh

The peak shaving application models the use of an energy storage device at an electricity sub-station in order to reduce the annual peak load in order to defer the need for capital investment in new transmission lines or other distribution assets (Eyer J. , 2009). The storage device provides power during the peak load each day, charging at night when electricity production costs are lower. In this application, the storage is operated as a normal peak shaving device, but the fiscal motivation for the deployment comes primarily from the ability to defer investment in costly upgrades of the distribution system. Additionally, such a deployment does not require a significant reduction in the maximum annual load (nor a significant quantity of energy storage) because the primary goal is to defer capital costs rather than move consumption to off-peak times. This application can be a better fit for scalable energy storage systems than a traditional peak shaving application because only small deployments are needed to defer capital investment and the storage will still produce value in a peak shaving role (Eyer & Corey, Energy Storage for the Electricity Grid: Benefits and Market Potential Assessment Guide, 2010) (Eyer J. , 2009).

The peak shaving application is based on the Sandia report <u>Electric Utility Transmission and Distribution Upgrade Deferral Benefits from Modular Electricity Storage</u> (Eyer J. , 2009). It is modeled by assuming that a system operator wants to reduce the annual maximum load (in MW) in a particular area by 5%. The energy storage is then scaled to provide that reduction from maximum. Using the 2008 Bonneville Power Authority (BPA) load data (5 minute sampling), this would result in the energy storage being used only for a few peak days each year (Bonneville Power Administration, 2009). Because the high capital cost of the storage has already been spent to mitigate the highest loads, it is further assumed that an operator would additionally use the storage for peak shaving on all days of the year. Thus, while the storage is scaled to reduce the highest peaks, it is also used to effectively transfer load to off-peak hours for each day in the year up to its energy limitations. While discharge is performed as required by the load, charging is distributed evenly over 5 hours each night, which is more than enough time to completely charge any of the studied technologies. A price of $40 per MWh is assumed for this nighttime charging, necessary in order to fairly compare storage technologies with different efficiencies. The model calculates the cost of performing the peak shaving service, moving load from peak hours to nighttime. Additionally, it should be noted that while the motivations are different, the peak shaving application is functionally very similar to an energy arbitrage application, at least as far as the storage operation is concerned, and thus the conclusions about energy storage properties for peak shaving should be applicable to energy arbitrage as well.

Table 3.6: Key peak shaving parameters.

Peak Shaving Parameter	Value
Modeled Period	1 year
Modeled Time Increment	5 minutes
Peak Shaving Requirement	5% of peak load
Charging Period	5 hours each night
Charging Energy Cost	$40 / MWh

The application described as wind integration in a wind/natural gas/storage baseload system utilizes a small amount of fast-ramping energy storage to remove the sharpest power spikes and drops from a wind farm to facilitate grid integration of that wind energy (Hittinger, Whitacre, & Apt, 2010). Conceptually, the energy storage acts as a shock absorber for the wind power and allows for a defined ramp rate limitation on the wind power. Actual 10-second time resolution wind data is used to model the wind generation (Southern Great Plains United States wind farm, sum of 7 turbines, 15 days, 10 second resolution, 46% capacity factor during this period). For this research, a ramp rate limitation for wind power of 6% per 10-second interval (36% per minute) is used. Energy storage is scaled to the minimum size required to provide the smoothing service. The modeling for this application has been described in a previous paper, where a natural gas turbine is modeled as the remainder of the system (Hittinger, Whitacre, & Apt, 2010). This wind/natural gas/energy storage generation block operates to deliver flat, baseload power within a small deadband range (0.5%).

Table 3.7: Key baseload wind integration parameters.

Baseload Wind Integration Parameter	Value
Modeled Period	15 days
Modeled Time Increment	10 seconds
Maximum Wind Ramp Rate	6% per 10 second interval

The final application, described as wind integration in a wind/natural gas/storage load-following system, is similar to wind integration in a baseload system described above, except that this application produces a load-following generation profile, while the baseload application has a flat power output. The load data set, sampled at 5-minute intervals, is the same BPA load data used in the peak shaving application. The load data set is chronologically aligned with the wind data, although the wind data is from a different region (Southern Great Plains). The load-following application is examined in this research because it requires a different charge/discharge pattern than the baseload application and thus produces different results.

Table 3.8: Key load-following wind integration parameters.

Load-following Wind Integration Parameter	Value
Modeled Period	15 days
Modeled Time Increment	10 seconds
Maximum Wind Ramp Rate	6% per 10 second interval

3.3.3 Calculations of Marginal Rate of Technical Substitution between Storage Properties

Each of the four application models has, as an output, the annualized cost of providing that particular energy service. By changing the value of one energy storage property and re-running the model, we can determine the effect that this change has on the cost of providing a service. This allows us to calculate the sensitivity of cost to that storage parameter, and the process is repeated for each of the energy storage properties listed in Tables 3.1-3.4. Normally, sensitivity analysis is used to determine the effect of using uncertain parameter values. In this research we make the assumption that the parameters are known and determine the effect that improving them would have on the annual cost of providing different energy services.

For each energy storage parameter and each application, we calculate the sensitivity of the cost of an energy service to the parameter by comparing the cost-of-service from the base-case assumptions to that when the studied property is slightly improved. Conceptually, the cost of providing a particular energy service is a function of the input parameters describing the studied energy storage technology (Equation 3.1). The marginal physical product[4] of parameter i (MP_{p_i}) shows the sensitivity of cost-of-service to parameter i (Equation 3.2), where c is the cost-of-service and p_i is the value of parameter i. The approximation in Equation 3.2 holds for small changes in p_i or cases where the relationship between p_i and c is linear, of which at least one is true for all cases studied. For each storage property, several alternative values are calculated to determine if the sensitivity is roughly linear, even though only two points are used in the calculation.

The marginal physical product is referred to below as the 'sensitivity' and is always reported as a positive number. Additionally, all figures are in percentage terms to facilitate comparisons across properties (i.e., we determine the percentage decrease in cost-of-service resulting from a percentage increase in energy capacity rather than the decrease in cost-of-service dollars from a MWh increase in energy capacity). Thus the results shown in Figures 3.3 through 3.6, showing the marginal product of various storage properties, are between zero (indicating a parameter that has no effect on cost-of-service) and one (indicating a parameter where a 1% improvement results in a 1% decrease in capital cost). Because each storage technology has different cost and operational properties, each technology has different marginal products for a given application. In general, this is a function of the ratios of the various parameters for each storage technology (though other properties, like modularization or the need for a constant maintenance power, also contribute). For example, a storage technology with high

[4] The marginal physical product of a production input is the additional output gained by employing one additional unit of that input while holding other inputs constant.

cost and high efficiency would generally be more sensitive to cost and less sensitive to efficiency than a technology that has low cost and poor efficiency.

$$c = f(p_i, p_j, \dots p_n) \tag{3.1}$$

$$MP_{p_i} = -\frac{\partial c}{\partial p_i} \approx -\frac{\Delta c}{\Delta p_i} \tag{3.2}$$

$$RTS_{p_i,p_j} = \frac{MP_{p_i}}{MP_{p_j}} \tag{3.3}$$

The relative importance (effect on annualized cost of providing an energy service) of different storage properties can be compared using the marginal rate of technical substitution (RTS_{p_i,p_j}), which is the ratio of the marginal products of the two input parameters (Equation 3.3). The rate of technical substitution gives the ratio of parameters i and j that must be exchanged in order to keep the overall cost-of-service constant. Alternately, over small changes in parameters, it indicates the ratio of improvements to parameters i and j that would have an equal effect on cost-of-service. Because the production function in Equation 3.1 is not perfectly elastic across different parameter combinations, the results will be increasingly inaccurate as the base-case parameters are changed, and cannot be considered applicable to all possible combinations of parameters. The effect that changes to the base-case parameters have on the results is discussed in Section 3.8.3.

Figure 3.2 is an example of the method used. This figure shows a sensitivity plot of four flywheel energy storage properties. 100% on the x-axis, where the lines all meet, is the base case result. As a single parameter is changed (along the x-axis), this results in a change in the cost of providing the energy service (on the y-axis). Some properties, such as module energy capacity in this example, have little or no effect on the cost of service while others, such as module capital cost, are far more important. This figure shows data only for flywheels providing frequency regulation service. The sensitivities of all four storage technologies applied to all four applications are collected and presented in the Results section below.

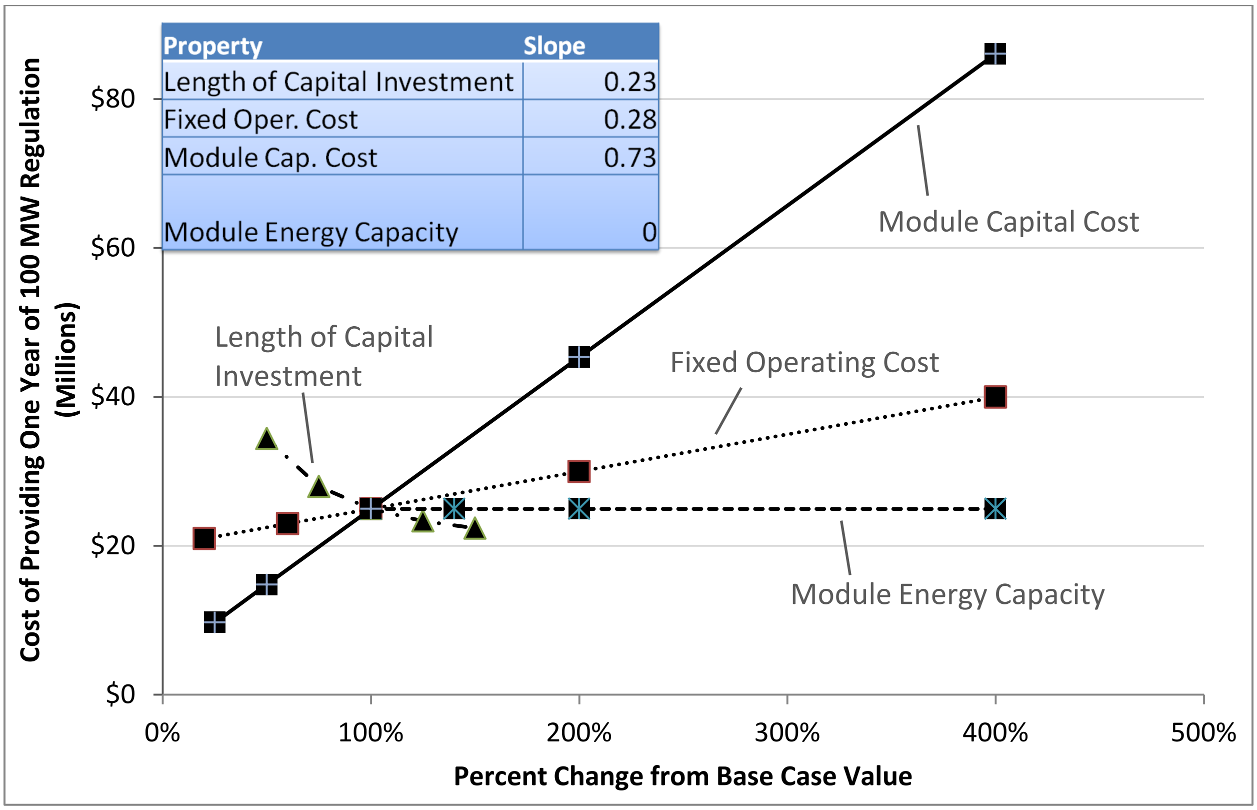

Figure 3.2: Sensitivity plot of flywheel energy storage properties. As a single parameter is varied (along the x-axis), the cost of providing 100 MW of frequency regulation service changes (along the y-axis). The cost of energy service is most sensitive to those parameters with a higher slope (such as module capital cost). The inset box gives the slope or sensitivity of the four lines in percent decrease in cost-of-service per percent improvement in the examined parameter.

3.4 Results

We focus on the relative importance of improvements in storage properties for decreasing cost-of-service. Using the four energy storage technologies and the four applications, sixteen different technology/application combinations were modeled. For each combination, sensitivity analysis was performed over each of the energy storage properties studied (between five and seven for each technology).

The results for NaS batteries are shown in Figure 3.3. We draw two conclusions. First, while each application is different, there are some general trends. Module capital cost is important in every application, while module maintenance power is found to have little effect on cost in all cases. Improvement of efficiency is found to be a relatively insensitive parameter in all applications. Second, the power and energy limitations are very important but their relative importance depends on the type of application. For the power-intensive services, such as frequency regulation, the power limit is the most important NaS battery property, while the existing energy capacity is non-binding and thus unimportant. On the other hand, for an energy-intensive application such as peak shaving, energy capacity is the property that most affects the cost of service, while the power limitation is non-binding.

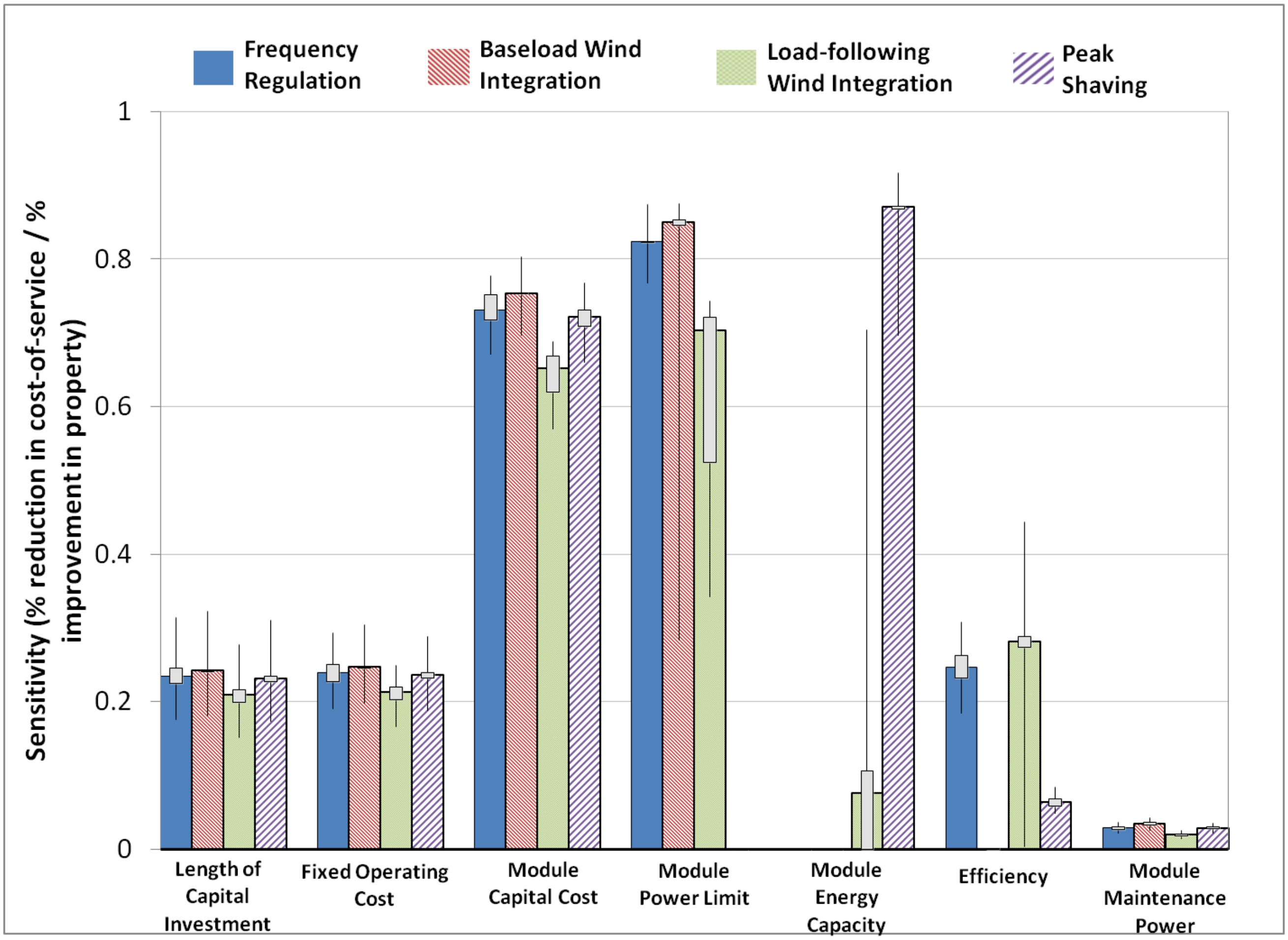

Figure 3.3: Sensitivities of NaS Battery properties across four applications. Properties with higher sensitivity have a greater effect on the cost of providing energy services. The base bars give the median result from the sensitivity analysis (described in the sensitivity analysis section). The box range indicates the 25th and 75th percentile values and the whiskers show the minimum and maximum values obtained in sensitivity analysis.

The results for Li-ion batteries are shown in Figure 3.4. For Li-ion batteries, the fixed operating cost was found to have a small effect on cost of energy services, while capital cost and lifetime were relatively important. The sensitivity to efficiency depends strongly on the application.

In contrast with NaS batteries, Li-ion batteries do not have as many properties that are highly sensitive. This is due partially to the fact that Li-ion battery systems were not constrained to NaS' pre-defined modular design. As a result, the optimal power-to-energy ratio can be chosen in each case. The modularization of storage technologies also has a strong effect on the sensitivity to efficiency. This is because the value of efficiency for customizable technologies is twofold: improving efficiency reduces both the amount of energy that is lost to inefficiency and the total amount of energy storage required. For modular technology, the latter does not apply unless efficiency improvements allow the purchase of at least one less module. We find that the value of the energy lost to inefficiency is smaller than the amortized capital cost of the storage itself, which results in efficiency being a less sensitive parameter for the modular technologies.

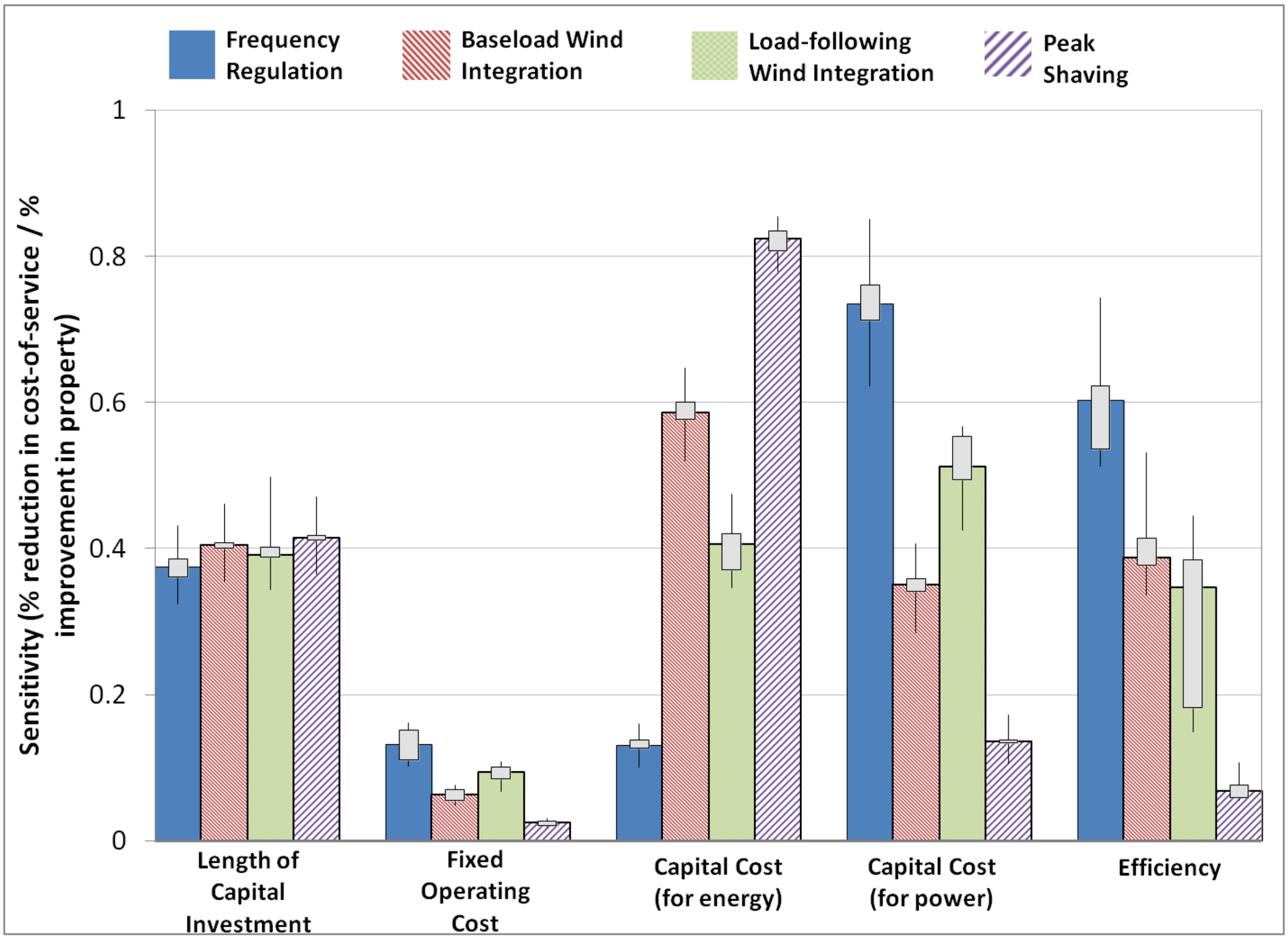

Figure 3.4: Sensitivities of Li-ion Battery properties across four applications. Properties with higher sensitivity have a greater effect on the cost of providing energy services. The base bars give the median result from the sensitivity analysis (described in the sensitivity analysis section). The box range indicates the 25th and 75th percentile values and the whiskers show the minimum and maximum values obtained in sensitivity analysis.

The results for flywheel energy storage are shown in Figure 3.5. For all applications, the most limiting energy storage property, and thus the property that most affects cost, is module capital cost. The efficiency and friction losses of the system are found to be of little importance in all applications except load-following wind smoothing. In this instance, the base-case system is very close to requiring one less flywheel module, thus slight improvements in efficiency or friction losses cause the system to decide upon one less module, resulting in an unexpectedly strong effect on cost. This non-linear effect is entirely due to the requirement for discrete flywheel modules, and is discussed further in the sensitivity analysis section of the Appendix (Section 3.8.3). As in the previous results, the relative importance of flywheel energy capacity and power limit vary by application. Flywheels are particularly suited to power intensive applications (Schoenung S. , 2001), and current flywheel designs may be inappropriate for energy-intensive applications, such as peak shaving. Frequency regulation is the grid application of choice for flywheels, and several flywheel installations, including the largest flywheel installation in the world, are currently providing this service in the US (Bradbury, 2011).

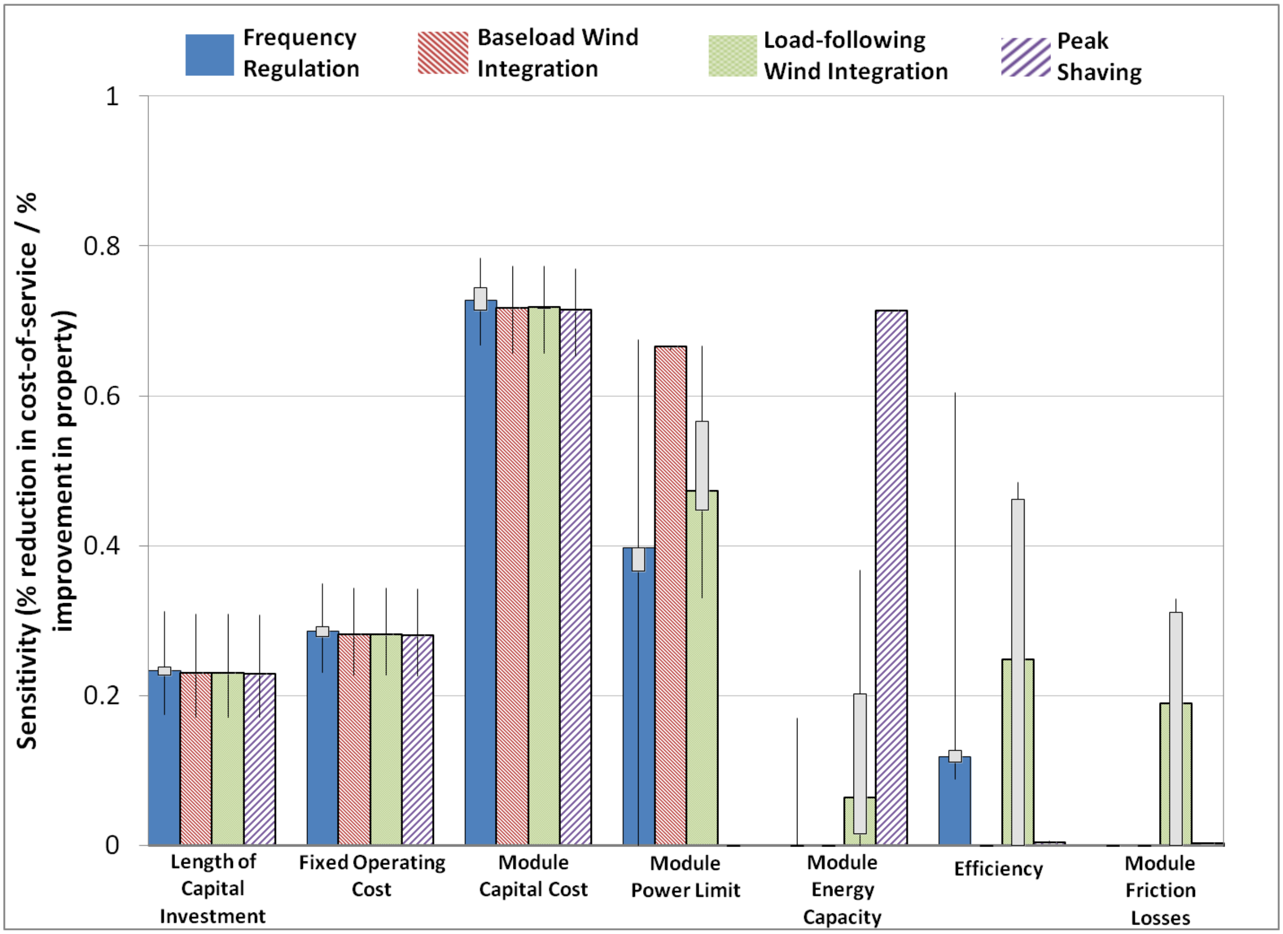

Figure 3.5: Sensitivities of flywheel energy storage properties across four applications. Properties with higher sensitivity have a greater effect on the cost of providing energy services. The base bars give the median result from the sensitivity analysis (described in the sensitivity analysis section). The box range indicates the 25th and 75th percentile values and the whiskers show the minimum and maximum values obtained in sensitivity analysis.

The results for supercapacitor energy storage are shown in Figure 3.6. These results are driven largely by the high capital cost per energy capacity of supercapacitors. This causes the capital cost for energy capacity and the duration of capital investment (which is linked to it through the discount rate) to overshadow the capital cost of power electronics and the fixed operating cost. Efficiency is found to be relatively important, as it affects the amount of energy storage required. Supercapacitors are best suited to applications requiring very high power and low quantities of energy (Schoenung & Hassenzahl, 2003). Of the applications examined here, frequency regulation is the most appropriate, though the very high capital cost for energy currently deters investment in this energy service. As with flywheels, results are provided for all four applications, even though supercapacitors may not be an appropriate technology choice for all of them.

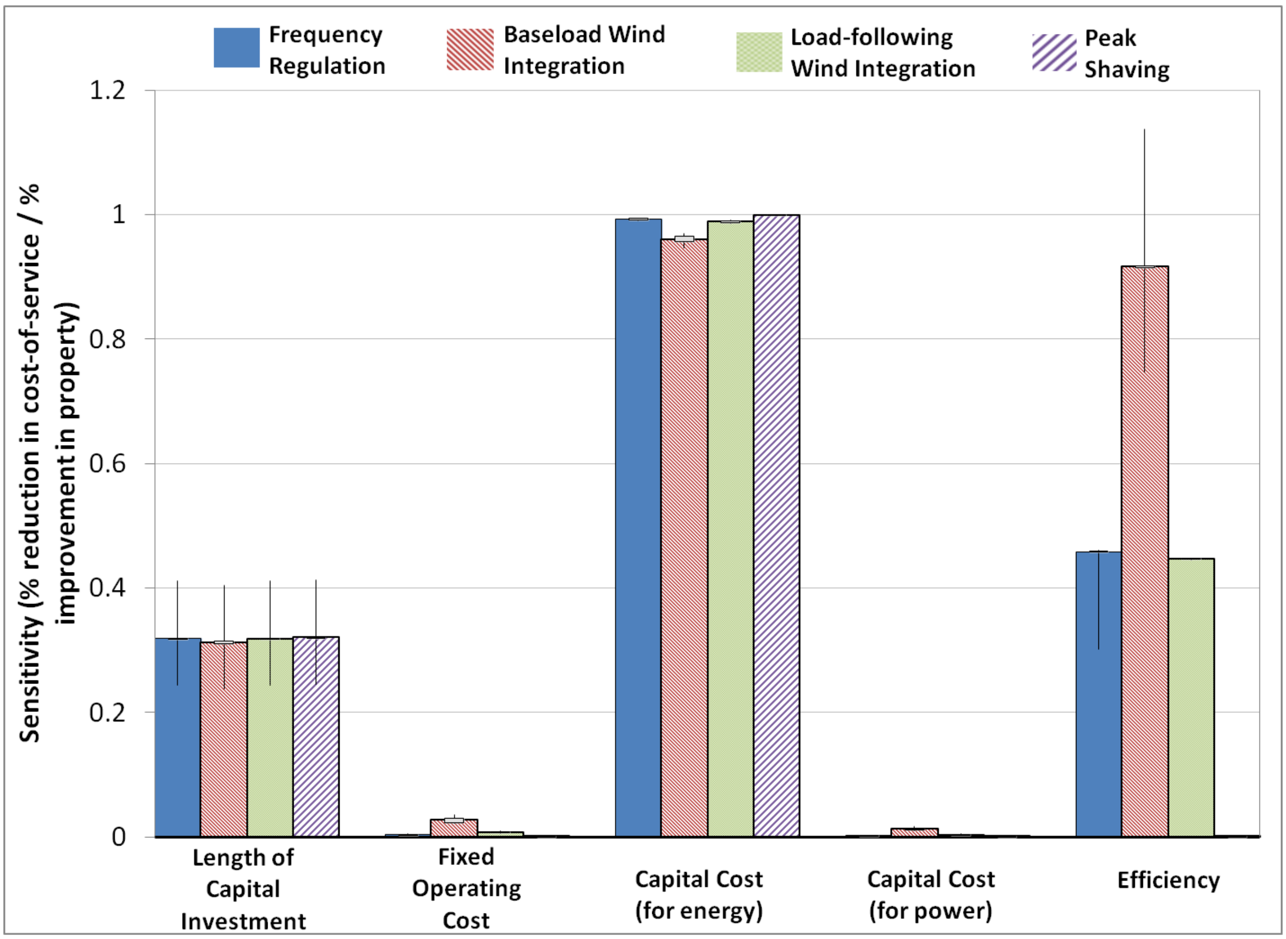

Figure 3.6: Sensitivities of supercapacitor energy storage properties across four applications. Properties with higher sensitivity have a greater effect on the cost of providing energy services. The base bars give the median result from the sensitivity analysis (described in the sensitivity analysis section). The box range indicates the 25th and 75th percentile values and the whiskers show the minimum and maximum values obtained in sensitivity analysis.

Sensitivity analysis is commonly used to test the robustness of results, by determining the effect that changes in input parameters have on those results. Since many of the parameters used here are uncertain or are continually being improved, sensitivity analysis is an appropriate tool for ensuring that small changes in energy storage parameters do not greatly affect the conclusions described above.

For each storage technology/application combination, we determine the effect that changing each input parameter has on the sensitivity of all parameters. Each storage parameter is reset to 75% and 125% of the base-case value with the exception of efficiency, which is not permitted to go above 100%. Then, the entire analysis is run again, calculating the sensitivity of all parameters. This process is performed for each of the sixteen storage technology/application combinations, and produces 1200 data points, most of which do not deviate much from the base-case results. Over all storage technologies and applications, a 25% change in a single storage parameter results in an average change of 0.02 to the calculated sensitivities, which is small considering that these sensitivities range from zero to one (see Figures 3.3-3.6). A 25% modification in a parameter generally has the strongest effect on the sensitivity towards that parameter (i.e., reducing the capital cost of storage normally has the greatest effect on the sensitivity towards capital cost), but even the modified parameters experience an average change in sensitivity of only 0.05. In almost all cases examined, changing any single parameter by 25% has little effect on the general shape of the results or the relative importance of different storage properties. The sensitivity analysis results are summarized in Figures 3.3 - 3.6 and discussed in greater detail in the appendix (Section 3.8.3).

3.5 Discussion

While each technology/application combination produces different results, there are some general trends. Capital cost, for either fixed modules or storage/power electronics combinations, is consistently a key limitation for the technologies examined. While researchers that study grid-level energy storage applications certainly understand this, there is sometimes an inconsistency between this understanding and funded research efforts, which may focus on less useful but more technically exciting improvements, such as efficiency or energy capacity. This could be due partly to the reasonable expectation that production costs of energy storage will naturally decrease over time for a variety of reasons, and that deliberate additional efforts are not required. While capital cost reductions can be expected, this does not necessarily mean that investment that further accelerates cost reductions would be imprudent. We find that, at least for the examined technologies and applications, small improvements in capital costs are the most consistent and effective way to improve the value proposition of energy storage.

Several entities have defined capital cost targets for energy storage. The US Department of Energy Office of Electricity Delivery & Energy Reliability Energy Storage Program has a target of $250/kWh for existing battery technologies (NaS, lead-acid, Li-ion, and flow batteries) (US DOE, Office of Electricity Delivery & Energy Reliability, 2011). American Electric Power has identified a cost target of $500/kWh for residential energy storage, where small energy storage devices are placed below the substation level in order to provide peak shaving and emergency backup services to small groups of residential customers (US Department of Energy Advanced Research Projects Agency-Energy, 2009). The US Department of Energy Advanced Research Projects Agency - Energy (ARPA-E) Grid-Scale Rampable Intermittent Dispatchable Storage (GRIDS) Funding Opportunity Announcement seeks "revolutionary new technology approaches to grid-scale energy storage" that have the potential for capital costs as low as $100/kWh (US Department of Energy Advanced Research Projects Agency-Energy, 2010).

We can use our models to calculate the sensitivities of storage properties if the capital cost of storage technologies met a $250/kWh target while holding other properties constant. For Li-ion systems, this reduces the capital cost of the batteries by 50%, but the sensitivity of cost-of-service to battery capital cost only drops by ~ 20% (on average across the four applications). This suggests that there is still significant value in reducing the capital cost of Li-ion batteries even if the target of $250/kWh has been met. Using $300/kW as the capital cost of power electronics, a NaS battery module would cost $165K (a 30% decrease). At this capital cost, the sensitivity to module capital cost decreases by ~ 12% and module capital cost is the second most sensitive parameter for each of the four applications (the same ranking as the base case results). If flywheel module capital cost were reduced by 50% (a similar reduction to the batteries above), sensitivity of cost-of-service to module capital cost is reduced by ~ 25% and module capital cost is still either the first or second most sensitive parameter in all of the four applications. The cost targets discussed above provide an estimate of what capital cost is required for the deployment of storage to be profitable, but do not necessarily mean that further improvement would be imprudent. While meeting existing technology targets would allow certain storage applications to break even, the value of energy storage will continue to increase as capital costs decrease. These results suggest that reducing capital cost will continue to be a practical strategy for reducing annualized energy service costs from storage even if current capital cost targets have been met.

Apart from capital cost, the other properties of high value are the power/energy limitations of energy storage. This manifests itself differently in the storage technologies that are modeled as modularized (NaS batteries and flywheels) and configurable (Li-Ion batteries and supercapacitors). In the modularized technologies, which have a fixed power/energy ratio, the power and energy limits are found to be quite important, but only one at a time depending on application. The power limit of the energy storage device is important for high power applications, such as frequency regulation, while the energy capacity is found to be limiting for energy intensive applications like peak shaving. In the technologies that are modeled as configurable, with power electronics and storage quantities independently selectable, the relative importance of power and energy limits shows up in the sensitivities for energy-related and power-related capital costs. While the value of increasing the energy capacity and power limit depends on the technology and application studied, improvements in these areas can be valuable if chosen appropriately.

While we can state which properties most strongly drive cost-of-service, there are other considerations that may determine how research efforts should be allocated due to uncertain and presumably unequal development costs for improving different properties. It may be the case, for example, that marginal improvements in a relatively insensitive property are far cheaper to implement and thus would be preferable. On the other hand, if it is determined that small improvements in sensitive properties (such as capital cost) are easiest to attain, this would provide a strong incentive to pursue those improvements.

While we do not attempt to calculate the costs of improving different storage properties, we do provide results that can aid entities making decisions about the development of energy storage technologies in the near-term. This includes manufacturers of energy storage devices, agencies that must make decisions about funding energy storage research, and entities that define technology targets for energy storage. Although government funding is traditionally focused on relatively basic science, there has been a recent trend towards funding research with the specific goal of improving near-term marketability of energy products, such as the Office of Electricity Delivery & Energy Reliability at the US Department of Energy, who recently initiated an Energy Storage Program that will "ensure that the technologies live up to their potential, and will assist in bringing these solutions into the commercial market" (US DOE, Office of Electricity Delivery & Energy Reliability, 2011). These results are focused on firm-level profitability of energy storage; government entities that want to encourage the commercialization of energy storage should consider funding the development of manufacturing and process improvements (with the goal of lowering capital cost) in addition to funding performance improvements.

3.6 Conclusion

We demonstrate that the energy storage properties that are most limiting to profitability for different fast-ramping storage technology/application combinations are capital cost and power/energy limits. Capital cost of storage is found to be consistently important for the examined applications, while the sensitivity to power/energy limits depends on the technology and application. Though there are some strong trends, we show that each combination of technology and application is different, allowing for few universal statements. While significant research funding has been put towards improving the performance of energy storage, decreasing the capital cost through manufacturing process improvements may be far more valuable in the near-term. These results suggest that entities seeking to improve energy storage technologies should carefully consider how this would affect the adoption of the technology, since different improvements have greatly different effects on the profitability of energy storage. Decision makers responsible for determining the future of energy storage can use these results to make more informed decisions regarding research funding and technology targets and improve the value proposition of energy storage for grid applications.

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3.8 Appendix

3.8.1 Modeling of storage technologies

Energy storage is modeled slightly differently for each technology, as appropriate to the way that the technology is operated and marketed commercially. For NaS batteries and flywheels, the systems come in modules with fixed power limitation and energy capacity. Thus, for these technologies, the amount of storage needed is the maximum of the amount required to provide the capacity needs and the amount required to provide the power needs, as only one of these constraints will be binding for a particular application model run. Li-ion batteries and supercapacitors are not offered exclusively in particular configurations, and the power and energy capacity requirements are considered separately for these technologies. Capacity fade of storage over time is not included in the model.

The round-trip efficiency (RTE) for the energy storage devices is defined as the ratio of AC energy in to AC energy out and applies to all storage technologies. NaS batteries and flywheels both require a fixed maintenance power which is unrelated to the round-trip efficiency of energy through the storage. The maintenance power requirement is a constant power required to keep the batteries hot (NaS batteries) or to overcome the friction losses (flywheels). In all applications, the storage is required to conclude the studied period with a charge state equal to or greater than the initial state. All energy required for charging/maintenance is required to come from the remainder of the system (for wind integration applications) or through the purchase of balancing energy (for frequency regulation and peak shaving).

The power out of the energy storage device comes at an efficiency penalty (Equation 3.4), and round trip efficiency of the energy storage device is divided geometrically between the charge and discharge portions of the cycle (Equation 3.5). $E_{batt}(t)$ is the charge state of the storage at time t, $E_{batt,out}$

is the energy discharged from the energy storage device, η_{batt} is the round-trip efficiency of the energy storage device, and $E_{batt,in}$ is the charge energy put into the energy storage device.

$$E_{batt}(t) = P_{batt,out}(t) * T_{step} * \sqrt{\eta_{batt}} - P_{batt,in}(t) * T_{step} / \sqrt{\eta_{batt}} \quad (3.4)$$

$$E_{batt}(t) = E_{batt}(t-1) - E_{batt,out}(t) * \sqrt{\eta_{batt}} + E_{batt,in}(t) / \sqrt{\eta_{batt}} \quad (3.5)$$

3.8.2 Modeling of applications

3.8.2.1 Frequency Regulation

For this application, the average cost of delivering 1 MW of frequency regulation service from an energy storage device is calculated. 5 days of 2-second frequency regulation signal were used. For frequency regulation, the amount of power output from the grid asset can vary between zero and the bid power of the asset. For example, if an asset bids 10 MW of frequency regulation, the dispatch signal will vary between 0 MW and 10 MW, with an average dispatched power of ~ 5 MW. As is normal for a frequency regulation signal, this signal requires the grid asset to rapidly change the power output within the agreed range.

Because energy storage is a net consumer of energy (due to inefficiency), we assume that some arrangement is made to allow the average frequency regulation power requirement to be slightly negative. This could be either through arrangement with the grid operator or through the purchase of balancing energy (at $50/MWh) to displace the net discharge required by the storage. The average required power and the total losses from storage inefficiency are calculated in advance and used to determine the zero point of the frequency regulation signal. By this strategy, the storage is able to choose the ratio of up and down regulation so that the average power requirement is slightly negative (on average, energy is going into the energy storage device) and offsets the losses of the storage.

3.8.2.2 Peak Shaving

The peak shaving model calculates the average cost of delivering a peak shaving service. It uses one year of 5-minute load data from BPA (which is scaled down to 100 MW) and determines the average cost of storage required to reduce the peak power requirement by 5% (a maximum of 95 MW). Because the annual peak is more than 5% higher than the daily peak on most days, using storage to reduce the power requirement to 95 MW would result in it only being used a few days each year. We assume that the operator of a capital-intensive energy storage system would also use it to shave the peak demand on other days to reduce generator startup costs or help reduce the day/night energy cost differential. Conceptually, this application is meant to simulate the operation of a storage system deployed in an area of growing demand in order to defer the need for new capital investment (such as a new, larger transmission line). While the storage is used every day in this application, the annual peak demand determines the scale of the storage.

The storage is sized so that it can reduce the annual peak demand by 5%, bringing the 100 MW maximum demand down to a 95 MW maximum demand. The storage is recharged at night at a constant rate between the hours of 11PM and 4AM. Because the transfer of energy from night to peak hours is the service provided by this application, the value of this transfer is not calculated, though the system is required to pay $40 / MWh for all net energy consumed in the process (through losses and inefficiency). On days other than the peak demand day, the storage is also used to capacity to reduce the daily peak to a flattened plateau and is charged at night.

3.8.2.3 Wind smoothing in a generation block producing baseload power

The modeled system consists of a co-located gas turbine, wind farm, and energy storage which is constrained to produce baseload power within a 0.5% deadband. The gas turbine has a maximum power output of 100 MW and the wind farm has a capacity of 67 MW. The storage is scaled to the minimum size required to meet the baseload power requirement. To identify the system that can produce power at lowest cost, a scenario analysis framework is used. The objective of the scenario analysis is to identify the system with the lowest average cost of power, given a particular fraction of delivered energy from wind. The lowest-cost system is always taken as the studied system. Parameters for this system are shown in Table 3.9. The wind smoothing application is based on previously published work, which can be consulted for further details (Hittinger, Whitacre, & Apt, 2010).

Table 3.9: Parameters for wind smoothing in a generation block producing baseload power and wind smoothing in a generation block producing load-following power.

Operational Inputs	Base-Case Value
Natural Gas (NG) Low Operating Limit	40% of nameplate capacity
NG Start-up Time	10 min
NG Ramp Rate Limit	25%/min
NG Minimum Run Time	60 min
NG Lifetime	30 years
Wind Lifetime	20 years

Cost Inputs	Base-Case Value
Blended Cost of Capital	8%
NG Capital Cost	\$620 / kW
NG Price	\$5/MMBTU
NG Variable Cost	\$0.0014 / MWh
NG Fixed Operating Cost	\$10 / kW-year
Wind Capital Cost	\$1500 / kW
Wind Variable Cost	\$0.015 / kWh
CO_2 Price	\$25 / tonne
NO_x Price	\$750 / tonne

The first cycle of the scenario analysis consists of 10 runs of the operational and cost models. The scenario analysis varies the target power output from 10% of total system generation capacity (gas capacity plus wind capacity) to 100% of total system generation capacity in 10% increments (10 levels). The scenario analysis collects data on each run of the model including average cost of power, energy from wind, energy from gas, CO_2 and NOx emissions, and magnitude of required energy storage.

In the second cycle of the scenario analysis, the target power output that resulted in the lowest average cost of electricity is identified. This "areas of interest" is investigated in finer detail in the second cycle by re-running the model as the system power output is varied +/- 10% around the lowest average cost point in 2% increments (10 levels). This results in another 10 runs of the operational and cost models. The relevant data are again extracted from each run and saved for later analysis. The minimum cost point, representing the system with the lowest average cost of power, is always very close to 100 MW, equal to the firm power provided by the gas turbine. While it is possible to have a relatively flat power output higher than the firm power, the cost of the storage then required to ensure power constrained within the deadband (+/- 0.5%) is so high that it drives the average price of electricity up. Or, to state it an alternate way, the lost value of the curtailed wind energy is less than the cost of the storage required to deliver it within the deadband.

For each system examined, the gas generator is modeled to operate such that it provides maximum fill-in power for the varying wind resource in an effort to bring the combined wind+gas power output to the target power output. If the gas turbine is unable to provide all of the required fill-in power due to insufficient ramping capability or cold-start limitations, the residual power is provided by an energy storage device. This residual power includes both positive and negative power requirements from the energy storage, which represent both the discharge energy from the device as well as the required charge energy. Actual 10-second time resolution wind data is used to model the wind generation (Southern Great Plains United States wind farm, sum of 7 turbines, 15 days, 10 second resolution, 46% capacity factor during this period). When necessary, the model allows for curtailment of wind energy (if the storage is fully charged but the combined wind+gas output is higher than the target) by assuming a communications link between the system control and the wind farm control station.

The model assumes a single gas turbine, which operates to provide fill-in power for the wind generation within its operational limitations and within the defined deadband. The gas turbine limitations are a high operating limit, a low operating limit, a ramp rate limit, a minimum run time, and a start-up time. The turbine is forbidden to operate above the high operating limit or below the low operating limit. The ramp rate limitation is applied by converting the ramp rate constant (in percent per minute) to a maximum power change per step, and restricting the power output change per step to that value. The minimum run time defines the minimum amount of time that the gas turbine must operate before it can shut down. If the gas turbine has been running for the required period and gets a signal to provide a power output of zero, then it immediately shuts down and ceases to deliver any power. Thus, as the power required from the gas turbine decreases, the gas turbine ramps down to the low operating limit then holds at that point until it is prompted to turn off completely. If the gas turbine is off and gets a signal to deliver any amount of power, then it begins the start-up process. This process is modeled as delivering no power for the duration of the start-up time and then immediately jumping to the low operating limit. The start-up process is not cancelled if the gas turbine ceases to receive a signal to produce power. The start-up and shut down processes are the only exceptions to the ramp rate limitation.

Once the gas turbine has provided all of the smoothing allowable by its operational constraints, the minimum size of the required energy storage device can be directly determined. Given the wind+gas generation, the residual power that must be handled by an energy storage device is calculated, including both charge and discharge energy. From this residual power profile, the power and energy capacity capabilities required from the energy storage can be calculated. When sizing the energy storage, the power requirement is equal to the maximum power required to/from the energy storage during the operational period. The energy capacity requirement is derived from the maximum energy span (difference between highest and lowest energy state) required from the energy storage. This is equivalent to assuming a storage device with infinite capacity, then observing the maximum energy span (which is also the minimum possible storage capacity) and using that value for the required storage capacity. The power requirement of the energy storage is used as determined directly from the model, but the energy capacity requirement is doubled from what the model determines as the minimum possible energy capacity. This reflects the understanding that the 15 days of wind data used might not present the worst case energy cycle to the storage device, as well as a conservative design stance towards this relatively unproven technology.

The model requires that the energy storage charge state at the end of the studied period be equal to or greater than its initial state. To do this, the model determines whether the defined residual power, given the round-trip efficiency of the energy storage, is sufficient to achieve a concluding charge state greater than the initial charge state. If the concluding state is determined to be lower, than the gas generation is adjusted to provide more charge energy.

If it is required that the gas turbine produce more power, this is done in a non-forward looking way that attempts to maximize the efficient use of the turbine. As long as more charge energy is required, the model first increases any local minima in the gas turbine power output. If there are no local minima, then it increases the lowest global point. If the gas turbine is at maximum power output at all points when it is operational, then the model extends the periods of operation. The energy output of the gas turbine is increased in this manner until there is sufficient energy through the energy storage device to meet the described constraints. If the gas turbine is operational at all points in time and is at the high operating limit the entire time, then the system is declared "insufficient", model execution is ceased, and no data is returned to the scenario analysis for that system.

In order to keep the study simple and general, the model is constrained to produce power with a small "deadband", allowing for the system output power to vary within 0.5% of the target power output. This is intended as a realistic simulation of the small allowable variation in real power systems (if the allowable deadband is set to zero, then the system is constrained to produce perfectly "flat" power).

The objective function of a single run of the model is to meet the target power output (within the deadband) while minimizing the Power (P_{batt}) and Energy (E_{batt}) requirements of the energy storage device (Equations 3.6 and 3.7), in order to prevent over-sizing of this expensive resource.

$$\textit{Minimize}\ \mathrm{E_{batt}} = \mathrm{E_{batt,max}} - \mathrm{E_{batt,min}} \tag{3.6}$$

and

$$\textit{Minimize}\ \mathrm{P_{batt,max}} \tag{3.7}$$

such that, at all points in time (t), the sum of wind, gas, and storage power minus curtailment and storage maintenance energy is within the deadband around the target power level (Equation 3.8). The gas generator has a ramp rate limitation (Equation 3.9), high and low operating limits (Equations 3.10 and 3.11), and a minimum run time (Equation 3.12).

$$\mathrm{P_{target}} \pm \mathrm{P_{db}} = \mathrm{P_{wind}(t)} + \mathrm{P_{gas}(t)} + \mathrm{P_{batt}(t)} - \mathrm{P_{maint}(t)} - \mathrm{P_{curt}(t)} \tag{3.8}$$

$$\left|\mathrm{P_{gas}(t)} - \mathrm{P_{gas}(t-1)}\right| \leq \dot{P}_{\mathrm{gas,max}} * \mathrm{T_{step}} \tag{3.9}$$

$$\mathrm{P_{gas}(t)} \leq \mathrm{P_{gas,max}} \tag{3.10}$$

$$P_{gas}(t) \geq P_{gas,max} * C_{lol} \tag{3.11}$$

$$P_{gas}(t) > 0 \quad \text{if } \exists x \text{ s.t. } \quad t - T_{mr} < x < t-1,\ P_{gas}(x) = 0 \tag{3.12}$$

where P_{target} is the target power output, P_{db} is the deadband power, P_{wind} , P_{gas} , P_{batt} and are the power outputs of wind, gas, and energy storage, P_{maint} is the maintenance power for the energy storage device, P_{curt} is the curtailed power, T_{step} is the step time (10 sec in this study), $P_{gas,max}$ is the maximum power output of the gas turbine, C_{lol} is the low operating limit constant, and T_{mr} is the minimum run time of the gas turbine.

Once the operation of the wind generation, natural gas turbine, and energy storage device has been determined, the emissions and costs of the system over the studied timeframe can be calculated. The emissions calculation uses results from Katzenstein and Apt showing the effect of partial load conditions on efficiency and CO_2 and NO_x emissions of a Siemens-Westinghouse 501FD gas turbine (Katzenstein & Apt, 2009). Capital, variable, and average costs of electricity are also calculated for each potential composite system, including amortized capital costs, other fixed costs, and variable costs of the wind generation, the gas turbine, and the energy storage device. NO_x and CO_2 prices are included in the cost calculation. Emissions allowance prices are applied directly to the emissions, and do not account for seasonal or regional variation, and thus present an upper bound on the cost of emissions.

3.8.2.4 Wind smoothing in a generation block producing load-following power

The modeling for the load-following application is identical to the above application except that the system is constrained to meet a load-following profile (within a 0.5% deadband) instead of a flat, baseload profile. Except what is described below, all modeling, parameters, and constraints are the same as the wind smoothing in a generation block producing baseload power application.

The load data used is 5-minute data from BPA, which was smoothed to 10-second increments by linearly interpolating the 5-minute data. The wind and load data are from different geographical areas, but were chronologically aligned so that daily cycles would be properly addressed. A scenario analysis structure is again used, scaling the load data to determine the least expensive way to operate the system under the load-following constraint. The scenario analysis varies maximum power of the load data from 10% of total system generation capacity (gas capacity plus wind capacity) to 100% of total system generation capacity in 10% increments (10 levels) and calculates the average cost of power at each point. As in the system above, the area around the lowest cost point is investigated in finer detail in the second cycle by re-running the model with the load data scaled +/- 10% around the lowest average cost point in 2% increments (10 levels).

3.8.3 Sensitivity Analysis

For each storage technology in each application, sensitivity analysis is performed on all of the storage parameters (both operational and cost) by varying each property +/- 25% (while keeping all other parameters constant) and re-calculating the sensitivity to all parameters. This results in a total of 1200 data points, across the four technologies and the four applications.

The sensitivity analysis results for NaS batteries are shown in Figure 3.7. The most modified result is a single point for module energy capacity in the load-following wind integration application. This point is for the sensitivity analysis case of efficiency at the unrealistically high value of 100%. In this case, due to the modular nature of the NaS batteries, the system is close to requiring one less module. A slight improvement in module energy capacity allows this to happen, resulting in capital savings and a higher sensitivity for module energy capacity. Some of the other divergent points also represent cases where a module is added or removed, but none have as large an effect as the case described above.

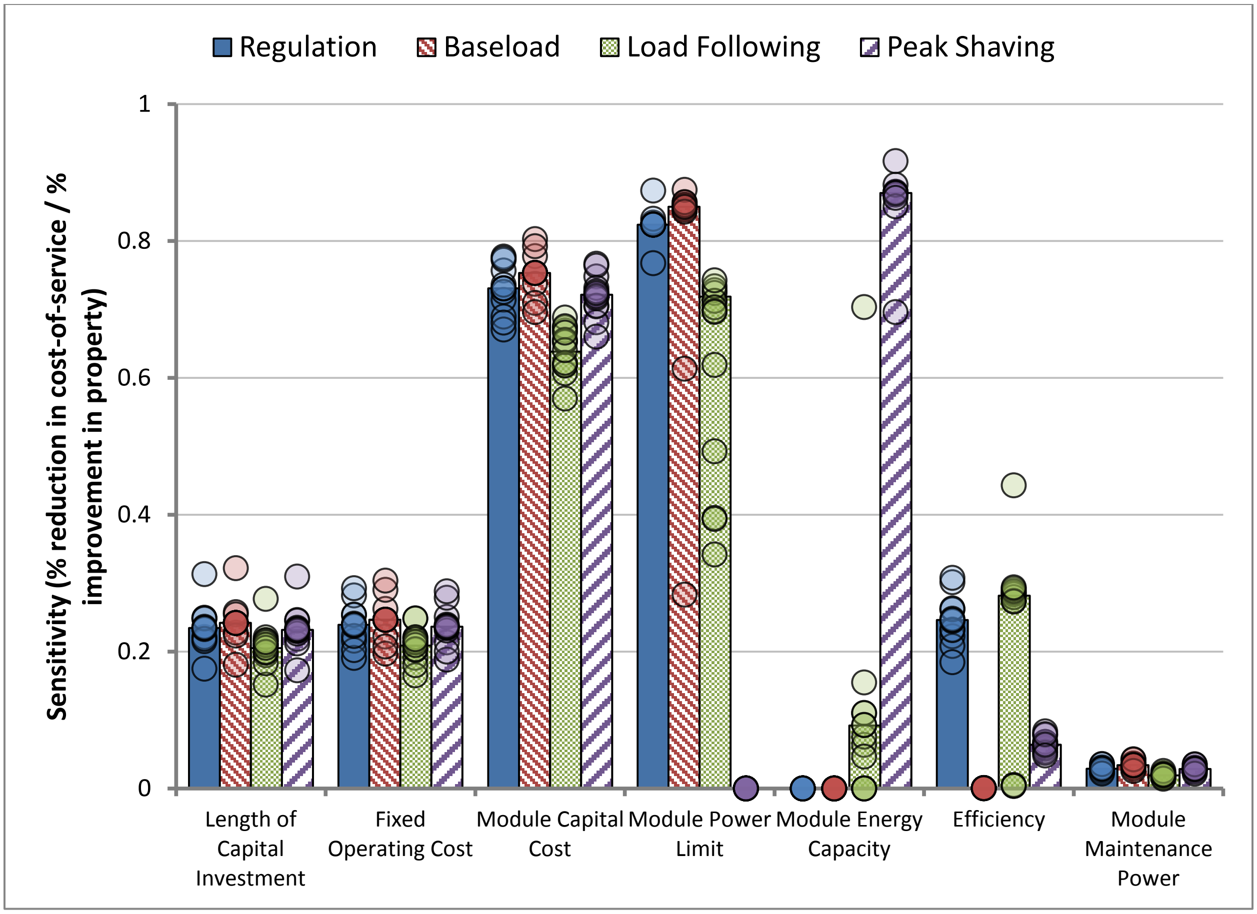

Figure 3.7: Sensitivity analysis results for NaS batteries. The bars show the base-case results, and display the same data as Figure 3.3. Each circle represents the result from one run of the sensitivity analysis. The circles are slightly transparent to allow stacked points to be discerned.

The sensitivity analysis results for Li-ion batteries (Figure 3.8), flywheels (Figure 3.9), and supercapacitors (Figure 3.10) produce similar results as those seen for NaS batteries. The sensitivity analysis results for flywheels show significant variability for several of the applications, which is due to two factors. As described in the results section, the base-case scenario for the load-following application was close to requiring one less flywheel module, which allows small improvements in the efficiency and friction loss parameters to have disproportionate effects on cost. The sensitivity analysis shows that in cases where the system is not close to such a boundary efficiency and friction losses are found to be much less important. Due to the quantity of sensitivity analysis runs, some of them will inevitably fall at a point where a slight improvement in performance will require one less module, affecting results for both NaS batteries and flywheels. In order to neutralize this discontinuous effect and determine more accurate values, the sensitivities for efficiency and friction losses were measured over large changes in their values, which averages out the discontinuities. By varying efficiency from 60% to 90% in the load-following application, the normalized sensitivity is found to be around 0.3, while the normalized sensitivity for friction losses is found to be around 0.16 when varied between 1% and 3%. As expected, these values are around the average of the values found in sensitivity analysis, and lower than the unexpectedly high base-case values (Figure 3.9).

The second effect that is causing variability in the sensitivity analysis results for flywheels providing frequency regulation is the fact that flywheels have an appropriate power/energy ratio for this application. While module power was found to be the limiting factor in this study, a 25% increase in module power or a 25% decrease in module energy capacity caused the sensitivity towards module power limit to drop to zero and sensitivity to energy capacity to rise significantly. These results suggest that the flywheels studied are relatively well optimized for proving frequency regulation, which is currently a common application for the technology (Bradbury, 2011).

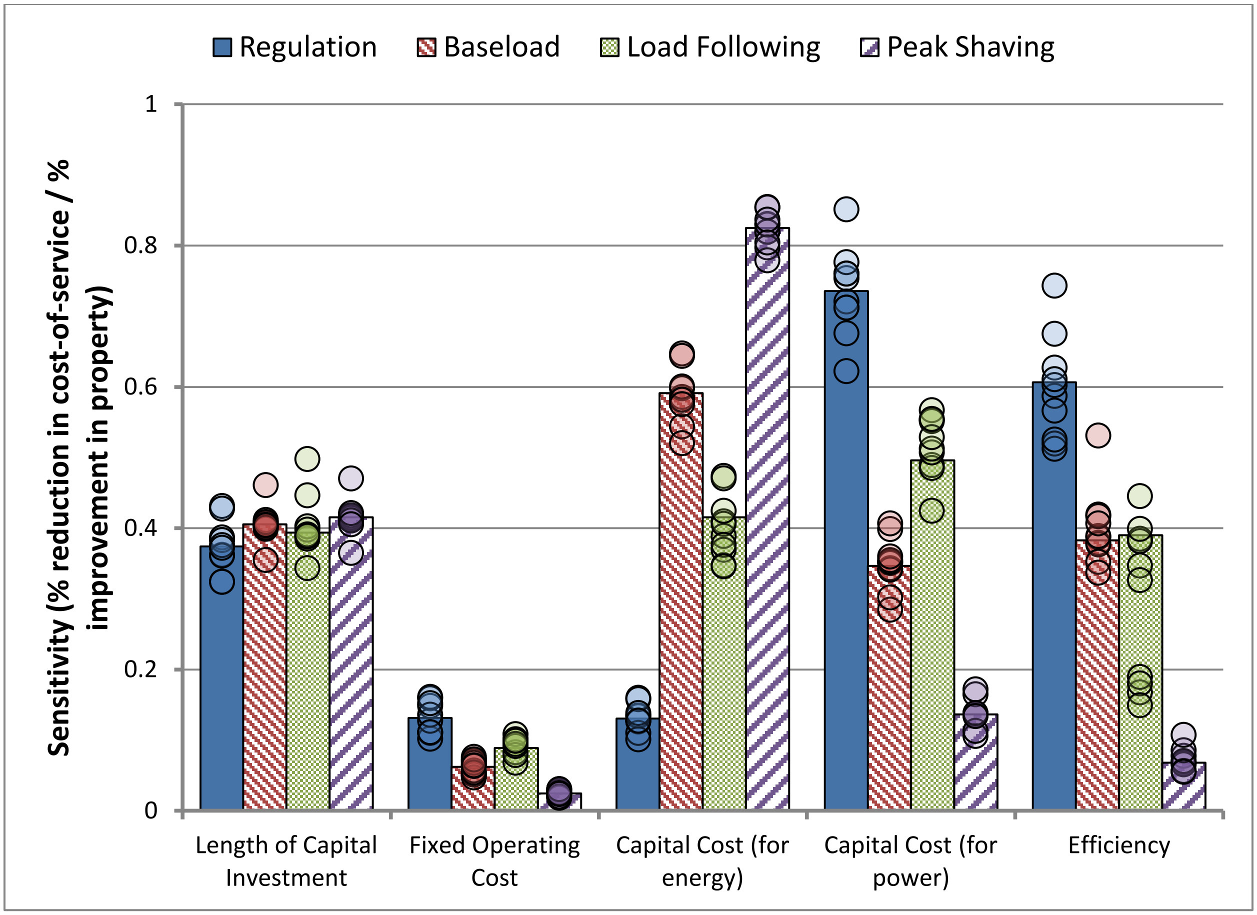

Figure 3.8: Sensitivity analysis results for Li-ion batteries. The bars show the base-case results, and display the same data as Figure 3.4. Each circle represents the result from one run of the sensitivity analysis. The circles are slightly transparent to allow stacked points to be discerned.

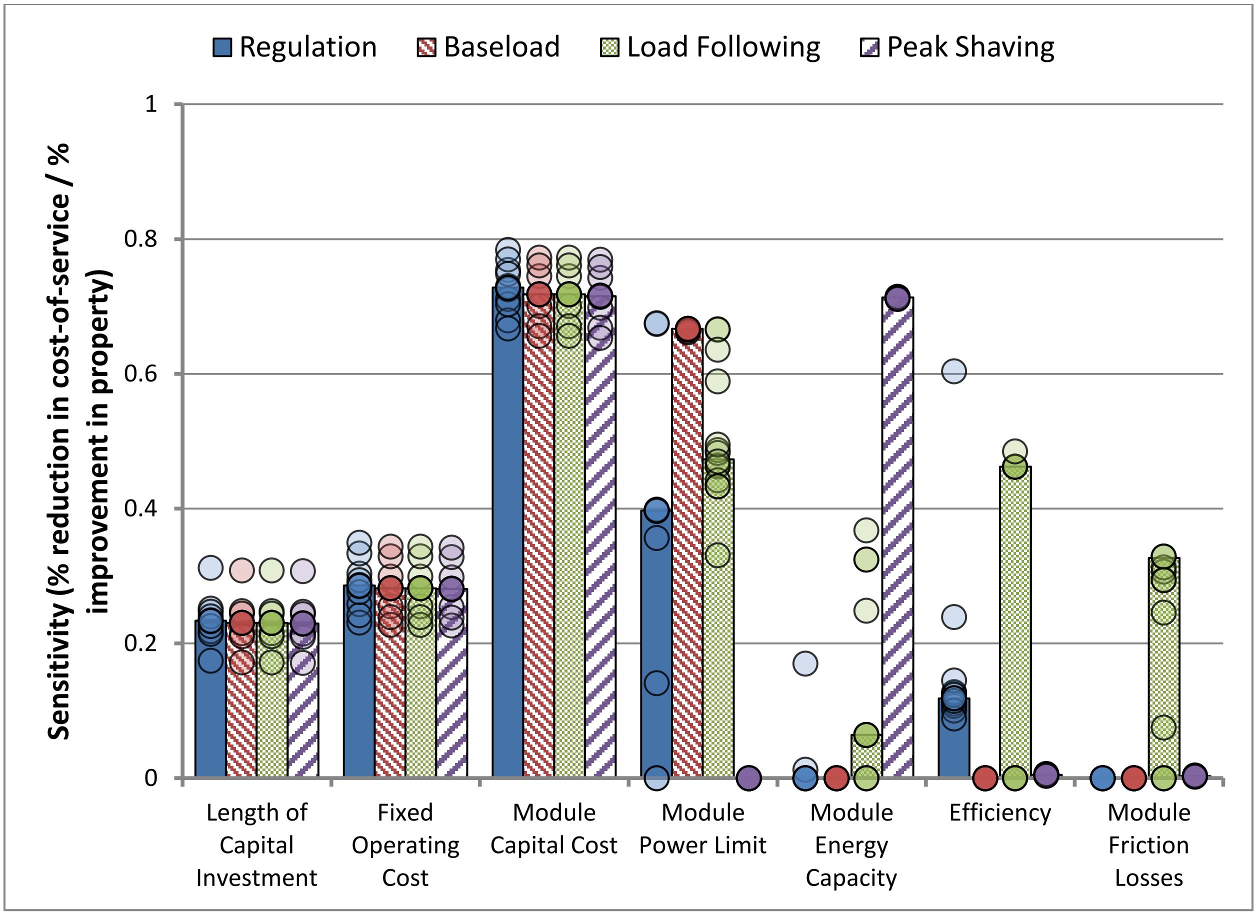

Figure 3.9: Sensitivity analysis results for flywheels. The bars show the base-case results, and display the same data as Figure 3.5. Each circle represents the result from one run of the sensitivity analysis. The circles are slightly transparent to allow stacked points to be discerned.

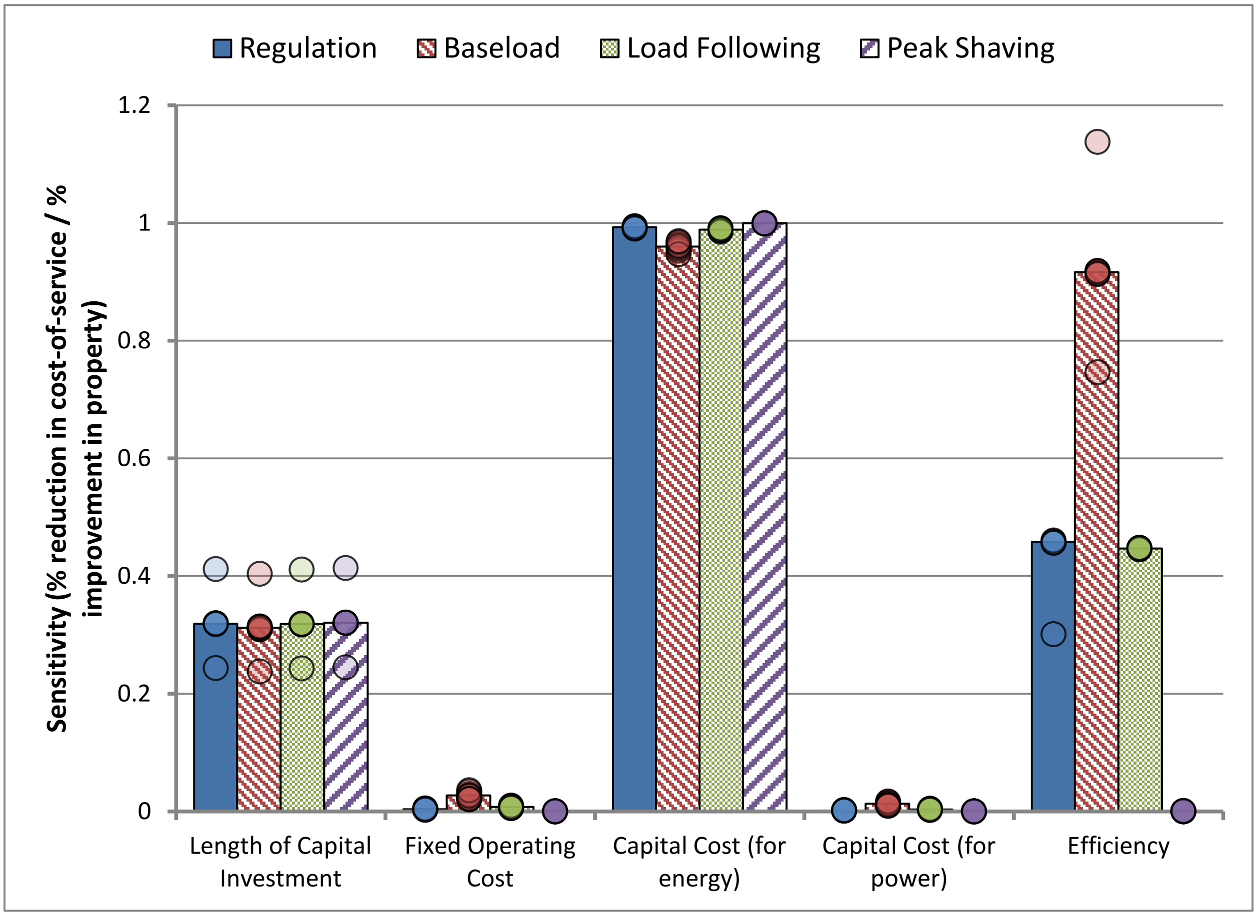

Figure 3.10: Sensitivity analysis results for supercapacitors. The bars show the base-case results, and display the same data as Figure 3.6. Each circle represents the result from one run of the sensitivity analysis. The circles are slightly transparent to allow stacked points to be discerned.

Chapter 4: The effect of variability-mitigating market rules on the operation and deployment of wind farms

4.1 Abstract

In some systems with a large amount of wind power, the costs of wind integration have become significant and market rules have been slowly changing in order to internalize or control the variability of wind generation. Various wind-related rules have been proposed and implemented, but the effects that different market rules might have are not clear. We examine several potential market strategies for mitigating the effects of wind variability and estimate the effect that each strategy would have on the operation and profitability of wind farms. We find that market scenarios that use existing price signals to motivate wind to reduce variability allow wind generators to participate in variability reduction when the market conditions are favorable, and can reduce short-term (30-minute) fluctuations while having little effect on wind farm revenue. For example, in scenarios where the ramp-rate of wind is limited, a lenient ramp rate allowance (up to 40% per 15-minutes) can reduce 30-minute fluctuations by around 35% while reducing wind farm revenue by 0.2%. The results can help system operators to evaluate different market strategies, enabling them to chose a set of rules that can achieve their variability-related goals with the minimum effect on wind farm revenue.

4.2 Background

The variability of wind power must be balanced by other system resources in order to be integrated into an electric grid. "Wind integration" describes methods of dealing with the variability of wind across the frequency spectrum, from increased need for frequency regulation to additional reserve requirements. In most electrical grids, the costs of wind integration are paid by entities other than the wind generators, normally being spread out amongst load-serving entities or traditional generators, making the variability of wind a negative externality handled by the remainder of the grid. Currently, this is not an important issue; most grids have a low penetration of wind, making the system cost of wind integration low in absolute terms. But wind integration costs (per MWh) are predicted to rise quickly with wind penetration (Wiser & Bolinger, 2010), and the expected increases in wind generation in the coming decades will greatly increase wind integration costs to billions of dollars per year in the US (US DOE, 2008). At these costs, it makes sense to seek strategies that reduce the system-wide costs of wind integration and to do so immediately so that informed policies can be put in place before massive amounts of new wind generation are put online.

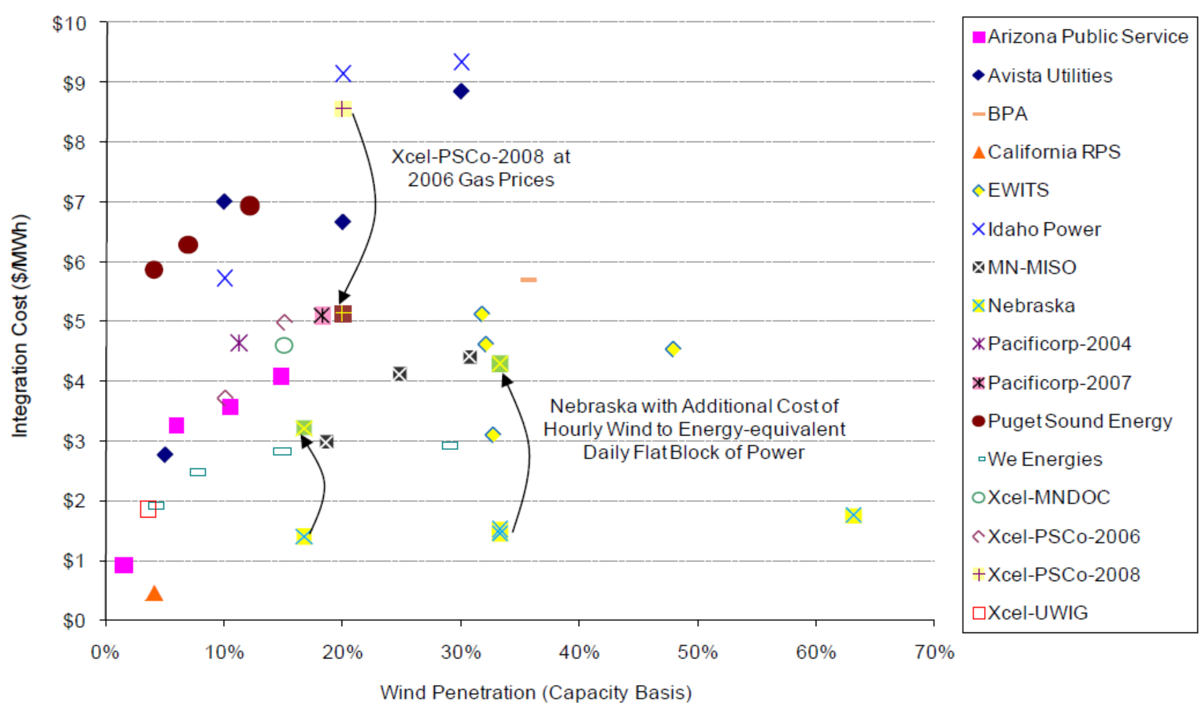

Figure 4.1: Estimated wind integration costs from various studies as a function of wind penetration. (Figure from US DOE, *2009 Wind Technologies Market Report*)

There is no doubt that wind power, with its variable output, can be successfully integrated into the electricity grid, but there is uncertainty regarding the costs, methods, and scale of that integration. Given the size of the electricity industry, small percentage reductions in wind integration costs can have very large effects and are worth investigating. In 2010, wind accounted for 2.9% (120,000 GWh) of US electricity generation (US Energy Information Administration, 2012). At a wind integration cost of $3/MWh (Figure 4.1), accommodating this amount of wind energy costs roughly $360M per year. If we were to meet the goal of attaining 20% of US electricity from wind, as proposed and described in the US Department of Energy (DOE) study "20% Wind Energy by 2030" (US DOE, 2008), the wind integration costs alone could be $7B annually, or about 2% of the current revenue of the entire US electricity industry (US Energy Information Administration , 2011).

The Federal Energy Regulatory Commission (FERC) has proposed changes to the rules governing the interaction between intermittent generation and electricity markets in order "...to address issues confronting public utility transmission providers and [variable energy resources] and to allow for the more efficient utilization of transmission and generation resources to the benefit of all customers." (Federal Energy Regulatory Commission, 2010). Already, electrical systems that utilize a relatively large fraction of wind energy are implementing new rules to address the effect that wind variability has on the grid. The Bonneville Power Administration (BPA), which operates the electricity grid in the Pacific Northwest, had almost 4 GW of wind capacity by the end of 2011, which is 40% of the 9.8 GW peak load and 60% of the 6.3 GW average load in 2011 (Bonneville Power Administration, 2012). Wind farms are rapidly being deployed in this area, and BPA predicts that the total installed capacity will reach 12 GW by 2016 (Bonneville Power Administration, 2010). With the goal of equitably assigning system operating costs, BPA has introduced a “Wind Balancing Service” and, in 2010, charged wind generators a tariff of

$1,090 per MW of wind nameplate capacity per month to supply the required balancing services (Bonneville Power Administration, 2009). This works out to around $5.70/MWh (depending upon capacity factor), though the BPA originally sought a higher rate that would have charged wind generators around $12/MWh, and has been increasing this tariff in each rate adjustment (Bonneville Power Administration, 2009) (Bonneville Power Administration, 2011).

In the Republic of Ireland, 1700 MW of wind generation was operational in 2010 (Irish Wind Energy Association, 2010), and the system's maximum wind output was 1,400 MW in 2011 (EirGrid, 2012). EirGrid, the Irish grid operator, experienced a peak load of 5,000 MW in 2010 and has an average load of 3,100 MW (EirGrid, 2012) (SONI & EirGrid, 2012). During certain low-load/high-wind periods, wind has provided 40% of EirGrid's power (Kanter, 2009). EirGrid requires wind farms to have power control systems that allow them to respond to frequency changes by adjusting their power output (Figure 4.2). EirGrid also requires wind farms to have a nominal power output slightly lower than their potential power output (the area between points B and C on Figure 4.2), producing a small reserve to respond to low frequency events (EirGrid, 2009). Wind generators are required to react to frequency changes at a rate of 1% of nameplate capacity per second. The precise settings for wind farm response depend on system conditions and wind farm location, and may be different for different wind farms.

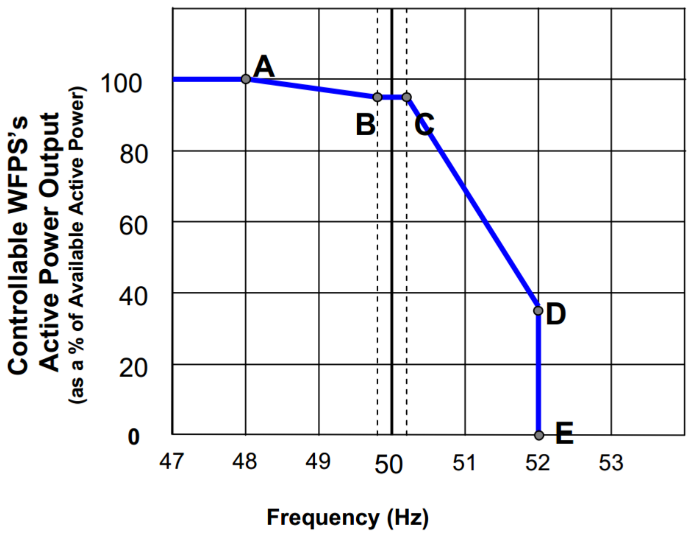

Figure 4.2: Wind Farm Power Station (WFPS) power output as a function of system frequency for the Ireland electric grid (EirGrid). Wind farms in the Republic of Ireland are required to have output control systems that enable them to changes power output as the system frequency changes. The points on the figure (A-E) are representative: EirGrid adjusts these points based on system requirements. (Figure from *EirGrid Grid Code Version 3.3 (Wind Grid Code Only)*)

Some system operators, such as ERCOT (ERCOT, 2010), Nord Pool (Morthorst, 2003), and EirGrid (EirGrid, 2009) are considering enacting or have enacted limitations on the ramp rate of wind power. In addition to the small curtailment to produce a reserve discussed above, EirGrid requires wind generators to control their ramp rates within 1-minute and 10-minute limits whenever reasonable, but allows that "...falling wind speed or Frequency Response may cause either of the maximum ramp rate settings to be exceeded" (EirGrid, 2009). In Texas, 9.8 GW of wind generation has been installed on a grid with a peak load of 68 GW and an average load of 38 GW(ERCOT, 2012). ERCOT, the system operator in Texas, limits wind farms to a ramp rate of 10% of nameplate capacity per minute when responding to or released from a deployment order[1] (ERCOT, 2010). ERCOT also requires wind generators to install and utilize automatic control systems that adjust power output to provide frequency regulation, though there is no requirement for a reserve-producing curtailment, meaning that

[1] In ERCOT, a deployment order is an instruction from ERCOT to a generator to generate at a certain power output over the next market period, similar to a dispatch order.

frequency response is limited to down ramping or periods when wind is curtailed for other reasons (such as curtailment under economic dispatch).

There is an extensive literature surrounding the question of what system operators should do to integrate large quantities of wind power. Many ISOs have commissioned studies investigating how particular markets need to change in order to better accommodate increased future wind (Hawaii Natural Energy Institute, 2011) (NYISO, 2008) (Alberta Electric System Operator, 2006). Other research papers have looked at related topics, like perverse incentives for wind in existing systems (Sioshansi & Hurlbut, 2010), or how changes to market rules could improve the predictability, and thus the value, of wind power (Obersteiner & von Bremen, 2009) (Makarov, Loutan, Ma, & de Mello, 2009). The prior literature has been focused on market design aspects like economic curtailment of wind, bidding rules for wind, bid/dispatch time increments, and forecasting. These are all important considerations for wind integration, but they assume a status quo regarding internalizing wind variability. Additionally, there is little discussion in the prior work of the short-term variability, which represents the area over which wind generators may have the most control.

There has been some work examining the effects of exposing wind generation to market prices, but this has been limited to whether feed-in tariffs should be replaced by a system more like those used in the US, where wind is affected by market prices[2] (Hiroux & Saguan, 2010) (Klessmann, Nabe, & Burges, 2008). In terms of internalizing the cost of wind variability, the most that these studies advocate is to suggest that wind bid into the market so that it can be economically curtailed, which is an increasingly standard practice. Other research has looked at the value of wind curtailment for electricity

[2] Feed-in tariffs, which are popular in Europe, guarantee a renewable electricity generator a fixed payment per MWh delivered. Under such a system, wind generators are motivated, for example, to generate electricity whenever possible, without regard for the prevailing energy prices. Under the US Production Tax Credit, wind generators get a fixed subsidy per MWh but are otherwise subject to market rates. While many wind farms sell electricity under fixed-rate long-term contracts, the negotiation and terms of these contracts are still affected by the prevailing energy costs and the needs of the purchaser, similar to other long-term power contracts.

grids. Ela shows the value of wind curtailment in a simple transmission network (Ela, 2009), and Wu and Kapuscinski find that the value of wind curtailment can be significant from a system perspective (Wu & Kapuscinski, 2011). While a feed-in tariff or "must-run" operation of wind generation maximizes the amount of delivered wind energy from a given set of resources, it is not the most economically efficient way to operate those resources.

The primary motivation for market rules that cause wind to internalize the costs of variability is market fairness or cost causation - if wind generation causes increased system costs, it seems reasonable that wind generators pay those costs. But if this were the only concern, permitting the free variability of wind power could be justified on the grounds that it merely constitutes a further subsidy to wind energy, a technology that is being actively supported for a variety of reasons. Perhaps more important than the concept of fairness, there is the possibility that wind generators are the entity that is able to decrease or compensate for variability at lowest cost under certain circumstances. If this is true, then forcing wind generators to (at least partially) internalize variability-related costs can lower the overall system costs, producing a surplus to be shared among the various parties. In their justification for the Wind Balancing Service, the Bonneville Power Administration states, "BPA's charges to integrate wind are based on cost causation and shift risk to wind generators where the wind generator is in the best position to manage the risk." (Bonneville Power Administration, 2009). When the Bonneville Power Administration instituted the Wind Balancing Service tariff, there was interest from stakeholders in allowing wind farms to self-supply or contract for part or all of the required balancing services (Bonneville Power Administration, 2009). This is now permitted, and wind generators are credited for the self-supplied or contracted ancillary services (Bonneville Power Administration, 2011).

There is a general trend in electricity markets around the world towards altering market rules so that the costs of wind generation are increasingly internalized. In some areas, this means exposing wind generators to market prices or requiring wind to bid into the market so that it can be economically curtailed. In other areas where wind integration costs have become non-trivial, more constraining rules are used, such as ramp-rate limits or curtailment to produce an operating reserve. Previous wind integration research has been focused on how to integrate increasing amounts of wind variability, and neither compares different variability-mitigating market rules nor examines the effect that these market rules might have on wind generators, imagining that wind generation can do little or nothing to manage its own variability. In this paper, we examine several different potential variability-mitigating market rules for wind generation, such as ramp rate limits or penalties for wind output that diverges from forecast, and investigate the effect that the rules have on the operation and profitability of wind farms. Because wind generators will seek to maximize revenue, we examine several possible reactions to each regulation set, such as economic curtailment, curtailment to produce an operating reserve, or installing energy storage. For each potential set of market regulations, we determine the favored wind farm operational strategy, the change in revenue of a wind farm, and the effect that the regulation has on the variability from the wind farm.

4.3 Data and Methods

This work uses time-series modeling of wind farms in ERCOT to determine what effects different wind variability market policies would have on the operational strategies, revenue, and variability of wind farms. This is accomplished by positing several different policy scenarios, each with a different set of wind variability-related market protocols. Under each scenario, wind farms attempt to maximize revenue, and several different potential operational responses, such as economic curtailment or installing energy storage, are examined. The strategy that produces the most revenue, and is thus preferred by the generator, is determined under each market scenario. The power output of the wind farms are determined for each scenario and the variability characteristics are compared across scenarios. Figure 4.3 shows a block diagram of the modeling approach.

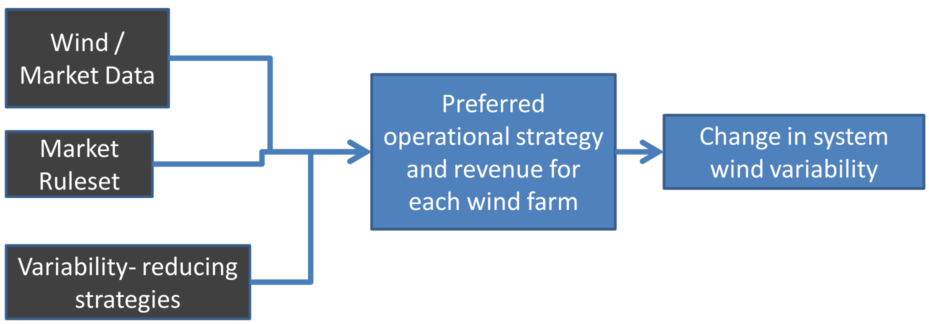

Figure 4.3: Block diagram describing modeling used in this research.

Six different market regulation scenarios are examined and each is investigated independently (Table 4.1). First, the base case where wind is free to sell energy on the balancing energy market without penalty or constraint. Second, the case where a fixed (per MWh) wind integration fee is assigned to wind energy. Third, the case where a BPA-style wind balancing tariff is applied (per MW of installed capacity per month). Fourth, the case where the up-ramping of wind power is limited to a certain percent of nameplate capacity per time step and wind is penalized for over-ramping. Fifth, the case where both up- and down-ramping of wind power is limited to a certain percent of nameplate capacity per time step and wind is penalized for over-ramping. Sixth, the case where wind power output must match a forecast (within a certain percent of nameplate capacity) or pay a penalty.

Table 4.1: Summary of the six market protocol scenarios examined in this research.

Scenario	Description
Base Case	Wind generators sell energy on the balancing energy market without restriction or penalty
Wind Integration Fee (per MWh)	Wind generators pay a fixed fee (per MWh) on all wind energy produced to cover the cost of wind-related ancillary services
Wind Balancing Tariff (per MW - month)	Wind generators pay a fixed tariff (per MW - month) to cover the cost of wind-related ancillary services
Limited up-ramping	Wind generators have a limited up-ramp rate (a percentage of nameplate capacity per time step) and must pay a penalty based on the frequency regulation cost if ramping is above the defined limit.
Limited up- and down-ramping	Wind generators have limited up- and down-ramp rates (a percentage of nameplate capacity per time step) and must pay a penalty based on the frequency regulation cost if ramping is above defined rate in either direction.
Penalty for diverging from wind forecast	Wind generators must match their power output to the 6-hour-ahead wind power forecast for the area, within an allowed deadband. The generator pays a penalty, based on frequency regulation price, for power output outside of the deadband.

In each examined scenario, each wind farm attempts to maximize revenue, given a potential power output from the wind farm, energy and frequency regulation prices, and the wind integration rules for that scenario. Time-series modeling of wind generation is used throughout this research with a time step of 15 minutes. The wind data set consists of actual 15-minute energy production from 16 wind farms in West Texas for the years 2008 and 2009 (ERCOT, 2009). The wind farms vary in scale from 25 MW capacity to 500 MW capacity, with capacity factors ranging from 18% to 41% (average of 31%) in the examined period. Market clearing prices for balancing energy service (BES) and frequency regulation in West Texas for 2008-2009 are used (Figure 4.4). The BES price was cleared at 15-minute increments, and had a mean of $39.5/MWh in 2008-2009. The BES price had a maximum of $2,320/MWh in this period, a minimum of -$1,981/MWh, and was between -$32/MWh and $105/MWh 90% of the time. The frequency regulation market was cleared hourly, and separated into regulation up and regulation down prices. The prices for both regulation services varied between approximately $1 and $500/MW-hour in 2008-2009. The average regulation up price was $16/MW-hour and the average regulation down price was \$13/MW-hour. Regulation up had a higher price during most hours of the day, especially during the daily peak, but regulation down prices were usually higher overnight due to generators' preference to stay on-line and thus prevent start-up costs. Wind forecast data, used for the forecast-matching scenario, is from AWS Truepower and predicts 6 hours ahead in 1 hour intervals (Zack, 2011).

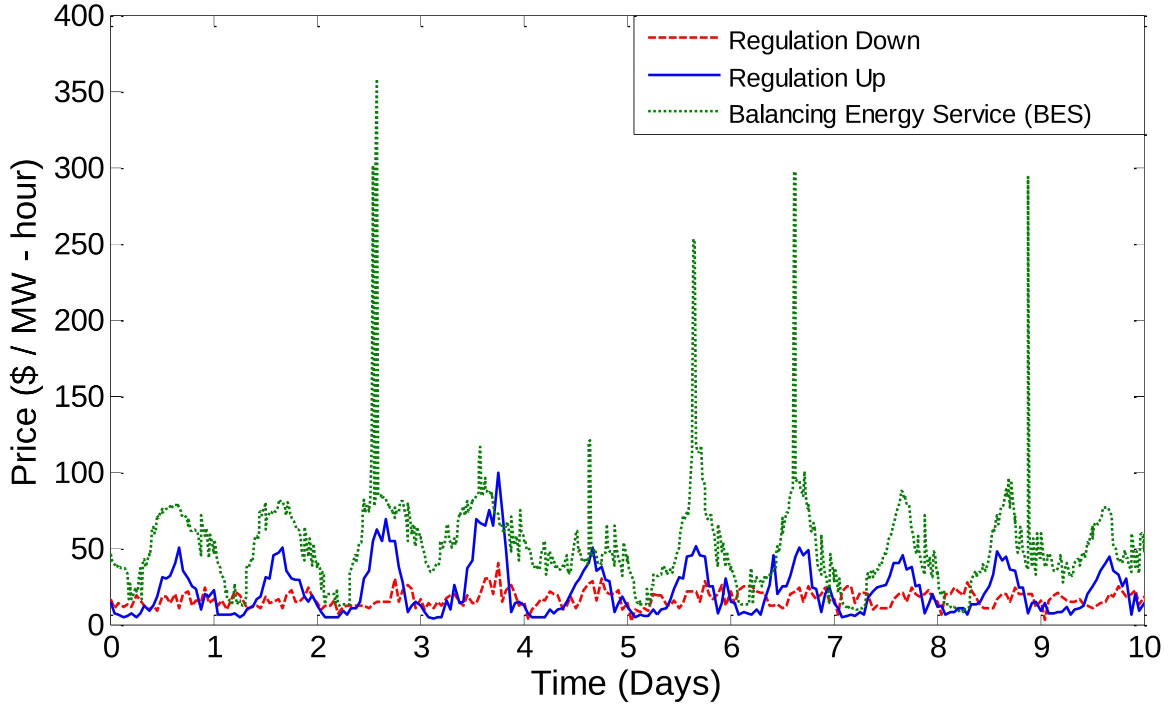

Figure 4.4: Energy and frequency regulation prices in ERCOT's West Texas Zone for 10 days in September 2008, showing an example of the variability in prices.

The responses available to wind generators that are considered are: economic curtailment, curtailment to produce an operating reserve, and use of energy storage. Both curtailment to produce a reserve and the use of energy storage were found to produce less revenue than economic curtailment in all of the examined scenarios. Because of this, the remainder of the main text is focused on wind farms using economic curtailment, while a discussion of the modeling and results related to curtailment to produce a reserve and use of energy storage can be found in Appendix A. The "must run" option is also considered in each case, though this strategy always results in less revenue than economic curtailment, due to the additional constraint that wind farms cannot curtail their output.

Under economic curtailment, a wind generator will reduce power output whenever the energy price plus Renewable Tax Credit ($21/MWh for 2008-2009) plus the Texas Renewable Energy Credit price (between $1.5 and $5 per MWh, varies by month) minus any penalties is below zero (Equation 4.1). Though many wind generators sell their energy at fixed prices through long-term power purchase agreements, there are three justifications for using this approach. First, the results and discussion are centered on the difference in revenue between the base scenario and an alternative scenario of interest, representing the cost of compliance with the policy, which would still be incurred for wind under long-term contracts. Second, under a long-term supply agreement, contract holders can request that wind curtail output, pay the wind farm for energy that would have been produced (including paying for the lost subsidies), and purchase energy from the balancing energy market whenever doing so would be more profitable. This would result in curtailments that are the same as those of a wind farm selling energy on the spot market, even though the payments in other periods would be different. Third, ERCOT market reports state that forward contract prices and spot prices converge over time in ERCOT, suggesting that policy changes that affect the revenue to spot market wind energy would have a similar effect on long-term contracts for wind energy (Potomac Economics, 2011) (Cullen, 2011). Thus, we use BES prices as a proxy for the revenue wind farms receive.

In the scenarios with penalties for over-ramping or diverging from forecast, the penalties are based on the frequency regulation prices. This is done because frequency regulation prices reflect the willingness of generators to change their output levels, which changes over time. For example, if wind ramps up too quickly, other generators must ramp down to compensate. The regulation down price indicates the payments that a generator requires to perform this ramp-down. If generators are very willing to ramp down, then the regulation down price will be low and the wind farm will not be (and should not be) heavily penalized. Alternately, if wind picks up quickly in a period where generators are unwilling to ramp down, the wind generator will face higher penalties. It is important to note that while frequency regulation prices are related to the ability of generators to ramp up and down over 15-minute time steps, this is not how frequency regulation service is actually used. In the absence of an actual wind-following ancillary service, frequency regulation prices are used as a substitute. The energy price is not included in the penalty scheme because any replacement energy is already paid from the market. For example, if a wind farm suddenly drops by 1 MW (over 1 hour) and another generator ramps up 1 MW to compensate, the market will pay the prevailing energy price for the replacement MWh to the generator. Because 15-minute penalty prices are required, the hourly frequency regulation prices are divided by four to generate four 15-min penalty prices for that hour. Penalties for over-ramping are assessed based on the change since the last time step, rather than changes since the last point where the wind farm was in compliance (see Appendix B).

Under economic curtailment, the wind farm chooses a power output between zero and the potential power output at each time step t, attempting to maximize revenue at each step (Equation 4.1). E(t) is the energy produced by the wind farm in period t, $P_{BES}(t)$ is the Balancing Energy Service price during period t, P_{PTC} is the value of the Production Tax Credit ($21/MWh in 2008/2009), P_{REC} is the Renewable Energy Credit price, and D(t) is the penalty payment.

$$\max\left(E(t) * (P_{BES}(t) + P_{PTC} + P_{REC}(t)) - D(t)\right) \tag{4.1}$$

For the scenario where a per MWh wind integration fee is applied, the payments are calculated using Equation 4.2, where W_f is the wind integration fee ($/MWh).

$$D(t) = E(t) * (W_f) \tag{4.2}$$

When a fixed (per MW-month) wind integration tariff is applied, the payments are calculated with Equation 4.3, where C is the capacity of the wind farm (MW) and W_T is the wind integration tariff ($/MW-month). The wind integration tariff is constant and unrelated to the wind energy production at time t.

$$D(t) = C * W_T / 2920 \tag{4.3}$$

When the up-ramp rate of a wind farm is limited, the penalty payments are calculated using Equations 4.4 and 4.5, where $A_{ramp\ rate}$ is the allowed ramp rate (percent of capacity per time step) and $P_{reg\ down}(t)$ is the regulation down price during period t ($/MW-hour), and M is the penalty multiplier.

$$D(t) = 0 \qquad (if\ \ E(t) \leq E(t-1) + C * A_{ramp\ rate}) \tag{4.4}$$

$$D(t) = [E(t) - (E(t-1) + C * A_{ramp\ rate})] * P_{reg\ down}(t) * M \qquad (if\ E(t) > E(t-1) + C * A_{ramp\ rate}) \tag{4.5}$$

For the scenario where the ramp rate is limited for both up- and down- ramping, Equations 4.6-4.8 are used to determine penalty payments.

$$D(t) = 0 \qquad (if\ \ E(t-1) - C * A_{ramp\ rate} \leq E(t) \leq E(t-1) + C * A_{ramp\ rate}) \tag{4.6}$$

$$D(t) = [(E(t-1) - C * A_{ramp\ rate}) - E(t)] * P_{reg\ up}(t) * M \qquad (if\ E(t) < E(t-1) - C * A_{ramp\ rate}) \tag{4.7}$$

$$D(t) = [E(t) - (E(t-1) + C * A_{ramp\ rate})] * P_{reg\ down}(t) * M \qquad (if\ E(t) > E(t-1) + C * A_{ramp\ rate}) \tag{4.8}$$

In the scenario where wind is penalized for diverging from forecast, the penalty payments are determined using Equations 4.9-4.11, where F(t) is the scaled wind energy forecast at time t (MW) and $A_{deadband}$ is the allowed deadband (percent of capacity).

$$D(t) = 0 \qquad (if\ F(t) * (1 - A_{deadband}) \leq E(t) \leq F(t) * (1 + A_{deadband})) \tag{4.9}$$

$$D(t) = [(F(t) * (1 - A_{deadband})) - E(t)] * P_{reg\ up}(t) * M \qquad (if\ E(t) < F(t) * (1 - A_{deadband}) \tag{4.10}$$

$$D(t) = [E(t) - (F(t) * (1 + A_{deadband}))] * P_{reg\ down}(t) * M \quad (if\ E(t) > F(t) * (1 + A_{deadband})) \quad (4.11)$$

All wind generators are assumed to be price-takers and the balancing energy prices are not modified for the different scenarios. Large wind integration policy changes could affect the balancing energy prices, especially in West Texas where the available wind power can influence the spot market price. These effects are complex, and beyond the scope of this work. As discussed in Appendix A, wind generators are allowed to purchase energy storage or intentionally curtail their output to produce an operating reserve, but it is assumed that they do not otherwise self-supply any ancillary services (from a co-located or nearby thermal generator, for example). Self-supplied balancing services would only be used if they were less expensive than the penalty payments, and would result in both better adherence to market rules and decreased revenue reductions for wind farms, making the results shown below an upper bound on the cost of compliance for wind farms under new market regulations.

Power spectral density (PSD) calculations are used to investigate the effect that market policies have on the variability of wind at different frequencies (Apt, 2007). Most of the market scenarios investigated result in reductions in the short-term (high frequency) fluctuations of wind generation (see Figure 4.6), and PSD analysis allows quantitative comparison of those reductions. Because the system operator is most interested in the effect on overall variability rather than the variability of individual wind farms, PSD calculations use the total power output from the sixteen wind farms. The variability at periods of 30 minutes, 120 minutes, and 480 minutes are calculated in order to approximate the power spectrum as three data points for comparison purposes. The spectra are noisy even after 8-segment averaging has been applied (see Figure 4.6), so the average of the nearest 29 data points to the exact frequency (approximately +/- 2% of the target period) is used to calculate the variability at 30, 120, and 480 minutes. Changes in market policy regarding wind generation were generally found to have the largest effect on the 30-minute variability of wind and most of the discussion below is focused on that value. Changes in 120-minute and 480-minute fluctuations are consistently in the same direction but with a smaller magnitude, and are generally limited to a change of 10% or less for most scenarios.

4.4 Results

This section is focused on the response of wind generators to changes in electricity market rules relating to wind output. A system operator would implement new rules with the goals of maintaining system stability, reducing overall system operation costs, and equitably allocating costs to market participants. But wind generators will seek to maximize revenue, and new market rules do not always have the intended results (Sioshansi & Hurlbut, 2010) (Wu & Kapuscinski, 2011). For each of the six market protocol scenarios described in Table 4.1, we determine the profit-maximizing operation for each wind farm and calculate the expected changes in revenue to each wind farm and the 30-minute variability from the collected set of 16 wind farms.

4.4.1 Economic Curtailment (Base Case)

In areas that have significant wind penetration, such as West Texas, market-clearing prices for energy can become negative in periods of high wind and low load. The negative prices occur because traditional generators will pay to avoid cycling and start-up costs and because wind generators receive subsidies per MWh produced and are thus willing to pay up to the subsidy price to produce electricity. When wind farms are operated using an economic curtailment strategy, where they curtail their power output to zero whenever the BES price plus wind subsidies is below zero, their revenue can increase if there are negative prices that are larger than the wind subsidies. In the 2008-2009 period, economic curtailment increases the revenue of the studied wind farms by 2.5%, or $3,500 / MW-year, over the revenue gained when wind farms are operated under a "must-run" strategy. All sixteen wind farms are more profitable under economic curtailment, with revenue increases ranging from 1.8% to 3.5%. Under economic curtailment, the wind farms produced around 13% (9.7% to 16%)[3] less energy. These results are used as the base case for comparison with the other market scenarios for two reasons. First, economic curtailment of wind produces more revenue for wind farms than a "must run" strategy and would be preferable in the absence of additional market rules. Second, because the goal of the other market scenarios is to elicit some operational response from wind generation, the results are only interesting if wind generators are willing to curtail output to increase revenue.

Though economic curtailment consistently increases the revenue to wind farms, it also increases the short-term variability in the wind energy output (Figure 4.5). This additional variability causes a noticeable increase in the power of short-term fluctuations from a wind farm, which is stronger at shorter time scales (Figure 4.6). Both the value of economic curtailment and the increased variability that it produces are a direct result of the negative prices in West Texas in the examined period. In areas that do not experience frequent negative prices, both effects would be diminished, though negative prices may be somewhat unavoidable in areas with high wind penetration and wind energy production subsidies.

[3] In the text, the average value for the sixteen wind farms will be provided, with the range of results in parentheses.

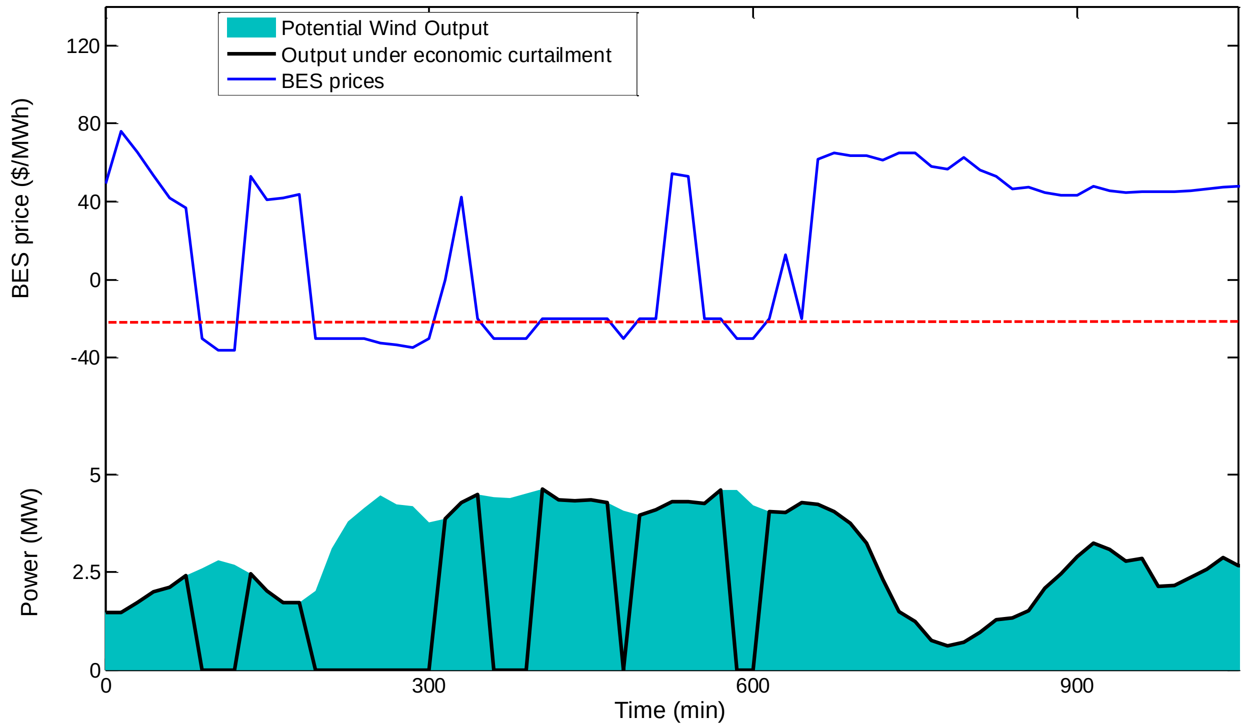

Figure 4.5: Example output of a wind farm under a must-run strategy (green area) and under economic curtailment (black line) and BES prices (upper line) over a 17 hour period that has frequent negative prices. The dashed red line indicates the breakeven price for wind energy, which is around -$24/MWh. Under economic curtailment, the wind farm stops producing energy during periods when that energy is unprofitable. While this strategy can increase the revenue to a wind farm and relieve transmission congestion, it also produces increased short-term wind fluctuations.

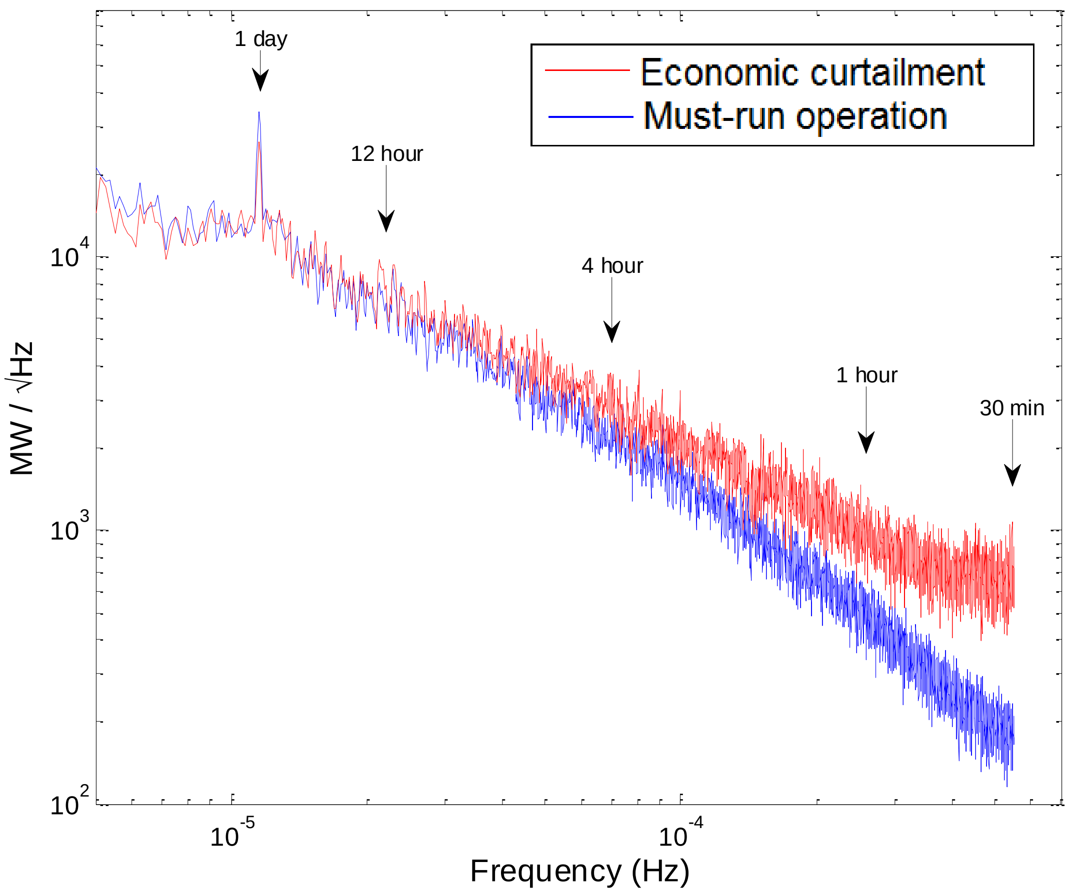

Figure 4.6: Power spectra of wind energy from one of the examined wind farms, under must-run (lower curve) and economic curtailment (upper curve) strategies. Increased variability under economic curtailment causes the power in higher frequencies to increase substantially: 350% at 30 minutes, 200% at 1 hour, and 35% at 4 hours.

4.4.2 Wind Balancing Tariff

A wind balancing tariff, which charges wind generators a fixed fee per installed capacity, should have no effect on the operation of existing wind generation. The wind balancing tariff takes a fixed ($/MW-month) fee from wind generators regardless of their output or operation, and a profit-maximizing generator will use the same operational strategy that they would without the tariff. Thus, there would be no effect on the variability produced by the wind farms. Under a tariff of $680/MW-month, the rate set by BPA for 2008, average wind farm revenue drops from $150,000 / MW-year ($97,000 to $204,000/MW-year) to $142,000/MW-year ($88,000 to $196,000/MW-year), a decrease of 5.6% (4.0% to 8.5%). The tariff rate has a linear effect on revenue to the wind farms, and a tariff at the 2010 rate of $1,090/MW-month will reduce revenue by an average of 9% (6.4% to 13.6%). For a wind farm that operates as must-run, the effects are similar. A tariff of $680/MW-month will reduce revenue by 5.8% (4.1% to 8.6%), and a tariff of $1,090/MW-month reduces revenue by 9.3% (6.6% to 13.8%).

4.4.3 Wind Integration Fee

A wind integration fee (in $/MWh produced) will have some effect on the operation of a wind farm. From the perspective of a wind generator, a fee of this sort would effectively be a decrease in the subsidy experienced by a wind generator, and would shift the price point below which wind is willing to curtail. The effect of an integration fee on wind farm revenue is approximately linear with the amount of fee and very consistent across wind farms. A $5/MWh fee reduces wind farm revenue by an average of 7.7% (7.3% to 8.1%) and a $10/MWh fee decreases revenue by 15.2% (14.4% to 16%).

Implementation of a wind integration fee ($/MWh) will cause wind farms to curtail more energy because it will raise the energy price at which producing wind energy is profitable. Going from no fee to a $10/MWh integration fee increases the average curtailed energy from 13% (9.7% to 16%) to 17% (13% to 20.5%). A wind integration fee does not directly motivate wind generators to reduce variability, and adding a fee of this sort could increase or decrease variability, depending on the wind energy output and the frequency and distribution of negative prices experienced by a wind farm. The total output of the sixteen wind farms showed an increase in variability in the 120 minute and 480 minute time periods, while the 30-minute variability initially increased and then decreased at higher fee rates (Figure 4.7). These trends were not robust and there was significant variation across the individual wind farms, making general conclusions difficult. If anything, this result suggests that a \$/MWh wind integration fee is not an effective way of decreasing variability, and may increase it instead.

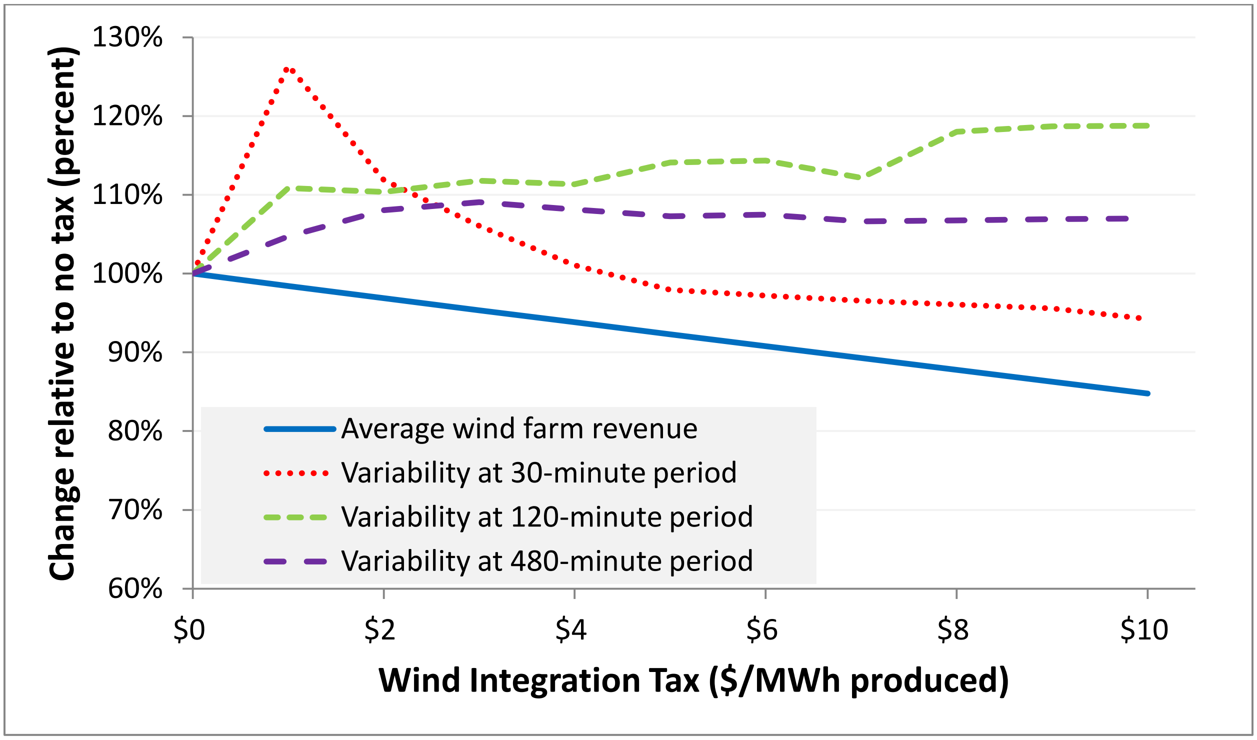

Figure 4.7: Average wind farm revenue and 30-, 120-, and 480-minute variability of wind power (sum of 16 wind farms) at different wind integration fee rates. The revenue to wind farms decreases approximately linearly with wind integration fee, and is very consistent between wind farms. While the total amount of 120-and 480-minute variability increased and the 30-minute variability eventually decreased with increasing wind integration fees, there was significant variation between wind farms.

4.4.4 Limited up-ramping of wind

Limiting only the up-ramping of wind energy is a sensible method of decreasing wind variability because modern wind generators normally have the ability to control their positive ramp rate through curtailment. Two parameters are examined within a market scenario that limits the up-ramping of wind: the ramp rate limitation, and the penalty for violation of the ramp limit. The ramp rate is defined as the percent of nameplate capacity that a wind farm is allowed to increase its power output per 15-minute time step. In this scenario, the wind farms are allowed to decrease output (down-ramp) as rapidly as they would like. The up-ramp rate limit is varied between 2% and 40% (per 15-minute time step) of a wind farm's nameplate capacity. The penalty for over-ramping is varied between 0.25 and 5 times the down-regulation price. Figure 4.8 shows the effect of different ramp rate limits and penalty amounts on the revenue to and variability of wind farms. Increasing the penalty reduces both the variability of wind output and the revenue to wind farms, while a decrease in the allowed ramp rate from 40% mainly affects the revenue to wind farms. Within the studied ranges for ramp rate and penalty, doubling the penalty decreased 30-minute fluctuations by an average of 4.5% and almost doubles (1.8x) the amount of revenue lost by the wind farms. Doubling the ramp rate limit increases fluctuations by a negligible amount (0.6%), but reduces the revenue losses to wind farms by 40%. If the goal of a ramp rate limitation is to decrease variability while having as little effect as possible on wind generation, this can best be achieved by using a higher (20-40%) ramp rate limit.

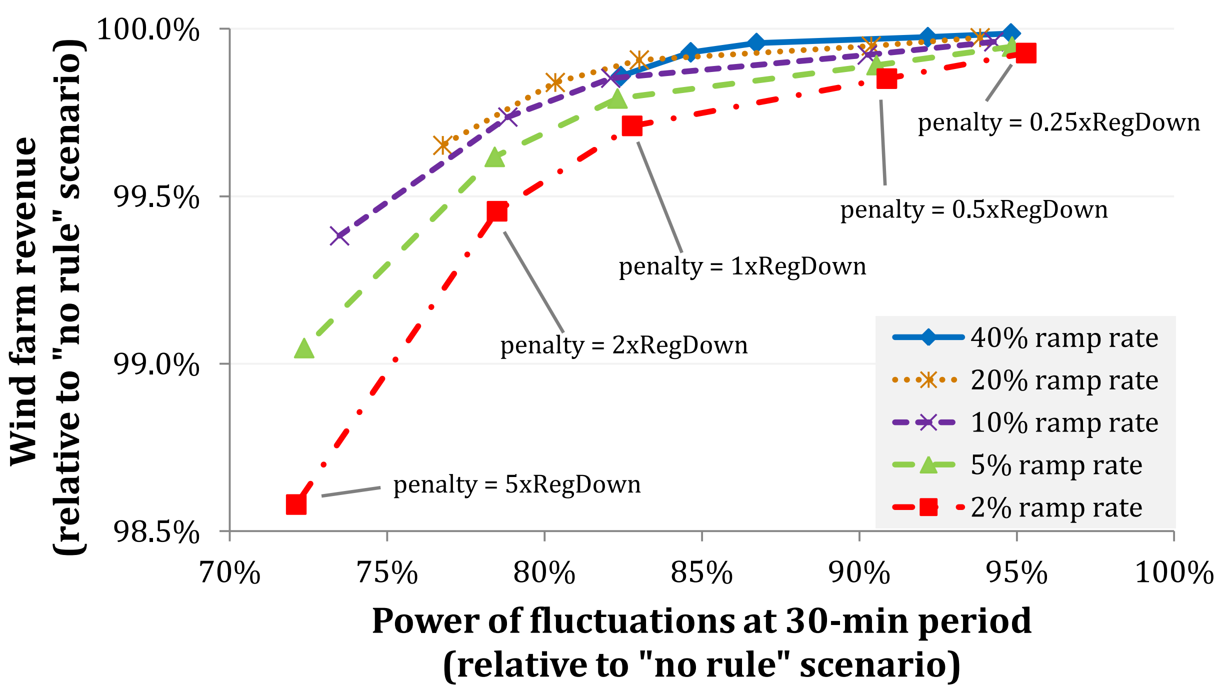

Figure 4.8: Average change in revenue (average of 16 wind farms) and change in 30-minute variability (from the total output of 16 wind farms) under a market scenario with a limitation on up-ramping of wind generators. Higher penalties for violation of the ramp limit result in decreased variability from a wind farm, while decreasing the ramp rate limit tends to affect only the wind farm revenue. If the goal of a ramp rate limitation is to decrease the variability of wind, this can be

accomplished with the least effect on wind generators by establishing a high ramp rate (20-40%) limit along with a high penalty payment. Ramp rate is per 15-minute time step.

It is natural to expect that using a much tighter ramp limitation should decrease variability significantly, though this was not found to be the case in the ramp rate-limited market scenarios that we studied. Figure 4.9 illustrates why a tighter ramp rate may result in little or no additional reduction in variability. Under any ramp rate limit, the wind farm will occasionally determine that the value of the available wind energy is greater than the penalty for violating the ramp rate, and ramp up to full power output. Under a tighter ramp limit, the power output of the wind farm will often be further from full output, resulting in a larger change in power output when the wind farms ramps up to full power. In general, using a tighter ramp limit results in fewer but sharper power output changes. Figure 4.9 and the discussion above are focused on a up-ramp limit, but the effect is very similar for a market scenario where wind farms face both up- and down-ramp limits.

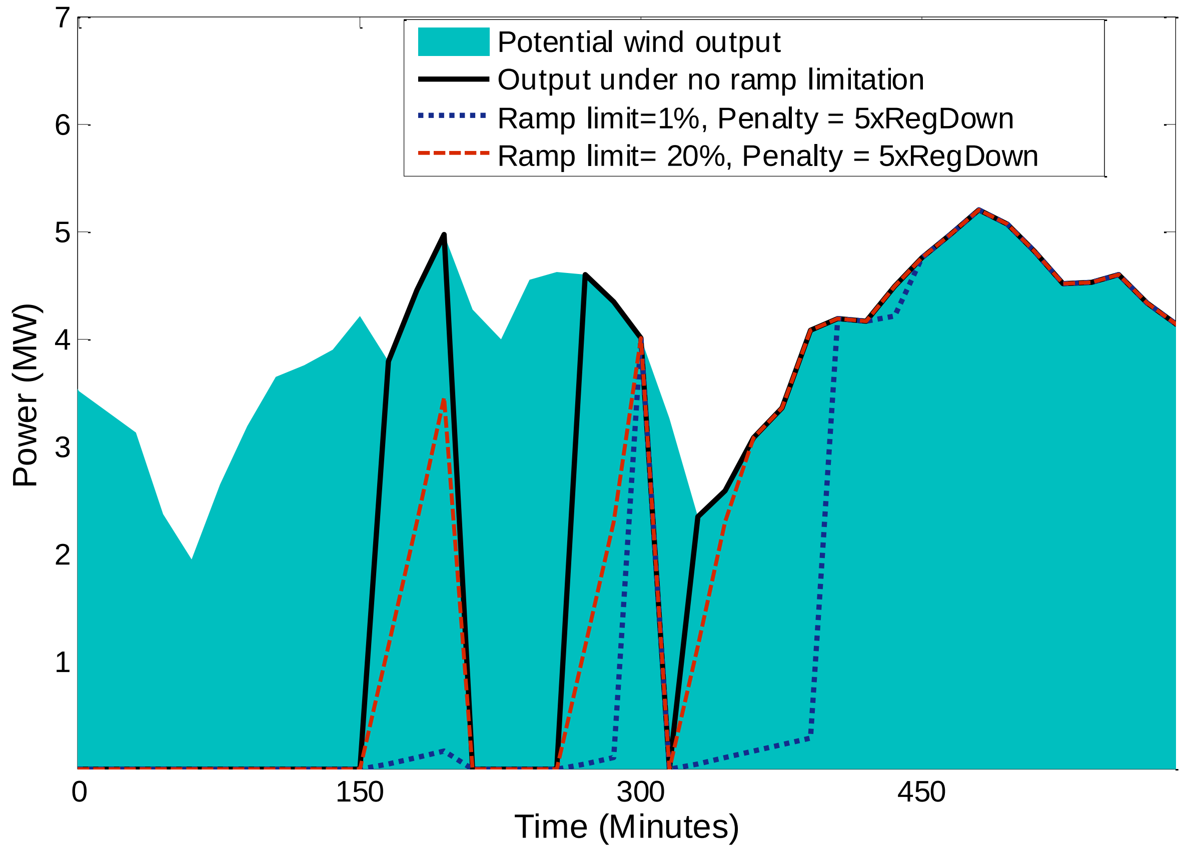

Figure 4.9: Example wind power output under no ramping limit, an up-ramp limit of 1% per 15-min time step, and an up-ramp limit of 20% per 15-min step, showing why a tighter ramp rate limit can result in higher short-term fluctuations. At 180 minutes, the tighter ramp limit results in a much smaller change in power output than the 20% ramp limit or no limit , as expected. At 300 minutes, the 1% ramp limit produces a sharper change in power output than the 20% ramp limit. Under both ramp rates, the wind farm finds that the value of the available wind energy is greater than the penalty payment and decides to produce at minute 300, but under a 1% ramp rate the power output comes up from a much lower level. A similar sharp change can be seen for the wind farm under a 1% ramp limit around minute 400, while the 20% ramp rate scenario results in a more gradual increase.

4.4.5 Limiting the up- and down-ramping of wind

Applying a limit on the up-ramping of wind output addresses only half of the potential changes in power output from a wind farm, and provides no motivation for wind generation to ramp down gradually. System operators may consider implementing a ramp rate limitation that applies to both the up- and down-ramping of wind farms. As with the up-ramp only scenario, two parameters are examined for market rules limiting both the up- and down-ramping of wind: the ramp rate limitation, and the penalty for violation of the ramp limit. The ramp rate limit is varied between 2% and 40% (per 15-min time step) of a wind farm's nameplate capacity. The penalty for over-ramping is varied between 0.25 and 5 times the appropriate frequency regulation price (up regulation price when wind ramps down too quickly and down regulation price for wind ramping up too quickly). The results (Figure 4.10) are qualitatively similar to the scenario where only up-ramping of wind is limited. When both up- and down-ramping limits are applied, the decrease in revenue is approximately double that observed for up-ramping limits, and the variability at a period of 30-min is further reduced, especially at higher penalty values. Across the penalties studied, a doubling of the over-ramping penalty resulted in an average decrease in 30-min variability of 10% and almost a doubling of lost revenue (1.75x). As the ramp rate is doubled, short term fluctuations increased by 1% on average and revenue was increased by 40%. As with the up-ramp limit scenario, the most effective way to use a ramp limit to reduce wind farm variability while minimizing the costs faced by wind generation is to apply a relatively loose ramp rate (40%) and a high penalty. Using a ramp rate of 40% and a penalty of five times the frequency regulation price, 30-min fluctuations from wind farms will decrease by an average of 40% while reducing revenue by only 0.25%, relative to the case where wind farms use economic curtailment in a system without any limits on the output of wind.

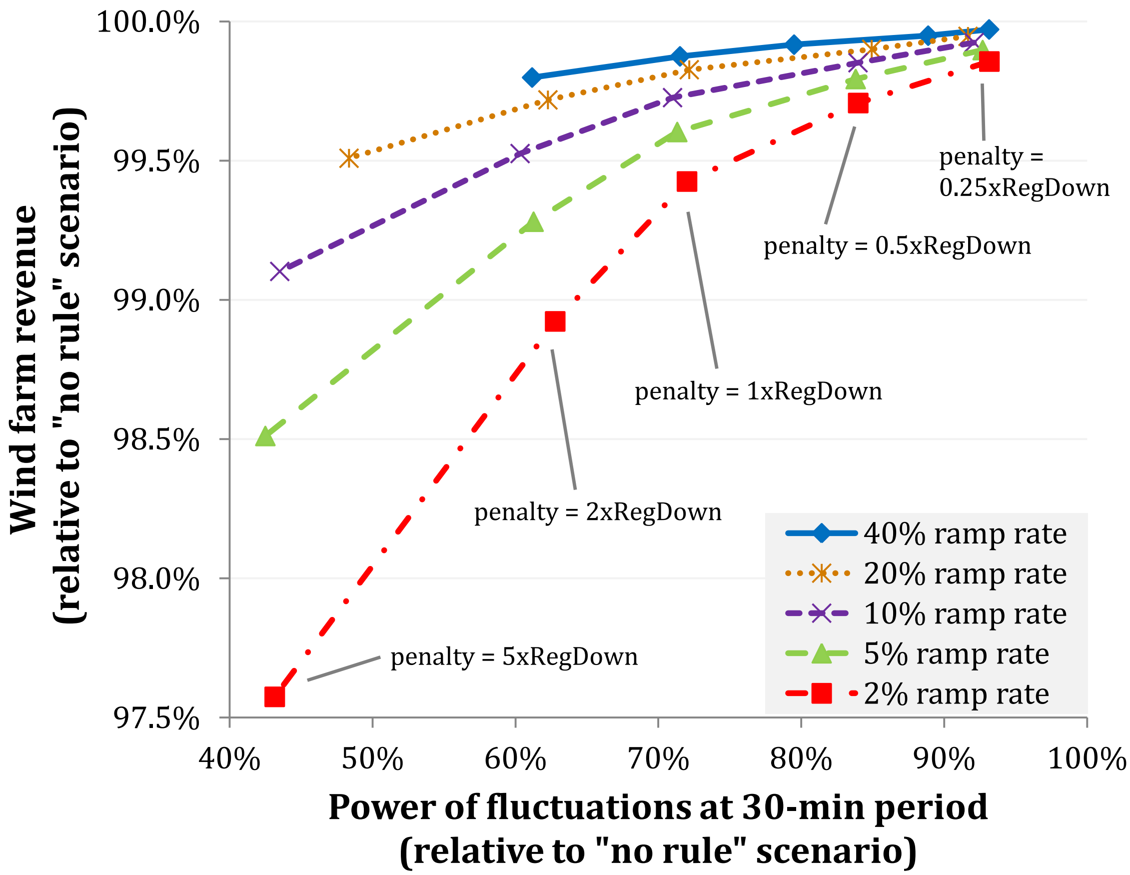

Figure 4.10: Average change in revenue (average of 16 wind farms) and change in 30-minute variability (from the total output of 16 wind farms) under a market scenario with a limitation on up- and down-ramping of wind generators. Higher penalties for violation of the ramp limit result in decreased variability from a wind farm, while decreasing the ramp rate limit tends to affect only the wind farm revenue. If the goal of a ramp rate limitation is to decrease the variability of wind, this can be accomplished with the least effect on wind generators by establishing a high ramp rate (40%) limit along with a high penalty payment. Ramp rate is per 15-minute time step.

Figure 4.11 shows the change in revenue and 30-minute variability for individual wind farms under an up- and down-ramp limit of 40% per 15-minute time step. The average line is similar to the top line in Figure 4.10, except that the 30-min fluctuations are evaluated for each wind farm individually rather than collectively. The reduction in 30-minute variability is relatively consistent across the set of wind farms, with most points within 10% of the average value. The distribution of revenue reduction is small at low penalty levels and larger at high penalty levels. This is due to some wind farms having an output that is naturally less variable and more amenable to ramping constraints. As the penalty for over-ramping is increased, this difference amplifies the relative change in revenue of the wind farms, as wind farms that are less able to control their ramping are more affected by the ramping limitations.

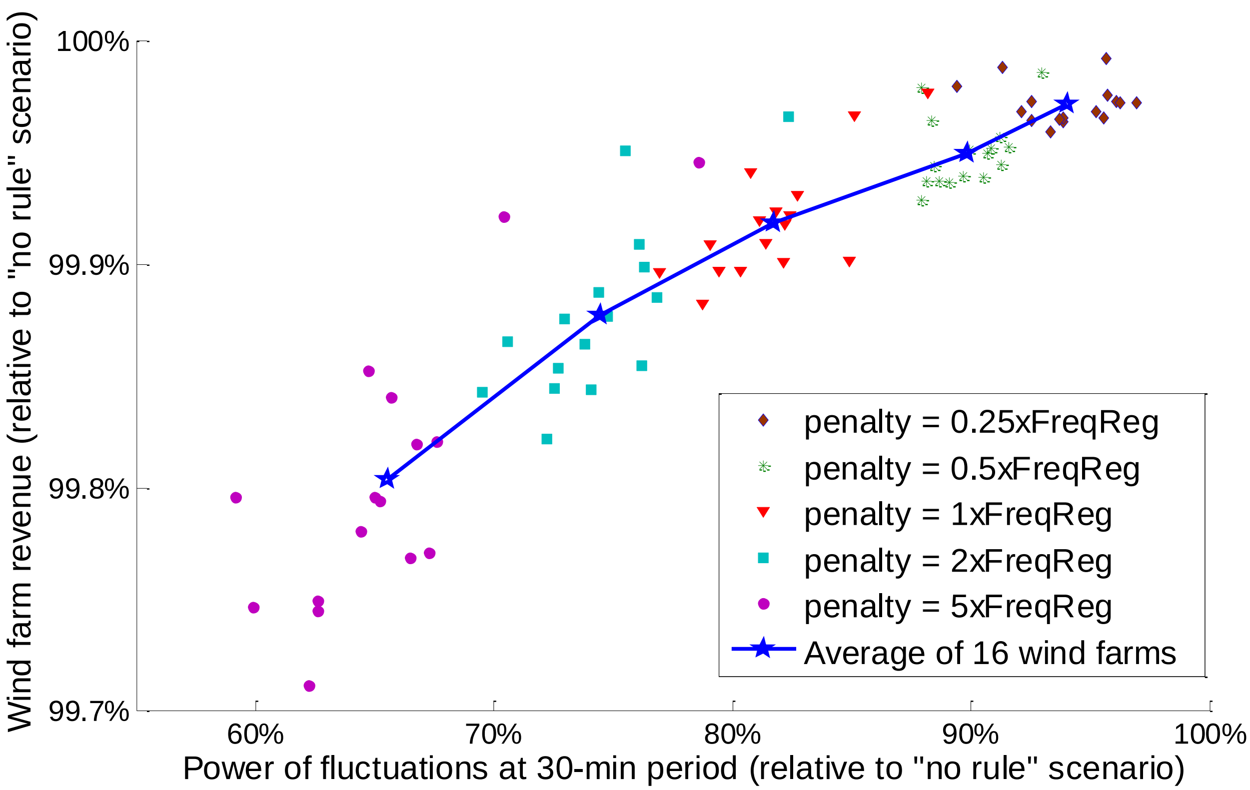

Figure 4.11: Change in revenue and 30-minute variability of sixteen wind farms under a market scenario with a limitation on both up- and down-ramping (ramp limit of 40% per 15-minute time step). The solid blue line and stars show the average results at each penalty level while the colored shapes show the results for individual wind farms.

4.4.6 Penalty for diverging from wind forecast

Instead of attempting to reduce the variability of wind power, a system operator could attempt to improve the predictability of wind by penalizing wind farms that diverge significantly from wind forecast. While this strategy does not directly address the variability of wind, it could reduce the costs associated with wind integration, and provides a market force that rewards more predictable wind generators. This structure has some similarities to the Midwest ISO Dispatchable Intermittent Resources Program and California ISO's Participating Intermittent Resources Program, where the operation of participating wind resources is constrained by wind power forecasts (Midwest ISO, 2011) (California ISO, 2012).

In the forecast-matching scenario, the power output of wind farms (as a percent of nameplate capacity) must be within an allowed deadband of the forecast wind output (as a percent of total capacity). Ideally, each wind farm would submit an individual forecast that they would be required to match, or this forecast would be provided by the system operator, as in the California ISO program (California ISO, 2012). In the absence of that data, the sixteen wind generators are required to match the 6-hour-ahead ERCOT system wind forecast, which is essentially a West Texas wind forecast because most of the ERCOT wind generation is in that area. Two parameters are examined: the size of the deadband is varied from 5% to 60% of nameplate capacity, and the penalty for producing outside the allowed deadband is varied between 0.25 and 5 times the appropriate frequency regulation price. Figure 4.12 shows the average effect that different parameters have on wind farm revenue and adherence to forecast, demonstrating that large deadband allowances (40-60%) can provide the same reduction in root-mean-square error as tighter deadband levels at lower cost to wind farms. In the base case "no rules" scenario, the average RMSE of the sixteen wind farms is 26.1% of nameplate capacity. Reducing the RMSE to 25.5%, a relatively small change, would result in a 3% reduction in the revenue to wind generators.

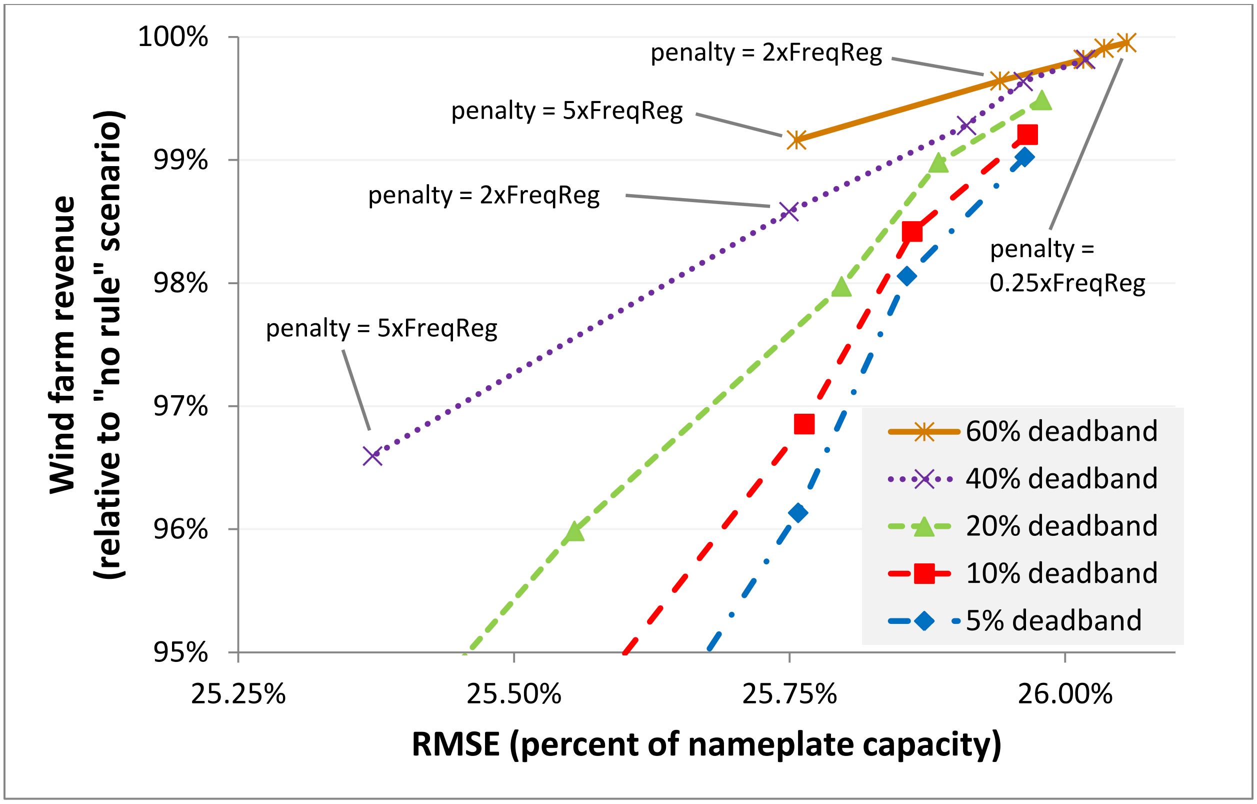

Figure 4.12: Average change in revenue and root-mean-square error (RMSE) under a market scenario where wind generators are penalized for diverging from the 6-hour forecast. Each point is the average of sixteen wind farms.

Under a market scenario where wind farms are required to meet a forecast, wind generators may prefer to be viewed as having a lower production capacity than is actually the case. This would mean that the forecast faced by a wind farm is proportionally reduced by a fixed amount. While forecasting entities seek to have no bias in their error - undeforecasting as much as overforecasting - a wind farm that had to pay for deviations from forecast would prefer to have more underforecasting than overforecasting. This is because a wind farm can reduce output for the cost of the curtailed energy, while increasing output can be done only with relatively expensive energy storage technology. From the perspective of a system operator, there seems no reason to prevent wind generation from pursuing an underforecasting strategy, as it could only improve adherence to forecast when coupled with a penalty for diverging from forecast. Towards this end, wind farms are permitted to choose their effective nameplate capacity as it relates to the forecast that they must match. This allows them to specify a smaller nameplate capacity than actual, decreasing the scale of the forecast that the wind farm is attempting to meet. The amount of underforecasting chosen by a wind generator is constrained to stay constant throughout the studied period.

For each scenario where wind generation is penalized for diverging from forecast, the amount of underforecasting that results in maximum revenue is determined for each wind farm. In some cases, when the penalty is low and the deadband is high, some wind farms choose to have little or no underforecasting. As the penalties and deadband amounts get more restrictive, the amount of underforecasting increases, as shown in Table 4.2. In the most restrictive scenarios, the amount of underforecasting is around 50% on average, but can be almost 80% for individual wind farms. As the amount of underforecasting increases, wind farms have a greater ability to meet forecast when the penalty is greater than the value of energy produced. But more underforecasting also shrinks the size of the deadband in absolute terms, and causes the forecast to be lower than the potential production on average. The chosen amount of underforecasting represents a balance between these effects. Capacity payments to wind farms are not considered in this approach because ERCOT does not operate a capacity market. In a system with a capacity market, capacity payments available to wind generation would cause wind generation to use less underforcasting, all else being equal.

Table 4.2: Average amount of underforecasting chosen by wind farms as a function of deadband allowance and penalty for diverging from forecast. In scenarios with more stringent forecast-matching requirements, wind generators choose more underforecasting because it is much cheaper to curtail down to a forecast power output than to purchase storage in order to bring output up to forecast. While increasing penalties have a small effect on the amount of underforecasting, they greatly reduce the revenue to wind farms (see Figure 4.13).

	Penalty (percent of Frequency Regulation price)				
Average amount of underforecasting chosen by wind generators	25%	50%	100%	200%	500%
5% deadband	45.9%	46.3%	46.7%	47.0%	47.6%
10% deadband	36.1%	36.5%	36.9%	37.2%	37.7%
20% deadband	22.6%	22.9%	23.1%	23.4%	23.7%
40% deadband	10.6%	10.6%	11.1%	11.1%	11.1%
60% deadband	6.6%	6.6%	6.6%	6.6%	6.6%

Figure 4.13 shows the average reduction in revenue and RMSE of wind farms under different deadband and penalty levels when underforecasting is permitted. When underforecasting is allowed, the situation is very different than when it is not permitted, as tighter deadband values with low penalties are best able to improve adherence to forecast while having little effect on wind revenue. This is because most wind farms use some amount of underforecasting and are better able to match a slightly diminished wind forecast. With underforecasting permitted, the improvements in RMSE are much better that when it is not permitted, resulting in a reduction in RMSE from 26% to 18% with a wind farm revenue loss of around 1%.

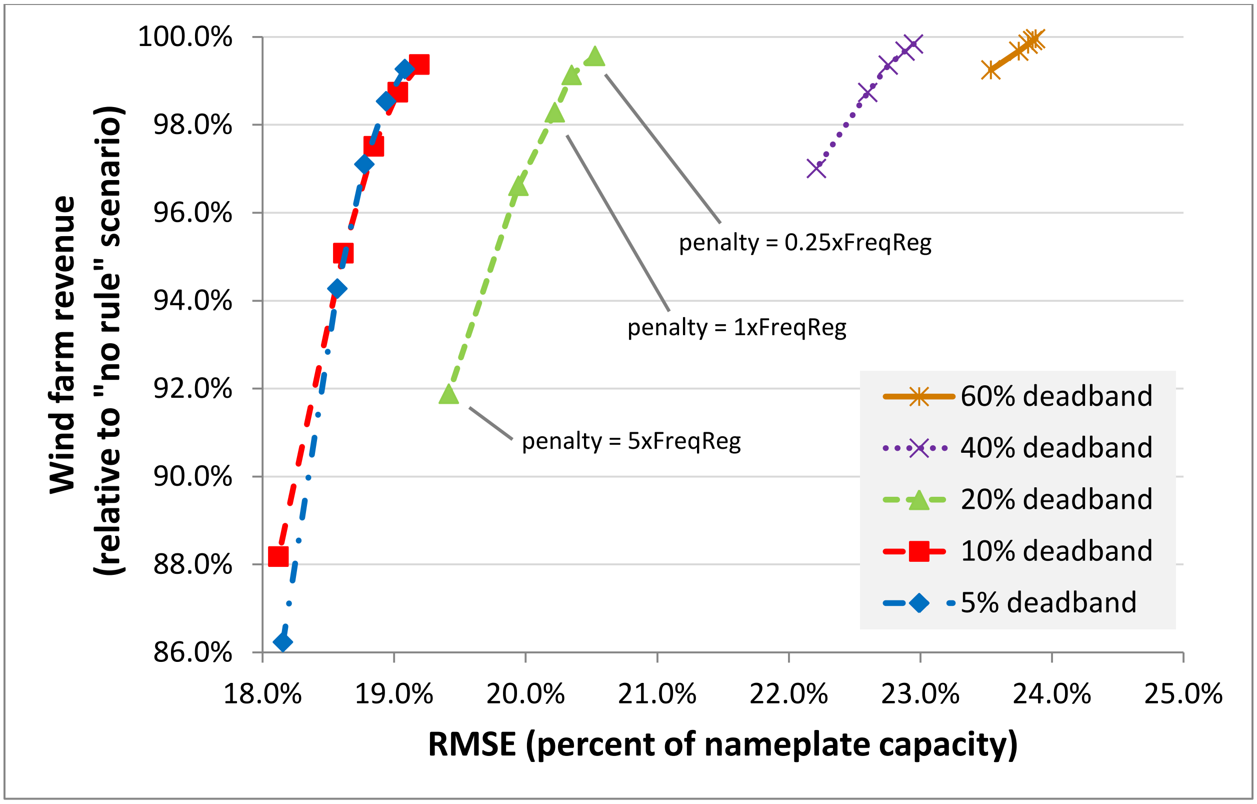

Figure 4.13: Average change in revenue and root-mean-square error (RMSE) of the collection of 16 wind farms under a market scenario where wind generators are penalized for diverging from the 6-hour forecast and wind generators are permitted to report a smaller-than-actual capacity (underforecasting). RMSE is expressed as percent of the actual nameplate capacity.

Figure 4.14 shows the RMSE and change in revenue for each wind farm in a market scenario where wind generators are penalized for diverging more than 10% from the 6-hour forecast and underforecasting is permitted. The RMSE values for the sixteen wind farms range over a factor of two, though small improvements are apparent for individual wind farms as the penalty is increased. The change in revenue is much less variable, though that variability increases as the penalty is increased. This is due to the natural ability of certain wind farms to better adhere to forecast (see Figure 4.19).

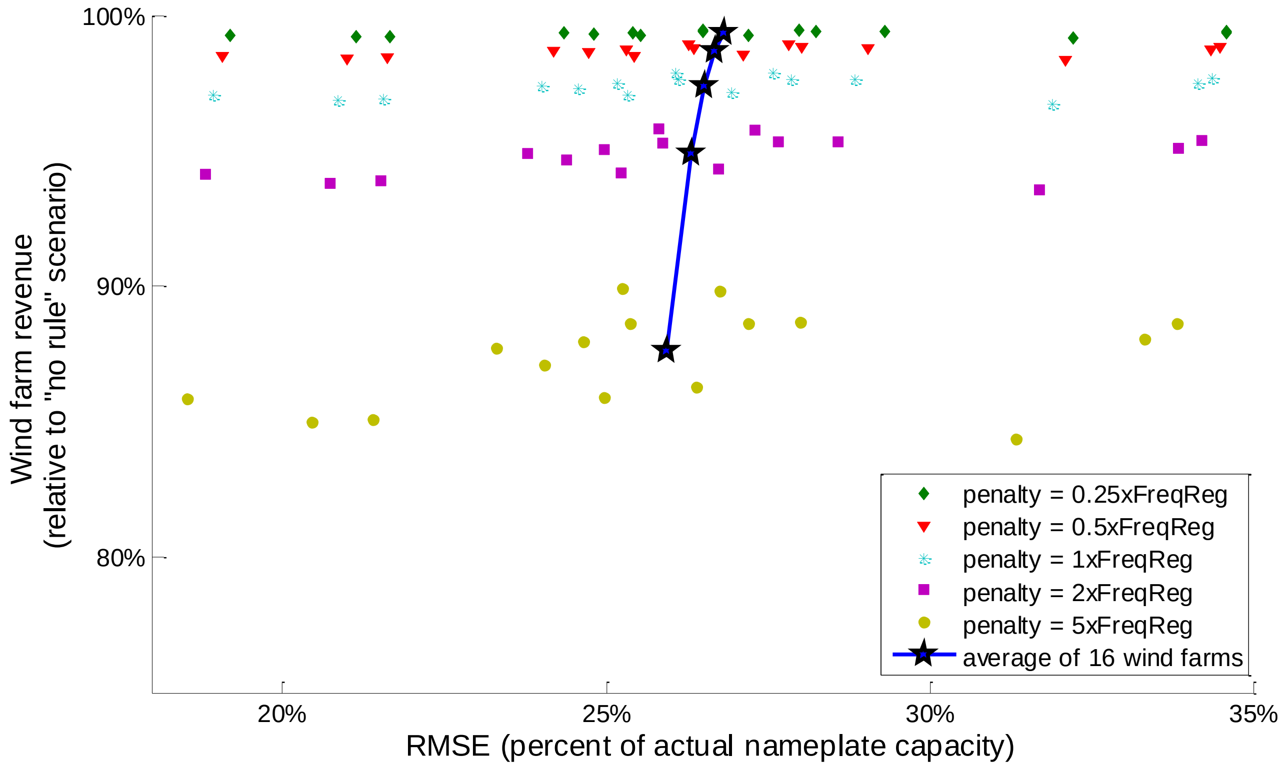

Figure 4.14: Change in revenue and root-mean-square error (RMSE) for sixteen wind farms under a market scenario where wind generators are penalized for diverging from the 6-hour forecast and wind generators are permitted to report a smaller-than-actual capacity (underforecasting). The results shown are for a deadband of 10%, similar to the left-most line in Figure 4.13, though these RMSE values are for individual wind farms rather than the collection of wind farms. RMSE is expressed as percent of the actual nameplate capacity.

4.4.7 Alternative operational strategies

In every scenario examined above, the wind farms are allowed to purchase energy storage, in the form of a sodium sulfur (NaS) battery. For several reasons, none of the studied scenarios result in wind purchasing energy storage. First, the high capital cost of this device means that only a very value intensive application will result in profitable operation. Because the focus of this work was to identify market scenarios that would have only minor effects on wind generators, the potential value of storage is small. Second, the use of energy storage was limited to the time-shifting of wind energy, so the extra benefit of charging from outside resources is lost. Third, the value of storage is greater at shorter time-scales and this work used a time step of 15 minutes (Hittinger, Whitacre, & Apt, 2010). It is possible that the value of storage would increase significantly in markets where the ramping of wind was limited on time-scales shorter than 15 minutes. Greater detail regarding the results and discussion relating to the purchase of energy storage can be found in Appendix A.

Another strategy that wind generators were permitted to choose was curtailing the wind output slightly to produce an operating reserve that could be used to buffer down-ramping (see Appendix A). This strategy only makes sense in the market scenario where wind is penalized for down-ramping, though it was never chosen as a strategy because the value of the lost wind was always greater than the value of the operating reserve. The revenue to wind farms is reduced by an average of 3.25% when the output is curtailed by 1% of nameplate capacity[4]. Under the strictest ramp limitation (2% up-and down-ramp rate, penalty of five times frequency regulation), the value of a 1% operating reserve is about half of the value of the energy. But under the preferred ramp limitation of 40% per 15-minute time step, the value of the operating reserve is negligible because the ramp limit is normally encountered only during wind curtailment, when wind generators can already control their ramp rate. Thus, curtailment to produce a reserve does not appear to be a good strategy for wind farms under any of the scenarios examined. As with the value of storage, curtailment to produce a reserve might be more valuable if evaluated under shorter time scales, such as the frequency regulation services provided by wind generation in Ireland discussed in the introduction.

[4] The percent of revenue lost is about three times the percent of curtailment because the capacity factor of the wind farms is around one third. Thus, a 1% curtailment eliminates around 3% of the energy of the wind farm.

4.4.8 Summary of results

The effect that different market rules have on the change in the power of 30-minute fluctuations and revenue to wind farms is summarized in Figure 4.15. Not all of the examined market rules directly attempt to reduce wind variability, so this figure does not express the full value of each market scenario. For example, while penalizing wind farms for diverging from forecast does reduce variability, the primary goal of that rule is to improve the predictability of wind power.

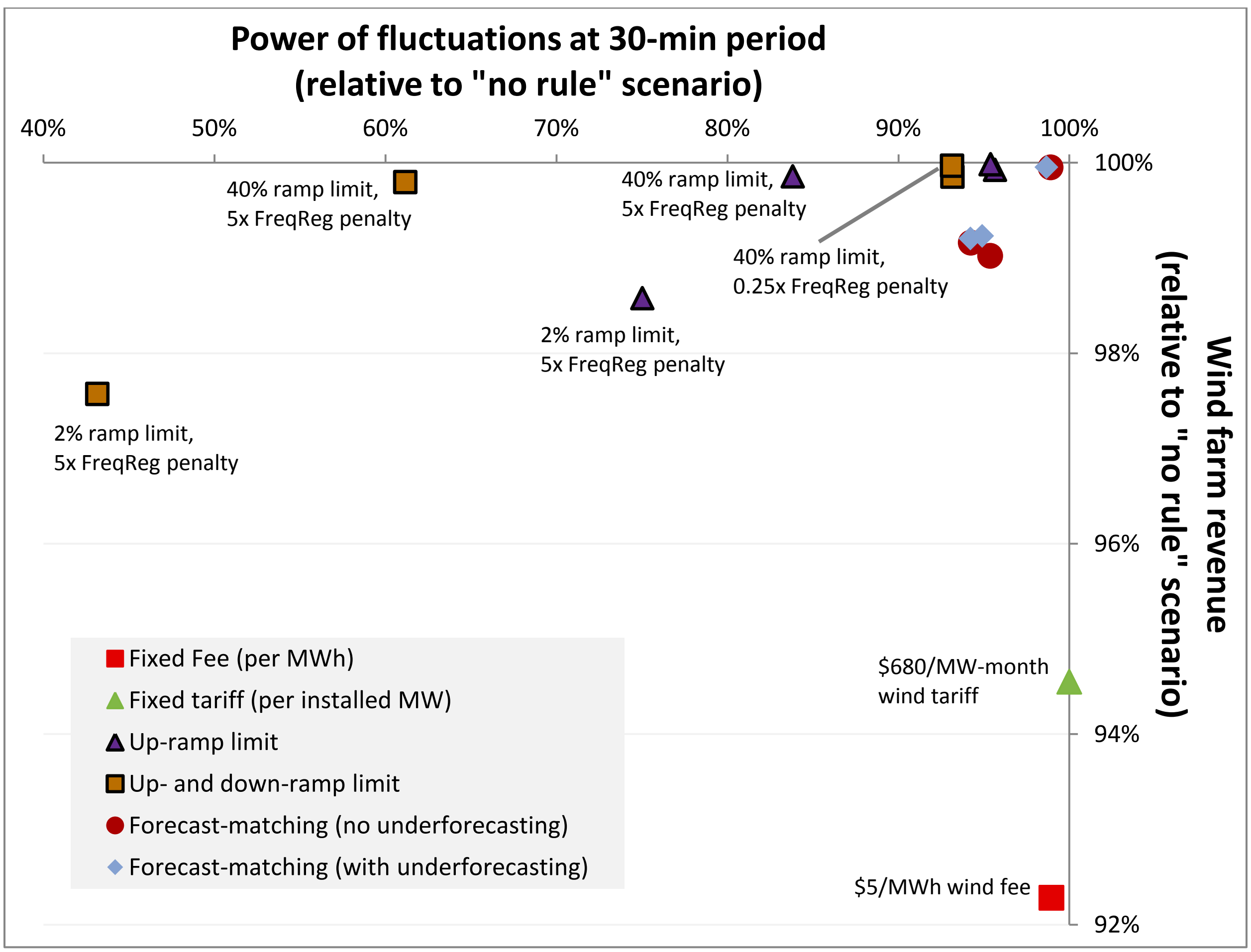

Figure 4.15: Average change in revenue and 30-minute variability of wind farms under selected market scenarios. For ease of interpretation, only a few points from each market scenario are displayed. Some market rules, such as a limitation on the ramping of wind, can reduce the 30-minute variability of wind without greatly reducing the revenue to wind generation. The "forecast-matching" scenarios do reduce variability, but their primary goal is improving adherence to forecast, which is not

expressed on this figure. Revenue is the average of sixteen wind farms, power of fluctuations is for the sum of all wind farms, and all scenarios permit economic curtailment of wind generation.

The results shown in Figure 4.15 are focused on the effect that different market policies regarding wind variability would have on wind generators. The effect on wind farm revenue is used as an important indicator of how acceptable these policies would be to wind generators, but most of the scenarios described include a penalty payment of some sort. These penalties would be collected by a system operator, are additional to any existing payments, and account for a significant fraction of the lost revenue. In the scenarios that penalize over-ramping of wind, about two-thirds of the lost revenue is due to penalty payments. For the scenarios where wind is penalized for diverging from forecast, 95-99% of the reduction in revenue is due to penalty payments. From a system perspective, these penalty payments represent a transfer of wealth rather than a loss and could be used in a number of ways, including being returned to wind generators. For example, if over-ramp penalties were redistributed to wind generators based on installed capacity in a revenue-neutral "feebate" program, wind farms that are less variable than average could earn a net payment.

Wind generators will naturally resist a set of market rules that introduces new costs to the operation of wind. But if the penalty payments or new wind subsidies are redistributed to wind generators, the costs of wind variability can be partially internalized to generators while having little or no effect on average revenue. Figure 4.16 shows the change in the power of 30-minute fluctuations versus wind revenue plus penalty payments, under various market scenarios. Including the penalty payments shows the losses from the system perspective, and indicates the average revenue to wind farms if the penalty payments are returned to wind generators in a "feebate" system.

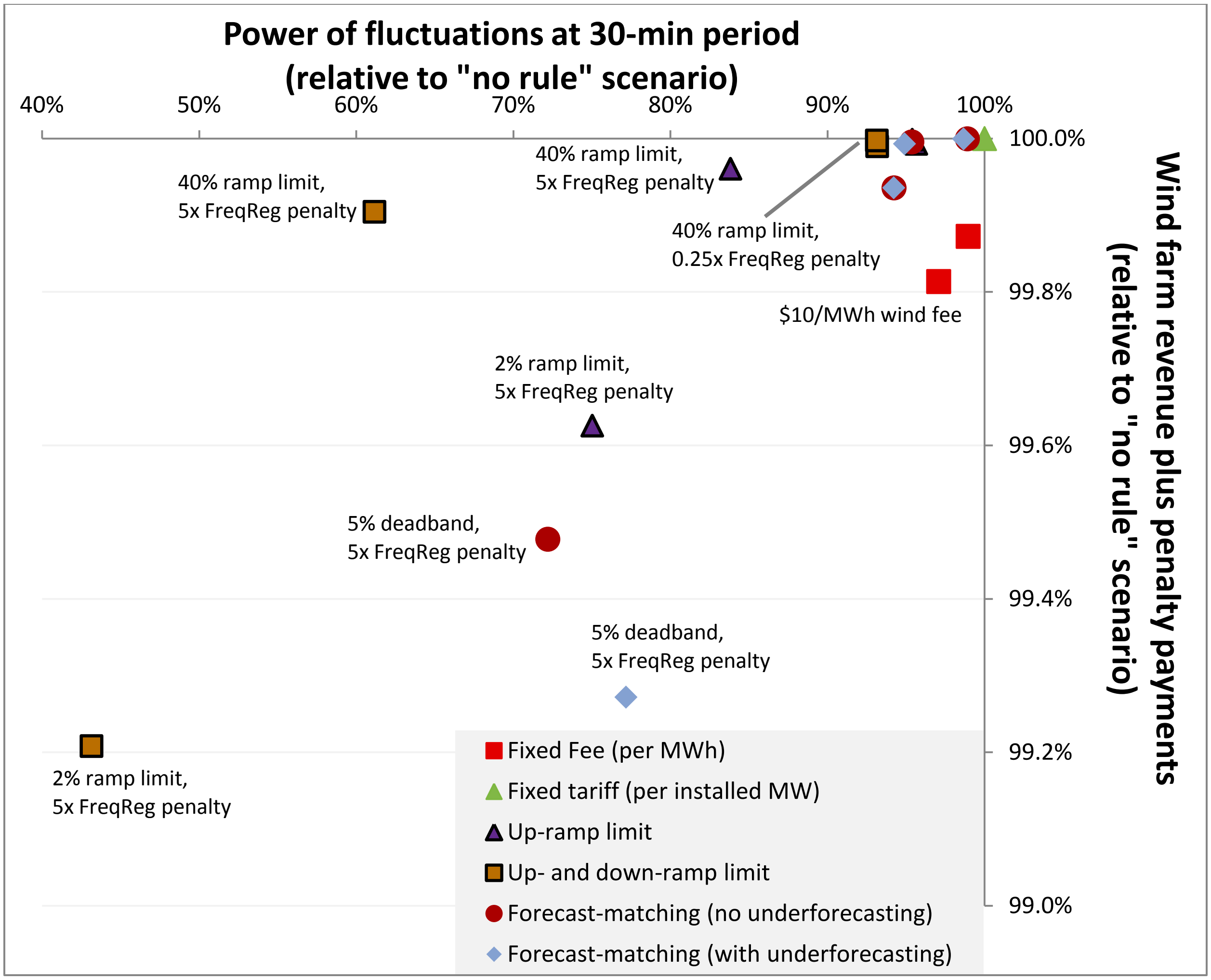

Figure 4.16: Average change in revenue+penalty payments and 30-minute variability of wind farms under selected market scenarios. Change in wind revenue plus penalty payments shows the average effect when all penalty payments are redistributed to wind generators (a "feebate" program). For ease of interpretation, only a few points from each market scenario are displayed. The "forecast-matching" scenarios do reduce variability, but their primary goal is improving adherence to forecast, which is not expressed on this figure. Revenue is the average of sixteen wind farms, power of fluctuations is for the sum of all wind farms, and all scenarios permit economic curtailment of wind generation.

FiguresFigure 4.15 andFigure 4.16 show that, of the market scenarios examined, limiting the ramp rate of wind farms is the best way to reduce the short-term (30-minute) variability of wind generation at lowest cost, from the perspective of both the wind farm and the system. Notably, the scenarios that require wind generation to match forecast can result in reductions in the 30-minute variability of wind, even though this is not a primary goal of the market rule (see Figure 4.16). While these scenarios may result in a significant reduction in wind revenue (up to 15% for the scenarios investigated), most of the revenue loss is due to penalty payments which could be redistributed to the wind generators. A summary of the effects of different market policies for wind variability is provided in Table 4.3.

Table 4.3: Effects of different market policies for wind integration on the revenue and variability of wind farms.

Scenario	Parameters	Decrease in wind farm revenue	Decrease in wind farm revenue under a "feebate" system	Decrease in 30-minute variability
Wind Integration Fee (per MWh)	$10/MWh fee	15%	0.2%	3%
Wind Balancing Tariff (per MW - month)	$680 / MW-month tariff	5.5%	0%	0%
Limited up-ramping	40% ramp limit, 5xFreqReg penalty	0.15%	0.05%	16%
Limited up- and down-ramping	40% ramp limit, 5xFreqReg penalty	0.25%	0.1%	40%
Penalty for diverging from wind forecast	60% deadband, 5xFreqReg penalty	0.9%	0.1%	6% (0.8% improvement in RMSE)
Penalty for diverging from wind forecast (underforecasting permitted)	5% deadband, 5xFreqReg penalty	14%	0.7%	23% (8% improvement in RMSE)

4.5 Discussion

These results demonstrate how modifications to wind variability market rules can affect the revenue and variability of wind farms. In West Texas over the 2008-2009 period, economic curtailment increased the revenue of the studied wind farms by an average of 2.5%, which could be a significant fraction of the wind farm profit. At the same time, economic curtailment greatly increased the variability of wind generation, due to the sharp changes in power output when the wind farm begins or ends a curtailment. On average, economic curtailment of a wind farm results in 3.5 times (2.5x to 5.5x) as much variability at a 30-minute period, 40% more (20% to 65%) variability at a 120-minute period, and 10% (2% to 20%) more variability at a 480-minute period as the same wind farms operated as must-run. Adding market rules that limit the ramp rate of wind can bring the variability back down, but none of the examined market scenarios bring the variability back to the level that results from operating wind as a must-run resource. For example, with a up- and down-ramp rate of 40% and a penalty of five times the frequency regulation, the power of 30-minute fluctuations is only 60% of the value under simple economic curtailment. But this is double the fluctuations of the same wind farms operated as must-run.

While it may appear that the use of economic curtailment causes excessive fluctuations at higher frequencies, these figures must be taken in the context of the market. With any sort of intervention into the operation of wind generation, such as economic curtailment or a ramp limitation, the fluctuations are no longer the random result of weather patterns, since they are also affected by the prices of energy and other services in the electricity market. Under economic curtailment, wind generators tend to stop energy production when the electricity price is below approximately -$25/MWh, and to start up again above that price. Thus, the wind tends to curtail when there is too much electricity production and to produce energy when this constraint is relieved, which is desirable from the system perspective. With the addition of over-ramping penalties, the wind fluctuations are also affected by the cost of having other generators ramp up or down. If the penalty payments are correctly designed, wind generators ramp up quickly only when the value of energy is greater than the cost of having other generators ramp down. When the price signals to wind generators better reflect the costs and benefits of their operation, the fluctuations from wind farms will be those that are most valuable and least troubling for the electricity grid. As a result, the wind fluctuations, while larger in absolute value, are more desirable (on average) from a system perspective.

4.5.1 The benefits of a market-based approach to ramp rate limitations

Figure 4.17 compares the power outputs of a wind farm under a scenario where wind farms are permitted to violate the ramping limits by paying a penalty with a scenario where wind farms must adhere to the ramping limits whenever possible. When the wind farm is permitted to violate the ramp limits (and pay a penalty), it does so whenever the price is sufficiently high or low. If the wind farm is required to meet the ramp rate limit whenever possible, it will occasionally curtail during very high energy prices or continue to output power at significantly negative energy prices, which may not be desirable for either the system or the wind generator.

In addition, the inclusion of a penalty scheme for over-ramping allows the system operator to collect penalty payments that could be used to cover wind integration costs or be returned to the wind generators. For example, the scenario where wind farms must adhere to a 40% up- and down-ramp limit and the scenario where wind farms have a 20% ramp limit and a penalty of five times the frequency regulation price result in very similar changes in wind farm revenue (0.44% versus 0.49%) and reductions in 30-minute variability (45% versus 45.5%). But in the scenario where the wind farm pays a penalty for over-ramping, around half of the revenue lost to the wind farm is collected by the system operator as penalty payments (0.26% of the 0.49% lost revenue), which is not available in the scenario where wind must adhere to the ramping limits. If these penalty payments are returned to the wind farms in a "feebate" system, the more market-based penalty rules can result in the same reduction in 30-minute variability as the case where wind must adhere to the ramp limit, while reducing the revenue of wind farms only half as much. Thus, allowing for over-ramping and collecting a penalty can result in equivalent reductions in variability and wind farm revenue as a market rule that requires wind generators to meet a ramp limit, while also producing penalty payments to the system operator and fluctuations that are more desirable from a system perspective (Figure 4.17).

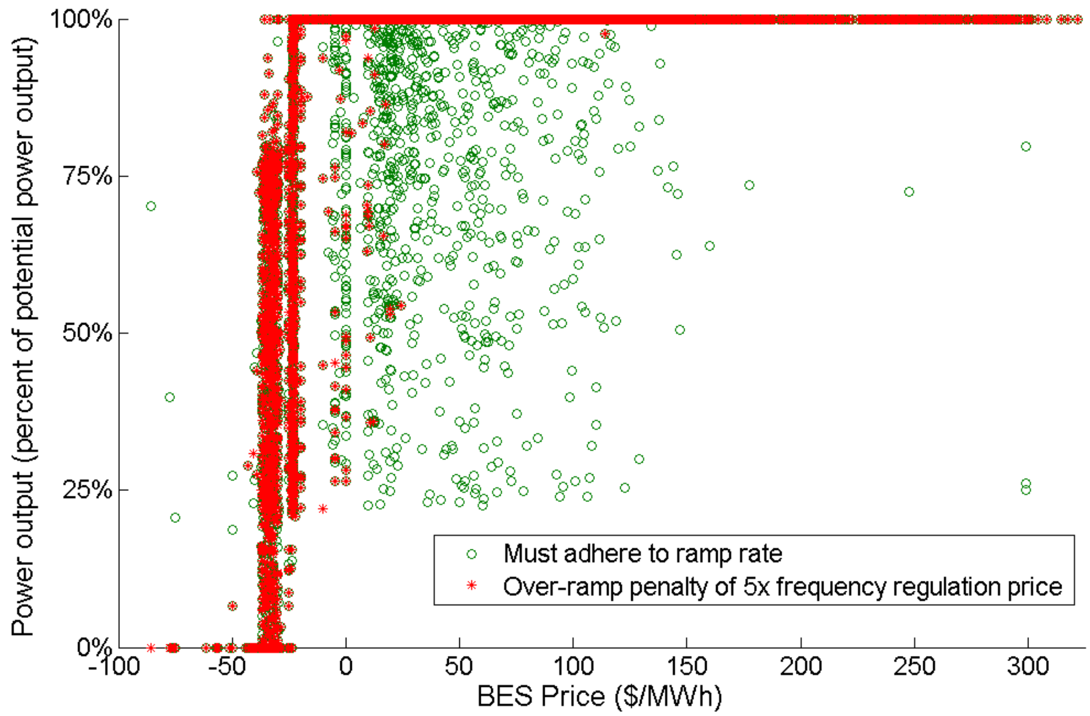

Figure 4.17: Power output of a wind farm versus energy price for each 15-min time step in the 2008-2009 period, under two scenarios with a 20% ramp rate on both up- and dpown-ramping. The green circles represent a scenario where wind must adhere to the ramp rate whenever possible, while the red stars represent the scenario where wind farms may violate the ramp rate and pay a penalty of five times the corresponding frequency regulation price. All intermediate power outputs (between 0% and 100% of potential power output) indicate periods where the wind farm is controlling output to meet the ramping limit. The wind farm that must adhere to the ramp rate is at an intermediate power output 19% of the time, while the wind farm under the over-ramp penalty scenario is at an intermediate state 17% of the time. When violations of the ramp rate are permitted, the wind farm is less linkely to adhere to the ramp rate when the prevailing energy price is further from the break-even energy price (around -$25/MWh).

4.5.2 The effect on future wind farm deployments

Modifying the electricity system market rules can have an immediate effect on the operation of existing wind farms, but may have a more important effect on the deployment of new wind farms. In a market scenario where the revenue to wind farms is significantly reduced, the amount of new wind turbine deployment will likely decrease. The implementation of market rules that penalize certain types of wind output, such as ramp limitations or the requirement that wind power match forecast, will influence which sites are chosen for new deployments of wind. For example, with penalties for over-ramping, wind developers will tend to seek locations that have less inherent wind variability and also have an incentive to spread turbines out in patterns that reduce the short-term variability from the wind farm.

Figure 4.18 shows the change in revenue versus the natural 30-minute variability for the sixteen wind farms under a scenario where up- and down-ramping is limited to 20% per 15-minute step, with a penalty of five times the frequency regulation price, and all penalty payments are returned to wind farms in proportion to their installed capacity. While the average wind farm still loses money under this revenue-neutral "feebate" system, some wind generators will actually earn more than they would without any limitations on wind power. There is a slight downward trend[5] to the data points, suggesting that wind farms that have a higher inherent 30-minute variability will be worse off under a ramp-limiting market policy.

[5] Using simple linear regression, the downward trend is significant at the 90% confidence level but not at the 95% level, and has a slope of -0.21.

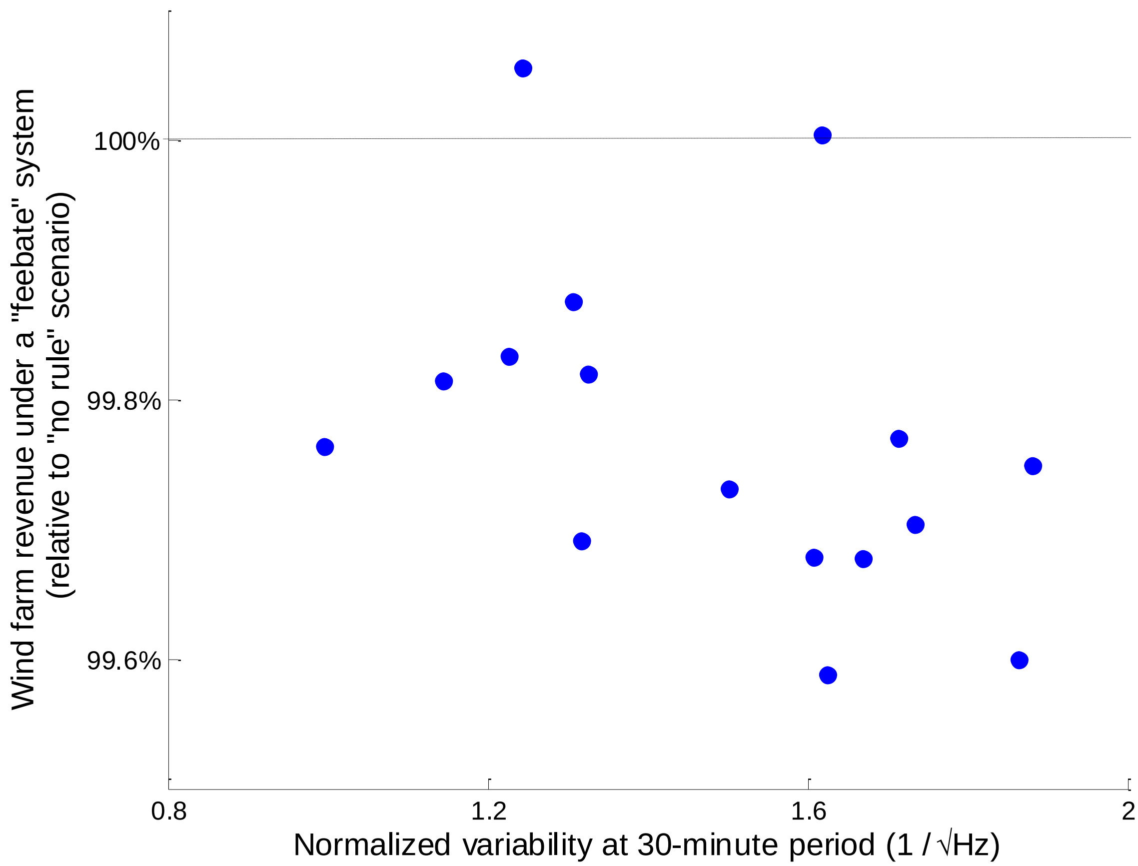

Figure 4.18: Wind farm revenue versus normalized natural variability at a period of 30-minutes for 16 wind farms in a market policy scenario where up- and down-ramping of wind is limited to 20% of nameplate capacity (per 15-minute step), penalties for over-ramping are five times the frequency regulation price, and all penalties are returned to wind generators in proportion to their installed capacity. The absolute variability at a period of 30-minutes (units of MW/√Hz) scales with the capacity of a wind farm and is normalized to installed capacity (units of MW/MW-√Hz , or 1/√Hz) in order to compare wind farms of different sizes. The x-axis shows the normalized variability of the actual measured wind data, showing the "natural" variability of that wind farm rather than their output under the ramp-limiting market policy. On average, wind farms lose revenue when over-ramping is penalized, even when all of the penalty payments are returned to wind. But a few wind farms acquire more revenue than they would if there were no limitation on wind ramping. The data show a slight downward trend, as wind farms with greater 30-minute variability lose more revenue.

Figure 4.19 shows the change in revenue versus natural RMSE of the sixteen wind farms in a market scenario where wind generation is penalized for diverging from forecast. The data show a strong relationship[6] between RMSE and revenue under a policy where wind is required to adhere to forecast. Under either market policy scenario, several wind farms earn more revenue than they would under a "no rules" scenario.

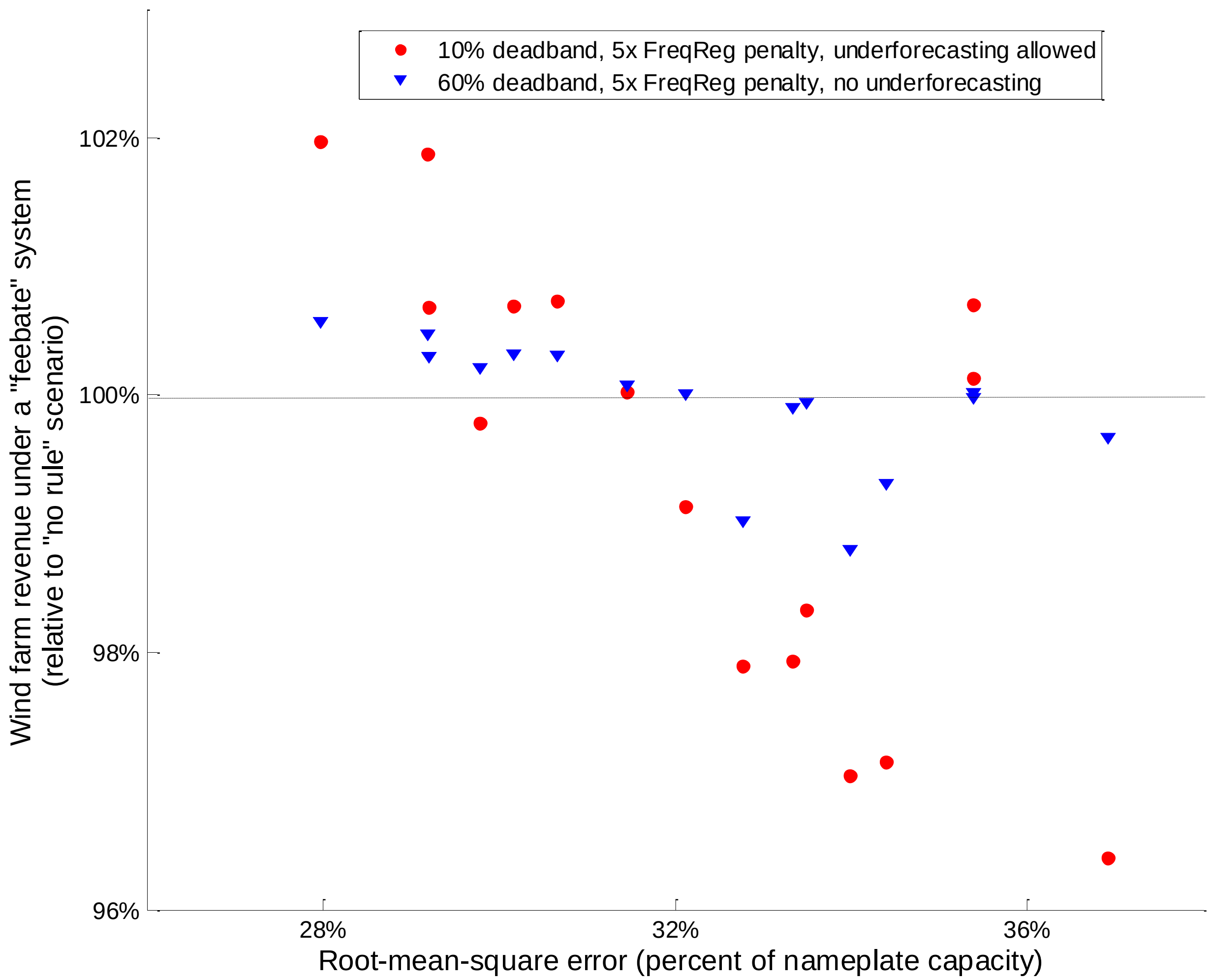

Figure 4.19: Wind farm revenue versus root-mean-squared error (RMSE) for 16 wind farms in a market policy scenario where wind farms are required to match the regional wind forecast and all penalties are returned to wind generators in proportion to their installed capacity. The x-axis shows the RMSE of the actual measured wind data, showing the "natural" adherence to forecast of each wind farm. On average, wind farms lose revenue when diverging from forecast is penalized, even when all of the penalty payments are returned to wind. Several wind farms acquire more revenue than they would if there were no limitations on wind generation. The data show a downward trend for both series, where wind farms with greater RMSE values lose more revenue. Using simple linear regressions, both series show a trend that is significant at the 95% confidence level.

[6] The trends for both data sets are significant at the 99% confidence level. The trend in the data points corresponding to a 10% deadband where underforecasting is not permitted have a slope of -1.9. The trend in the data for a 60% deadband where underforecasting is permitted have a slope of -0.5.

Under a revenue-neutral feebate system where undesirable wind output is penalized based on current price signals (such as the scenarios referenced in Figure 4.18 and Figure 4.19), wind generators that are better able to provide the desired output are rewarded while the undesirable behavior is reduced across all wind farms. These policies will also have an important effect on the deployment of new wind farms. Because the undesired wind output affects revenue, it is internalized into a wind farm's cost structure and should be part of the decision of where to site new wind generation. This will shift the deployment of new wind turbines towards locations that produce wind power output that better matches the system goals. If the market policies relating to wind generation reflect the needs of the electricity system, both the operation of existing farms and the deployment of new wind generation will improve, reducing the cost of wind integration for the rest of the system.

This paper has examined market rules that limit or penalize the operation of wind generation, which will reduce wind farm revenue and may be unpopular with wind developers. Some electricity systems would prefer to encourage deployment of wind energy, and may be hesitant to embrace the market rules discussed above. Yet it is quite possible for a system to capture the value of the market rules while not penalizing wind generation if a small subsidy is provided to wind at the same time that new operational limitations are established. For example, in the scenario where up- and down-ramping of wind is limited to 20% of capacity per 15-minute step with a penalty of five times the frequency regulation price, 30-minute variability is reduced by 45%. The average revenue to wind farms is reduced by 0.5% ($0.32/MWh), though penalty payments make up about half of that loss. If all penalty payments plus a small subsidy of $0.13/MWh are distributed to wind generators, the wind generators just break even (on average), though the 45% reduction in short-term variability will still be realized. A subsidy higher than $0.13/MWh would mean that wind farms are, on average, better off under the new system, even though that system adds new limits to wind operation. Thus, pursuing the benefits of market-based limitations to wind output does not necessarily require wind generators to be worse off.

4.6 Conclusion

As the quantity of wind generation on electricity grids increases, the costs related to wind integration will become increasingly significant, resulting in increasing pressure to return some or all of these costs to wind generators. Market rules that use existing price signals to incentivize decreased variability, such as ramp limitations with penalties based on the frequency regulation price, allow wind generators to participate in variability-reduction when the market conditions are favorable. These market-based strategies can both reduce wind variability and gather payments that can be used for increased ancillary services requirements, and can be better for both wind generators and system operators.

Different market rules can have very different effects on the profitability and operation of wind generators, and the appropriate market policy depends on the needs of the electricity system. In areas with small amounts of wind generation or where further deployment of wind power is desired, having no restriction on wind variability can encourage further deployment and prevent increased regulatory burden. In electricity systems where the variability of wind is becoming costly or problematic, market rules that limit the ramping of wind (with penalty payments for violating the ramp limits) can reduce the short-term variability of wind significantly with only minor reductions in the revenue to wind farms. In areas where the deviation from forecast makes wind integration difficult, system operators should consider penalizing wind generation for diverging from forecast. Regardless of system needs, using a market-based approach to internalizing wind variability costs allows wind generation to participate in the market for wind integration services, which can reduce overall system costs.

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4.8 Appendix A: Alternative Operational Strategies

4.8.1 Curtailment to Produce an Operating Reserve

The "curtailment to produce a reserve" operational strategy is modeled by assuming that a wind farm curtails its power output by a fixed amount (a percentage of nameplate capacity), in order to create a small operating reserve. When the wind drops off quickly, the wind farm can use the reserve to reduce the observed ramp rate, by increasing the actual power output closer to the potential power output. For example, a 100 MW wind farm could always curtail 1% of the available wind power in order to buffer sudden drops in the wind. If this wind farm is producing at nameplate capacity, then a 1% curtailment is 1 MW, and the wind farm's actual output is 99 MW. If the wind drops suddenly to a level where the wind farm is only able to produce 95 MW, the wind farm can manage the power output change, keeping it to a 4 MW step change (rather than the 5 MW change without the intentional curtailment). Without the intentional curtailment, down-ramping events cannot be controlled without storage.

4.8.2 Use of Energy Storage

The energy storage option allows the wind farm to install a sodium sulfur (NaS) battery, which can then be used to either increase wind farm revenue or decrease variability. The NaS battery is modeled after the currently-available PQ modules produced by NGK Insulators, the only established supplier for this technology (NGK Insulators, 2005). Because NaS batteries are commercially available only in a pre-defined modular form as noted above, their power-to-energy ratio is fixed. NaS batteries require a temperature of ~ 325 degrees Celsius to operate and thus require a continual "maintenance power" to maintain that temperature (accounted for in this model). NaS batteries have a continuous power rating of 0.05 MW, and have a manufacturer-defined pulse power capability (also accounted for in the model) under which they can provide up to four times the normal power rating for 15 minutes, making their maximum power output 0.2 MW. NaS batteries were chosen as the energy storage technology because they are a relatively established energy storage technology, have an appropriate power to energy ratio for this application, are modular and appropriate to the scale of a wind farm, and have been utilized for wind integration in the past(LaMonica, 2010)(EPRI-DOE, 2002)(NGK Insulators, 2005). Table A.1 shows the NaS battery properties used in the battery model.

Table 4.4: NaS battery properties examined and their base-case values.

NaS Battery Parameter	Base-Case Value
Round-trip Efficiency	80%
Module Energy Capacity	0.36 MWh
Module Power Limit	0.2 MW
Module Maintenance (Heating) Power	2.2 kW
Module Capital Cost	$240K ($670K / MWh)
Module Fixed Operating Cost	$8K / module - year ($22K / MWh-year)
Length of Capital Investment	20 years

NaS batteries are assumed to be co-located with the wind farm and are operated to maximize revenue. While the batteries could be used with the goal of reducing power fluctuations, an energy storage owner is unlikely to do so unless it is either the most profitable mode of operation or they are directed to by market protocols. To maximize revenue, NaS batteries are charged whenever the apparent energy price to the wind farm (including subsidies and penalties) is below a fixed "charge price", and discharged whenever the effective energy price is above a fixed "discharge price". Between the charge and discharge prices, the storage does nothing. Several alternative storage operational strategies were examined, including adjusting the charge/discharge prices as a function of state-of-charge, season, day of the week, or prevailing energy price, but the resulting revenues were similar or lower than those from the simple model. The optimal charge and discharge prices are determined separately for each wind farm in each policy scenario using a genetic algorithm optimization that searches for revenue-maximizing values of the charge and discharge prices.

The operation of storage under perfect information is also examined and compared with the simple model described above. Under the perfect information model, at each time step the operator looks ahead at the wind output and energy prices over the next 24 hours. The revenue-maximizing operation of the NaS battery over the next 24 hours is calculated, but only the operation in the current step is retained. In other words, an entire day of battery operation is calculated in order to determine the charge/discharge level in a single time step. The operation of the battery is constrained to end the 24-hour period at the same charge state that it began with, though the boundary effect is insignificant because the NaS battery is able to charge and discharge several times over a 24-hour period.

A genetic algorithm was used to determine the "charge price" and "discharge price" that resulted in the highest wind+battery revenue (Figure 4.20). Both the charge and discharge price were relatively high, and were consistent across different market policy scenarios. Under the "no rules" scenario, the average charge price was $62/MWh, meaning that the NaS battery would charge whenever the energy price dropped below $62/MWh, and the battery would discharge only when energy price was above $175/MWh. The overall revenue was not very sensitive to changes in these values: a 10% change in either parameter resulted in less than 1% change in revenue. The elevated charge price kept the energy storage fully charged most of the time, and the battery was only discharged when the electricity prices were very high. This is because most of the revenue from the storage came during infrequent price spikes, and the optimal strategy was to maintain a high state of charge to capture all the possible revenue from a potential future price spike. This result is similar to Fertig and Apt's finding that an optimally-dispatched compressed air energy storage (CAES) system in ERCOT would store energy 91% of the time and only discharge 3% of the time, as it attempts to capture all of the potential value of price spikes (Fertig & Apt, 2011). Figure 4.20 provides an example of the battery output under perfect information and the simple "buy below/sell above" model.

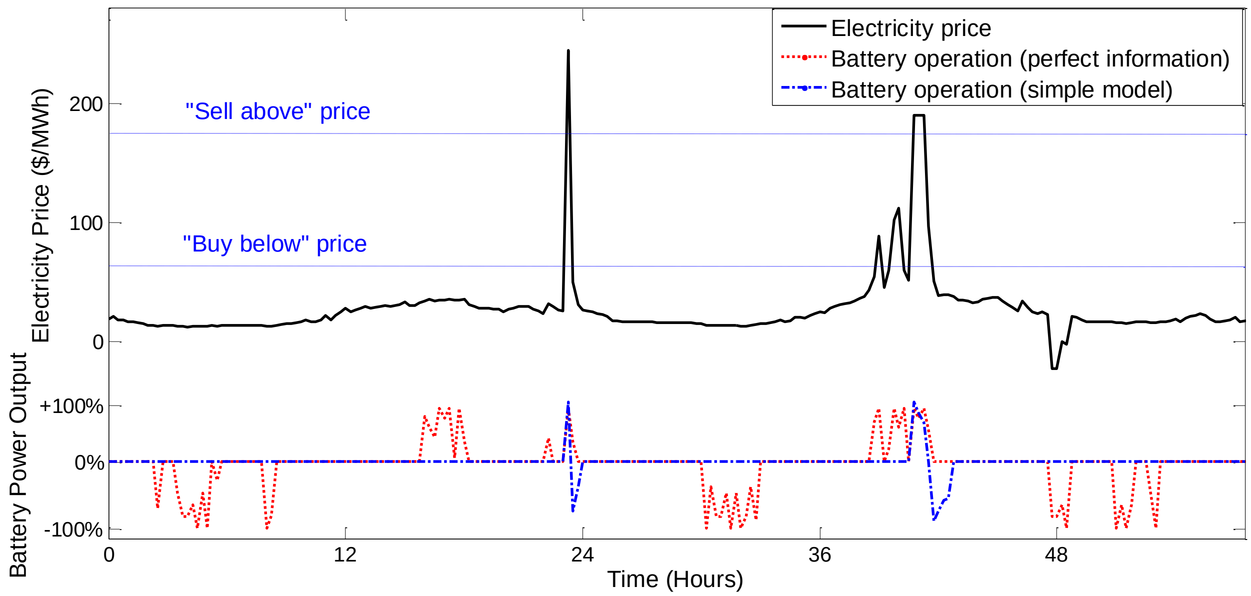

Figure 4.20: Example of battery operation under perfect information and a simple "buy below/sell above" operation over 60 hours. The "sell above" and "buy below" prices used for the simple model are shown in the dashed lines on the top part of the figure. The battery power output is shown in percent, from +100% (full discharge) to -100% (full charge). Under perfect information, the battery is able to extract value from smaller price changes (such as hour 17) while retaining enough energy for price spikes (hour 23), and charges when electricity price is lowest (hour 32). Under a simple "buy below/sell above" operation, the battery only discharges during relatively high price spikes and tends to recharge to capacity immediately afterwards.

Without any wind-related market rules, where it is providing only time-shifting of wind energy, a NaS battery earns revenue equivalent to around 17% of its annualized cost under a simple "buy below/sell above" operation, resulting in a large net loss. Under very strict rules, such as a 1% up- and down-ramp limit and a penalty of five times the frequency regulation price, the value of a NaS module increases only a few percent to around 20% of annualized cost. While there are other costs involved, the primary contributor to annualized cost is the capital cost of the storage, which is $240K per module or $700/kWh. Given the assumptions and limitations discussed above, energy storage only becomes a profitable investment for the wind farms at a cost of $120-$150 per kWh, even under the stricter scenarios discussed above.

The value of storage improves significantly if the battery is operated under perfect information, knowing the future prices and wind energy. This is due primarily to the ability to take complete advantage of energy price spikes in both the positive and negative direction. Under perfect information and a scenario where wind is not penalized for variability, a NaS battery recovers around 33% of its annualized cost. This increases slightly to around 38% under the strictest ramp-rate limitation. Even under perfect information, storage is profitable only if the cost is less than $250 / kWh. While more advanced wind and price forecasting could make the operation of energy storage more profitable, most of the increased revenue from the perfect information operation comes from taking full advantage of price spikes, which are very difficult to predict (Weron, Modeling and Forecasting Electricity Loads and Prices, 2006)(Weron, Bierbrauer, & Truck, Modeling electricity prices: jump diffusion and regime switching, 2004)(Zhao, Dong, Li, & Wong, A Framework for Electricity Price Spike Analysis With Advanced Data Mining Methods, 2007)(Zhao, Dong, Li, & Wong, A general method for electricity market price spike analysis, 2005)(Lu, Dong, & Li, 2005).

4.9 Appendix B

One relevant question regarding implementation of a ramp rate limit that has a large effect on both revenue and fluctuations is whether a wind farm's output should be tied to the most recent non-violation power output or if it should be tied only to the output in the prior time step. If the output of a wind farm is tied to the last point at which it did not violate the ramp limit, then a wind generator is penalized for any energy delivered above the original ramp-up profile. Alternately, the wind generator output can be related only to the energy output in the previous step, and is thus charged an over-ramp penalty in only one time step (the difference in the two potential rules is illustrated more clearly in Figure 4.21). This latter version of the rule is more forgiving towards over-ramping, and we find that it also results in much lower penalty charges to wind farms while having approximately the same effect on variability. From the system perspective, there is little reason to tie a wind farms current power output to past power outputs (except the immediately past output). Throughout this work, the ramping constraints are tied only to the immediately prior power output, as this is better for both wind farms and the electricity system.

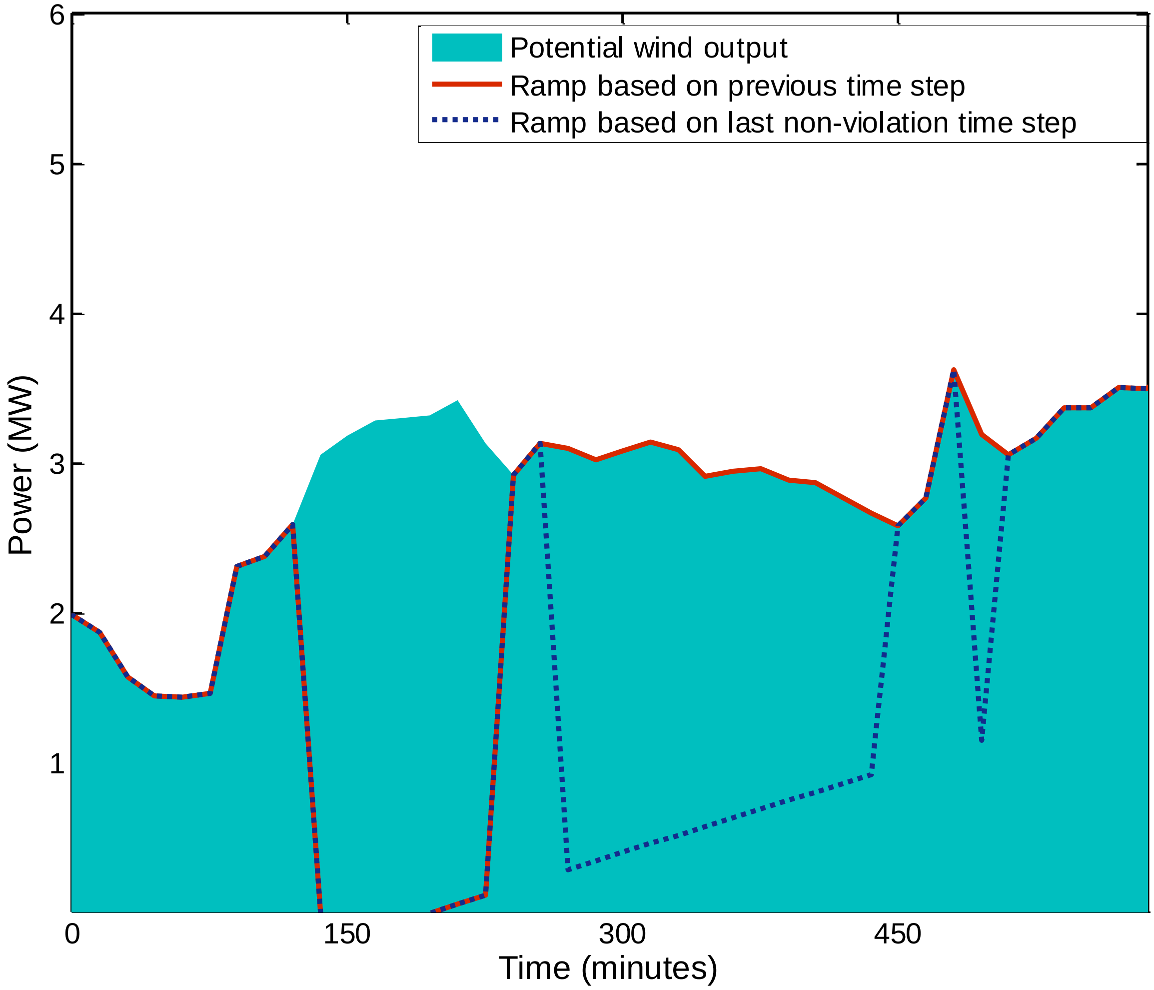

Figure 4.21: Example output of a wind farm under two alternative ramping rules when only up-ramping is limited. The dashed blue line shows the output of a wind farm when the allowed power output is based on a fixed ramp-up from the last time step that did not violate the ramp limit. Under this rule, the wind farm is constrained to the ramp-up that starts around minute 200, and goes to full power output whenever the price of energy minus the penalty cost results in profit for the wind generator (around minutes 225, 450, and 500), but returns to the original line when energy price is no longer higher than the penalty. This can cause significant short-term variability, as wind output goes back and forth between the allowed ramp-up and maximum energy output. The solid red line shows the output of a wind farm when the allowed power output is the previous power output plus a limited up-ramp. When the wind farm violates the ramp limit at minute 225, it only pays the violation penalty during that time step and is no longer coupled to the original ramp-up line.

Chapter 5: Conclusion

1.1 Summary of Results

In Chapter 2, examination of a co-located wind/natural gas turbine/energy storage generation block demonstrated a potential method for wind integration and a potential application for energy storage. A scenario analysis identified system configurations that can generate power with 30% of energy from wind, a variability of less than 0.5% of the desired power level, and an average cost around $70/MWh. In these systems, the energy storage is used to smooth the sharpest wind fluctuations, allowing the rest of the system (the gas turbine) to provide fill-in energy. The optimal amount of energy storage in these systems was very small, as the superior ramping capability of storage is balanced with its high capital cost. Even in a system with 30% wind energy, the cost of storage amounts to only 1% of the average cost of electricity from the wind/natural gas/ energy storage generation block.

In Chapter 3, an extensive sensitivity analysis was used to determine which properties of energy storage are most valuable. Over four storage technologies and four potential applications, reductions in capital cost were found to be the most consistently valuable change. Increasing the power and energy capacities was also of great value, though this depends on which application was considered. Other energy storage properties that are often the focus of research efforts, such as lifetime or efficiency, were found to have a smaller effect on the value of storage.

Chapter 4 examines the response of wind generators to various market policy scenarios that attempt to internalize or mitigate wind integration costs. The use of economic curtailment of wind in a system with frequent negative prices can lead to greatly increased short-term variability. At the same time, market scenarios that motivate wind to reduce variability when the value of energy is low can result in significant reductions in short-term wind variability. For example, if wind up- and down-ramping is limited to 20% per 15-minute time step, with an over-ramping penalty of five times the frequency regulation price, 30-minute variability can be reduced by 50% while wind farm revenue is decreased by only 0.5%. By adopting system rules that allow wind to partially participate in the market for wind integration, significant reductions in wind variability can be achieved at little cost to wind farms. Furthermore, these system rules will also affect future wind development in a region, shifting it towards sites and layouts that are better able to meet the desired output.

1.2 Future Work

If there is a common theme to this thesis, it is the search for better ways to use emerging electricity technologies. I believe that there is great value in further investigations of how different market structures and operational strategies can better capture the value of energy storage and wind energy and how these two technologies might complement one another.

The application described in Chapter 2 takes advantage of the strengths of fast-ramping energy storage, permitting a small amount of storage to contribute a critical wind integration service in a co-located system. Yet the grid is not co-located, and it is not clear where storage would should be located to perform a similar service in a larger system, or how much storage should be used in a more realistic system. Furthermore, current system rules provide very little incentive for any entity to purchase storage for this co-located wind integration application. It would interesting to examine different market rules that might incentivize the deployment of storage performing a similar service.

The examination of system policies that internalize or mitigate the variability of wind in Chapter 4 provides many paths for further research. This work was based on the 2008-2009 ERCOT electricity grid, and it would be interesting to see if a different electricity system (possibly one with fewer negative prices) would produce similar results. Alternately, one could examine the same policies in ERCOT in more recent years, after the transition from zonal markets to nodal markets in 2010. Chapter 4 looked at several possible modifications to wind integration policy, but there are many alternative regulatory changes that could be examined, such as other ways to limit wind variability or changes in the bid/dispatch interval for energy or ancillary services. I am confident that market-based limitations for wind can make the power output of wind easier and cheaper to integrate with the rest of the grid, but I have little confidence that the best strategies to accomplish this have been determined.

1.3 Policy Discussion and Conclusion

Electricity is a commodity. For energy storage and wind power to become significant contributors to the operation of electricity grids, they must be a less expensive source of energy services (or provide greater value, such as lower emissions of wind power) than the competitors. And, as relatively new technologies, wind and storage must prove their reliability and value to the risk-averse electricity industry. Wind energy is already cost competitive or close to competitive with other new generation in many systems, and its value is only increased when the true costs of emissions are accounted for. But there is a long-standing and very reasonable question of how this variable and non-dispatchable energy source should be integrated with the rest of the grid. Likewise, the value of energy storage will continue to increase as both load and generation become more variable, but it is not clear how this expensive new technology should be valued and operated.

The energy storage technologies examined in this thesis have one important strength: their ability to change power output (or input) extremely quickly, usually on the order of milliseconds. While fast ramping is not problematic, these technologies are capacity-limited unable to deliver (or receive) a continual flow of energy for extended periods. These properties of fast-ramping storage are exactly the opposite of traditional generators, which have varying but limited abilities to ramp and are better at providing a constant energy output. It is sensible that fast-ramping energy storage technologies should be used for energy services that require very high amounts of ramping and little energy input/output, where they can complement the abilities of traditional generation.

Both wind power and energy storage are entering an established industry with structure and regulations developed for a traditional generation base over the last hundred years. But neither wind power nor energy storage fit neatly within the existing regulatory structure, and the early response to these technologies was generally to exempt or exclude them: wind is often treated as inelastic negative load, and storage is forced to impersonate a traditional generator delivering traditional energy services. Chapter 4 demonstrated that wind farms can reduce variability at low cost when market rules allow them to participate in wind integration. Chapter 2 discussed a unique application that takes advantage of the strengths of fast-ramping energy storage, but there is little motivation to perform this service in current electricity markets. If the full value of these technologies is to be realized, we must establish market structures and services that allow wind and storage to participate in electricity markets on their own terms.

The most formidable obstacle to large-scale deployment of energy storage is understanding the value proposition of this expensive technology. Over time, the benefit of storage will increase while the costs decrease. The increasing variability of load and rapid deployment of wind and solar power all make energy storage a more valuable grid asset. At the same time, innovations in the technology can decrease the costs of energy storage. Chapter 3 showed that capital cost and power/energy limits are the most valuable properties to improve for fast-ramping energy storage. Yet these properties do not consistently get the most attention or funding. As energy storage technologies move out of the laboratory and onto the grid, storage developers and funding sources must accept the nature of electricity as a commodity and pursue the provision of energy services at lowest cost.