Coupling Wind Generation with Controllable Load and Storage: A Time-Series Application of the SuperOPF

Final Project Report

Power Systems Engineering Research Center

Empowering Minds to Engineer the Future Electric Energy System

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Executive Summary

As electric utilities are required to purchase increasing amounts of energy from renewable resources, the intermittent nature of these resources will play a significant role in shaping power system operations and planning. The anticipated capacity of wind power to be installed suggests that significant increases in regulation reserves will be required, which will fundamentally alter the traditional generation technology mix. This will place a greater value on technologies with flexible and rapid response capabilities, highlighting an increased role for storage technologies and demand response in the new regime.

PSERC researchers at Cornell have developed a new planning tool that is a stochastic form of Security Constrained Optimal Power Flow (SCOPF), the SuperOPF. Two key features of the SuperOPF that distinguish it from most other planning models are 1) the effects of equipment failures (contingencies) and the uncertainty of potential wind generation are considered explicitly, and 2) the amount of reserves required to maintain reliability is determined endogenously instead of adding predetermined constraints for fixed levels of reserves in different regions. From a planning perspective, determining reserve requirements endogenously is an essential feature for evaluating the effects of adding intermittent sources of generation such as wind power. The model also includes the ramping costs of mitigating wind variability explicitly in the optimization. In the final chapter, a new multi-period version of the SuperOPF is used to demonstrate how different types of storage can be managed optimally and reduce total system costs substantially.

Initial phases of the analysis required developing a dataset for the wind resources and creating an hour ahead forecast of wind power generation. In Chapter 2, a singular component analysis was performed on a wind resource database from the National Renewable Energy Laboratory [1], in order to determine the appropriate level of wind resource to model for the Northeast United States. The wind resource was geographically smoothed following [2], and an AR(1) algorithm was applied to develop the hour ahead wind generation forecast. Finally, K-means clustering was applied to the wind data to determine the best K levels of potential wind generation for each hour and the probabilities of transitioning from each given level in one period to each one of the K levels in the next time period.

Building upon the single, hour ahead forecast, the next stage of the analysis in Chapter 3 presents a framework for utilizing multistage wind power forecasts to determine the optimal use of hour ahead and 10-minute ahead demand response resources in mitigating wind variability. The results demonstrate that wind power can participate successfully in day-ahead electricity markets, with the total amount of wind accepted being increased by the use of paired demand response resources.

The first application of the SuperOPF in Chapter 4 analyzes the effects of ramping costs on the optimal patterns of dispatch and reserves using a small 30-bus test network with a high penetration of wind turbines. The results show 1) the higher system costs anticipated when ramping costs increase for individual conventional turbines are caused mainly by dispatching less wind generation and more conventional generation, 2) if ramping costs are excluded in the optimization, as they are in practice, much more wind is dispatched because the high ramping cost of cutouts at high wind speeds is ignored, and 3) reliability can be maintained with different levels of ramping cost by having adequate levels of reserves, and these reserves can be reduced substantially when storage capacity is available.

The analysis in Chapter 5 explains why there is "missing money" for some conventional generators when there is a high penetration of wind generation. Since wind generation can displace most conventional sources of generation, wholesale prices are generally lower when wind generation increases. At the same time, net revenues paid in the wholesale market to conventional generators above their out-of-pocket operating costs are also reduced. These net revenues may be too low for some generators to be financially viable even though these units may be essential for maintaining the reliability of supply. This is the source of missing money, and we argue that the "Financial Adequacy" of generators is an important issue for planning that should be considered along with the conventional criteria of Operating Reliability and System Adequacy. From an economic perspective, the lower wholesale prices associated with high penetrations of wind generation are not a good measure of net system benefits. In general, the lower energy prices ($/MWh) with wind generation result in higher capacity prices ($missing money/MW). Consequently, using storage to mitigate wind variability and reduce the conventional capacity needed for Operating Reliability, and the associated missing money, does provide positive net benefits for the system.

Chapter 6 uses the new multi-period version of the Cornell SuperOPF that makes it possible to 1) optimize the use of storage capacity over a planning horizon, 2) incorporate a realistic representation of the stochastic characteristics of wind generation, and 3) determine the optimum level of reserve generating capacity needed to cover equipment failures (contingencies) and ramping requirements. The analysis uses a simplified network topology representing New York State and New England. The initial results show that the optimum dispatch is very different if the stochastic properties of wind generation are ignored. With deterministic wind, the system costs are lower and less wind is spilled. The main results show the allocation of total costs in the wholesale market for five different cases, a base case and four cases with additional wind capacity at 16 sites. One case adds unconstrained transmission capacity, another adds deferrable demand at five load centers, and the last one adds Energy Storage Systems (ESS) collocated at the 16 wind sites.

Although policy debates of how to integrate more wind generation into the grid generally conclude that building additional transmission capacity is essential, our results show that it is also important to mitigate the inherent variability of wind generation effectively. Adding deferrable demand or ESS actually leads to more wind being dispatched than upgrading the transmission in this example. The results also show that deferrable demand provides a slightly higher revenue stream for the wind generators than the case with collocated ESS even though more wind is dispatched with ESS.

The main cause of lower production costs is that conventional generation is displaced by wind generation. The two cases with storage have the lowest costs and there is little difference between them using this criterion. However, deferrable demand lowers congestion on the grid by lowering the peak purchase of energy from the grid. The main difference in the total system costs for the two storage cases is that the amount of non-wind generating capacity needed and the associated capital cost are both much lower with deferrable demand.

We have argued before that a successful smart grid must yield economic benefits for customers and customers who have deferrable demand have the highest net benefits. The main reason is that deferrable demand can be used to lower a customer's purchase of power from the grid at the peak system load, and thereby, reduce the total amount of non-wind generating capacity needed to maintain reliability. Deferrable demand also provides ramping services that mitigate the variability of wind generation and reduce the ramping by conventional generators.

A very important barrier to deferrable demand at this time is the current structure of the retail rates paid by most customers. These rates do not reflect the correct economic incentives. For example, getting the economic benefit of reducing one's demand at the peak system load requires that customers pay for their actual demand at the peak system load. We argue that substantial changes in retail rate structures will be needed to make the smart grid financially attractive to customers. Given the complexity of the wholesale market, particularly if the demand-side can be paid for providing some ancillary services, it is likely that Aggregators of Residential Customers (ARC) will be needed to use real-time price information effectively by controlling their customers' appliances using wireless signals. With deferrable demand, such as charging electric vehicles and thermal storage, customers should still receive the same energy services and not be inconvenienced. They will benefit by paying lower bills.

In summary, analysis with the SuperOPF demonstrates that coupling controllable load with wind generation is an effective way to offset much of the period-to-period variability of wind generation, reduce congestion on the network and flatten the daily pattern of generation for conventional generators. The SuperOPF is shown to be well suited for this type of evaluation because it deals with the stochastic characteristics of wind effectively and determines the reserve requirements needed for reliability of the network endogenously.

References

[1] National Renewable Energy Laboratory, "NREL: Wind Systems Integration – Eastern Wind Integration and Transmission Study," http://www.nrel.gov/wind/systemsintegration/ewits.html.

[2] P. Nørgaard and H. Holttinen, "A Multi-Turbine Power Curve Approach," Presented on the Nordic Wind Power Conference, Göteborg (SE), pp. 1-2, 2004.

Project Publications

C. L. Anderson, J. B. Cardell, "*The Impact of Wind Energy on Generator Dispatch Profiles and Carbon Dioxide Production*," Proceedings of Hawaiian International Conference on System Sciences, Jan. 2012.

C.L. Anderson and J. B. Cardell, "A Decision Framework for Optimal Pairing of Wind and Demand Response Resources," under revision for the *Special Issue in the IEEE Systems Journal.*

J. B. Cardell, C. L. Anderson, "The Effect of Wind and Demand Uncertainty on Electricity Prices and System Parameters," in *Proceedings IEEE PES T&D*, New Orleans, LA, April, 2010.

C. L. Anderson, J. B. Cardell, "Analysis of the System Costs of Wind Variability," in *Proceedings of Hawaiian International Conference on System Sciences, Jan. 2010.*

Tim Mount, Alberto Lamadrid, Surin Maneevitjit, Bob Thomas and Ray Zimmerman, "The Hidden System Costs of Wind Generation in a Deregulated Electricity Market", *Journal of Energy Economics*, 33 (1), 173-198, 2011.

Tim Mount, Alberto Lamadrid, Wooyoung Jeon and Hao Lu, "Is Deferrable Demand an Effective Alternative to Upgrading Transmission Capacity?" *Proceedings of the 31st Annual CRRI Eastern Conference*, Shawnee PA, May 16-18 2012.

Tim Mount and Alberto Lamadrid, "Using Deferrable Demand to Increase Revenue Streams for Wind Generators" *Proceedings of the 25th Annual CRRI Western Conference*, Monterey CA, June 27-29 2012.

Alberto Lamadrid, "Alternate Mechanisms for Integrating Renewable Sources of Energy into Electricity Markets," *Proceedings of the 2012 IEEE PES General Meeting*, 22 - 26 July 2012, San Diego, CA, USA.

Lamadrid, A.J., and T. Mount, "Ancillary Services in Systems with High penetrations of Renewable Energy Sources, the Case of Ramping," *Energy Economics*, 34:1959 – 1971, 2012.

Wooyoung Jeon, Jung Youn Mo, and Tim Mount, "Developing a Smart Grid that Customers can Afford: The Impact of Deferrable Demand," submitted to *the Journal of Energy Policy,* Aug. 2012.

Alberto Lamadrid, Wooyoung Jeon and Tim Mount, "The Effect of Stochastic Wind Generation on Ramping Costs and the System Benefits of Storage," accepted for the *46th IEEE HICSS Conference*, Maui, HI, January 2013.

Student Theses

Holle, Lindsay, "An Analysis of New York Energy Policy Targeting Renewable Energy and Energy Conservation," B.S. Honors Thesis, Smith College, May 2011.

Holliday, Jennifer," Rural Electrification in South Africa - Technology and Policy Considerations," B.S. Honors Thesis, Smith College, *to be completed* May 2013.

Lukuyu, June, "Design and Analysis of Hybrid Power Systems for Remote Village in Northern Kenya," B.S. Honors Thesis, Smith College, *to be completed* May 2013.

deMijolla, Genevieve, "Customer Interface for real-time electrical demand using privacy-centered systems design," B.S. Honors Thesis, Smith College, *to be completed* May 2013.

Tee, Chin Yen, "Evaluating the Dynamics of Using Responsive Loads for Ancillary Services in an Islanded Microgrid," B.S. Honors Thesis, Smith College, May 2011.

Maneevitjit, Surin, "The Economic Value of Reliability in Deregulated Electricity Markets," PhD Thesis, Cornell University, 2012.

Mo, Jung Youn, "Economic Analyses of Plug-In Hybrid Electric Vehicles, Carbon Markets, and Temperature-Sensitive Loads," PhD Thesis, Cornell University, 2012.

Lamadrid, Alberto "The Welfare Effects of Integrating Renewables in Electricity Markets," PhD Thesis, Cornell University, 2012.

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1. Introduction

1.1 Background

Throughout the United States, regions and individual states have statutes and policy recommendations that require electric utilities to purchase a specified amount of energy from renewable sources. One of the main technologies that is capable of fulfilling these requirements is wind power. With some of these requirements approaching 30% of energy served by renewable resources, the intermittent nature of the wind resource will play a significant role in shaping future power system operations and planning. Other technologies, including storage and demand response, as well as traditional sources such as gas turbines and hydro-electric facilities, will be required to balance the variable and often uncertain output from wind farms.

The anticipated capacity of wind power to be installed suggests that more than incremental changes to the power system will take place. Significant increases in regulation reserves are anticipated by some studies, suggesting up to 5% of the installed wind capacity will need to be paired with technologies capable of providing regulation. Such technologies are required to be flexible with respect to startup, shut down and ramping capability – more flexible than the average generating technology currently installed in the power system. This suggests a significant change will be required in the traditional generation technology mix, with a greater percentage of the installed capacity being used to balance wind variability. These requirements for response capability will thus place a greater value on technologies that can provide it, with most storage technologies and demand response as prime technologies in the new regime.

In order to adequately address these emerging issues, new analytical tools for power system operations and planning will be required. Over the past few years, PSERC researchers at Cornell have developed a new type of planning tool for electric networks, a stochastic form of Security Constrained Optimal Power Flow (SCOPF) called the SuperOPF.[1] Two key features of the SuperOPF that distinguish it from other planning models are 1) the effects of equipment failures (contingencies) and the uncertainty of potential wind generation are considered explicitly, and 2) the amount of reserves required to maintain reliability is determined endogenously instead of adding predetermined constraints for fixed levels of reserves in different regions. In fact, determining reserve requirements endogenously is an essential feature for evaluating the effects of adding intermittent sources of generation such as wind power.

Three case studies using the SuperOPF are presented in this report. The first two use a single-period version of the SuperOPF to analyze a 30-bus test network, and the third uses a multi-period version to analyze a 36-bus reduction of the network in New York and New England. In the first case study, the effects of adding the cost of ramping conventional generators into the optimizing criterion are analyzed to determine how ramping affects total operating costs

[1] The name SuperOPF reflects the fact that the optimizing criterion minimizes the expected cost over a super set of system states.

and the amount of potential wind generation that is spilled. In the second case study, coal capacity at a remote location is replaced by wind capacity to determine how the uncertainty of wind generation affects total system costs while ensuring that conventional generators are financially viable. The basic tradeoff is between the lower operating costs with wind generation and the higher amount of "missing money"[2] paid to conventional generators. The third case study uses the multi-period capabilities of the second generation SuperOPF to analyze the effects of utility-scale storage and deferrable demand[3] on system costs for a network with stochastic wind at multiple locations.

1.2 Overview of the Problem

This project evaluates the effects of using controllable load and storage capacity to offset the effects of intermittent wind generation on overall system performance and on the operating costs and revenues for different loads and generators. The project has developed an analytical framework that can be used to evaluate technologies, such as Plug-in Hybrid Electric Vehicles, thermal storage (ice batteries) and batteries, and assess their effects on system reliability and costs. This task was accomplished by enhancing the current capabilities of the SuperOPF developed at Cornell to model sequential time periods that capture the effects of daily load cycles, storage charge/discharge cycles, and the ability to shift load among time periods. With both controllable load and storage, less conventional generating capacity is needed for reserves and there is less wear and tear on the generators assigned to follow load net of wind generation. The SuperOPF is shown to be well suited for evaluating how adding wind capacity affects both the reliability of the network and the financial implications for conventional generators and customers.

A significant part of this project was allocated to modifying the SuperOPF to model sequential time periods and capture the effects of daily load cycles, storage charge/discharge cycles, and the ability to shift load among time periods. This modification is the first step toward adding a unit commitment capability to the SuperOPF, part of ongoing research efforts at Cornell.

One benefit of the project has been to develop an analytic understanding of the system effects of the inherent variability of wind generation, in terms of both reserves requirements and costs. A second benefit is the availability to PSERC members of a new analytical tool, the new version of the SuperOPF, for the analysis of specific regional case studies.

1.3 Report Organization

Chapter 2 presents the wind resource data and the forecasting methods used to develop inputs of wind power generation for the SuperOPF. Chapter 3 introduces a framework for determining an optimal strategy for using hour

[2] Missing money corresponds to the revenue paid to conventional generators above earnings in a wholesale market through, for example, a capacity market.

[3] Deferrable demand refers to decoupling the purchase of energy from the grid from the delivery of an energy service to customers. Charging the batteries in electric vehicles and thermal storage are two important examples.

ahead and 10-minute ahead demand response resources to mitigate wind variability. The report next introduces three case studies using the SuperOPF. In Chapter 4, the objective is to evaluate the effects of ramping costs on the level of reserves needed, the system costs and the amount of potential wind generation spilled. Chapter 5 discusses the issue of financial adequacy for conventional generators for a system with a high penetration of wind generation. Finally, Chapter 6 uses the new multi-period version of the SuperOPF to demonstrate how coupling wind with storage results in a higher dispatch of wind generation, lower levels of reserve capacity for ramping and lower overall system costs. With deferrable demand there are additional benefits of a lower peak load and less congestion on the network compared to a system with equivalent storage capacity collocated at the wind sites.

2. Modeling Wind Data and Wind Power Generation Forecasts

This chapter discusses the modeling of wind power data performed for this report. The analysis presented below proceeds along the following stages. First, wind speed data for locations in the Northeast were obtained from the National Renewable Energy Lab [1]. Next, the wind speed data were converted to aggregated wind farm power output. The regional wind power generation data are analyzed with an ARMA model of order one, in order to develop an hour ahead forecast.

2.1 Identifying Wind Farm Locations

The basic properties of the wind are its speed, direction, and fluctuations in this speed and direction. These properties are affected both by local terrain, in terms of vegetation, buildings, and topography, and by the height of the wind above these features. The data for this study is obtained from the National Renewable Energy Lab Eastern Wind Integration Transmission Study database (NREL EWITS) [1].

A geographic representation of the test system to be fully discussed in Chapter 4 is shown in Figure 2.1.

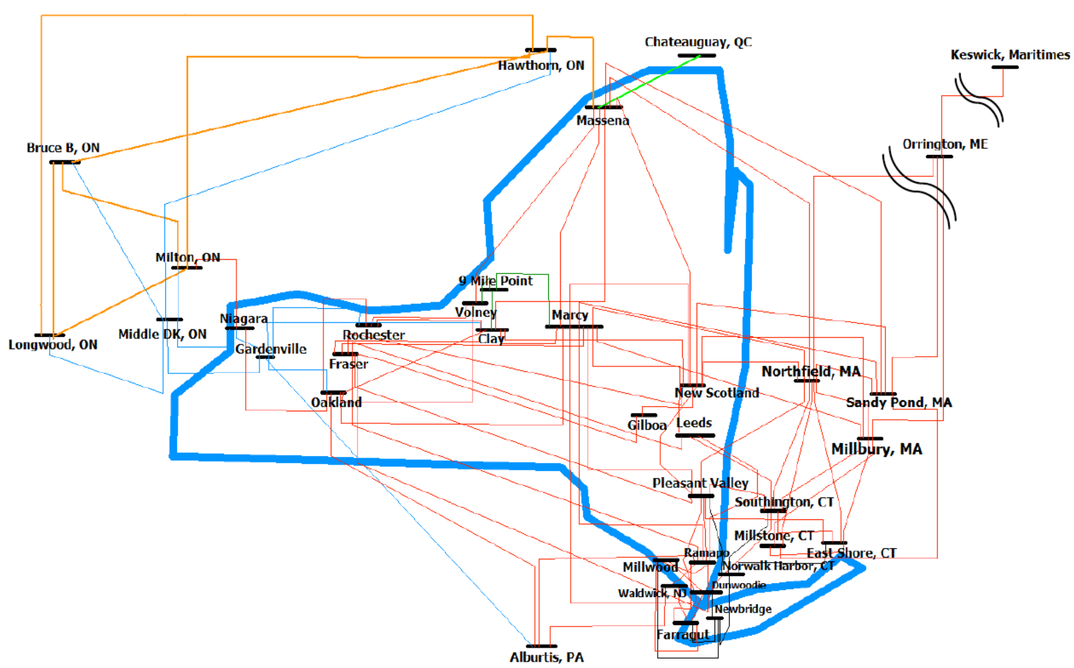

Figure 2.1 Test System with Buses Geographically Located

Using singular component analysis to analyze the available wind sites as identified in the EWITS database, results for New York State are shown in Figure 2.2 and Table 2.1. The data for New England is shown in Figure 2.3 and Table 2.2.

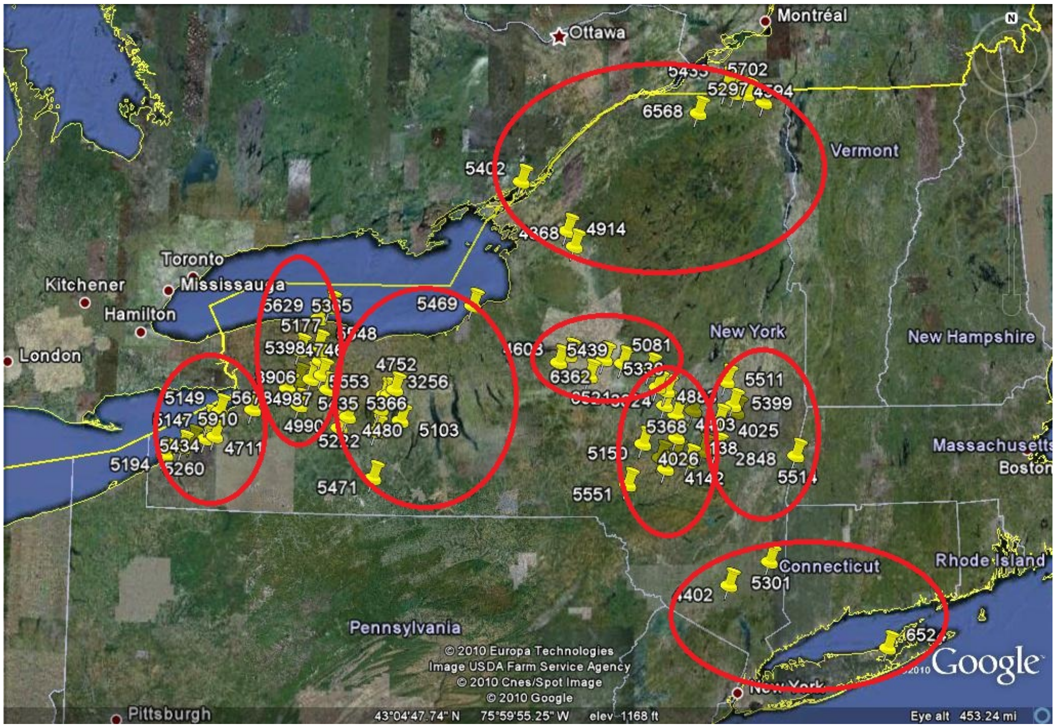

Figure 2.2 EWITS Wind Data Locations in New York

Table 2.1 Wind Power Potential at New York Clustered Buses

NPCC Bus	Potential MW
Niagara	3031.6
Fraser	3810.5
Rochester	1587
Massena	2476.7
Marcy	1133.6
New Scotland	1407.4
Pleasant Valley	1095.7
Ramapo	199.3
Farragut	117.6
TOTAL	14859.4

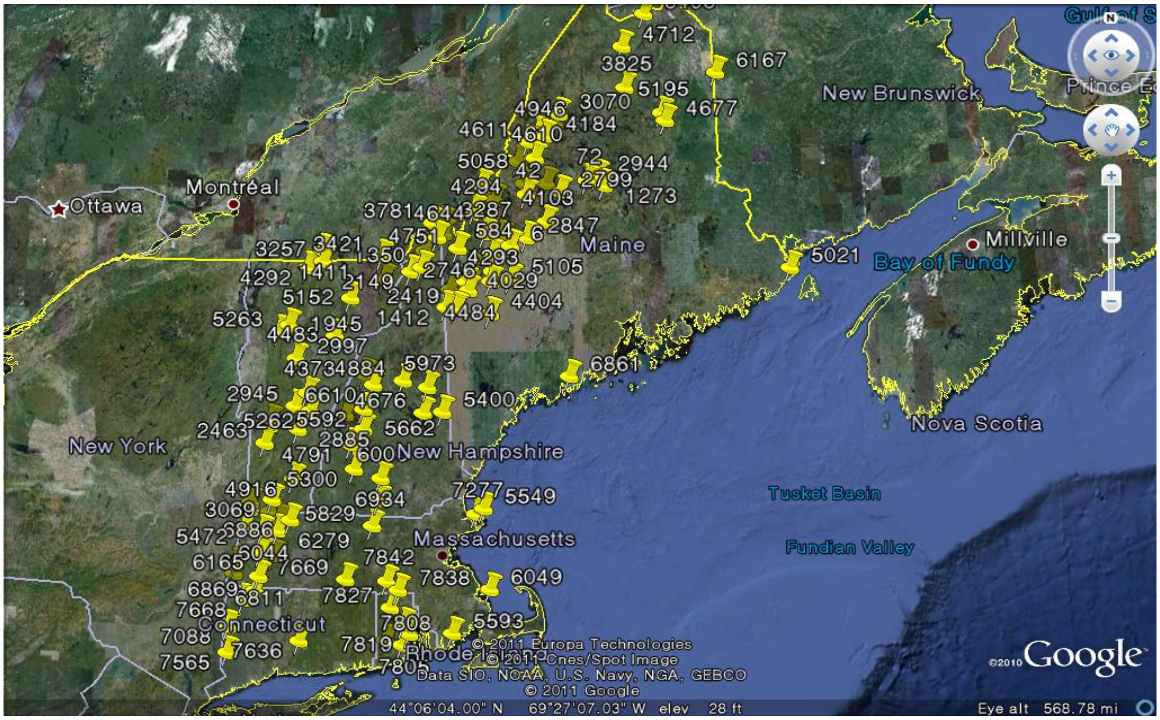

Figure 2.3 EWITS Wind Data Locations in New England

Table 2.2 Wind Power Potential at New England Clustered Buses

Cluster	Test System Bus
Group 1	Southington, CT
Group 2	Millbury, MA
Group 3	Northfield, MA
Group 4	Sandy Pond, MA
Groups 5, 6, & 7	Orrington, ME

2.2 Converting Wind Speed Data to Wind Turbine Power Output

The power generation from a wind farm is modeled using time series wind speed data that is translated to power output using a turbine power curve. Ten-minute wind speed data from EWITS is used in conjunction with the GE 2.5MW turbine power curve [2] to represent the output from a 580 MW wind farm. This hypothetical wind farm represents approximately 10% of the generating capacity in the test system. To capture the effect that geographic diversity has on decreasing the variability in wind power generation, the method presented in [3] was implemented. This algorithm involves adjusting the wind speed data that was recorded at a single point with a moving block average to represent the wind speed across the wind farm. The specific algorithm was tested and implemented by researchers in Denmark and Finland in [3] for wind resources in Nordic countries. The turbine power curve is also adjusted as part of the algorithm in [3] to represent the effective aggregated power curve from the multiple turbines in the wind farm.

The adjusted wind speed data is translated to power output using the aggregated power curve. Figures 2.4, 2.5 and 2.6 show the original and adjusted wind speed data, power curve, and power output respectively, demonstrating the positive role of geographic diversity in decreasing the variability in wind power generation.

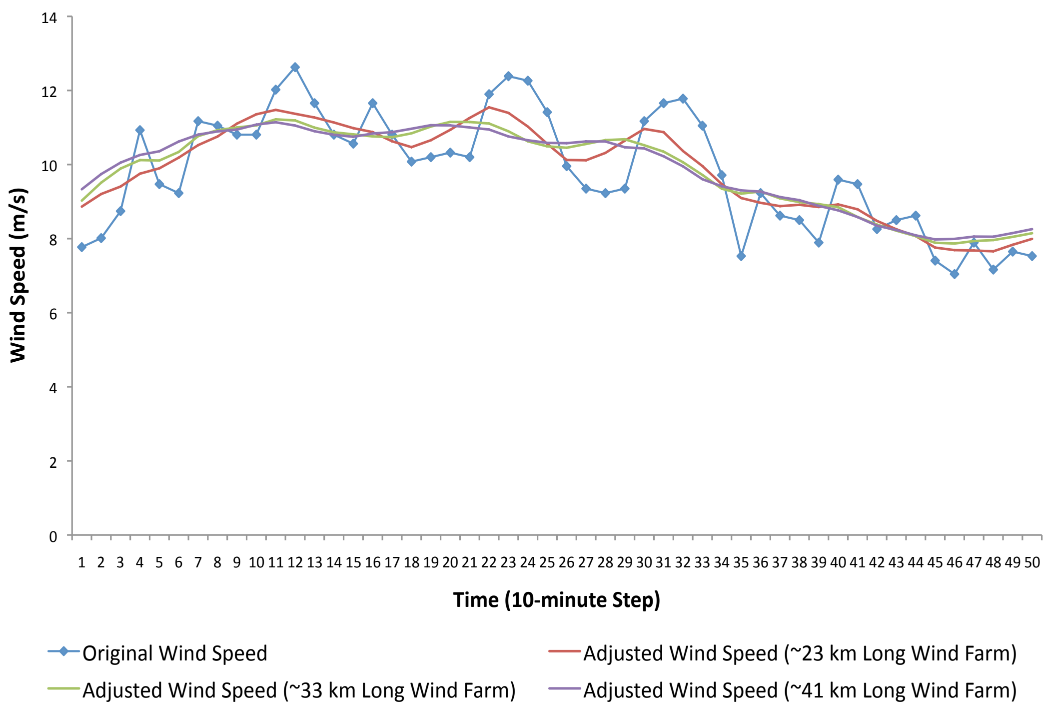

Figure 2.4 Windspeed Data Geographically Adjusted for Diversity

As illustrated in Figure 2.4, the effect of adjusting this wind speed data for diversification causes a reduction in the variability of the wind speed time series. It is shown in Figure 2.5 that the resulting power curve has a slightly smoother transition at the cut out speed of the turbine. In reality, this effect would result from the spatial diversity of the wind across the area of the wind farm.

The final result of this diversification is summarized in Figure 2.6. This figure shows the wind power output from a theoretical wind farm using the original windspeed data with the theoretical turbine power curve, as well as the adjusted wind speeds with the power curve (shown in Figure 2) representing a small wind farm of approximately 25 square kilometers.

The decrease in variability in the wind speed and the power output is shown in figures 1 and 3 respectively. These adjustments model the actual decrease in wind variability as experienced in aggregate across the geographic area of a windfarm in comparison to the wind variability at a single point, as developed in

[3].

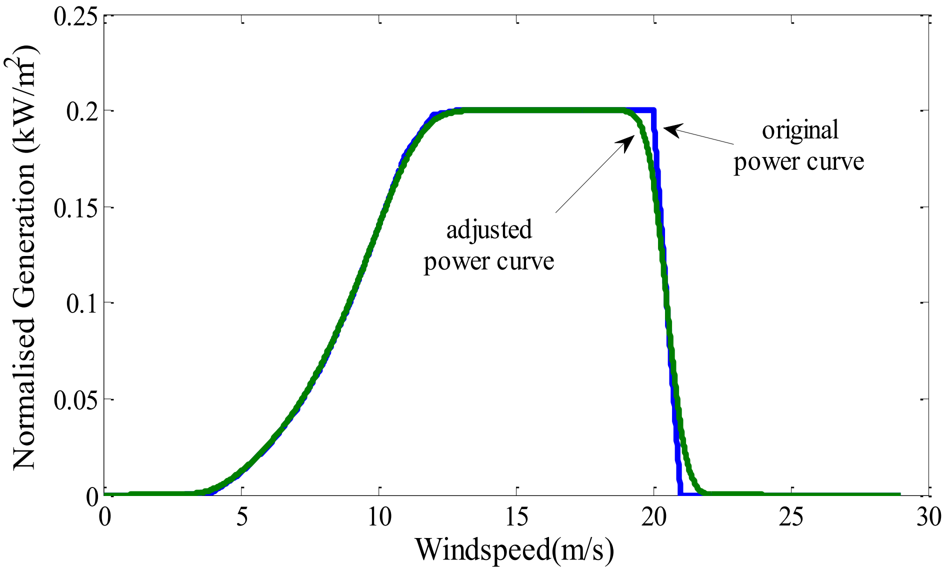

Figure 2.5 Original and Aggregated GE 2.5MW Power Curve

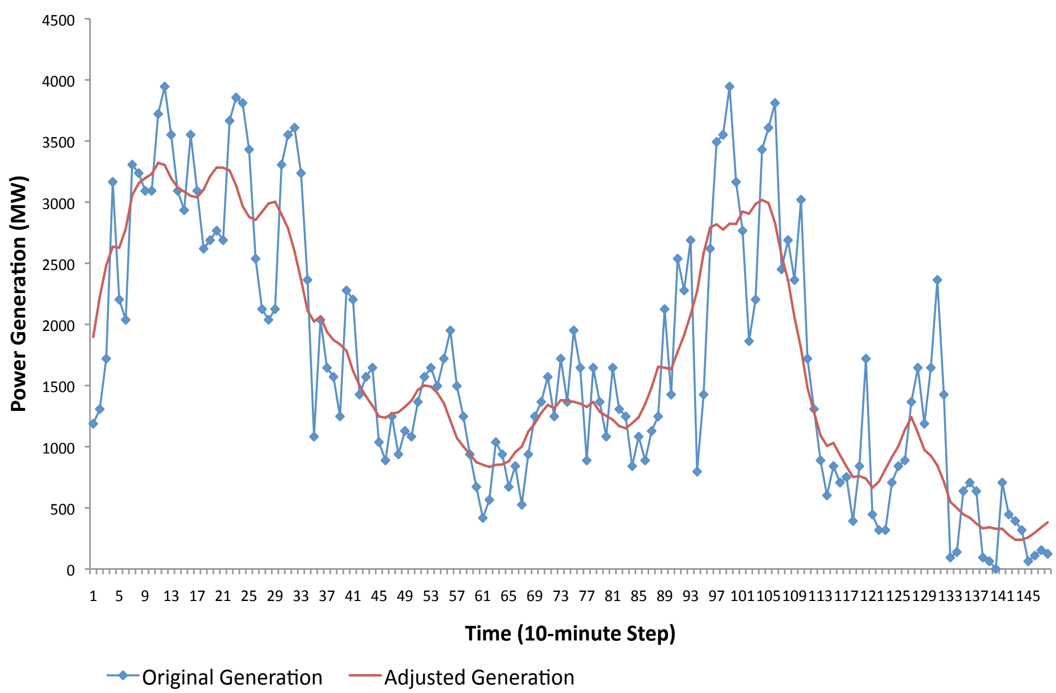

Figure 2.6 Windfarm Output: Original and Adjusted

2.3 Auto-Regressive Model for Day-Ahead Wind Power Forecast

The area of wind forecasting is advancing rapidly and many sophisticated models exist for forecasting wind speeds over various time horizons [4] – [8]. For the purposes of this paper, we develop a first-order ARMA model, as has been used in early wind speed and wind power forecasting [9] – [10], and proposed here predominantly for use in forecasting the next-ten-minute wind power output. The purpose of this model is to provide a basis for developing a mechanism to forecast wind output variability, at the wind farm level, and then mitigate this variability through the use of an alternative, dedicated resource such as demand response. Although a more sophisticated forecasting technique would improve the accuracy of the forecast, it would also likely require more time to actually calculate the forecast. The approach used here, of a first order ARMA model, is fast enough to be implemented for the ten-minute time frame and is sufficiently accurate for our exploration of using dedicated demand response resources for reducing wind power generation variability.

Wind speed data at ten minute intervals was obtained from the EWITS database. The wind speed data is converted to theoretical wind power output using geographic aggregation algorithm described below.

The development of the day-ahead forecast is discussed next. For developing the forecasts for the next hour and next ten-minute wind power generation, a first order autoregressive model is used. This model takes the form:

$$X_t = \alpha + \beta X_{(t-1)} + \varepsilon_t \qquad 4$$

The resulting parameters for sample data for Dartmouth MA [11] this model are summarized in Table 2.3.

Table 2.3 Autoregressive Model Parameters

parameter	10 Minute-Model	Hour-Ahead Avg. Model
Site 1		
α	106.7	138.5
β	0.90	0.87
R^2	0.81	0.76
Site 2		
α	34.4	51.25
β	0.943	0.92
R^2	0.89	0.84
Site 3		
α	163.7	195.1
β	0.87	0.84
R^2	0.75	0.70
Site 4		
α	149.6	196.7
β	0.88	0.84
R^2	0.77	0.70
Site 5		
α	76.5	97.4
β	0.92	0.90
R^2	0.85	0.82

It is interesting to note that the accuracy of the average hour-ahead AR(1) model is slightly higher than the model developed for the 10 minute-ahead prediction. However, the hour-ahead model uses the previous hourly average to predict the average wind generation in the next hour. The effect of averaging this data over six ten-minute time intervals is to dampen the fluctuations. As a result, the AR(1) is slightly more effective at predicting hour-ahead than 10-minute ahead observations.

Using data from the EWITS database for Nantucket Sound, sample results of these models applied to the forecasting of hour-ahead time series are provided in Figure 2.7. Visual inspection of the data in Figure 2.7 indicates that the AR(1) forecasting model, while not as sophisticated as those used in practice, does provide a reasonable basis for discussing the framework presented in this report.

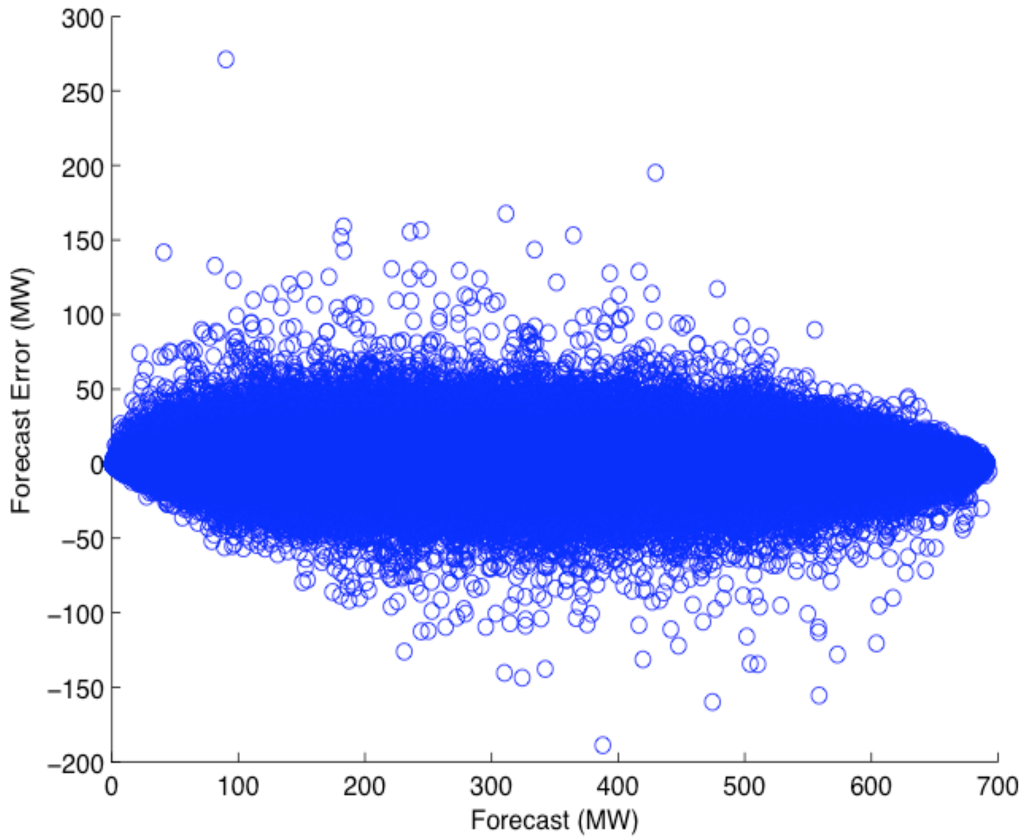

Figure 2.7 Forecast vs. Error (AR1 Model)

2.4 K-Means Clustering

To represent the probability of wind power generation at one time period at a specific output level transitioning to a new, specific output level in the next time step, a K-means clustering algorithm is applied. For example, if wind farm output is categorized as high, medium and low, there will be specific probabilities associated with an output level of high, medium or low in the next time step.

References

[1] National Renewable Energy Laboratory, “NREL: Wind Systems Integration – Eastern Wind Integration and Transmission Study,” http://www.nrel.gov/wind/systemsintegration/ewits.html.

[2] GE Energy, 2.5MW Series Wind Turbine, [Online]. http://www.gepower.com/prod_serv/products/wind_turbines/en/2xmw/index.htm

[3] P. Nørgaard and H. Holttinen, "A Multi-Turbine Power Curve Approach," Presented on the Nordic Wind Power Conference, Göteborg (SE), pp. 1-2, 2004.

[4] R. Zavadil, J. King, N. Samaan, and J. Lamoree, "Final Report - 2006 Minnesota Wind Integration Study Volume 1," EnerNex Corporation, Technical Report November 30 2006.

[5] GE Energy Consulting, "Intermittency Analysis Project: Appendix B Impact of Intermittent Generation on Operation of California Power Grid," PIER Final Project Report, CEC-500-2007-081-APB, July 2007.

[6] EnerNex Corporation, “Final Report – 2006 Minnesota Wind Integration Study Volume 1,” Nov. 30, 2006, [Online] Available: http://www.puc.state.mn.us/docs/windrpt_vol%201.pdf

[7] WindLogics, Inc. St. Paul, MN. www.windlogics.com.

[8] AWS Truewind, LLC., Troy, NY. www.awstruewind.com

[9] M.C. Alexiadis, P.S. Dokopoulos, and H.S. Sahsamanoglou. “Wind Speed and Wind Power Based on Correlation Models,” *IEEE Transactions on Power Conversion*. vol. 14, no. 3, Sep. 1999.

[10] L. Söder, “Simulation of Wind Speed Forecast Errors for Operation Planning of Multi-Area Power Systems,” in *Proc. 8th International Conference on Probabilistic Methods Applied to Power Systems*, Iowa State University, Ames, IA, Sep. 2004.

[11] Center for Energy Efficiency and Renewable Energy. University of Massachusetts. Amherst, MA. [Online]. Available: http://www.ceere.org/rerl/publications/resource_data/index.html

3. A Decision Framework for Optimal Pairing of Wind and Demand Response Resources

3.1 Overview

Day ahead electricity markets do not readily accommodate power from intermittent resources such as wind because of the scheduling difficulties presented by the uncertainty and variability in these resources. Numerous companies have developed methods to improve wind forecasting and thereby reduce the uncertainty in a day ahead schedule for wind power generation. This chapter introduces a decision framework for addressing the inevitable remaining variability resulting from imperfect forecasts. The framework uses a paired resource, such as demand response, gas turbine or storage, to mitigate the generation scheduling errors due to wind forecast error. The methodology determines the cost effective percentage, or adjustment factor, of the forecast error to mitigate at each successive market stage, e.g., one hour and 10 minutes ahead of dispatch. This framework is applicable to any wind farm in a region with available pairing resources, although the magnitude of adjustment factors will be specific to each region, as the factors are related to the statistics of the wind resource and the forecast accuracy at each time period.

Historical wind data from New England are used to illustrate and analyze this approach. Results indicate that such resource pairing via the proposed decision framework will significantly reduce the need for an ISO to procure additional balancing resources when wind power participates in the markets.

3.2 Introduction

Many states in the US have passed either voluntary or mandatory requirements for a percentage of energy in their region to be served by renewable resources [1]. With hydro resources already exploited in most regions, it is assumed that wind power will be a main contributor in meeting these new standards. Though the energy generated by wind turbines is close to zero cost, non-zero costs are incurred when the power system as a whole responds to the uncertainty and variability associated with the wind resource itself. These costs arise from the need to dispatch other resources to ramp up or down in order to mitigate wind power deviating from its forecasted output.

System analyses often focus on the costs of using the existing power system, and hence conventional technologies such as gas turbines, to mitigate wind [2, 3] and increasingly include the option of storage as well. A third option is to use responsive demand to mitigate the variations in wind output that arise from forecasting errors.

This chapter presents a methodology to reduce the net variability of the wind power output, and so allow wind to participate more fully in forward markets. The proposed methodology uses power generation forecasts one hour, and ten minutes ahead of dispatch. These forecasts are compared, successively, to the submitted day-ahead schedule in order to quantify the expected MW deviation in output (i.e., the variability) for the next time period (hour and ten-minute). The proposed framework next schedules a dedicated paired resource, such as responsive load or storage, to mitigate the deviation from the day-ahead schedule. The optimal amount of the forecast error to be mitigated at an hour- and ten minutes ahead of real-time is determined through the proposed methodology.

Results demonstrate that the optimum level of mitigation with the paired resource is related to the relative costs of the resource, the accuracy of the wind forecast, and the penalty imposed for spilling wind energy. The capacity of a paired resource that would be required and the costs associated with the use of responsive load as the pairing resource are presented in a case study.

Section 3.3 discusses the government regulations and recent state-level developments related to the participation of wind generation in electricity markets. Section 3.4 presents the results of the modeling and quantifies the capacity that would be required from each of the paired resource options in order to maintain the net wind generation output to within acceptable deviation from the submitted day ahead schedule. Section 3.5 outlines the wind speed data used and section 3.6 presents results and conclusions.

3.3 Wind Power and Electricity Markets

Electricity market structures operated by Independent System Operators (ISO) in the United States include day ahead, hour ahead and real time markets, as well as an increasing number of ancillary services markets. As investment in wind generation grows and regional expansion plans include possibilities for significant wind capacity, the uncertainty and variability in wind generation do impose real costs on system operation in terms of efficient unit commitment, and through providing services such as balancing and regulation.

The characteristic of uncertainty in wind generation can be addressed to some extent by improving the accuracy of forecasting the wind resource. To this end, the Minnesota Public Utilities Commission ordered a study to investigate the impacts of incorporating wind generation at the level of 20 percent of retail electricity sales by the year 2020 [4]. For this study, sophisticated meteorological modeling was performed by WindLogics [5] for the years 2003, 2004 and 2005. The results of this study demonstrated that the day ahead forecast errors were as low as 20 percent. In addition, the broader analysis as performed by EnerNex found that as spatial and geographic diversity of the wind turbine sites increased, the error decreased by up to 43 percent [4].

A report conducted by GE Energy consulting on behalf of the CAISO [6], showed that the implications of ignoring forecasts were so significant that a central forecasting approach was implemented. A mechanism to facilitate the use of the state-of-the-art wind forecasting has been implemented in California through the Participating Intermittent Resource Program, PIRP [7] [8]. If the participating resources submit schedules consistent with the ISO-approved forecasts, then they are not subject to penalties for deviations from the forecasts.

The PIRP in California has been operating since August 2004, and achieved cumulative average deviation of the forecast close to one percent by 2005 and 2006 [9].

A recent study from the New York ISO provides a detailed analysis of the impacts of increasing wind penetration on power system operations and the need for transmission system expansion [2]. The analysis is based upon serving 'net load,' determined by subtracting the variable wind generation from the variable load data series. As with many previous analyses, the NYSIO study assumes wind plants will operate in the markets as price takers, which allows this use of net load.

These state level analyses and programs demonstrate that wind forecasting decreases the uncertainty in day ahead schedules, and when combined with flexible market structures and settlements facilitate increased involvement of wind power generation in the day ahead markets.

Some of the inherent variability in wind generation remains though, even as the uncertainty is reduced. To address this variability, this chapter investigates pairing wind output with responsive demand in order to reduce the variability in the net wind output. On the surface, this appears similar to using a net-load data stream as in the NYISO study. The difference is that for the analysis presented in this chapter responsive load (not the entire system load) is actively paired with wind, and both are assumed to participate in the markets. Recent advances in demand response that would enable this pairing are discussed in earlier work from this project [10].

A contribution of the analysis presented in this chapter is to advance the discussion of whether wind plants can and should participate fully in electricity markets. Such an assumption carries with it the need to demonstrate that such participation will not degrade the efficiency of the markets or harm system operations. This chapter demonstrates the ability of wind to participate in electricity markets as facilitated by the proposed method for mitigating the day-ahead schedule deviations with optimized dispatch of demand response. This method addresses the issue of whether wind will or should always assume a passive price-taker role in electricity markets, or whether, as the presence of wind increases significantly, so should its active participation in more aspects of power system and electricity market operations.

3.4 A Framework for Pairing Wind and Demand Response Resources

The proposed framework, discussed in this section, determines the optimal amount of a paired resource to schedule in order to mitigate the variability in wind power generation. The proposed framework uses updated wind forecasts at each market stage to schedule the pairing resource, as the time horizon approaches real time dispatch. The amount of the paired resource scheduled at each time period is related to the magnitude of the discrepancy between the updated forecast and the day ahead schedule.

At each time period considered, the shortfall or overshoot of forecasted wind production is assessed and the need for demand response or other paired resources is determined. The framework is shown in Figure 3.1. As seen in this flow chart, the first step is to compare the day ahead schedule to the hour ahead schedule (both discussed in more detail below). The result of this comparison is a MW value of generation shortfall or excess expected between the day ahead and hour ahead schedules; see box 3 in Figure 3.1. Based on the magnitude of this discrepancy, a decision will be made whether to activate the demand response resource or not; see box 4 in Figure 3.1. The purpose of this assessment one hour ahead of dispatch is to take advantage of the additional weather information available and to be able to utilize slower responding resources to mitigate some fraction of the expected scheduling deviation. Since further deviations are expected between the hour ahead schedule and real time output though, the paired demand response resource will never be dispatched to meet completely the deviation between the day ahead and hour ahead schedules. The framework developed below is used to determine the optimal portion of the mismatch to mitigate at each time step. The remaining excess or shortfall in wind power output will be addressed with faster responding demand response alternatives, to be dispatched after each next-ten-minute forecast is made, boxes 6–8 in Figure 3.1.

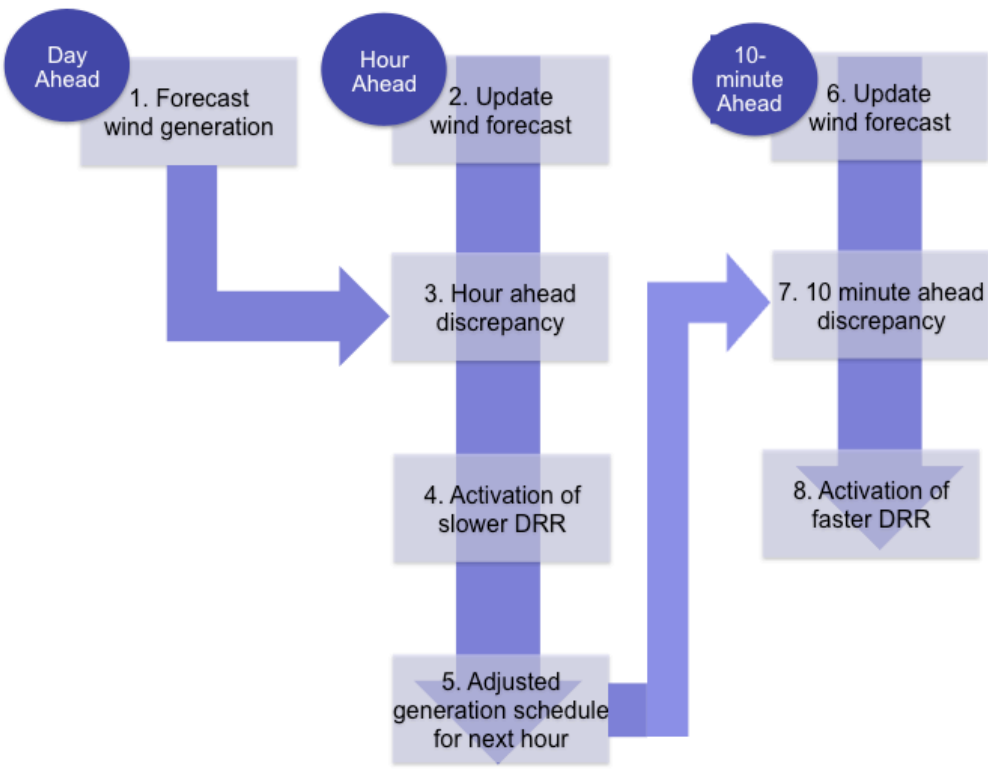

Figure 3.1 Flowchart for Deciding Use of Paired (demand response) Resource

3.4.1 Day Ahead Forecast

The day ahead forecast determines the day ahead schedule (G1) for the wind farm. For this project a linear persistence model is used for forecasting wind generation one day ahead.

$$G_1 = \alpha_{24\mathrm{h}} + \beta_{24h} P_{24h}, \quad (3.1)$$

where α_{24h} and β_{24h} are regression parameters and P_{24h} is the wind generation observed twenty-four hours ahead.

Though more sophisticated forecasting algorithms are required for actual wind farm scheduling, for purposes of illustrating the proposed framework the linear regression model is sufficient. Figure 3.2 provides a sample histogram of forecast errors as a percentage of capacity for a single site in New England. The Mean Absolute Error (MAE) corresponding to this data is approximately 5%. This corresponds well to the forecasting accuracy of the NYISO at 4.8% of the hour ahead forecast [7].

3.4.2 Hour Ahead Corrections

Though the day ahead forecast is useful for initial day ahead scheduling, better information on wind speed is available in the hour ahead time frame. Though the most accurate wind speed data will not be available until five to ten minutes ahead of actual dispatch, a first estimate of the final discrepancy between the day ahead forecast and real time generation can be made 60 to 90 minutes ahead of real time. The correction an hour ahead of dispatch is determined by the discrepancy, Δ_{1h}, between the day ahead schedule and the updated hour ahead forecast (determined 90 minutes in advance of dispatch).

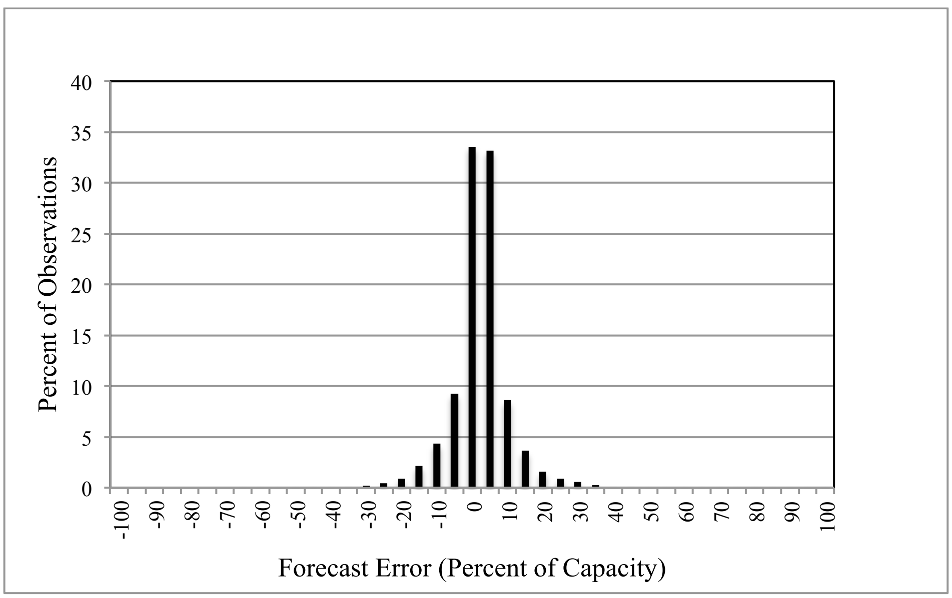

Figure 3.2 Distribution of Forecast Errors as Percent of Capacity

Once again, a regression model is used for forecasting. At one hour ahead, the accuracy of a persistence model is significantly higher than it is day ahead.

$$\Delta_{1h} = G_1 - \left(\alpha_{1h} + \beta_{1h} P_{1h}\right), \text{ and}$$
$$\mathrm{DR}_{1\mathrm{h}} = \begin{cases} \Delta_{1h}\gamma_{1h} & \text{if } \Delta_{1h} > 0 \\ 0 & \text{otherwise} \end{cases} \qquad 3.2$$

where DR_{1h} is the quantity of demand response resource to schedule one hour ahead of dispatch, γ_{1h} is the fraction of forecasted deviation to cover with the paired resource, one hour ahead.

A main contribution of the framework proposed here is to determine the value of γ_{1h} (and of γ_{10M}, see below) that will trade off between minimizing the deviation in wind generation in real time with minimizing the cost of dispatching the paired resource. The case study in section V demonstrates the process for selecting γ_{1h} and γ_{10m}.

3.4.3 Ten-minute Ahead Corrections:

Ten minutes before real time dispatch a third forecast is determined. At this time, the discrepancy between the hour ahead schedule and ten minute forecasts is estimated (box 7 in Figure 3.1), where this discrepancy, Δ_{10M}, is between the day ahead schedule and the sum of the 10 minute forecast and scheduled demand response resulting from the hour ahead forecast, DR_{1h}. This is described as follows:

$$\Delta_{10M} = G_1 - DR_{1h} - \left(\alpha_{10M} + \beta_{10M} P_{10M}\right), \text{ and}$$
$$DR_{10M} = \begin{cases} \Delta_{10M}\gamma_{10M} & \text{if } \Delta_{10M} > 0 \\ 0 & \text{otherwise} \end{cases} \qquad 3.3$$

where γ_{10M} and DR_{10M} are the fraction of forecasted deviation to cover and the quantity of demand response resource to schedule ten minutes ahead, respectively (box 8 in Figure 3.1).

3.4.4 Minimizing Paired Resource Costs Associated with this Strategy

The final step in the proposed framework uses the cost of the demand response resources that are utilized across all time scales. The fractions of the shortfall or over-generation to mitigate at each decision point, γ_{1h} and γ_{10M}, are estimated by minimizing the overall cost of paired resources in this strategy. This cost is given by

$$C_T = \Delta_{1h}\gamma_{1h}C_{1h} + \Delta_{10M}\gamma_{10M}C_{10M} + \Delta_{RT}C_{RT}$$

The fractions to mitigate at both the one hour and ten minute ahead time horizons are determined by selecting the mitigation fractions (γ_i) to minimize the overall cost of the strategy. In order to simplify notation, henceforth the decision points will be denoted with numbers [1, 2, 3] representing hour ahead, 10 minutes ahead, and real time, respectively. The overall framework is presented mathematically as follows:

$$\begin{aligned}
&\underset{\gamma_i,\, i=1,2,3}{\operatorname{argmin}}\left[C_T = \gamma_1\Delta_1^{+}C_1 + \gamma_2\Delta_2^{+}C_2 + \Delta_3^{+}C_3 + \Delta_3^{-}C_P\right]\\
&\text{Subject to}\\
&C_{RT} > C_{10M} > C_{1h} > 0\\
&C_p \geq 0\\
&0 \leq \gamma_i \leq 1, \text{for } i = 1,2,3
\end{aligned} \tag{3.4}$$

Note that it is assumed here that $C_{1h} < C_{10M} < C_{RT}$. In fact, the actual costs are not important in determining the appropriate mitigation fractions (γ) as long as the relative costs can be estimated. Also note that over-generation penalties can be included in this framework by defining the penalty cost for over-production as $C_P>0$, otherwise when $C_P=0$, there is no penalty for over-generation and the last term in the cost function (C_T) is zero.

The next step is application of this framework to a case study. For this purpose, wind data from Nantucket Sound in Massachusetts is selected and discussed in Section IV.

3.5 A Case Study Region: Nantucket Sound

In order to test the feasibility of this decision framework, a case study of a hypothetical wind farm is presented. The wind farm is modeled using data for Nantucket Sound, obtained from [11] and includes wind speed measurements at ten minute intervals.

In order to represent the aggregate output of a wind farm instead of a single turbine, the effects of geographic diversity across the installation area are considered. These effects inherently decrease the variability of the wind generation, and include two factors; the propagation of the wind and its associated dynamic events (e.g., wind gusts) through the wind farm, and the smoothing of the aggregate power curve due to multiple turbines. To model the decreased variability from the geographic diversity, the 10 minute raw data is processed based on the algorithm presented in [12], as discussed above.

3.6 Results

In this section, the decision framework from Section III is applied using the data from Nantucket Sound discussed in Section IV. The steps required for this analysis are: determination of the optimal mitigation fractions, γ_{1h} and γ_{10M}, implementation of the framework using historical data and forecasts, and analysis of cost and variability outcomes.

Note that these results do not represent a 24-hour time series simulation, but rather are analyses of distinct snap-shots at different time steps, gradually approaching real time, with the day-ahead schedule initiating the analysis as depicted in Figure 3.1.

3.6.1 Determining the Mitigation Fractions, γ_T

In section IV, the proposed decision framework was discussed as a general approach. The objective of this framework is determining the magnitude of the forecast error to mitigate with the alternative resource at each step. These magnitudes are represented by the parameter γ_T, where T denotes the time remaining to real time dispatch. As previously mentioned the value of γ_T must depend on the accuracy of the forecast and the cost of the pairing resource. The fact that forecast accuracy improves as T decreases (as the time to dispatch gets closer) means that each γ_T is likely to have a different value at each time horizon (T). However, faster ramping resources often have higher marginal costs, and therefore the cost of the pairing resource increases as T decreases.

Balancing these opposing factors is necessary in order to determine the optimal γ_T value for each T, and can be quantified by optimization. In order to frame the optimization, it is not necessary to know the *actual* costs of the alternative resources at each T, but only to know the *relative* costs. For illustration, we consider a range of demand response resources costs (DRR) and the resulting, γ_T, values. The optimization is straightforward and solved in this case study using Solver™ tool in Microsoft Excel.

Representative results from applying the equations in Section IV are provided in Figures 3.5 through 3.7. These figures illustrate the optimal mitigation fractions for hour-ahead and ten-minute-ahead demand response resources given different ratios of real-time to hour ahead resource costs. Note that each figure includes information for the mitigation factor, γ_T, at both time steps, hour ahead and ten-minute ahead, assuming any additional forecast error between the ten-minute ahead time frame and real time will be mitigated by the real time resources. In Figures 3.5 through 3.7, the x-axes represent an increasing *cost ratio* for real time to hour ahead demand response resources. Each figure then graphs the optimal γ_T values for mitigating wind variability first with hour-ahead DRR, γ_{1h}, and then with ten-minute ahead DRR, γ_{10m}. The figures differ in terms of the assumed fixed ratio of ten-minute ahead to hour ahead resource costs. For illustrative purposes, Figure 3.5 assumes a cost ratio of unity, Figure 3.6 a ratio of 1.5 and Figure 3.7 a cost ratio of 3.0, meaning that the relative cost of 10-minute resources is increasing through the figures. These figures are discussed in more detail below.

Figure 3.5 depicts a scenario in which the cost for demand response resources is the same at one hour and ten minutes ahead of dispatch. In this case, the optimal γ values show that no demand response resources should be used to cover deviations at an hour ahead, *i.e.*, the solid line for γ_{1h} is equal to zero for all real-time to hour-ahead DRR cost ratios. Since there is no additional cost incurred for waiting to mitigate the wind power forecast errors until ten minutes ahead of the real time dispatch, it is optimal to use the more accurate forecast at ten minutes before dispatch to make decisions on mitigating the wind variability. It is also shown in Figure 3.5 that unlike γ_{1h}, γ_{10m} (shown with the dashed line) varies with the ratio of real-time to hour-ahead DRR costs. For the scenario in Figure 3.5, in which the hour-ahead and ten-minute-ahead DRR have the same cost, the optimal fraction of the wind variability to mitigate in the ten-minute ahead time period increases to 100% for the situation in which real-time DRR costs are 150% or more of the cost of hour ahead.

Figure 3.6 illustrates the case of DRR that at 10 minutes ahead of dispatch, demand response costs are 150% of the hour-ahead resources. This difference is significant enough to overcome the cost associated with the forecast inaccuracies at one hour ahead. In this case, the expected deviation in wind generation at one hour ahead should be mitigated by the cheaper hour ahead DRR in entirety, even with the knowledge that the anticipated deviation is likely to change once the improved ten-minute ahead forecast is available.

Similar to the situation in Figure 3.5, for Figure 3.6 the mitigation fraction at ten minutes ahead, γ_{10m}, varies in a predictable way as a function of the cost of real time DRR. Initially none of the ten-minute ahead DRR are cost effective. Once the real-time costs reach twice the cost of ten minute resources however, the ten-minute mitigation factor, γ_{10m} γ_{10min} reaches 100%.

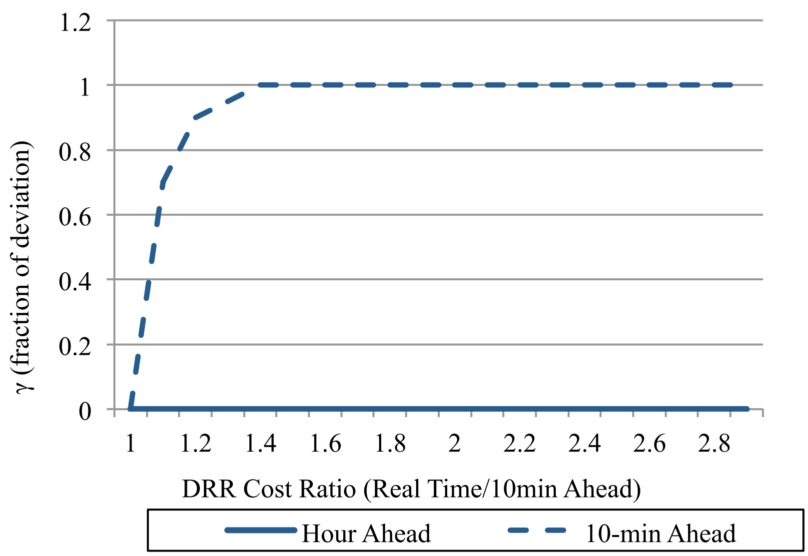

Figure 3.3 γ Values: DRR Cost 10 min Ahead/Hour Ahead = 1

Finally, Figure 3.7 shows similar results, but for the scenario in which the cost of ten-minute ahead DRR is twice that of hour ahead resources. In this situation it is also cost effective to mitigate the entire expected deviation with hour-ahead resources. In contrast to Figure 3.6, the results for Figure 3.7 show that it is not until the cost ratio for real time to hour ahead resources reaches 3.6 that it is optimal to mitigate the entire ten-minute ahead deviation with the ten-minute DRR.

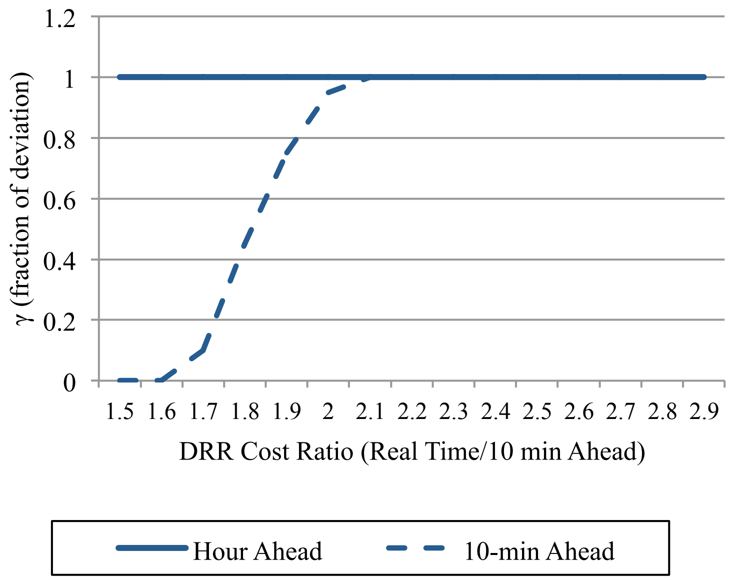

Figure 3.4 γ Values: DRR Cost 10 min Ahead / Hour Ahead = 1.5

Figures 5, 6 and 7 illustrate the optimal fraction of the wind scheduling error to be mitigated at each market stage, given different cost ratios for the demand response resources that can respond in the different market time periods. These figures are applicable when there is no financial penalty associated with scheduling errors.

In general, electricity market design has imposed a penalty on generators that deviate more than 1.5%, for example, from their schedule. This financial incentive to meet a submitted schedule is consistent with the operation of dispatchable generators. However, it has been recognized that such penalties are not consistent with the operation of generators that rely on an intermittent resource such as wind, since the operator of such a non-dispatchable generator would rarely be responsible for schedule deviations. Therefore, the penalties for scheduling deviations included in Open Access Tariffs are routinely waived for wind farms, at least at the current level of low penetration.

The case study presented here recognizes that the schedule deviation penalties could be imposed on non-dispatchable forms of generation as penetration of these resources increases. The case studies are not embedded in any specific market design, but rather include the possibility of such penalties and analyze their effect.

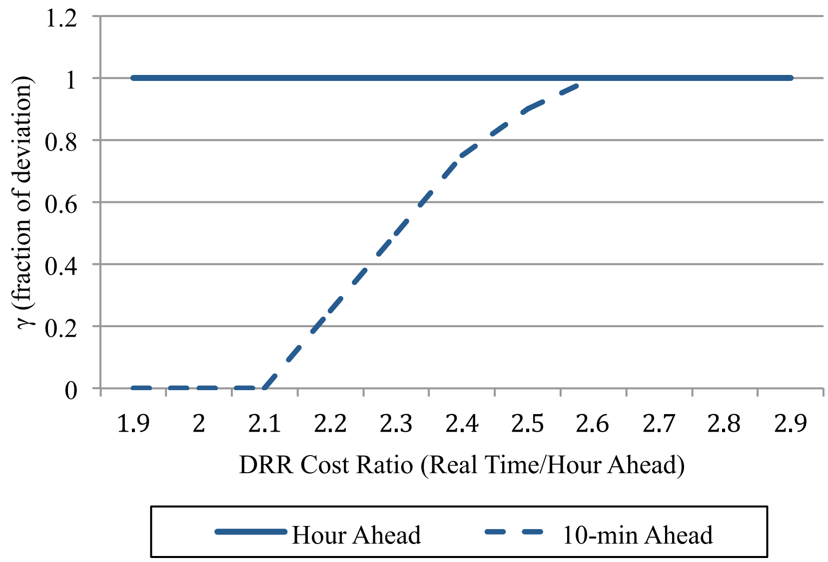

Figure 3.5 γ Values: DRR Cost 10 min Ahead / Hour Ahead = 3

Figure 3.8 builds upon the scenario in Figure 3.7 by analyzing the effect of a penalty for not meeting the submitted day-ahead schedule. If there were to be penalties imposed on wind generation for generation deviations in real time (based upon the day-ahead forecast), then there would be additional financial incentives to schedule a paired resource for mitigating the wind variability.

Figure 3.8 compares the cost effective mitigation fractions, γ1h and γ10M, when there is a penalty associated with over generation, in comparison with the same scenarios without over generation penalty. Note that this penalty could be a direct financial penalty imposed by an ISO, or could be the opportunity cost associated with unnecessarily spilling wind that appeared to be excess generation an hour or 10 minutes ahead of dispatch.

Figure 3.8 shows that with a penalty for over generation, the hour ahead mitigation fraction (γ_{1h}) does not ever reach unity, regardless of the fact that the resources that can respond one hour ahead are assumed to be only half the cost of the faster resources that respond in the 10 minute time frame. This result is consistent with the fact that if too much of the hour ahead DRR is scheduled, there is significant risk of incurring an over-generation penalty in real time.

Figure 3.8 also shows that it only becomes cost effective to mitigate the entire forecast error at the 10 minute time frame when the relative costs of real time to hour ahead resources reach a ratio of 3.8, when an over-generation penalty is imposed.

It is cost effective to cover the entire deviation at lower cost ratios, for both the hour- and 10 minute-ahead time frames, only when the wind generator is not penalized for over-generating.

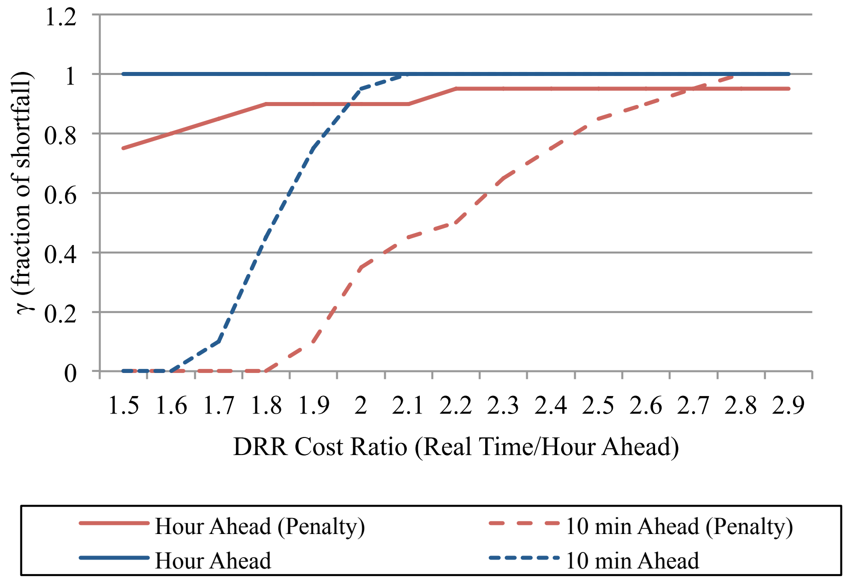

Figure 3.6 Comparison With and Without Spillage Penalty

The results for the particular γ_T shown here are specific to the data set from Nantucket Sound, the forecasting method uses, and the scenarios defined in Figures 3.5 through 3.8. The overall pattern of the results is useful for demonstrating implementation of the proposed decision framework for determining the amount of a paired resource to schedule for mitigating the uncertainty in wind power schedules.

In the next section, we further analyze the Nantucket Sound, case and the resources and costs associated with the implementation of this strategy for this case.

3.6.2 Cost Results for Nantucket Sound Case-Study

In considering the benefit of using of the proposed strategy for mitigating wind variability, it is important to consider the availability of the proposed pairing resources as well as the cost of implementation. To this end, we analyze the outcome of the decision framework using the Nantucket Sound site and DRR costs as shown in Table 3.1. These costs are consistent with Figure 3.8, and assuming the real time to hour ahead cost ratio (x-axis) to be 3.0.

Table 3.1 Assumed DRR Costs for Nantucket Sound

Demand Response Resource	*Cost ($/MW)*
Hour Ahead	$0.10/MW
10 Minutes Ahead	$0.15/MW
Real Time	$0.20/MW

For comparing the use of the proposed decision framework to two somewhat naive approaches, three scenarios with different sets of gamma values are analyzed, shown in Table 3.3.

The first scenario is the case in which no DRR used until real time, and the simplest approach. The second scenario represents arbitrary values, as would likely be chosen if there were no guiding decision framework. For this example, these values are selected to bracket the gamma values that would result from applying the decision framework proposed here. Thus the third set of gamma values are those obtained from Figure 3.9, assuming a real time to hour ahead cost ratio of 1.5.

Table 3.2 γ Values for Three Different Mitigation Strategies

γ_T	*Scenario 1*	*Scenario 2*	*Scenario 3:* γ_T from Figure 3.8
γ_{1h}	0	0.25	0.9
γ_{10M}	0	0.25	0.35

Using this strategy the annual usage of DRR is summarized for the three scenarios (described in Table 3.2) in Figures 3.7 through 3.10. These figures compare the DRR usage for each time step prior to dispatch: hour ahead, ten minutes ahead, and real time. Figure 3.10 illustrates a fourth scenario, when there is no penalty for over-production at the wind farm. In this case, the optimal gamma variables are γ_{1h}= 1.0 and γ_{10M}= 0.90.

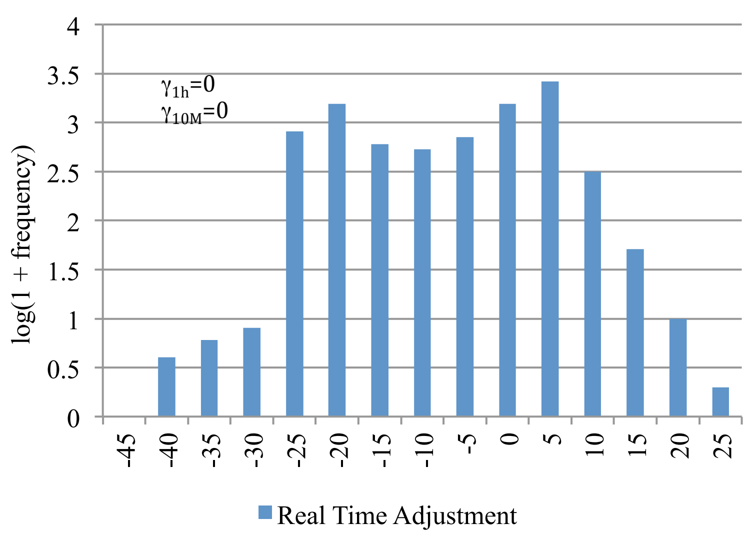

Figure 3.7 Histogram of Demand Response Usage, Scenario 1

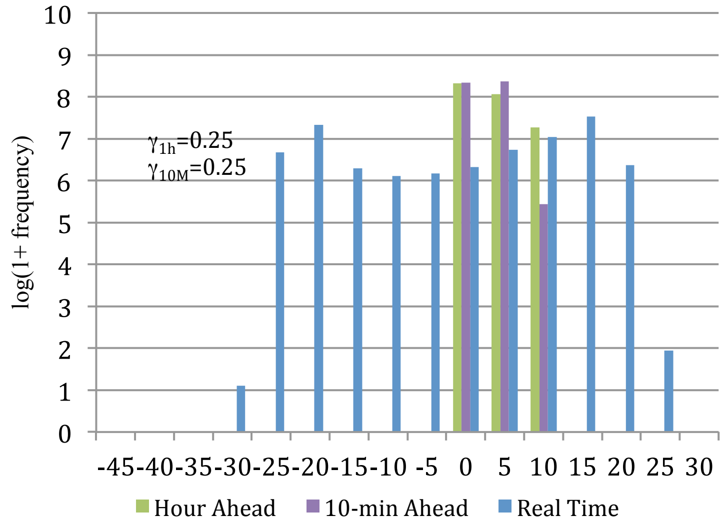

Figure 3.8 Histogram of Demand Response Usage, Scenario 3

Figures 3.7 through 3.10 show that the usage patterns of paired resources have an impact on cost. Of scenarios 1 through 3, where there is a minor penalty for overproduction, the optimal strategy (0.90, 0.35) is not intuitive but does produce lower overall costs for covering deviations. Table 3.3 summarizes the average non-zero use of demand response resources at each decision point, and the relative overall cost of alternative resources at for each of the scenarios discussed, with the naïve scenario as a baseline. It is interesting to note that if over generation penalties are not imposed, the decision framework proposed here can save over 200% of the cost of using demand response resources to mitigate wind power variability, as compared to a naïve strategy of mitigating the entire deviation in real time.

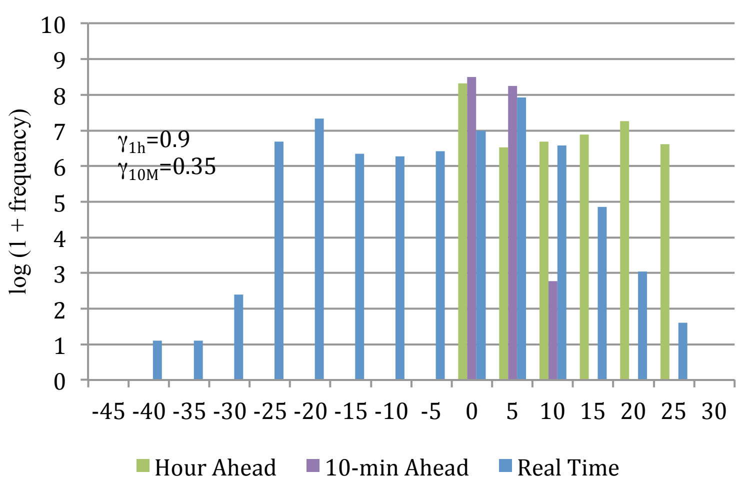

Figure 3.9 Histogram of Demand Response Usage, Scenario 3

It is important to consider both the relative costs these strategies and the availability of this level of DRR in the relevant region of New England. Therefore, in Table 3.4, we summarize the maximum single use of demand response resource usage for each scenario. In this table, TTD is the time to dispatch, for hour ahead (HA), 10 minute ahead and real time (RT) market stages.

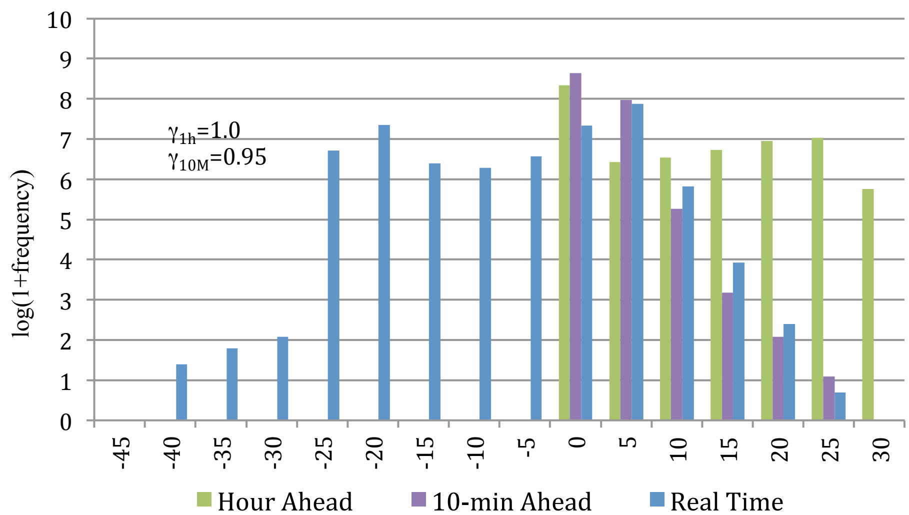

Figure 3.10 Histogram of Demand Response Usage, No Overproduction Penalty

Table 3.3 Average DRR Savings for Nantucket Sound Cases

Scenario	MW used (*10^3)				[4]Cost Savings (%)
	HA	10 M	Real Time		
			up	down	
1	0	0	3.5	-14	-
2	3.7	3.0	10	17	7%
3	13	1.0	3.9	16	15%
4	15	1.9	3.6	14	217%

The size of the largest single use of demand response resources at each decision point is important in assessing the resources necessary for implementing such a strategy. It appears that scenario two uses the smallest amount of paired resource. However, comparison with Table 3.3 and Figure 3.11 shows that real time DRR is used very frequently in this scenario. It is common in DRR contracts for the number of uses to be contractually limited, and therefore larger, less frequent uses might be more desirable. In the case without

[4] Savings are relative to naïve strategy of mitigating 100% of deviation at each time step.

over generation penalties, the average magnitude of over production in real time is actually smaller than in other scenarios, however data in Table 3.4 shows that there are a small number of over generation events that are larger than in the other scenarios. The optimal balance depends on the specific DRR contracts of the region, and as a result the optimal gamma values should be quantitatively determined on a case-by-case basis. It is also important to note that the error distributions can be non-stationary, especially with a basic forecast model such as the one implemented here. The use of more sophisticated (and proprietary) forecasting models will result in more reliable error statistics and therefore more confidence in the optimal mitigation fractions estimated.

Table 3.4 Maximum Single Use of DRR

Scenario	Maximum Single Usage (MW)			
TTD	HA	10M	RT (up)	RT (down)
1	27	22	21	45
2	6.7	5.7	23	31
3	24	7.8	22	43
4	27	21	21	44

3.7 Conclusions

In general, the uncertainty and variability in load is accepted as the basis for power system operations. These same characteristics in the wind resource raise significant obstacles for the integration of wind power generation into system and market operations. This chapter introduces an analysis of pairing wind generation with dedicated resource (e.g., demand response resources) in order to decrease the net variability of the wind generation.

Results from the application of this decision framework to a Nantucket Sound case study indicate that the balance between forecasting accuracy, availability, and cost of pairing resources (in this case demand response) is complex. Therefore determination of the optimal level of mitigation of forecasting errors at each time step must be determined quantitatively on a site by site basis using specific forecasting methods, cost ratios and wind data.

The results demonstrate that wind power can participate in day-ahead electricity markets through submitting schedules with price offers, and do not need to be restricted to participating as price-takers. The analysis presented here also shows that the imposition of penalties for over generation at wind farms is the major contributor to the cost of the strategy. This highlights the importance of market policy and rules, as well as the importance of accurate forecasting techniques for the successful implementation of wind in existing power markets and systems.

References

[1] Pew Center on Global Climate Change, "Renewable & Alternative Energy Portfolio Standards," ed. Press Release SB 459, 2009.

[2] New York Independant System Operator, "NYISO Wind Generation Study, Final Draft," NYISO June 2010.

[3] California Independant System Operator, "Integration of Renewable Resources," November 2007 2007.

[4] EnerNex Corporation, "Final Report - 2006 Minnesota Wind Integration Study Volume I," Dec 12 2006.

[5] WindLogics Inc. (2010. Available: http://www.windlogics.com

[6] GE Energy Consulting, "Intermittency Analysis Project, Appendix B: Impact of Intermittent Generation on Operation of California Power Grid," June 2007.

[7] J. Batchford, *et al.* (2010, May 6). Analysis of CAISO Participating Intermittent Resource Program (PIRP) Forecasting Methodology. *California Independant System Operator*, 1-9.

[8] D. Yen-Nakafuji, *et al.*, "Intermittency Analysis Project: Final Report," Jul 10 2007.Available:http://www.ncbi.nlm.nih.gov/entrez/query.fcgi?db=pubmed&cmd=Retrieve&dopt=AbstractPlus&list_uids=related:2dNcT1LlgNgJ

[9] A.W.S. Truewind. *AWS Truewind LLC*. Available: http://www.awstruewind.com

[10] C. L. Anderson and J. B. Cardell, "Reducing the Variability of Wind Power Generation for Participation in Day Ahead Electricity Markets," in *Hawaii International Conference on the System Sciences*, Waikoloa, Hawaii, 2008, p. 178.

[11] Center for Energy Efficiency and Renewable Energy and University of Massachussetts - Amherst. (2006. Available: http://www.ceere.org/publications/resource_data/index.html

[12] P. Norgaard and H. A. Holttnen, "A Multi-Turbine Power Curve Approach," presented at the Nordic Wind Power Conference, Goteberg, Sweden, 2004.

4. The Effects of Ramping Costs

4.1 The Problem[5]

The objective of this chapter is to present an analytical framework for evaluating how the ramping costs associated with the inherent variability of wind generation affect the optimal dispatch of conventional generating units. The major contributions are that the software used for the analysis 1) provides a stochastic framework for optimizing power systems operations with variable sources of generation (the SuperOPF), and 2) identifies how wholesale markets for electricity should be modified to provide the correct economic signals for energy storage, ramping capabilities and controllable demand that reflect the system costs/benefits of ramping services and also reduce the capital cost of maintaining System Adequacy. The scope of the analysis is, however, limited by the software because it only optimizes the dispatch of generating units for a single period. A multi-period version of the software is presented in Chapter 6.

The analysis focuses on internalizing the cost of ramping in the optimization used by an Independent System Operator (ISO). Previous work by Wang and Shahidehpour (1995) includes welfare considerations for optimal load shedding to support the provision of ramping services. Outhred (1998) discusses the market design used in Australia and the remuneration structure for allocating the cost of ancillary services, noting the concern about competition and the proper provision of these services. Shrestha et al (2004) evaluate different ramping services, from changes that do not affect rotor life, to changes in output that require compensation due to fatigue of the machinery elements. Zhang et al. (2000) include ramping constraints as a factor in an analysis of strategic bidding in the market for supplying energy, and Bouffard (2005) develops a probabilistic model for operating the market for energy. Karki (2006) develops an enhanced model of wind variability to improve reliability models. Condren (2006) presents an extended formulation of Expected Security-Constrained Optimal Power Flow (ESCOPF). This ESCOPF includes ramping costs as a function of pre and post-contingency flows, physical ramping constraints and considers constraints that account for differences in the operating points for a single period Optimal Power Flow (OPF). Tuohy (2009) proposes a Monte Carlo simulation approach for a Mixed Integer Program (MIP), modeling the transitions from period to period as physical ramping constraints in a Direct Current (DC) model. Other modeling approaches, such as Paul (2002), involve Computable General Equilibrium models (CGE) that include typical generators and the constraints in flows between specified regions.

The model presented in this chapter is based on Chen (2005), and it uses a modified objective function for optimizing dispatch that minimizes the expected cost of both energy and reserves in a co-optimization framework (CO-OPT).

[5] This chapter summarizes the results of a research paper that has been accepted for publication in *Energy Economics* (Alberto Lamadrid and Tim Mount, "Ancillary Services in Systems with High Penetrations of Renewable Energy Sources: The Case of Ramping").

Thomas et al. (2008) adopt this type of CO-OPT and introduce the "SuperOPF", a stochastic form of SCOPF. The SuperOPF specifies a set of credible contingencies, and their probabilities of occurrence, to augment the intact system, and it determines the expected cost of energy and reserves over this super-set of system states for an Alternating Current (AC) network. The model determines the optimum spatial pattern of energy and reserves endogenously, and identifies the positive and negative reserves needed for both real and reactive power. Additionally, following Bouffard (2006), the model includes Load Not Served (LNS) as a possible outcome in any state that is priced at a high Value of Lost Load (VOLL). By including the cost of LNS in the objective function it becomes a measure of (negative) social welfare. In addition, by treating contingencies as "soft" economic constraints rather than as "hard" physical constraints, this framework makes it feasible to determine an economic cost for maintaining the reliability of supply.

There is growing evidence, particularly from Europe, that the cost of cycling and ramping conventional generating units is significant (Hamal (2006), Troy (2011) and Lefton (2011)). There are three main sources of these ramping costs: 1) increased heat rates and losses in efficiency, 2) increased operation and maintenance costs, and 3) increased probability of forced outages. Ramping may also have adverse effects on the environmental emissions from generating units (Academies (2010)).

The model discussed in the next section extends the original SuperOPF framework to include ramping costs. This makes it possible to account for the system costs of mitigating the variability of generation from renewable energy sources in the system. In contrast, most standard models of system operations incorporate ramping as physical constraints on generating units rather than as an economic cost. This extension of the SuperOPF makes it feasible to determine the amount of potential wind generation dispatched/spilled endogenously. Basically, even if wind generation is offered into the energy market at a cost of zero, the SuperOPF demonstrates that it may be still be optimum to spill some of the potential wind generation and dispatch more expensive sources of generation to reduce expected ramping costs on the system.

4.2 The Analytical Framework

The main theme of this chapter is the modeling of ramping costs in an ESCOPF caused by changes in the dispatch points for individual generating units from one period to the next. The model also includes different contingencies and limits load shedding. All of the costs for energy, reserves, ramping and load shedding are identified explicitly in the objective function, and the optimum pattern of dispatch and reserves corresponds to minimizing the expected cost over the intact system and all contingencies.

The US Energy Policy Act of 2005 acknowledges the importance of reliability standards for the ``Bulk-Power System" and the Electricity Modernization Act of 2005 gives the Federal Energy Regulatory Commission (FERC) the authority to enforce these standards. The FERC appointed the North American Electric Reliability Corporation (NERC) as the Electric Reliability Organization (ERO) that is responsible for specifying explicit standards for reliability. The latest set of reliability standards (NERC (2010)) cover a wide range of topics and identify the following two general concepts for evaluating the reliability of the Bulk-Power System:

1. Resource Adequacy (adequacy): the ability of supply-side and demand-side resources to meet the aggregate electrical demand (including losses).

2. Operating Reliability (security): The ability of the bulk power system to withstand sudden, unexpected disturbances such as short circuits, or unanticipated loss of system elements due to natural or man-made causes.

In Chapter 5, we argue that in addition to the two concepts used by the NERC, ``Financial Adequacy'' should also be considered as a planning metric (Mount et al. (2010)). However, in this chapter, the focus is mainly on the two NERC concepts and how they are incorporated into the SuperOPF.

In practice, different measures have been adopted to quantify the NERC concepts. The Loss of Load Expectation (LOLE) and the Loss of Load Probability (LOLP) are widely used as adequacy metrics, and an "n-1" standard as a security metric (i.e., the system should be able to withstand the loss of any one network element and continue to meet the system load). The time horizons for adequacy and security differ. The adequacy metrics normally include the uncertainty of load forecasts (due to weather and economic conditions), as well as the characteristics of generating resources, such as the number of generating units, their corresponding capacities, forced outage rates, maintenance schedules, seasonal de-ratings, emergency operating procedures for maintaining reliability, and transmission interconnections to other systems. The objective of the adequacy metrics is to represent reliability in the future for planning purposes. In practice, the adequacy metrics are used mainly for generation expansion planning. On the other hand, the security metrics focus on the short-term and how to determine the spatial pattern of dispatch and reserves to operate a given system reliably.

The SuperOPF framework assumes that an Independent System Operator (ISO) runs a two-settlement market. In the first step, the ISO determines optimal contracts for energy and reserves that meet the security requirements for the second step (e.g., day-ahead). In the second step, the ISO determines how to re-dispatch the committed units in real time to deal with the actual realized state of the system.

In this framework, the first and second steps have a common formulation, with additional constraints imposed in the second step. Focusing on the common part of the problem, the first step assumes that the initial system is intact (i.e., no contingency is realized) and it contracts ahead for energy to cover this intact state and for reserves to cover the contingencies.

Objective function:

$$\min_{\Theta,V,P,Q,P^+,P^-,Q^+,Q^-} \sum_{k\in\mathscr{K}} \pi_k \sum_{i\in\mathscr{G}^k} \begin{array}{l} C_{P_i}(p_{ik}) + C_{Q_i}(q_{ik}) + \\ C^+_{P_i}(p^+_{ik}) + C^+_{Q_i}(q^+_{ik}) + \\ C^-_{P_i}(p^-_{ik}) + C^-_{Q_i}(q^-_{ik}) + \end{array} \tag{1}$$

subject to

$$g^k_P(\theta^k, V^k, P^k, Q^k) = 0, \quad \forall k \in \mathscr{K} \tag{2}$$

$$g^k_Q(\theta^k, V^k, P^k, Q^k) = 0, \quad \forall k \in \mathscr{K} \tag{3}$$

$$h^k(\theta^k, V^k, P^k, Q^k) \leq 0, \quad \forall k \in \mathscr{K} \tag{4}$$

$$p^t_{ik} - \hat{p}^{t-1}_{ci} - p^{+,t}_{ik} \leq 0, \quad -p^{+,t}_{ik} \leq 0, \ \forall i \in \mathscr{G}, k \in \mathscr{K} \tag{5}$$

$$q^t_{ik} - \hat{q}^{t-1}_{ci} - q^{+,t}_{ik} \leq 0, \quad -q^{+,t}_{ik} \leq 0, \ \forall i \in \mathscr{G}, k \in \mathscr{K} \tag{6}$$

$$p^{+,t}_{ik} - \hat{r}^{+,t}_{Pi} \leq 0, \quad q^{+,t}_{ik} - \hat{r}^{+,t}_{Qi} \leq 0, \ \forall i \in \mathscr{G}, k \in \mathscr{K} \tag{7}$$

$$\hat{p}^{t-1}_{ci} - p^t_{ik} - p^{-,t}_{ik} \leq 0, \quad -p^{-,t}_{ik} \leq 0, \ \forall i \in \mathscr{G}, k \in \mathscr{K} \tag{8}$$

$$\hat{q}^{t-1}_{ci} - q^t_{ik} - q^{-,t}_{ik} \leq 0, \quad -q^{-,t}_{ik} \leq 0, \ \forall i \in \mathscr{G}, k \in \mathscr{K} \tag{9}$$

$$p^{-,t}_{ik} - \hat{r}^{-,t}_{Pi} \leq 0, \quad q^{-,t}_{ik} - \hat{r}^{-,t}_{Qi} \leq 0, \ \forall i \in \mathscr{G}, k \in \mathscr{K} \tag{10}$$

$$-R^{\text{PHYS}-}_{Pi} \leq p^t_{ik} - p^t_{i0} \leq R^{\text{PHYS}+}_{Pi}, \forall i \in \mathscr{G}, k \in \mathscr{K} \tag{11}$$

$$-R^{\text{PHYS}-}_{Qi} \leq q^t_{ik} - q^t_{i0} \leq R^{\text{PHYS}+}_{Qi}, \forall i \in \mathscr{G}, k \in \mathscr{K} \tag{12}$$

The actual forms of the equality constraints in (2) and (3) are the following power balance equations for active and reactive power:

$$\begin{aligned} p_{i,k} - \sum_{j\in n_B} |v_{j,k}||v_{i,k}| \Big[G_{ij,k}\cos(\theta_i - \theta_j) \\ + B_{ij,k}\sin(\theta_i - \theta_j) \Big] = 0, \quad \forall i \in \mathscr{B}, k \in \mathscr{K} \end{aligned} \tag{13}$$

$$\begin{aligned} q_{i,k} - \sum_{j\in n_B} |v_{j,k}||v_{i,k}| \Big[G_{ij,k}\sin(\theta_i - \theta_j) \\ - B_{ij,k}\cos(\theta_i - \theta_j) \Big] = 0, \quad \forall i \in \mathscr{B}, k \in \mathscr{K} \end{aligned} \tag{14}$$

The inequality constraints in (4) are two sets of branch flow limits that are functions of the bus voltages and angles for the *"from"* and *"to"* flows on each branch (Wood and Wollenberg (1996)). Equations (5) and (6) are the inter-temporal constraints for positive deviations in active and reactive power, and (8) and (9) are the equivalent for negative deviations. They link the dispatch in one period to the realized dispatch in the previous period (e.g., hour). Equations (7) and (10) determine the permissible limits for each generating unit, given the amount of positive and negative reserves previously contracted. Equations (11) and (12) represent the physical ramping constraints for each generation unit.

There are additional constraints related to the bounds of each one of the variables (e.g., voltage magnitudes and angles and physical limits on generating units and loads). These and other constraints are implemented using the MATPOWER extensible OPF formulations (Zimmerman ((2011). Additional technical details of the optimization procedures are provided in the paper cited at the beginning of this chapter (Appendix A).

4.3 The Specification of the Case Study

The extended version of the SuperOPF was used to evaluate the effects of wind generation on the 30-bus test network shown in Figure 4.1. This is a highly modified version of the IEEE 30-bus system (Alsac (1974) and Ferrero (1997)), and the composition of generating capacity and fuel type are set to match the proportions observed in Allen el al. (2008). The line capacities and the locations of the generating units were modified to represent a system with an urban area (Area 1), with expensive sources of generation, high loads and a high VOLL, and two rural areas (Areas 2 and 3), with relatively inexpensive sources of generation, lower loads and a lower VOLL.

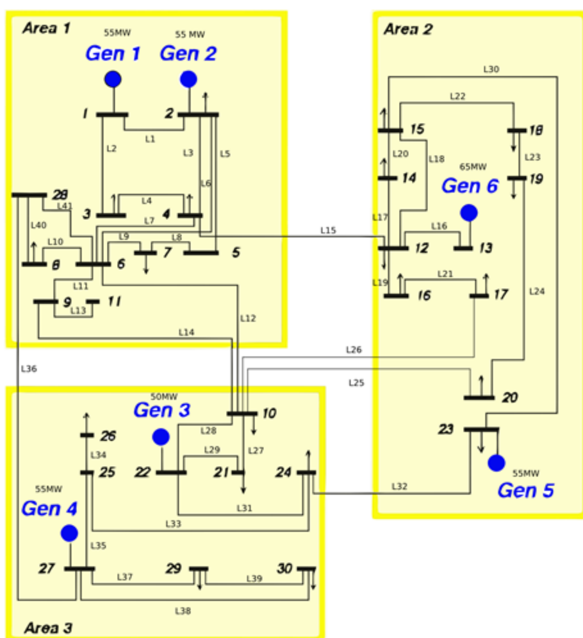

Figure 4.1: The 30-Bus Test Network

In an economically efficient dispatch, the generating units in Areas 2-3 are used to cover the local load and as much of the load in Area 1 as possible, but the capacities of the major tie lines linking Area 1 to Areas 2-3 limit how much power can be transferred. All loads in the system are modeled as negative injections of power (i.e., as dispatchable loads), allowing for load shedding in cases where the system is stressed. Typically, any load shedding occurs in one or more of the contingency states. In these cases, a relatively large VOLL is multiplied by a relatively small probability of occurrence, leading to only a modest increase in expected system costs.

Table 4.1 presents a summary of the characteristics of the generating units. The letters in parentheses next to the fuel type indicate whether the units are peaking (p), shoulder (s) or base load (b) capacity. Nuclear, Hydro and Refuse (NHR) have both base load and shoulder units, while all Combined Cycle Gas (CC Gas) capacity is considered shoulder and all Gas Combustion Turbines (GCT) are considered peaking. For each type of fuel, generating capacity is located at two buses. The column Generation Cap shows the total capacity and the capacity at each bus (the bus numbers identify the locations in Figure 4.1). The generation costs are calibrated using realistic data for the northeastern states. The cost of ramping is modeled as a linear function, and the values used for ramping are consistent with the costs found in the literature (Maloney (2001) and Wolak (2007)).

Table 4.1: The Composition of Generating Capacity by Fuel Type and Bus

Fuel name	(t)	Generation Cap. MW (bus cap. MW)	Fuel Cost ($/MW)	Res. Cost ($/MW)	Ramp Cost ($-$t$/MW)
Oil	(p)	65: b1(35), b2(30)	95	10	0
GCT	(p)	45: b1(20), b2(25)	80	10	0
CC Gas	(s)	40: b22(20), b27(20)	55	20	30
NHR	(s)	65: b20(30), b27 (35)	5	20	30
Coal	(b)	70: b13(35), b23(35)	25	30	60
NHR	(b)	50: b13(20), b23(30)	5	30	60

Wind capacity is added to the network in most of the cases studied and this capacity is always located at one or two of the rural buses in Ares 2 and 3. The specific wind model used to determine the potential wind generation in a given hour is based on a discrete representation of the probabilistic distribution of hourly wind speed data from New England, following the methodology in Anderson (2008). The three main components of the wind model are:

1. Select a set of time-series data for hourly wind speeds (data for New England sites in the spring 2005 was used for this analysis)

2. Fit an ARMA model to predict the hour-ahead wind speed at a given location. These predictions are treated as the best available forecasts that are used by the ISO to contract for generating capacity one hour ahead

3. Use a power curve for a specified type of wind turbine to convert the forecasted wind speed into the potential amount of wind generation.

Wind generation is offered into the market at a zero cost that is assumed to reflect the short-run marginal cost of this resource. The contracts made by the

ISO for all generating units, including wind generation, minimize the expected system cost. Hence, wind generation is not a "must-take" requirement for the ISO, and some of the potential wind generation may be spilled in the optimum dispatch.

The effects of coupling an Energy Storage System (ESS) with wind generators and of geographical averaging across different wind sites are included in the cases studied. For the ESS modeling, the charging and discharging cycles are reflected as reductions in the uncertainty of potential wind generation. In this analysis, the levels of potential wind generation with ESS are assumed to be constant because the ESS uses some wind generation to charge when the wind speed is high and it discharges energy when the wind speed is low. This representation corresponds to a situation in which the ESS is collocated with the wind resource. Modifying the levels of potential wind generation exogenously as a way to model the effects of ESS is, however, a very simplistic way to represent storage. It was adopted because the first generation SuperOPF only optimizes the dispatch for one period at a time. A more realistic model of storage is presented in Chapter 6 when a multi-period optimization is used. With this new framework, charging ESS at low load periods and discharging it at peak periods can be modeled explicitly without modifying the wind inputs.

Demand Response (DR) is specified as a resource that is controlled by an ISO to support the system when it is stressed and improve reliability. The example of DR in this analysis is specified as interruptible demand that can be used to offset low wind conditions when the nodal prices at the load buses are high enough. The amount of DR capacity was chosen to match the amount of ESS capacity, and the specific procedures used to do this are presented in detail in Appendix A.

The following cases were considered:

1. No Wind.

2. Baseline Wind: A 50 MW (12% of installed capacity) wind farm is located at Bus 13 with a zero offer price.

3. No Congestion: Case 2 after eliminating the resistance and all transmission ratings for all lines.

4. Constant Wind: Case 2 with constant potential wind generation to reflect coupling with ESS.

5. Distributed Wind: Two 25 MW wind farms located at Buses 13 and 27 with negatively correlated wind.

6. Distributed Constant Wind: Case 5 with constant potential wind generation to reflect coupling with ESS.

7. Baseline Distributed Wind: Case 5 with potential wind generation derived from historical data for each site.

8. Demand Response: Case 7 with some DR in the urban area that can respond to low wind conditions and contingencies.

9. Controllable Demand: Case 7 with a flat daily load profile.

The contingencies considered include 1) line outages in the urban area, 2) line outages between the urban and the rural areas, 3) full generation outages at each generation bus, and 4) different realizations of potential wind generation, including cutouts at very high wind speeds. The set of contingencies is the same in both steps of the market for every hour. All cases except Case 9 are run with and without ramping costs. The optimization is solved for each hour in sequence for three identical days (the optimum dispatch for one hour determines the initial conditions for the next hour) to obtain steady state solutions,

Figure 4.2 summarizes the implications of the different cases for the hourly levels of potential wind generation over the day. There are essentially two types of potential wind generation. The basic wind input used in Cases 2, 3, 7, 8 and 9 (with and without ramping) is highly variable and exhibits three cutouts during the day. Hence, the constant wind input used in Cases 4, 5 and 6 (with and without ramping) represents a much nicer resource for the system to accommodate. (In Case 5, the potential wind generation at each site does vary but the sum for the two sites is constant.)

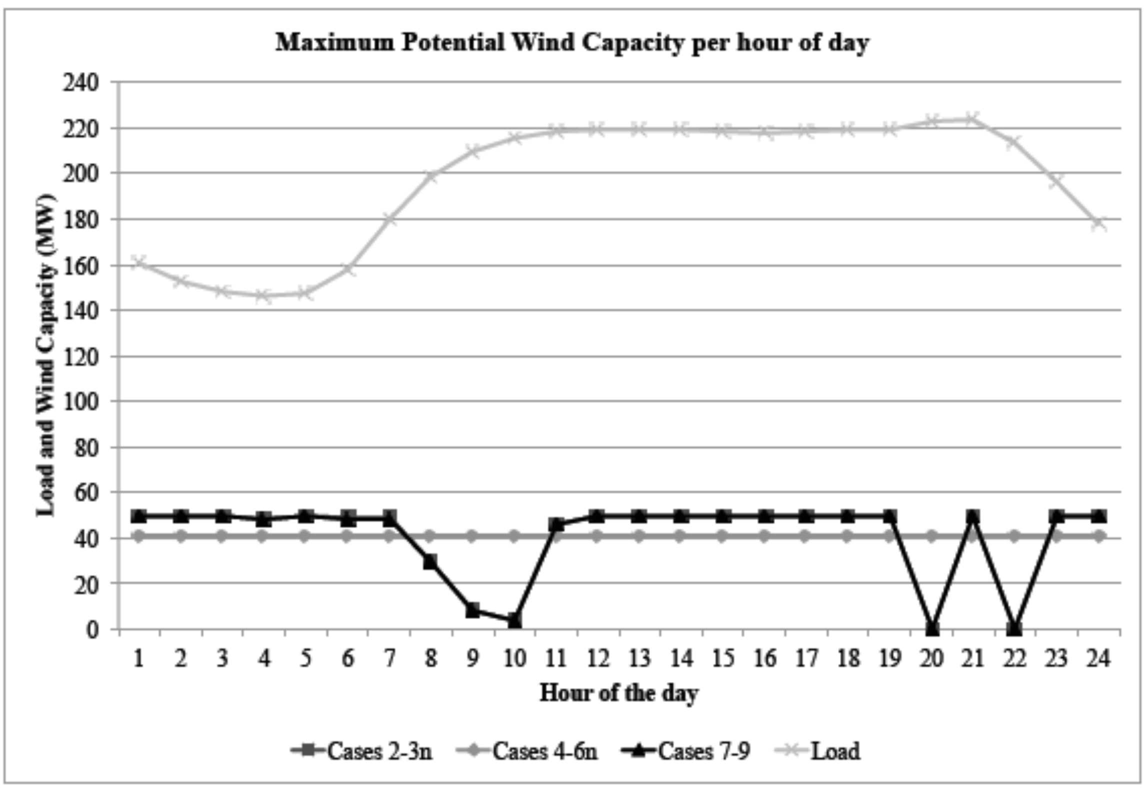

Figure 4.2: The Total Potential Wind Generation for Different Cases*

* The values for Cases 2-3n and for Cases 7-9 are identical in this application

4.4 The Results of the Case Studies

The three main questions addressed in the case studies are:

1) What is the effect of ramping costs on expected system costs?

2) How do ramping costs affect the dispatch of wind generation?

3) What is the effect of ramping costs on operating reliability?

A summary of the key results for the nine cases is presented in Tables 4.2 and 4.3.

Table 4.2: Summary of Daily Operating Costs and Wind Generation

	E[Operating Costs] ($thousand/day)			E[Wind Generation] (MWh/day)		
	With	Without	Percentage	With	Without	Percentage
Case	Ramping	Ramping	Change	Ramping	Ramping	Change
1	118	109	-7.63%	0	0	na
2	92	80	-13.04%	428	870	103.27%
3	58	42	-27.59%	612	953	55.72%
4	83	74	-10.84%	734	966	31.61%
5	80	67	-16.25%	773	934	20.83%
6	81	67	-17.28%	807	946	17.22%
7	81	73	-9.88%	586	865	47.61%
8	77	67	-12.99%	641	865	34.95%
9	72	na	na	754	na	na

The values shown in Table 4.2 for E[Operating Costs] and E[Wind Generation] represent the sum of the hourly expectations over all of the specified states (contingencies) of the system. E[Operating Costs] for the cases with ramping costs are lowest for No Congestion (Case 3) followed by Controllable Demand (Case 9) and Demand Response (Case 8), and E[Operating Costs] is highest for Base Wind (Case 2). Overall, all cases with wind generation have lower operating costs than No Wind (Case 1).

All of the cases with no ramping costs have lower E[Operating Costs] than the corresponding cases with ramping costs, as expected, and Cases 3 is still the lowest and Case 2 the highest. The lower values of E[Operating Costs] are not just due to making all ramping costs zero because ramping costs are relatively small compared to the cost of burning fossil fuels. The main reason for the lower costs with no ramping is that the levels of E[Wind Generation] are substantially higher. Since the total amount of potential wind generation is the same in all cases, less wind is spilled with no ramping costs, and therefore, more fossil fuel generation is displaced by wind generation.

As expected, the highest levels of E[Wind Generation] with ramping costs occur in the cases with constant potential wind generation (Cases 4-6), and the lowest in Base Wind (Case 2). With no ramping costs, E[Wind Generation] increases by at least 17% in all cases and actually doubles in Case 2. These increases reflect the system costs of accommodating variable wind generation when ramping costs are considered. The relative differences in E[Wind Generation] between constant wind (Cases 4, 5, and 6) and variable wind (Cases 2, 3, 7, 8, and 9) are much larger when ramping costs are considered. The overall conclusion from the evidence presented in Table 4.2 is that ramping costs do have significant effects on both E[Wind Generation] and E[Operating Costs] and should be included in an ESCOPF used to determine optimum patterns of dispatch and reserves.

In Table 4.3, the amount of Max[Conventional Capacity] measures the sum of the maximum amounts of generating capacity dispatched in any state of the system in any hour for every non-wind generating unit. (The E[Reserve Capacity] for ramping up each hour is defined as (Max[Conventional Capacity] - E[Conventional Capacity Dispatched]).) Ramping costs are, however, incurred when generating units ramp down as well as up. Hence, Max[Conventional Capacity] is the amount of non-wind generating capacity required to operate the system reliably and is a measure of the capacity that should be committed to maintain System Adequacy. Comparing the cases with and without ramping costs, Max[Conventional Capacity] is essentially the same in No Wind (Case 1), No Congestion (Case 3) and the cases with no wind variability (Cases 4, 5 and 6). In the other cases with variable wind (Cases 2, 7 and 8), Max[Conventional Capacity] increases with no ramping costs. The reason is that the higher levels of E[Wind Generation] with no ramping costs (see Table 4.2) make it necessary to commit more non-wind generating capacity to cover possible cutouts of wind generation and maintain reliability.

Table 4.3: Summary of Conventional Capacity and Load-Not-Served

	Max[Conventional Capacity] (MW)			E[Load-Not-Served] (hours/day)		
	With	Without	Percentage	With	Without	Difference
Case	Ramping	Ramping	Change	Ramping	Ramping	
1	224	224	0.00%	0.014	0.014	0.000
2	255	273	7.06%	0.000	0.014	0.014
3	271	271	0.00%	0.014	0.000	-0.014
4	225	225	0.00%	0.014	0.014	0.000
5	230	230	0.00%	0.014	0.014	0.000
6	224	225	0.45%	0.014	0.014	0.000
7	265	271	2.26%	0.014	0.014	0.000
8	242	256	5.79%	0.034	0.034	0.000
9	206	na	na	0.020	na	na

It is interesting to note that Controllable Demand (Case 9) is the only one of the cases with ramping costs in which Max[Conventional Capacity] is lower than it is in No Wind (Case 1). In other words, the capacity value of the wind capacity is negative and more non-wind capacity is needed to accommodate the variability of the wind generation in Cases 2-8. Even if the potential wind generation is constant, as it is in Cases 4, 5, and 6, the Max[Conventional Capacity] is still slightly higher than it is in Case 1. The reason is that more reserve generating capacity is committed compared to Case 1 to cover the possibility of a cutout of wind generation in one of the contingency states even though no cutouts are actually realized in these cases. As expected, Max[Conventional Capacity] is significantly higher for the cases with ramping costs and variable wind (Cases 2, 7, 8 and 9), except for No Congestion (Case 3), than it is for the cases with ramping costs and constant wind (Cases 4, 5 and 6). These differences reflect the additional reserve capacity needed to maintain reliability.

Some load is shed in some contingencies in all but two of the cases with and without ramping costs. The amounts of E[Load-Not-Served] are, however, relatively small and probably reflect the small size of the network rather than serious reliability problems. The differences between the cases with and without ramping costs are trivial. There is no obvious explanation for the relatively high value of E[Load-Not-Served] in Demand Response (Case 8). The overall conclusion from the results presented in Table 4.3 is that ramping costs only affect reliability indirectly by changing the total amount of non-wind generating capacity committed to maintain reliability. Since Max[Conventional Capacity] is generally higher when E[Wind Generation] is higher, the cases with variable wind generation and a network (Cases 2, 7, 8 and 9) have less non-wind generating capacity committed when ramping costs are included in the model.

4.5 Summary and Conclusions

The main contribution of this chapter is to illustrate the importance of treating the determination of the optimum dispatch of generating units as a stochastic as opposed to a deterministic problem. In simple terms, this is done by changing the objective function of a typical SCOPF from minimizing the cost of meeting load for the intact system subject to physical constraints representing contingencies to minimizing the expected cost of meeting load for a specified set of states of the system that represent the intact system and contingencies. Using the latter approach, the expected cost is determined by specifying probabilities for each of the system states. For the first, deterministic approach, costs are only associated with the intact state, and the optimum pattern of dispatch and reserves ensures that generating units can redispatched to cover the contingencies and not violate their physical ramping constraints. For the second, stochastic approach, costs are evaluated in all specified system states and ramping costs can be included as well as physical ramping constraints.

The specific form of stochastic SCOPF used in the analysis is the SuperOPF and it is applied to a small 30-bus test network to provide an empirical example of how ramping costs affect the optimum dispatch and the associated expected system costs. This analytical framework uses co-optimization to determine the optimal expected pattern of both dispatch and reserves endogenously, and the optimum amount of reserve capacity is sensitive to system conditions, such as the amount of wind generation available. The model also determines how much of the expected amount of potential wind generation should be dispatched or spilled in each system state.

Three specific questions were raised at the beginning of Section 4.4, and the answers that follow are based on the results discussed in that section.

1) What is the effect of ramping costs on expected system costs?

   Adding ramping costs to the objective function does increase the expected operating costs but not primarily because of these direct costs. When wind generation is added to the network, expected operating costs are lower because this source displaces more expensive generation from fossil fuel units. However, the variability and uncertainty of wind generation results in more wind being spilled when ramping costs are included. In other words, the same amount of potential wind generation results in more generation from fossil fuel units with ramping costs included. As a result, expected operating costs are higher compared to equivalent cases with no ramping costs.

2) How do ramping costs affect the dispatch of wind generation?

   The expected amount of physical ramping needed to maintain reliability increases when an inherently variable source of wind generation is added to a network. The specification of the wind resource in the case study makes it challenging to accommodate because there is a relatively high probability of cutouts occurring as well as actual cutouts being realized. Consequently, the expected amount of potential wind generation that is spilled increases when ramping costs are included to reduce the size to the possible cutouts and the associated amount of reserve ramping capacity needed. In this way, adding ramping costs has a direct effect on reducing the amount of potential wind generation that is dispatched.

3) What is the effect of ramping costs on operating reliability?

   Even though the SuperOPF allows for load shedding as an option, implementing this option has a very high cost and it is only optimum to use it in a few contingency states with low probabilities of occurring. The variability of wind generation and guarding against the possibility of a cutout affect the optimum amount of potential wind generation spilled and the optimum amount of reserve generating capacity needed to avoid expensive load shedding. When the wind resource is less variable, due, for example, to collocating storage capacity at the wind sites, it is optimum to dispatch more of it and less reserve capacity is needed to maintain operating reliability. Hence, ramping costs affect the total amount of non-wind generating capacity committed and the optimum amount of potential wind generation dispatched. The level of operating reliability (E[Load-Not-Served]), on the other hand, stays roughly the same.

The overall conclusion is that ramping costs do matter. They affect the composition of dispatch, the amount of reserves of non-wind generating capacity needed and how effectively wind resources can be used. These effects are likely to become more important over time with increasing dependence on variable sources of generation. Even though a network can be operated reliably with variable sources of generation, there is a cost to accommodating these sources. The objective of the next chapter is to discuss these costs and to demonstrate that total system costs can increase when capital costs are considered even if renewable sources of generation lower total operating costs. The next chapter focuses on the second feature of the SuperOPF that identifies how wholesale markets should be modified to provide accurate economic signals to all participants.

References

[1] Academies, N., 2010, “Hidden Costs of Energy: Unpriced Consequences of Energy Production and Use”. The National Academies Press, 2010. http://www.nap.edu/openbook.php?record id=12794

[2] Allen, E., Lang, J., Ilic, M., Aug. 2008. “A combined equivalenced-electric, economic, and market representation of the Northeastern Power Coordinating Council, U.S. electric power system.” Power Systems, IEEE Transactions on 23 (3), 896–907.

[3] Alsac, O., Stott, B., May 1974. “Optimal load flow with steady-state security”. Power Apparatus and Systems, IEEE Transactions on PAS-93 (3), 745 –751.

[4] Anderson, C. L., Cardell, J. B., 2008. “Reducing the variability of wind power generation for participation in day-ahead electricity markets.” Proceedings of the 41st Annual Hawaii International Conference on System Sciences. IEEE Computer Society, Washington, DC, USA, p. 178.

[5] Balijepalli, V., Khaparde, S., Gupta, R., Pradeep, Y., 2010. “Smartgrid initiatives and power market in India.” Power and Energy Society General Meeting, 2010 IEEE. pp. 1-7.

[6] Bouffard, F., Galiana, F., Conejo, A., Nov. 2005. “Market-clearing with stochastic security-part formulation - part i: power systems,” IEEE Transactions on 20 (4), 1818–1826.

[7] Bouffard, F., Galiana, F., Conejo, A., 2006. “Market-clearing with stochastic security - part ii: case studies.” Power Engineering Society General Meeting, 2006. IEEE.

[8] Callaway, D., Hiskens, I., 2011. “Achieving controllability of electric loads.” Proceedings of the IEEE 99 (1), 184 –199.

[9] Chen, J., Mount, T. D., Thorp, J. S., Thomas, R. J., 2005. “Location-based scheduling and pricing for energy and reserves: a responsive reserve market proposal.” Decision Support Systems. 40 (3-4), 563–577.

[10] Condren, J., Gedra, T., Damrongkulkamjorn, P., May 2006. “Optimal power flow with expected security costs.” Power Systems, IEEE Transactions on 21 (2), 541–547.

[11] FERC, 2010. “Assessment of demand response and advanced metering.” Technical Report, < http://www.ferc.gov/legal/staff-reports/2010-dr-report.pdf#xml=http://search.atomz.com/search/pdfhelper.tk?sp_o=1,100000,0>

[12] Ferrero, R., Shahidehpour, S., Ramesh, V., Aug. 1997. "Transaction analysis in deregulated power systems using game theory." Power Systems, IEEE Transactions on 12 (3), 1340 –1347.

[13] Hamal, C., Sharma, A., 2006. "Adopting a ramp charge to improve performance of the Ontario market." Technical report, LECG. https://www.ieso.ca/imoweb/pubs/consult/mep/MP_WG-20060707-ramp-cost.pdf

[14] Hau, E., 2006. "Wind turbines: fundamentals, technologies, application, economics." Springer. http://books.google.com/books?id=Z4bhObd65IAC

[15] Hiskens, I., 2006. "Load as a controllable resource for dynamic security enhancement." IEEE Power Engineering Society General Meeting.

[16] Karki, R., Hu, P., Billinton, R., 2006. "A simplified wind power generation model for reliability evaluation." Energy Conversion, IEEE Transactions on 21 (2), 533 – 540.

[17] Katzenstein, W., Apt, J., 2008. "Air emissions due to wind and solar power." Environmental Science & Technology 43 (2), 253–258. http://dx.doi.org/10.1021/es801437t

[18] Keane, A., Milligan, M., Dent, C. J., Hasche, B., D'Annunzio, C., Dragoon, K., Holttinen, H., Samaan, N., Soder, L., O'Malley, M., 2010. "Capacity value of wind power." Power Systems, IEEE Transactions on Power Systems (99). http://www.nerc.com/docs/pc/ivgtf/ieee-capacity-value-task-force-confidential%20(2).pdf

[19] Lamadrid, A. J., Mount, T. D., Thomas, R. J., 2011. "Integration of stochastic power generation, geographical averaging and load response." Working paper series, Cornell University. http://dyson.cornell.edu/research/researchpdf/wp/2011/Cornell-Dyson-wp1109.pdf

[20] Lefton, S. A., 2011. "Power plant asset management." Technical report, UWIG Spring Workshop, Kansas City.

[21] Li, H., Tesfatsion, L., 2010. "ISO net surplus collection and allocation in wholesale power markets under LMP." Power Systems, IEEE Transactions on Power Systems (99).

[22] Machowski, J., Bialek, J., Bumby, J., 2008. "Power system dynamics: stability and control." Wiley. http://books.google.com/books?id=37BnCjCNSBoC

[23] Maloney, M. T., 2001. "Economies and diseconomies: Estimating electricity cost functions." Review of Industrial Organization 19, 165–180, http://dx.doi.org/10.1023/A:1011140400951

[24] Mello, J., Souzea, M., Moreira, F., Prandinis, T., 2010. "The Brazilian market-based expansion and low carbon energy future - issues and solutions." CIGRE (Ed.), CIGRE 2010. No. C1-107 in 2010. CIGRE, 21, rue d'Artois, F75008 Paris, pp. 1–9.

[25] Milano, F., Canizares, C., Conejo, A., Nov. 2005. "Sensitivity-based security-constrained OPF market clearing model." Power Systems, IEEE Transactions on 20 (4), 2051–2060.

[26] Mount, T., Maneevitjit, S., Lamadrid, A., Thomas, B., Zimmerman, R., 2012. "The hidden system costs of wind generation in a deregulated electricity market." The Energy Journal 33 (1), 161–186.

[27] Mount, T. D., Lamadrid, A., Maneevitjit, S., Thomas, R. J., Zimmerman, R., 2009. "A symbiotic role for plug-in hybrid electric vehicles in an electric delivery system." Proceedings of the 22nd Rutgers Western Conference. Monterey, CA.

[28] Murtag, B. A., Saunders, M. A., 1998. "Minos5.5 user's guide." Technical Report SOL83-20R, Stanford University Systems Optimization Laboratory. http://www.stanford.edu/group/SOL/guides/minos55.pdf

[29] NERC, 2010. "Reliability Standards for the Bulk Electric Systems of North America." North American Electric Reliability Corporation, 116-390 Village Road, Princeton, NJ, 08540. http://www.nerc.com/files/Reliability Standards Complete Set.pdf

[30] Outhred, H., 1998. A review of electricity industry restructuring in Australia. Electric Power Systems Research 44 (1), 15 – 25. http://www.sciencedirect.com/science/article/B6V30-3TW320D-3/2/a8ca131ef5cd3be4694b3d40d706c402

[31] Paul, A., Burtraw, D., 2002. "The RFF haiku electricity market model." Technical report, Resources for the Future.

[32] Price, W., Hargrave, A., Hurysz, B., Chow, J., Hirsch, P., Aug 1998. "Large- scale system testing of a power system dynamic equivalencing program." Power Systems, IEEE Transactions on 13 (3), 768 –774.

[33] Shrestha, G., Song, K., Goel, L., 2004. "Strategic self-dispatch considering ramping costs in deregulated power markets." Power Engineering Society General Meeting, 2004. IEEE. p. 1146 Vol.1.

[34] Smith, P., Cuffe, P., Grimes, S., Hearne, T., 2010. "Ireland's approach for the connection of large amounts of renewable generation." Power and Energy Society General Meeting, 2010 IEEE. Pp. 1–3.

[35] Thomas, R., Mount, T., Schuler, R., Schulze, W., Zimmerman, R., 2006. “Markets for reactive power and reliability: A white paper.” Technical report, E3RG, Cornell University. <http://e3rg.pserc.cornell.edu/>

[36] Thomas, R., Murillo-Sanchez, C., Zimmerman, R., July 2008. “An advanced security constrained OPF that produces correct market-based pricing.” Power and Energy Society General Meeting - Conversion and Delivery of Electrical Energy in the 21st Century, IEEE. pp. 1–6.

[37] Troy, N., 2011. “Generator cycling due to high penetrations of wind power.” Ph.D. thesis, School of Electrical, Electronic and Communications Engineering, University College, Dublin, Ireland.

[38] Tuohy, A., Meibom, P., Denny, E., O’Malley, M., May 2009. “Unit commitment for systems with significant wind penetration.” Power Systems, IEEE Transactions on 24 (2), 592 –601.

[39] US Congress, 2005. “Energy Policy Act.” 109th Congress of the United States of America.

[40] Wang, C., Shahidehpour, S., Feb. 1995. “Optimal generation scheduling with ramping costs.” Power Systems, IEEE Transactions on 10 (1), 60 –67.

[41] Wang, H., Murillo-Sanchez, C., Zimmerman, R., Thomas, R., 2007. “On computational issues of market-based optimal power flow.” Power Systems, IEEE Transactions on 22 (3), 1185 –1193.

[42] Wolak, F. A., 2007. “Quantifying the supply-side benefits from forward contracting in wholesale electricity markets.” Journal of Applied Econometrics 22 (7), 1179–1209. http://dx.doi.org/10.1002/jae.989

[43] Wood, A., Wollenberg, B., 1996. “Power Generation, Operation and Control,” 2nd Edition. Wiley Interscience.

[44] Zhang, D., Wang, Y., Luh, P., Aug. 2000. “Optimization based bidding strategies in the deregulated market.” Power Systems, IEEE Transactions on 15 (3), 981–986.

[45] Zhang, Y., Zhu, S., Chowdhury, A., Zhang, P., 2010. “An integrated transmission planning framework for including renewable energy technologies in a deregulated power system.” Power and Energy Society General Meeting, 2010 IEEE. 1–7.

[46] Zimmerman, R. D., Murillo-Sanchez, C. E., Thomas, R. J., 2011. “Matpower: Steady-state operations, planning, and analysis tools for power systems research and education.” Power Systems, IEEE Transactions on 26 (1), 12-19.

5. Reliability and Financial Adequacy

5.1 The Problem[6]

An important study initiated by the US Department of Energy (DOE) evaluated the effects of increasing national dependence on wind energy to 20% of the total generation of electricity by 2030. The study is relatively positive about this scenario and states:

> *"Until recently, concerns had been prevalent in the electric utility sector about the difficulty and costs of dealing with the variability and uncertainty of energy production from wind plants and other weather-driven renewable technologies. But utility engineers in some parts of the United States now have extensive experience with wind plant impacts, and their analyses of these impacts have helped to reduce these concerns…… wind's variability is being accommodated, and given optimistic assumptions, studies suggest the cost impact could be as little as the current level - 10% or less of the value of the wind energy generated."*

The DOE study focuses on the initial capital cost of installing the wind capacity and upgrading the transmission network and compares these costs to the lower operating costs when wind energy displaces fossil fuels. The issue addressed in this chapter shows that there are other, hidden costs of wind power associated with the need to maintain the "Financial Adequacy" of conventional generating capacity.

Since wind capacity is essentially a non-dispatchable source of energy, it contributes relatively little capacity for meeting the reliability standard of "Generation Adequacy" compared to conventional generators. Nevertheless, wind generation, when it is available, is essentially free and it displaces most conventional sources of generation. As a result, the capacity factors of conventional generators are typically reduced when wind capacity is added. This happens even though the total amount of conventional capacity needed to maintain reliability may actually increase. Consequently, these conditions lead to increasing amounts of "missing money" for generators that are generally paid through some form of Capacity Market in most deregulated markets in the USA. For example, generating units in New York City have in the past been paid over $100,000/MW/year. This paper argues that "Financial Adequacy" should be treated as an additional criterion for planning purposes that would complement the standard engineering criterion of maintaining "System Adequacy".

The case study presented in this chapter shows that the total system costs charged to customers increase if a new wind farm replaces an existing coal unit on a network. With the wind farm in place, the increase in missing money is larger than the decrease in total operating costs in the Wholesale Market. For an

[6] This chapter summarizes the results of a research paper published in the *Journal of Energy Economics* (Mount, Timothy D.; Alberto J. Lamadrid, Surin Maneevitjit, Robert Thomas, and Ray Zimmerman. "The Hidden System Costs of Wind Generation in a Deregulated Electricity Market". *Journal of Energy Economics*, 33 (1), 173-198, 2011).

investment to be economically viable from the perspective of economic planning, the total annual cost of maintaining the existing system must go down and this decrease in cost must be bigger than the annualized cost of financing the investment.

In the case study, when some form of storage capability such as a battery mitigates the variability of wind generation, the total annual cost of the existing system does decrease. The battery charges when the wind speed is higher than the forecast and discharges when it is lower than the forecast, and in this way, the net wind generation on the grid is smoothed over time. As a result, there is an effective floor on the amount of generation from wind capacity when the indirect generation from discharging the battery is included. The presence of this floor reduces the total amount of conventional generating capacity that is needed to meet the peak system load and maintain System Adequacy, and as a result, the amount of missing money is also reduced. In addition, the total amount of wind that is spilled (i.e., wasted) is reduced when batteries are collocated at the wind farm.

The specific objectives of this paper are to demonstrate through a case study:

1) why Financial Adequacy is an important concept that should be considered by system planners,
2) why the social value of storage and controllable load increases when intermittent sources of generation are added to a network, and
3) how the cost of missing money to customers differs between a regulated and a deregulated market.

The case study considers the system effects of replacing a coal unit by a large wind farm with three times the installed capacity of the coal unit. Since the wind farm causes more congestion on the network when the wind blows, a series of additional scenarios show the effects of upgrading the capacity of a tie line to reduce this congestion. Since congestion rents on the network are treated as one source of income for transmission owners, changing these rents implies that there will be more or less missing money that must be paid by customers outside the Wholesale Market to ensure that the transmission owners are financially viable. The missing money for both generators and transmission owners contributes to the total annual system cost of maintaining System Adequacy and Financial Adequacy.

5.2 The Modeling Framework

The Energy Policy Act of 2005 (EPACT05) gives the Federal Energy Regulatory Commission (FERC) the overall authority to enforce reliability standards throughout the Eastern and Western Inter-Connections (see FERC [5]), and the North-American Electric Reliability Corporation (NERC) has been appointed by FERC as the new Electric Reliability Organization (ERO). Although the NERC has the responsibility to specify explicit standards for reliability such as System Adequacy, there is a major complication in how the North American Bulk Power Network is governed. There are many layers of governance, and in general, State regulators determine the rules for maintaining System Adequacy.

The NERC uses the following two concepts to evaluate the reliability of the bulk electric supply system:

1. Adequacy — The ability of the electric system to supply the aggregate electrical demand and energy requirements of customers at all times, taking into account scheduled and reasonably expected unscheduled outages of system elements.
2. Operating Reliability — The ability of the electric system to withstand sudden disturbances such as electric short circuits or unanticipated failure of system elements.

To simplify the concept of Operating Reliability, it is convenient to adopt a single measure, and the traditional NERC standard of one day in ten years for the Loss of Load Expectation (LOLE) is still treated by many regulators as the appropriate measure for the reliability of the bulk transmission system (i.e., this does not include outages of the local distribution systems caused, for example, by falling tree limbs and ice storms). Adequacy implies that past investments in the capacity of the electric delivery system must be sufficient to make the real-time operations meet the reliability standards. As a result, the Adequacy standard has important economic and financial implications that should be addressed by regulators in a more systematic and transparent way. That is why we argue that a new criterion of "Financial Adequacy" should be treated as a standard measure by system planners to evaluate the desirability of proposed changes to system capacity.

The modeling framework used for the case study is based on a stochastic form of single-period Security Constrained Optimal Power Flow (SCOPF), the SuperOPF. The basic structure of this model is identical to the one described in the previous chapter that was used to evaluate the effects of ramping on system costs (Section 4.2). The formal description of the model will not be repeated here. In the analysis that follows, it is assumed that all ramping costs are zero but this simplification does not affect the general conclusions about the need for Financial Adequacy.

Chen et al. (2003) have proposed an alternative way to determine the optimal dispatch and nodal prices in an energy-reserve market using "co-optimization" (CO-OPT). The proposed objective function minimizes the total expected cost (the combined production costs of energy and reserves) for a base case (intact system) and a specified set of credible contingencies (line-out, unit-lost, and high load) with their corresponding probabilities of occurring. Using CO-OPT, the optimal pattern of reserves and the amount of potential wind generation that is dispatched are determined endogenously and they adjust to changes in the physical and market conditions of the network. For example, the amount of reserves needed typically increases for a network with a variable source of generation from a wind farm.

In the SuperOPF, the CO-OPT criterion is modified to include the cost of Load-Not-Served (LNS), and it also distinguishes between positive and negative reserves for both real and reactive power. A high Value Of Lost Load (VOLL) is specified as the price of LNS. In practice, the number of contingencies that affect the optimal dispatch is much smaller than the total number of contingencies. In other words, by covering a relatively small subset of critical contingencies, all of the remaining contingencies in the set can be covered without shedding load. In a conventional SCOPF used by most System Operators, the n-1 contingencies are treated as "hard" constraints rather than as economic constraints as they are in the SuperOPF.

Increasing the stress on a network by, for example, increasing the peak system load over a planning horizon eventually causes load shedding, and typically, load shedding occurs first in one or more of the contingencies. Since the expected cost of LNS in a contingency is determined by multiplying a large VOLL by a small probability, the overall effect on the total expected system cost may be modest. From an economic planner's perspective, the standard of one day in ten years for the LOLE should correspond to equating a reduction in the expected annual cost of operating the system, including changes in the expected cost of LNS, with the annual cost of making an investment in additional capacity.

The following section describes the characteristics of the 30-bus test network used in the case study and the specifications for the simulations. The basic objective of this analysis is to evaluate the effects of replacing an existing coal unit by a large new wind farm. The initial amounts of installed capacity are sufficient to meet the standard for System Adequacy, and since wind generation is inherently intermittent, the installed capacity of the wind generators is substantially larger than the capacity of the coal unit. In addition, the analysis determines the economic benefit of upgrading a transmission tie line to transfer more wind generation from a remote location to an urban center.

5.3 The Scenarios Evaluated in the Case Study

The case study is based on a 30-bus test network that has been used extensively in our research to test the performance of different market designs using the MATPOWER platform. The one-line-diagram of this network is shown in Figure 1 below. The 30 nodes and the 39 lines are numbered in Figure 5.1 and this numbering scheme provides the key to identifying the locations of the specific contingencies described in the following discussion. In addition, the six generators are also identified. The network is divided into three regions, Areas 1 – 3, and Area 1 represents an urban load center with a large load, a high VOLL and expensive sources of local generation from Generators 1 and 2. The other two regions are rural with relatively small loads, low VOLLs and relatively inexpensive sources of generation from Generators 3 – 6. Consequently, an economically efficient dispatch uses the inexpensive generation in Areas 2 and 3 to cover the local loads and as much of the loads in Area 1 as possible.

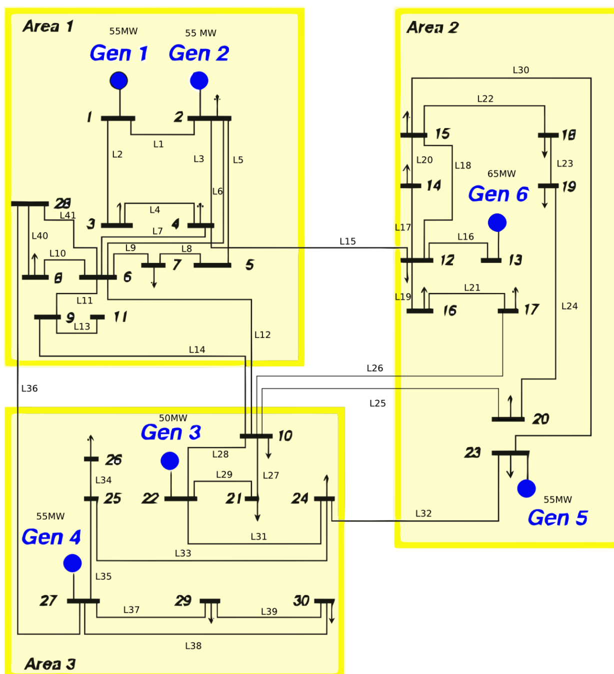

Figure 5.1: A One-Line-Diagram of the 30-Bus Test Network.

The capacities of the transmission tie lines linking Areas 2 and 3 with Area 1 (Lines 12, 14, 15 and 36) are the limiting factors. Since lines and generators may fail in contingencies, the generators in Area 1 are primarily needed to provide reserve capacity. The general structure of the network poses the same type of problem faced by the system operators and planners in the New York Control Area. Most of the load is in New York City (i.e., Area 1) and the inexpensive sources of baseload capacity (hydro, coal and nuclear) are located upstate (i.e., Areas 2 and 3).

5.3.1 The Realizations of Potential Wind Generation

There are three different forecasts of the level of wind generation (high, medium and low), and each forecast has four possible outcomes, summarized for NORMAL Wind and NICE Wind in Table 5.1. With no wind capacity installed, the contingency k = 0 corresponds to the intact system using the forecasted level of load (i.e., the network shown in Figure 5.1). The analysis that underlies the information presented in Table 5.1 has three components that are described in a paper by Anderson and Cardell (2008). The first component is a set of time-series data for hourly wind speeds at a specific location (in New England for this case study). The second component is an ARMA model for predicting wind speed (one hour ahead for this case study), and finally, there is a power curve for a wind turbine that converts a given wind speed to the potential amount of energy generated (wind turbines are also specified as a potential source of positive reactive power in the SuperOPF).

The following four different Cases for wind generation are considered:

1) NO Wind; with a 35 MW coal unit installed at Generator 6,
2) NORMAL Wind; with the coal unit replaced at Generator 6 by 105MW of wind capacity, using the realizations of potential wind generation in Table 5.1 and zero for the offer price in the wholesale auction,
3) NICE Wind; the same as Case 2 with a different set of specifications for the realizations of potential wind generation (see Table 5.1) that represent the net effect of collocating the wind farm with a 35MW battery,
4) NASTY Wind; the same as Case 2 with the offer price in the wholesale auction set to -$1,500/MWh to "force" acceptance of wind generation in the auction and represent a "Must-Take" form of contract between the wind farm and the System Operator.

In addition, the same four Cases are rerun after making an upgrade to Transmission Line L15 in Figure 5.1. This upgrade doubles the transfer capacity of the main tie line linking the wind farm in Area 2 to the urban center in Area 1. These Cases are referred to as Case 1UP, Case 2UP, etc.

Table 5.1: Specifications of the Potential Wind Generation

Forecasted Wind Speed	Probability of Forecast Occurring[a]	Potential Wind Generation[b]		Output Probability (%)[c]
		NORMAL	NICE	
LOW (0-5meters/second)	11	0	35	66
		7	35	26
		33	35	5
		73	38	3
MEDIUM (5–13meters/second)	46	6	41	24
		38	55	20
		62	55	18
		93	58	38
HIGH (>13meters/second)	43	0	35	14
		66	70	4
		94	70	3
		100	70	79

[a] Average Annual values for a typical day.
[b] % of Installed Wind Capacity, 105MW of wind capacity installed.
[c] Conditional on Forecast.

An important feature that underlies the levels of NORMAL Wind in Column 3 of Table 5.1 is that the ranges of realized wind speeds for each wind forecast (Low, Medium or High) are much larger than the range of the forecasted wind speeds that define each bin. Consequently, the ranges of potential wind generation for a given forecast are also very large. For NORMAL Wind, the ranges of potential wind generation are 0-73%, 6-93% and 0-100% of the installed capacity for the Low, Medium and High forecasts, respectively. The four realizations for each type of forecast are treated as different states (contingencies) in the SuperOPF. The main challenge for a System Operator is with the High wind forecast because the realizations are bimodal with modes at 100% and at 0% of installed capacity (due to cutouts at wind speeds >25 meters/second to protect the turbines). A sensible procedure under these circumstances is to spill some potential wind generation at high realized wind speeds <25 meters/second to reduce the effective size of the cutout contingency.

The ranges of realized potential wind generation in Column 4 for NICE Wind are much smaller than the corresponding ranges in Column 3 for NORMAL Wind. They represent the effect of collocating a battery at the wind farm to produce a higher quality wind resource. At high wind speeds, some of the wind generation is used to charge the battery, and at low wind speeds, discharging the battery augments the available wind generation (that may be zero). An important consequence is that the minimum potential wind generation (including discharging the battery) for the High wind forecast is now 35% instead on 0% of installed wind capacity and the maximum size of the cutout contingency is reduced from 100% to 35%.

The levels of potential wind generation for NICE Wind in Table 5.1 were derived from an off-line simulation of the effects of a simple charging/discharging strategy on potential wind generation (charge for high wind speeds and discharge for low wind speeds and cutouts). Clearly, this is a very simple representation of the role of storage because it assumes that it is used solely to mitigate wind variability. This simplification is necessary because the SuperOPF used in this chapter only optimizes for a single time period. A multi-period version of the SuperOPF is presented in the next chapter, and this model makes it possible to determine the optimum charging/discharging strategy for storage endogenously and flatten the daily pattern of dispatch for conventional generating units.

5.4 Results for the Wholesale Market

The results presented in this section summarize the economic costs for the network shown in Figure 5.1 of meeting the same annual pattern of load for the eight different scenarios discussed in the previous section. For this analysis, it is assumed that the wholesale market is deregulated. The main questions of interest are 1) how much generating capacity is needed to maintain System Adequacy, and 2) what happens to the wholesale prices and operating costs?

The four different types of wind generation considered are NO Wind, NORMAL Wind, NICE Wind (i.e., wind sites collocated with storage) and NASTY Wind (i.e., must-take contracts for wind generation), and the order of the eight scenarios, with and without an upgrade of the tie line, is:

1. Case 1; NO Wind
2. Case 1UP; NO Wind + Upgrade
3. Case 2; NORMAL Wind
4. Case 2UP; NORMAL Wind + Upgrade
5. Case 3; NICE Wind
5. Case 3UP; NICE Wind + Upgrade
7. Case 4; NASTY Wind
8. Case 4UP; NASTY Wind + Upgrade

For each scenario, the reported annual costs are the sum over 100 load levels of the expectation of the costs for the three forecasts of wind speed shown in Table 5.1 using the second-stage optimization of the SuperOPF.[7]

The key results for the eight scenarios are presented in Table 5.2. The first row (Load Paid) shows that the annual payments made by customers in the wholesale market are substantially lower than the NO Wind scenario (Cases 1 and 1UP) for all of the wind scenarios except NASTY Wind (Case 4). These cost reductions represent the displacement of fossil fuels by wind generation whenever the wind blows, and at low load levels, the expected generation from

[7] In other words, the expected costs are computed for the 18 different contingencies for each one of the three forecasts of wind speed.

wind is the dominant source. For NICE Wind with the upgraded tie line (Case 3UP), the customers only pay one sixth of the corresponding cost with NO wind (Case 1) in the wholesale market. Wind also displaces fossil fuels in the Case 4, but the wholesale prices paid by customers are still high because of the increased cost of dealing with additional congestion on the network.[8]

Table 5.2: Summary of Results for the Wholesale Market

	Case 1	Case 1UP	Case 2	Case 2UP	Case 3	Case 3UP	Case 4	Case 4UP
Load Paid[a]	68,915	66,171	22,373	14,705	23,560	11,934	78,570	36,650
GenCap*,[b]	283	288	288	286	242	259	295	292
MaxWC*,[c]	0	0	35	83	43	73	105	105
C.Gen[d]	100	100	88	86	78	75	56	55
LNS[e]	16	15	4	4	7	7	34	20

* 105MW of Wind capacity replaces 35MW of Coal capacity in Cases 2, 3 and 4.
[a] \$1000/Year.
[b] Gen. Capacity Needed (MW).
[c] Max Wind Committed (MW).
[d] Conventional Generation (%).
[e] Load Not Served (Hours/Year).

The generally lower wholesale costs of purchases with wind generation in Table 5.2 contrast with the amounts of conventional generating capacity needed for System Adequacy (Gen Capacity Needed is the maximum capacity committed over the year). The capacity needed is roughly the same with NORMAL Wind (Cases 2 and 2UP) as it is with NO Wind (Cases 1 and 1UP), and it is even higher with NASTY Wind (Cases 4 and 4UP). It is only with NICE Wind that the capacity needed is substantially lower (Cases 3 and 3UP). The underlying reason is that the storage capacity coupled with wind generation in Cases 3 and 3UP provides a floor on the potential wind generation and reduces the size of the cutout contingency at high wind speeds. As a result, less reserve capacity is needed for Operating Reliability and more of the potential wind generation is dispatched.

[8] When wind generation is the dominant source at low load levels, it is difficult to accommodate this generation on the network. With a must-take contract in Case 4, there is an economic penalty for not using all of the potential wind generation even though this source increases the marginal system cost substantially.

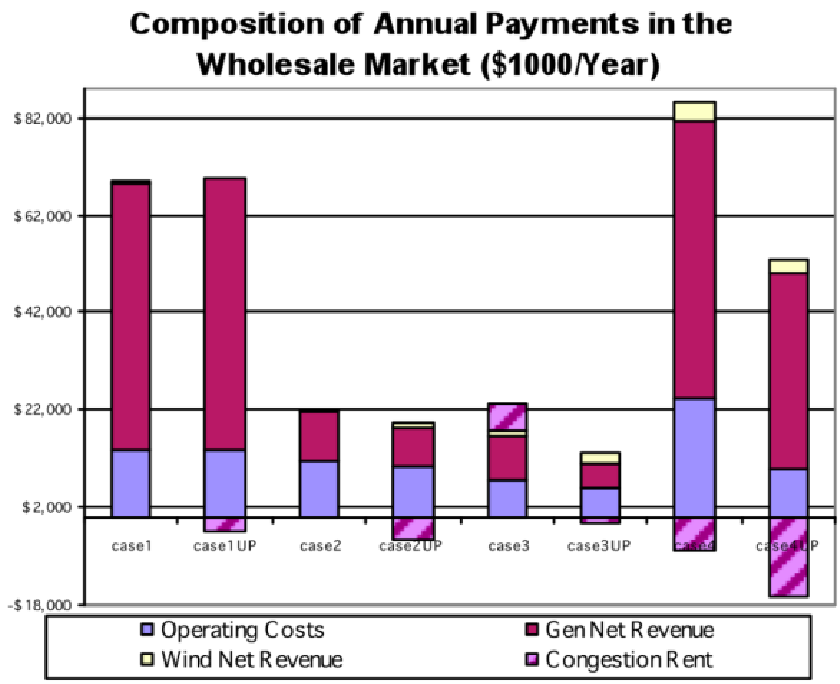

Figure 5.2: The Composition of Payments by Customers in the Wholesale Market

Even though the production cost and price offer of wind generation is set to zero for NORMAL Wind, the maximum amount of wind generation dispatched (Max Wind Committed) is only 35MW compared to the true maximum of 100MW because of the high cost of covering the contingency when the wind turbines cutout. More wind generation can be used economically when the tie line is upgraded (Case 2UP) or if storage capacity is coupled with the wind generation (Cases 3 and 3UP). However, the amount of wind capacity that is dispatched is not really limited by the physical capacity of the network. In Cases 4 and 4UP with must-take contracts, all 105MW are dispatched but the consequence is that customers have to pay a lot more in the wholesale market for congestion and a lot more to maintain Operating Reliability to cover the cutout contingency.

The overall cost of purchases in the wholesale market for the different scenarios is summarized in Figure 5.2. For NO Wind in Case 1, the total cost to customers is relatively high and most of this total is Net Revenue for the conventional generators above their true operating costs. The Operating Costs make up about one fifth of the total payments. A small payment in Case 1 goes to Congestion Rents (the difference between the payments by customers and the payments to generators), and with the tie line upgrade in Case 1UP, the Congestion Rents are negative. With NORMAL Wind and NICE Wind, the total payments drop substantially compared to NO Wind, and most of the reductions come from much lower Net Revenues for the conventional generators. In addition, the Net Revenue for the wind generators is also relatively small. The results for NASTY Wind are very different. Operating Costs and the Net Revenue for conventional generators are both higher than they are in Case 1 unless the tie line is upgraded in Case 4UP. Accommodating large quantities of unmitigated wind generation on the network is expensive and does not benefit customers. It is interesting to note that the Net Revenue for wind generators is still relatively small.

The sum of the Net Revenues earned by the conventional generators and the Congestion Rent is the Operating Surplus in the wholesale market, and this quantity represents the amount of money available to cover capital costs. In the same way, the Net Revenue for the wind generator can be used to cover the investment in the wind farm. Using NO Wind (Case 1) as the base for comparison, the Operating Surplus is much lower for NORMAL and NICE Wind (Cases 2 and 3) and slightly higher for NASTY Wind (Case 4). The Operating Cost in Case 4 is high because the mix of generating capacity dispatched is very different from the least-cost merit order due to network constraints and congestion. In all four cases, upgrading the tie line reduces the Operating Cost and makes it possible to rely more on the inexpensive sources of generation.

5.4 Determining the Amount of Missing Money

The final component of the analytical framework is to describe how much missing money is required by generators above their annual earnings in the Wholesale Market to ensure that they are financially viable. This is the main implication of requiring that an electric delivery system should maintain Financial Adequacy as well as Physical Adequacy. In addition, changes in the amount of congestion rents collected by the System Operator in the Wholesale Market affect how much additional money is needed to pay transmission owners a regulated rate of return on their capital investment in transmission and distribution. Even though the total payment made to transmission owners is the same in all scenarios, the proportion of this amount coming from congestion rents is determined endogenously in the analysis.

Under a regulated regime, the rates charged to customers are set so that utilities receive enough revenue to cover all operating costs and a fair rate of return of and on the depreciated book value of the capital assets that are considered by the regulators to be “used and useful”. This procedure is assumed to still be the method used to pay for transmission and distribution assets in a deregulated market. For merchant generators, however, their revenue in a deregulated market comes from 1) being paid the nodal prices for their generation and ancillary services in the Wholesale Market[9], and 2) payments for capacity in a Capacity Market if such a market exists. These generators expect to earn a market rate of return on the market value of their generating assets. Given the physical durability of conventional generating units relative to the standard regulatory accounting rates of depreciation, the market value of conventional capacity is typically substantially higher than the book value would have been under continuous regulation[10]. This is a major additional cost that should be

[9] These payments may also be made through forward contracts, but the contract prices will still reflect the expectations of traders about future prices in the Wholesale Market. In addition, there may be bilateral contracts that include two-part payments for energy (or an ancillary service) and capacity.

[10] The late Mike Rothkopf was one of the few economists to raise this issue as an important reason for being skeptical about the widely held belief among academics and regulators that deregulating electric utilities would benefit customers.

compared with any gains in economic efficiency in the Wholesale Market that lower operating costs.

The amount of missing money for a conventional generator is determined by specifying the minimum annual earnings needed to maintain its Financial Adequacy. In a deregulated market, it is assumed that the minimum annual earnings above the annual operating costs correspond to the replacement value for each generating unit. The values used in the analysis are shown in Table 5.3. As long as the annual earnings in the Wholesale Market are bigger than the minimum earnings, the generating unit meets the standard of Financial Adequacy and there is no missing money. On the other hand, if the annual earnings in the Wholesale Market are less than the minimum earnings, the difference between the minimum earnings and the actual earnings measures the amount of missing money. Dividing the amount of missing money by the amount of generating capacity needed for System Adequacy gives the minimum annual price of capacity ($/MW/Year) needed for Financial Adequacy. In other words, as long as the price paid in a Capacity Market is larger than the minimum price for every conventional generating unit, it is big enough to maintain Financial Adequacy.

The final step in the calculation of the total amount of missing money for conventional generators is to specify a structure for the Capacity Market. The Capacity Market is assumed, following the structure of the market in New York State, to be divided into two regions; Area 1, the urban region, Areas 2 and 3, the rural region. Each region sets its own capacity price and this price is equal to the highest of the minimum capacity prices needed for Financial Adequacy for all of the generating units in a region. The market price is paid for all of the generating capacity in a region that is needed to meet the peak system load and maintain System Adequacy. This procedure follows the standard practice used to make payments in a uniform price auction.

The simplest type of missing money is for transmission owners. It is assumed for all scenarios that transmission owners received $30 million/Year to cover all of their costs for the existing network including the annualized capital costs. The Congestion Rent in the wholesale market (see Figure 5.2) covers part of this total and the remaining part corresponds to the missing money. For scenarios in which the ISO pays more to generators than the amount received from customers, the Congestion Surplus is negative and the corresponding missing money will be larger than $30 million/Year. However, customers still pay the same total cost of transmission and the only feature that changes from scenario to scenario is the amount of money contributed in the wholesale market.

For generators, the situation is more complicated because the amount of conventional generating capacity needed for reliability purposes varies from scenario to scenario as well as the total annual operating costs. Nevertheless, the total annualized capital cost of the conventional generating units is paid in a similar way to the payments for transmission. Some of the money comes from the wholesale market (Gen Net Revenue in Figure 5.2) and the rest is paid as

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See Michael H. Rothkopf, "Dealing with Failed Deregulation: What Would Price C. Watts Do?" The Electricity Journal 20(7), pp.10-16, July-August 2007.

missing money through a Capacity Market. The calculations for determining the amount of missing money in a deregulated market are illustrated in Table 5.3 for the NO Wind scenario. Note that Generators 1 and 2 are in one capacity market and Generators 3-6 are in the other capacity market.

Table 5.3: The Missing Money for Conventional Generators (Case 1)

	1	2	3	4	5	6	7	8
	Minimum Earnings/MW $1000/MW/year	**Required Capacity MW**	**Minimum Earnings $1000/year**	**Actual Earnings $1000/year**	**Difference Actual - Min. $1000/year**	**Missing Money Max(-Diff, 0) $1000/year**	**Price of Capacity $1000/MW/year**	**Capacity Payments $1000/year**
Gen 1	$88	20.00	$1,760	$1,452	-$308	$308	$15	$1,623
	$88	15.42	$1,357	$106	-$1,252	$1,252	**$81**	$1,252
Gen 2	$88	25.00	$2,200	$2,204	$4	$0	$0	$2,029
	$88	25.00	$2,200	$406	-$1,794	$1,794	$72	$2,029
Gen 3	$460	30.00	$13,800	$12,784	-$1,016	$1,016	$34	$5,113
	$131	20.00	$2,620	$845	-$1,775	$1,775	$89	$3,409
Gen 4	$460	35.00	$16,100	$14,775	-$1,325	$1,325	$38	$5,965
	$131	0.00	$0	$0	$0	$0	$0	$0
Gen 5	$460	20.00	$9,200	$5,791	-$3,409	$3,409	**$170**	$3,409
	$230	35.00	$8,050	$2,911	-$5,139	$5,139	$147	$5,965
Gen 6	$460	30.00	$13,800	$9,255	-$4,545	$4,545	$152	$5,113
	$230	27.76	$6,385	$3,796	-$2,589	$2,589	$93	$4,731
TOTAL		**283.18**	**$77,472**	**$54,324**	**-$23,148**	**$23,153**		**$40,639**

The steps used to calculate the payments for capacity outlined in Table 5.3 were completed for each scenario. These payments together with the payments to transmission owners are added to the Total Annual Operating Costs to give the Total Annual System Cost charged directly in the wholesale market and indirectly as missing money to customers.

In a traditional regulated market, regulators set the rates paid by customers to cover all of the prudent operating costs and capital costs of the conventional generators. These rates typically would include fixed rates for energy and possibly for capacity for some customers, and real time rates and capacity rates for other customers. However, the effects of different rate structures on load are ignored for all scenarios in this paper and the focus is on the differences in Total Annual System Costs for the same annual pattern of load. The main differences in a regulated market from the procedures used for a deregulated market in Table 5.3 are 1) the Minimum Earnings/MW in Column 1 are determined by the book value of capital rather than the market value, and 2) the capacity payments cover the missing money for each unit in Column 6 and would also confiscate excess profits (i.e., positive differences in Column 5). In other words, even if the lower book values in Column 1 are ignored, the customers would only pay $23 million/Year (Column 6) under regulation rather than $40 million/Year (Column 8) in a Capacity Market.

In the next section, The Total Annual System Costs paid by customers are calculated for the eight wind scenarios for the following three types of market (note that the cost components in the wholesale market for a given wind scenario, shown in Figure 5.2, are identical in all three markets).

1) Mkt1: A deregulated Market that pays the missing money through a Capacity Market based on a uniform price auction. This implies that the Required Capacity (Column 2 in Table 5.3) is paid the highest Price of Capacity (Column 7) in each of the capacity markets (pay Column 8).

2) Mkt2: A market that pays the actual missing money only (i.e., pay Column 6 instead of Column 8 in Table 5.3).

3) Mkt3: A regulated Market that pays legitimate capital costs using a book value equivalent to 50% of the market value (i.e., pay Column 5 using 50% of the values in Column 1 of Table 5.3).

5.5 Total Annual System Costs in Different Markets

Typically, generating units in an economically efficient market do not receive enough net revenue in the wholesale market to maintain Financial Adequacy. The mechanism for paying the cost of capital for generating units in the three different markets is similar to the way that transmission owners are paid. Some of the income needed for Financial Adequacy comes from the Net Revenue in the wholesale market and the rest from missing money. In Mkt2, the missing money is paid directly to individual generators. In a deregulated market (Mkt1), the missing money is paid indirectly through a Capacity Market and results in higher payments than Mkt2. In the Regulated Market (Mkt3), the Minimum Earnings/MW for the individual generating units is only half as big as it is in the other two markets.

In any one of the three markets, if the levels of the different types of generating capacity needed for System Adequacy remain the same in different cases, the generators' capital costs also stay the same. Lower earnings in the wholesale market are simply offset by higher payments for missing money. Hence, the only effective ways to reduce the total annual payments to generators for capital costs in a given market are 1) to reduce the amount of conventional capacity needed for System Adequacy, and, to a lesser extent, 2) to change the mix of generating units needed for System Adequacy.

Figure 5.3 summarizes the overall results of the analysis for the three different markets by showing the composition of the Total Annual Systems Costs for the four wind scenarios with no tie line upgrade. The first three components (the lowest three) are the Operating Costs, the Generator Net Revenue and the Wind Net Revenue shown in Figure 5.2. For each wind case, these wholesale payments (and total payments to transmission owners) are identical for the three different markets, but the payments to generators for missing money are highest in a deregulated market (Mkt1) and lowest in a regulated market (Mkt3). The payments made to generators in the wholesale market are substantially lower with NORMAL and NICE Wind (Cases 2 and 3) compared to NO Wind (Case 1), but this reduction for NORMAL Wind is effectively offset by the increase in the amount of missing money paid to generators in Mkt1 and Mkt2. This missing money is much lower for NICE Wind because less generating capacity is needed to maintain System Adequacy, and as a result, the Total Annual System Cost is the lowest in all three markets compared to the other cases. For NASTY Wind (Case 4), both the Operating Costs and the total payments for capital are higher than the corresponding values for the other three cases. The main conclusion is that focusing on a reduction in the average wholesale price when wind capacity is introduced into a deregulated market and implicitly treating the capital cost of existing generating units as a sunk cost can be very misleading unless the effects on the missing money needed by the conventional generators and transmission owners is also considered.

An underlying reason for calculating the Total Annual System Costs is to determine the viability of making investments in, for example, wind capacity and upgrading a tie line. The economic justification for making an investment corresponds to having a reduction in the Total Annual System Costs that is bigger than the annual capital cost of financing the investment. The Total Annual System Costs for NO Wind are $139, $122 and $114million/Year for Mkt1, Mkt2 and Mkt3, respectively, and Table 5.4 summarizes the savings in the Total Annual System Costs for a given market from investing in the three different wind scenarios (Cases 2-4) compared to NO Wind (Case 1). For all three markets, the savings for NASTY Wind (Case 4) are negative, and as a result, there is no economic justification for making this investment. For NORMAL Wind (Case 2) and NICE Wind (Case 3), the savings are highest and positive in a regulated market (Mkt1) and lowest, and slightly negative, for NORMAL Wind in a deregulated market (Mkt1). Finally, the additional savings comparing NICE Wind to NORMAL Wind measures the value of having storage capacity mitigate wind variability. This value is smallest in a regulated market because the price of conventional capacity (missing money/MW) is lower than it is in the other two markets.

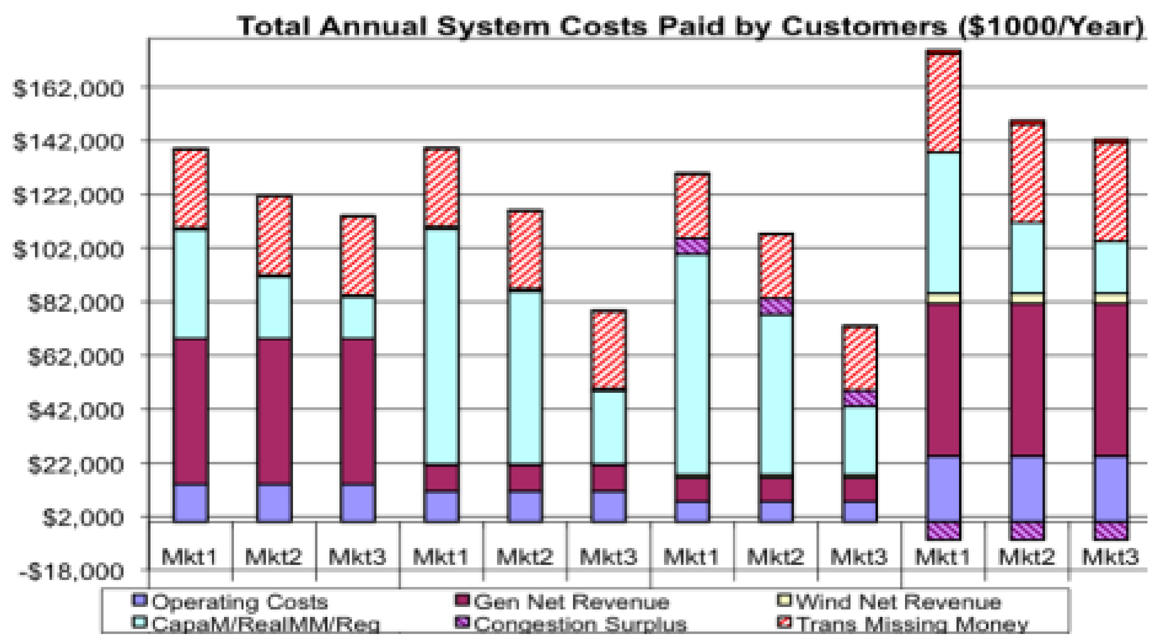


Figure 5.3 The Total Annual System Costs Paid by Customers

(Case 1: columns 1-3, Case 2: columns 4-6, Case 3: columns 7-9, Case 4, columns 10-12)

Table 5.4 Savings in the Total Annual System Cost Compared to Case 1

($1000/Year) Case 1-Case s	Case 1	Case 2	Case 3	Case 4
Mkt1	0.00	−218.00	9,310.00	−30,035.00
Mkt2	0.00	5,548.00	14,139.00	−21,340.00
Mkt3	0.00	35,152.00	40,938.00	−21,831.00

Table 5.5 summarizes the savings in the Total Annual System Costs from upgrading the tie line for Cases 1-4 in the three different markets. The savings from the upgrade are computed for each combination of wind case and market. In a deregulated market (Mkt1), the savings are positive for all four of the wind cases. The largest savings are for NASTY Wind (Case 4) because of the need to accommodate the maximum 105MW of wind generation under a must-take contract. The savings are smallest for NICE Wind (Case 3) because the storage capacity effectively reduces the maximum wind generation dispatched on the network (i.e., at high wind speeds, some wind generation is used locally to charge the battery). In fact, the savings from upgrading the tie line are negative in Mkt2 and Mkt3 for NICE Wind. The savings from the upgrade are also negative in Mkt2 and Mkt3 for NO Wind (Case 1). Comparing the results for NICE Wind and NASTY Wind demonstrates that coupling storage capacity with wind generation in Case 3 is, in effect, a substitute for adding transmission capacity. Once again, using only the changes in the wholesale prices as a guide for determining the benefit of additional transmission capacity may be highly misleading.

Table 5.5: Savings in the Total Annual System Cost from Upgrading a Tie Line

($1000/Year) Case sUP–Case s	Case 1	Case 2	Case 3	Case 4
Mkt1	7,177.00	6,930.00	1,872.00	25,593.00
Mkt2	−1,959.00	531.00	−2,765.00	24,256.00
Mkt3	−1,509.00	480.00	−1,321.00	49,637.00

5.6 Conclusions

This paper considers the practical need of determining which generating units will be needed on a network to maintain reliability when some generation comes from variable wind sources, and how to keep them financially viable. The overall recommendation of the paper is to propose that Financial Adequacy should be considered as an additional criterion for planning purposes in deregulated markets. The specific objectives of this paper are to demonstrate why it is important when evaluating different wind scenarios to 1) determine the amount of conventional generating capacity needed to maintain System

Adequacy endogenously, and 2) evaluate the economic effects of wind generation on the financial viability of these conventional generators.

The first objective addresses the physical nature of System Adequacy, and it is accomplished using the co-optimization capabilities of the SuperOPF. The endogenous amounts of generating capacity needed to meet the same peak system load in different scenarios can vary substantially, and these different amounts of capacity define the requirements for maintaining System Adequacy on a given network. In general, the total amount of conventional generating capacity needed (dispatched capacity plus upward reserve capacity) may increase when a variable source like wind generation replaces conventional generation. This can occur even when the generation from wind displaces a substantial portion of the conventional generation. Typically, the capacity factors of some conventional generating units will be lower when wind capacity is added.

Meeting the second objective is accomplished by determining the total annual earnings above the operating costs for individual generating units in a wholesale market. These earnings are compared with specified minimum levels of earnings, and if the actual amount earned for any generating unit is less than the corresponding minimum level, there is "missing money", implying that an additional source of income is needed to maintain the Financial Adequacy of that unit. Three different types of market are considered to calculate the payments made for the missing money. Mkt1 is a deregulated market that has the highest payments because 1) the missing money is determined using the market value of the generating units, and 2) the payments made in a capacity market set the capacity price at the highest amount of missing money/MW for any generating unit. Mkt2 is the same as Mkt1 except the payment corresponds to the actual missing money needed for each generating unit (i.e., there is no capacity market and the implicit price for capacity paid is not the same for every generating unit). Mkt3 is a regulated market that has the lowest payments because 1) the missing money is determined by the depreciated book value of the generating units rather than the market value, and 2) generators are paid only for legitimate capital costs (i.e., similar to Mkt2).

For each type of market, the overall implication of evaluating the Financial Adequacy of generating units is that if a unit needs missing money, reducing the earnings of the unit in the wholesale market simply increases the amount of missing money needed. In terms of the annual earnings, it is a zero-sum game. Since adding wind capacity to a network will tend to lower the earnings of the conventional generators in the wholesale market, these lower earnings will be offset to a large extent by higher amounts of missing money.[11]

The real net benefits associated with adding wind capacity to and/or upgrading transmission for a network come from the following three sources:

1) Reducing the real operating costs (e.g., using less fossil fuels) of the conventional generating units,

[11] A similar zero-sum game exists for regulated transmission owners. Some earnings come from the congestion rents in the wholesale market and the rest is made up as additions to the retail rates charged to customers.

2) Reducing the total amount of conventional generating capacity needed to maintain System Adequacy,
3) Reducing the excess profits of the conventional generators.[12]

The message for the State regulators who are responsible maintaining reliability standards in deregulated markets is that it may be very misleading to interpret reductions in the average wholesale price as indicative of positive net benefits from an investment. In some of the cases considered in this paper, the total annual payment by customers in the wholesale market decreases at the same time that the Total Annual System Cost increases. For planning purposes, it is essential to measure the Total Annual System Costs and consider the Financial Adequacy of the conventional generators as well as the wholesale prices when evaluating the economic net benefits of investments in wind capacity and transmission upgrades.

References

[1] Anderson, C.L. and J.B. Cardell (2008), "Reducing the Variability of Wind Power Generation for Participation in Day Ahead Electricity Markets," Proceedings of the 41st Annual Hawaii International Conference on System Sciences, IEEE Computer Society, Washington, DC, USA, p. 178.

[2] BentekEnergy (2010). "How Less Became More: Wind, Power and Unintended Consequences in the Colorado Energy Market," Technical

[3] Billinton, R. and G. Bai (2004). "Generating capacity adequacy associated with wind energy," Energy Conversion, IEEE Transactions on, 19(3): 641–646.

[4] Bird, L., C. Chapman, J. Logan, J. Sumner, and W. Short (2011). "Evaluating renewable portfolio standards and carbon cap scenarios in the U.S. electric sector," Energy Policy, 39(5): 2573–2585. http://www.sciencedirect.com/science/article/B6V2W-529SWC03/2/2112bda19624da724fc d6dfdb653cbc8.

[5] Bouffard, F., F. Galiana, and A. Conejo (2005). "Market-clearing with stochastic security - part i: formulation," Power Systems, IEEE Transactions on, 20(4): 1818–1826.

[6] Bouffard, F., F. Galiana, and A. Conejo (2006). "Market-clearing with stochastic security - part ii: case studies," Power Engineering Society General Meeting, IEEE, 1.

[12] Excess profits imply that the actual earnings for a generating unit are larger than the minimum amount needed for Financial Adequacy. This amount depends on the type of market considered. For example, excess profits are highest in a deregulated market and are zero in a regulated market.

[7] Chen, J., T.D. Mount, J.S. Thorp, and R.J. Thomas (2005). “Location-based scheduling and pricing for energy and reserves: a responsive reserve market proposal,” Decision Support Systems, 40(3–4): 563– 577.

[8] Chen, J., J.S. Thorp, R.J. Thomas, and T.D. Mount (2003). “Locational Pricing and Scheduling for an Integrated Energy-Reserve Market,” Proceedings of the 36th Annual Hawaii International Conference on System Sciences, IEEE Computer Society, Washington, D.C., USA, 54.1.

[9] DOE (2008). “20% Wind Energy by 2030,” Technical Report NA, U.S. Department of Energy (DOE). http://www1.eere.energy.gov/windandhydro/pdfs/41869.pdf.

[10] Fu, Y., M. Shahidehpour, and Z. Li (2006). “AC contingency dispatch based on security-constrained unit commitment,” Power Systems, IEEE Transactions on, 21(2): 897– 908.

[11] GE Energy (2010). “Western Wind and Solar Integration Study,” Technical report, The National Renewable Energy Laboratory.

[12] Hittinger, E., J. Whitacre, and J. Apt (2010). “Compensating for wind variability using co-located natural gas generation and energy storage,” Energy Systems, 1: 417–439. 10.1007/s12667-010- 0017-2. http://dx.doi.org/10.1007/s12667-010-0017-2.

[13] Holttinen, H., P. Meibom, C. Ensslin, L. Hofmann, J. McCann, J. Pierik, J.O. Tande, E. Hagstrøm, A. Estanqueiro, H. Amaris, L. Soder, G. Strbac, and B. Parsons (2006). “Design and Operation of Power Systems with Large Amounts of Wind Power, IEA collaboration,” in Nordic Wind Power Conference, Espoo, Finland.

[14] Katzenstein, W. and J. Apt (2008). “Air Emissions Due To Wind And Solar Power,” Environmental Science & Technology, 43(2): 253–258. http://dx.doi.org/10.1021/es801437t.

[15] Kopka, H. and P. Daly (1999). “A Guide to LATEX,” Harlow, England: Addison-Wesley.

[16] Lopez-Lezama, J., C. Murillo-Sanchez, L. Zuluaga, and J. Gutierrez-Gomez (2006). “A Contingency- Based Security-Constrained Optimal Power Flow Model For Revealing The Marginal Cost of a Blackout Risk-Equalizing Policy in the Colombian Electricity Market,” Transmission and Distribution Conference and Exposition: Latin America, 2006. TDC ’06. IEEE/PES, 1–6.

[17] Milligan, M., K. Porter, E. DeMeo, P. Denholm, H. Holttinen, B. Kirby, N. Miller, A. Mills, M. O’Malley, M. Schuerger, and L. Soder (2009). “Wind power myths debunked,” Power and Energy Magazine, IEEE, 7(6): 89–99.

[18] Mount, T.D., A. Lamadrid, S. Maneevitjit, R.J. Thomas, and R. Zimmerman (2009). "A Symbiotic Role for Plug-in Hybrid Electric Vehicles in an Electric Delivery System," Proceedings of the 22nd Rutgers CRRI Western Conference, Monterey, CA.

[19] Murillo-Sanchez, C. and R. Thomas (1998). "Thermal unit commitment including optimal AC power flow constraints," System Sciences, 1998., Proceedings of the Thirty-First Hawaii International Conference on System Sciences, 3: 81–88.

[20] Murillo-Sanchez, C., and R. Thomas (1999). "Thermal unit commitment with nonlinear power flow constraints," Power Engineering Society 1999 Winter Meeting, IEEE, 1: 484–489.

[21] North-American Electric Reliability Corporation (NERC) (2007). "2007 Long-Term Reliability Assessment 2007–2016," Technical Report UW-CS-TR- 1481, NERC. http://www.nerc.com/files/ LTRA2007.pdf.

[22] North-American Electric Reliability Corporation (NERC) (2009). "Reliability Standards for the Bulk Electric Systems of North America," NERC 116-390 Village Road, Princeton, NJ, 08540. http://www.nerc.com/files/Reliability Standards Complete Set 2009Sept14.pdf.

[23] NYISO, (2007). "2007 State of the Market Report New York Electricity Markets," Independent market advisor, NYISO, Potomac Economics. www.nyiso.com/regulatory/filings/2010/08/AttB_BRM_Analysis_Final_NY_Presentation_6_2010.pdfisor reports/2007 NYISO SOM presentation 51908.pdf.

[24] Rothkopf, M.H. (2007). "Dealing with Failed Deregulation: What Would Price C. Watts Do?" The Electricity Journal, 20(7): 10–16. http://www.sciencedirect.com/science/article/B6VSS-4PC4F462/2/27c528783c63c2dd93bfa7380a74a942.

[25] Smith, J., M. Milligan, E. DeMeo, and B. Parsons (2007). "Utility Wind Integration and Operating Impact State of the Art," Power Systems, IEEE Transactions on, 22(3): 900–908.

[26] Thomas, R., C. Murillo-Sanchez, and R. Zimmerman (2008). "An advanced security constrained OPF that produces correct market-based pricing," in Power and Energy Society General Meeting - Conversion and Delivery of Electrical Energy in the 21st Century, 2008 IEEE, 1–6.

[27] Zimmerman, R., C. Murillo-Sanchez, and R. Thomas (2009). "MATPOWER's extensible optimal power flow architecture," Power Energy Society General Meeting, 2009. IEEE, 1–7.

[28] Zimmerman, R.D., C.E. Murillo-Sanchez, and R.J. Thomas (2011). "MATPOWER: Steady-State Operations, Planning, and Analysis Tools for Power Systems Research and Education," IEEE Transactions on Power Systems, 26(1): 12–19.

6. Coupling Wind Generation with Storage

6.1 The Problem[13]

The primary objective of this chapter is to evaluate how installing storage capacity on a network affects the amount of potential wind generation that is dispatched and the real-time revenue stream from the wholesale market for wind generators. Two different types of storage are considered. One uses utility-scale batteries collocated at the wind sites to deal with the variability of the potential wind generation. When wind speeds are high, some of the potential wind generation is stored on-site and the batteries are discharged when the wind speeds are lower. In this way, the variability of the wind energy (direct generation plus discharging the batteries) actually submitted to the grid is much lower than it is with no storage capacity.

The second type of storage is to develop deferrable demand at load centers so that the purchases of some electric energy from the grid can be decoupled from the delivery of the energy service that customers want. Charging the battery in an electric vehicle is one example of deferrable demand, but the use of thermal storage is likely to have a larger impact on the grid. With the latter type of deferrable demand, ice is made at night, for example, when the price of electricity is low and melted to provide cooling services when they are needed during the day. The overall effect of deferrable demand is to flatten the daily profile of purchases at the load centers from the grid. In this way, the amount of congestion on the grid and the amount of conventional generation needed to maintain Operating Reliability are both reduced.

Traditionally, the system operators who manage operations of the grid that delivers electricity to customers have focused on managing different sources of supply and have treated the demand by customers in a relatively passive way. The daily pattern of the aggregate demand from customers on a distribution network is predictable, and the operating criterion in a typical Security Constrained Optimal Power Flow (SCOPF) (Condren et al, 2006) is to minimize the cost of meeting a predicted pattern of demand and of covering a specified set of equipment failures (contingencies). Treating demand as an exogenous input for planning expansion of the grid has resulted in a situation in which the peak system load grew faster than the annual demand for electric energy. Consequently, the average capacity factors of generators have decreased over time and some units are only used for a few hours each year. Supply systems in most regions are designed to meet the summer peak load caused by the demand for air conditioning. There are, however, already signs that conditions are changing. In the 2010 Long-Term Reliability Assessment published by the North American Electric Reliability Corporation (NERC, 2010), electric energy is forecasted to grow slightly faster than the peak demand over the next ten years

[13] This chapter summarizes the results of a research paper presented at a recent conference organized by the Rutgers University Center for Research on Regulated Industries (Tim Mount and Alberto Lamadrid, "Using Deferrable Demand to Increase Revenue Streams for Wind Generators", Proceedings of the 25th Annual CRRI Western Conference, Monterey CA, June 27-29 2012.).

due to the electrification of the transportation sector and increased demand-side management.

The empirical examples in this paper use a new stochastic form of multi-period SCOPF developed at Cornell (the second generation SuperOPF) and a simplified representation of the bulk power network in the Northeastern states to evaluate different specifications of wind generation and transmission capacity. The most important features of the SuperOPF for this analysis are that 1) the stochastic characteristics of potential wind generation at multiple sites can be represented in different ways, 2) the amount of conventional generating capacity, including reserves, needed to maintain Operating Reliability is determined endogenously and it depends on how the stochastic characteristics of potential wind generation are represented, and 3) the additional ramping costs caused by the inherent variability of wind generation can be incorporated into the objective function. As an example, if the use of storage reduces the variability of wind generation, ramping costs are reduced and less conventional generating capacity is needed for reserves to maintain reliability. Since the capacity of the electric delivery system is designed to meet the peak system load, reducing this peak and the associated capital cost of equipment (e.g., peaking units with low capacity factors) is an important way to reduce the total system costs as well as reduce the maximum level of congestion on the grid.

The overall results show that the use of deferrable demand can mitigate the inherent variability of wind generation, reduce total system ramping by flattening the daily pattern of dispatch of conventional generating units, improve the overall performance of the network and lower the total cost of the conventional supply system. The main source of savings comes from reducing the total amount of conventional generating capacity needed to maintain reliability. At the same time, the use of deferrable demand implies that customers still receive the same level of energy services when they want them. Considering the specific objective of this analysis, the case with deferrable demand also leads to the highest revenue paid to wind generators even though more wind generation is dispatched in the case with storage collocated at the wind sites. The reason is that increasing the system load at night with deferrable demand increases the nodal prices paid to the wind generators. With collocated storage the nodal prices at night are very low and sometimes zero.

The chapter has the following structure. Section 6.2 presents a general description of a SCOPF followed in Section 6.3 by a description of its specific features, such as storage capacity, the representation of deferrable demand and the stochastic characteristics of potential wind generation. The description of the case studies and the empirical results are presented in Section 6.4, followed by the conclusions in Section that include recommendations for the regulatory changes required to provide the necessary economic incentives for customers to make investments in deferrable demand. Obtaining savings in the total cost of the conventional electric delivery system is an essential step to making electricity affordable to customers and to covering the additional costs of renewable generation and of developing a smart grid. The analysis does not, however, determine the magnitude of these additional costs. This important issue will be addressed in future research.

6.2 Specifications of the Model

The second-generation SuperOPF is a stochastic multi-period SCOPF that co-optimizes endogenous reserves to provide ramping for mitigating wind variability and covering a set of credible contingencies (Thomas et al, 2008). This model is an extension of the single-period model used in Chapters 4 and 5, and it is implemented using *Matpower*'s extensible architecture (Zimmerman et al, 2011).

The objective criterion of the new SuperOPF is to maximize the expected sum of producer and consumer surplus over a twenty-four hour horizon for a set of contingencies, including the uncertainty about the amount of potential wind generation. It also allows for storage and deferrable demand. Rather than using the standard criterion of minimizing cost subject to covering physical contingencies, shedding load at a high Value of Lost Load (VOLL) is allowed if it is economically efficient to do so. This formulation determines the optimal dispatch of a set of previously committed generating units subject to their physical characteristics (e.g., rated capacity, cost and ramping capabilities) and the network's topology (e.g., transmission line constraints). The model solves the cost for a number of high probability cases for wind generation (`base cases'), as well as a set of credible contingencies that occur relatively infrequently. The expected cost is minimized over the base cases and the contingencies using probabilities that reflect the relative likelihood of the different states of the system. This formulation has the advantage of determining endogenously the amounts of different ancillary services (e.g., contingency reserve and ramping reserve to mitigate wind variability) needed to meet the load profiles and maintain the reliability of the delivery system. The optimum dispatch is determined in the spirit of a day-ahead contract, incorporating the best available information the Independent System Operator (ISO) has at that time of the settlement.

A simplified representation of the objective function for the SuperOPF is shown in Table 6.1 and the notation is defined in Table 6.2. This model is essentially a multi-period version of the single-period model presented in Chapter 4. The objective function is subject to meeting the levels of load (less Load-Not-Served) at different nodes and all of the nonlinear AC constraints of a network. The nodal levels of load are fixed blocks for each time period and are modeled as negative injections with associated negative costs (the Value of Lost Load (VOLL) at the substation level). Since this specification allows for load shedding in some states of the system, minimizing the expected cost, including the cost of load shedding, is the negative of maximizing the expected total sum of consumer and producer surplus. In other words, the negative of the objective function is a measure of the total surplus and a valid measure of net economic benefits.

Table 6.1 Objective Function for the Multi-Period SuperOPF

$$
\begin{aligned}
\min_{G_{itsk}, R_{itsk}, \mathrm{LNS}_{jtsk}} & \sum_{t\in\mathscr{T}} \sum_{s\in\mathscr{S}^t} \sum_{k\in\mathscr{K}} \pi_{tsk} \Bigg\{ \sum_{i\in\mathscr{I}} \Big[C_{G_i}(G_{itsk}) + \\
& \mathrm{Inc}^{+}_{its}(G_{itsk} - G_{itc})^{+} + \mathrm{Dec}^{-}_{its}(G_{itc} - G_{itsk})^{+} \Big] \\
& \sum_{j\in\mathscr{J}} \mathrm{VOLL}_j \mathrm{LNS}(G_{tsk}, R_{tsk})_{jtsk} \Bigg\} + \\
& \sum_{t\in\mathscr{T}} \rho_t \sum_{i\in\mathscr{I}} [C^{+}_{R_{it}}(R^{+}_{it}) + C^{-}_{R_{it}}(R^{-}_{it}) + C^{+}_{L_{it}}(L^{+}_{it}) + \\
& C^{-}_{L_{it}}(L^{-}_{it})] + \sum_{t\in\mathscr{T}} \rho_t \sum_{s_2\in\mathscr{S}^t} \sum_{s_1\in\mathscr{S}^{t-1}} \sum_{i\in\mathscr{I}^{ts_2 0}} \\
& [\mathrm{Rp}^{+}_{it}(G_{its_2} - G_{its_1})^{+} + \mathrm{Rp}^{-}_{it}(G_{its_2} - G_{its_1})^{+}]
\end{aligned}
$$

Table 6.2 Definitions of the Variables in Table 6.1

$\mathscr{T}$	Set of time periods considered, n_t elements indexed by t.
$\mathscr{S}^t$	Set of scenarios in the system in period t, n_s elements indexed by s.
$\mathscr{K}$	Set of contingencies in the system, n_c elements indexed by k.
$\mathscr{I}$	Set of generators in the system, n_g elements indexed by i.
$\mathscr{J}$	Set of loads in the system, n_l elements indexed by j.
π_{tsk}	Probability of contingency k occurring, in scenario s, period t.
ρ_t	Probability of reaching period t.
G_{itsk}	Quantity of apparent power generated (MVA).
G_{itc}	Optimal contracted apparent power generated (MVA).
$C_G(\cdot)$	Cost of generating $(\cdot)$ MVA of apparent power.
$\mathrm{Inc}^{+}_{its}(\cdot)^{+}$	Cost of increasing generation from contracted amount.
$\mathrm{Dec}^{-}_{it}(\cdot)^{+}$	Cost of decreasing generation from contracted amount.
VOLL_j	Value of Lost Load, (\$).
$\mathrm{LNS}(\cdot)_{jtsk}$	Load Not Served (MWh).
$R^{+}_{it} < \mathrm{Ramp}_i$	$(max(G_{itsk}) - G_{itc})^{+}$, up reserves quantity (MW) in period t.
$C^{+}_{R}(\cdot)$	Cost of providing $(\cdot)$ MW of upward reserves.
$R^{-}_{it} < \mathrm{Ramp}_i$	$(G_{itc} - min(G_{itsk}))^{+}$, down reserves quantity (MW).
$C_R(\cdot)$	Cost of providing $(\cdot)$ MW of downward reserves.
$L^{+}_{it} < \mathrm{Ramp}_i$	$(max(G_{i,t+1,s}) - min(G_{its}))^{+}$, load follow up (MW) t to $t+1$.
$C^{+}_{L}(\cdot)$	Cost of providing $(\cdot)$ MW of load follow up.
$L^{-}_{it} < \mathrm{Ramp}_i$	$(max(G_{its}) - min(G_{i,t+1,s}))^{+}$, load follow down (MW).
$C_L(\cdot)$	Cost of providing $(\cdot)$ MW of load follow down.
$\mathrm{Rp}^{+}_{it}(\cdot)^{+}$	Cost of increasing generation from previous time period.
$\mathrm{Rp}^{-}_{it}(\cdot)^{+}$	Cost of decreasing generation from previous time period.

Table 6.2 Definitions of the Variables in Table 6.1, Cont'd.

$\mathscr{T}$	Set of time periods considered, n_t elements indexed by t.
$\mathscr{S}^t$	Set of scenarios in the system in period t, n_s elements indexed by s.
$\mathscr{K}$	Set of contingencies in the system, n_c elements indexed by k.
$\mathscr{I}$	Set of generators in the system, n_g elements indexed by i.
$\mathscr{J}$	Set of loads in the system, n_l elements indexed by j.
π_{tsk}	Probability of contingency k occurring, in scenario s, period t.
ρ_t	Probability of reaching period t.
G_{itsk}	Quantity of apparent power generated (MVA).
G_{itc}	Optimal contracted apparent power generated (MVA).
$C_G(\cdot)$	Cost of generating $(\cdot)$ MVA of apparent power.
$\text{Inc}^+_{its}(\cdot)^+$	Cost of increasing generation from contracted amount.
$\text{Dec}^-_{it}(\cdot)^+$	Cost of decreasing generation from contracted amount.
VOLL_j	Value of Lost Load, (\$).
$\text{LNS}(\cdot)_{jtsk}$	Load Not Served (MWh).
$R^+_{it} < \text{Ramp}_i$	$(max(G_{itsk}) - G_{itc})^+$, up reserves quantity (MW) in period t.
$C^+_R(\cdot)$	Cost of providing $(\cdot)$ MW of upward reserves.
$R^-_{it} < \text{Ramp}_i$	$(G_{itc} - min(G_{itsk}))^+$, down reserves quantity (MW).
$C_R(\cdot)$	Cost of providing $(\cdot)$ MW of downward reserves.
$L^+_{it} < \text{Ramp}_i$	$(max(G_{i,t+1,s}) - min(G_{its}))^+$, load follow up (MW) t to $t+1$.
$C^+_L(\cdot)$	Cost of providing $(\cdot)$ MW of load follow up.
$L^-_{it} < \text{Ramp}_i$	$(max(G_{its}) - min(G_{i,t+1,s}))^+$, load follow down (MW).
$C_L(\cdot)$	Cost of providing $(\cdot)$ MW of load follow down.
$\text{Rp}^+_{it}(\cdot)^+$	Cost of increasing generation from previous time period.
$\text{Rp}^-_{it}(\cdot)^+$	Cost of decreasing generation from previous time period.

6.2.1 The Test Network

Figure 6.1 shows a one-line diagram of the network used in the case study. This is a New York/New England centric network and a reduction of the Northeastern Power Coordination Council - NPCC (Allen et al, 2008) that has been further modified to include detailed information about the generating units at each bus. The generation information was derived from data provided by the *PowerWorld Corporation*.

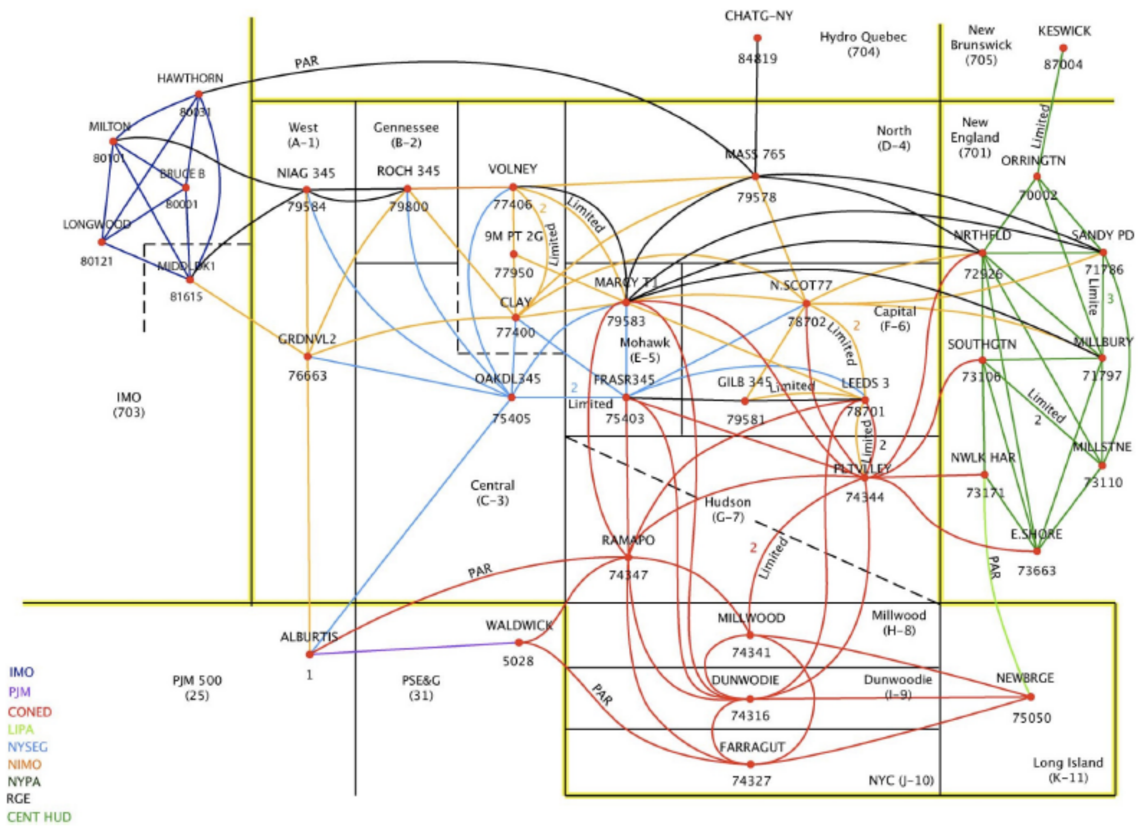


Figure 6.1 A One-Line-Diagram of the 36-Bus Northeastern Test Network

Although the peak load of the system is 138 GW and the installed generation capacity is 144 GW, the pattern of net transfers of power into the New York and New England regions are fixed in the case studies. As a result, the effective peak load is only 62 GW with 63 GW of installed generation capacity (26 GW of baseload and 37 GW of peaking capacity) and 3 GW of net imports. For the case studies, one day in a high demand period was calibrated using historical load information from August 2008 that specified different profiles for urban and rural nodes. The coincident peak system load occurs at 3PM, caused mainly by high demand in the urban regions. Table 6.3 has a summary of the generation capacities and loads for New York and New England. The average fuel costs vary by location, with the highest coal and oil costs in New England and the highest natural gas costs in New York.

Table 6.3 Installed Generation and Peak System Load (MW)

Fuel Type	New York	New England	TOTAL
Natural Gas	18,185	9,219	27,404
Oil	5,265	4,327	9,592
Coal	4,557	1,840	6,397
Nuclear	4,714	5,698	10,412
Hydro+	7,430	1,878	9,308
Net Imports			3,000
TOTAL	**40,151**	**22,962**	**66,113**
Peak Load	**38,274**	**23,847**	**62,121**

6.2.2 Specifications for Stochastic Wind Generation

The case studies analyze cases with a penetration of wind generation close to 15% of the peak system load and the stochastic characteristics of potential wind generation are an important input that affects the optimum dispatch and amount of reserve capacity needed to maintain system reliability. The procedures used follow the methods presented in Chapter 2, and the specification of potential wind generation is divided in two main tasks: specifying the locations and sizes of the wind resources on the network, and characterizing the variability of these wind resources to account for geographical relationships among the different sites.

The locations of the wind farms are derived from the National Renewable Energy Laboratory (NREL) Eastern Wind Integration and Transmission Study (EWITS) (NREL, 2010). To match the data from NREL to the available buses in the network shown in Figure 6.1, a principal components analysis of the NREL sites was performed. Nine sites in New York and seven sites in New England were identified that correspond to specific nodes on the network[14]. The total installed wind capacity is 32GW but the capacity factor for the summer day analyzed in the case studies was only 21%. The capacities specified for each site are proportional to the corresponding total capacities in the NREL data.

To characterize the variability of the wind resources in spatial and geographical terms, a clustering analysis was implemented using the *k-means* method for scenario reduction (Gan and Ma, 2007). The determination of the scenarios was done using the hourly wind speeds for the 16 different locations from the EWITS data. The wind speeds were then converted to the potential

[14] The location of the wind farms are at the following buses: Orrington, Sandy Pond, Millbury, Northfield, Southington, Millstone, Norwalk Harbor, Millwod, Newbridge, 9 Mile Point, Leeds, Massena, Gilboa, Marcy, Niagara and Rochester.

wind generation using a multi-turbine modeling approach (Norgaard and Hottlinen, 2004). The data used for clustering represent the hourly values at 16 locations for a sample of selected summer days that have similar characteristics in terms of wind speed. These daily profiles were then reduced to the best k = 4 scenarios to represent the hourly values for a typical day. Since each day in the sample can be assigned to one of the clusters for each hour in the typical day, it is possible to estimate the probabilities of each scenario occurring in each hour and the corresponding transition probabilities of moving from one scenario to each one of the other scenarios in the next hour. The overall objective is to model the variability of wind realistically in a way that captures geographic averaging and is consistent with the EWITS data.

6.2.3 Specifications for Deferrable Demand

The modeling of deferrable demand assumes that, for a specified percentage of the total daily demand, the timing of the purchase of electricity can effectively be decoupled from the timing of the energy service delivered. Examples include charging the batteries in electric vehicles and thermal storage for space conditioning (e.g., traditional central Air Conditioning (AC) systems can be augmented with Ice Batteries). In effect, there are now two hourly demand profiles. Conventional demand must be supplied in real time from the grid. In contrast, deferrable demand must also be supplied in real time but the supply can come from storage and/or the grid. For the case studies presented in the next section, however, there is only a single constraint on the total daily amount of deferrable demand rather than an hourly profile.

Five urban buses are selected for deferrable demand. The total amounts of deferrable demand (as a percentage of the total demand) are location specific. Deferrable demand accounts for 28% of the total demand for the two New York City buses and for 25% at the Buffalo bus. For the Millbury bus and the Sandy Pond bus in New England, the values are 11\% and 20% of the total demand, respectively. These values correspond to the average values estimated econometrically from historical patterns of demand in the different regions for the years 2007 to 2010 (Mo, 2011). The total power capacity of deferrable demand was 23GW and the total energy capacity was 136GWh

6.2.4 Specifications for Storage Collocated at Wind Sites

To model Energy Storage Systems (ESS) installed at the 16 wind sites, special generators were specified with different charging and discharging efficiencies to represent the physical properties of the ESS. The capacity at each site was proportional to the installed wind capacity at that site, and the total capacity for all sites was identical to the corresponding values for deferrable demand (23GW of power and 136GWh of energy). This specification makes it easier to make comparisons between the cases with ESS and deferrable demand.

The energy available in an ESS can be used to provide energy in the different wind scenarios and to help support the grid in contingencies. The optimal use of storage is dependent in part on the value assigned to the stored energy. If it is valued at zero, then stored energy is always used in contingencies and in the last hour of the planning horizon. There is, however, an opportunity cost for discharging the ESS that provides a high threshold for discharging. If the nodal price in a terminal state is very low, for example, it would be optimum to not discharge the ESS and wait until a later period when the price is higher than the high threshold. A similar argument can be made for charging the battery, and a low threshold provides the opportunity cost for charging. It is optimum to charge the ESS if the price is below the low threshold. If the price is between the two thresholds, the optimum is to do nothing and save the stored energy for use later. In the next section, however, only the high threshold was implemented for the case studies.

To determine the threshold price of the stored energy for discharging, the initial pattern of dispatch for generators and the initial amounts of stored energy, an iterative process is implemented in which the same daily dispatch is simulated several times, using the same input specifications, until the differences in the threshold price and initial conditions are stable and below a tolerance. These final values can be treated as the steady state solution.

6.3 Results of the Case Studies

The results in this section summarize the cost of serving a specified hourly demand profile for a typical summer day in four different cases. The net imports of power from other regions into the New York and New England region (NYNE) are fixed, and for this reason, the results include information only for NYNE. The analysis assumes that the wholesale market is deregulated and run by an Independent System Operator (ISO). Many studies of the effects of renewable generation on system costs focus on the lower payments made by customers in wholesale markets and the associated decrease in the energy prices when renewable energy sources are available. We have argued in earlier research that this emphasis ignores the financial adequacy issue for conventional generators (Mount et al, 2010). Since the offers submitted by renewable sources are effectively zero, average nodal prices are generally lower. Therefore, these new renewable sources displace fossil fuels and the conventional generators receive less net revenue to cover their capital expenses. To rectify this situation and still maintain system reliability, generators are further compensated in capacity markets that help to provide the "missing money". To avoid the distortions from evaluating a policy based solely on the wholesale payments from customers, the different cases are evaluated using measures that reflect the total system costs. The specific measures used for this analysis are:

1) The out-of-pocket operating costs incurred by conventional generators
2) The amount of wind generation dispatched by the system.
3) The maximum amount of non-wind capacity needed to maintain system reliability.

The simulation starts at 7AM and finishes the next day at 6AM. The main interest of the analysis is the dispatch of stochastic wind generation and the provision of load following reserves. Since the time steps are hours, the analysis does not consider the provision of regulation services that require rapid changes in the dispatch patterns to balance demand and supply in real time.

6.3.1 Specifications of the Cases

The analysis compares the results for different cases are specified for the NYNE network for a representative day with a relatively high peak system load. The following five cases are specified and they correspond to incremental modifications to the system:

Case 1: Base: Initial system with no new wind capacity

Case 2: Wind, Case 1 + 29 GW of wind capacity at 16 locations

Case 2u: Case 2 + an upgrade of the transmission system

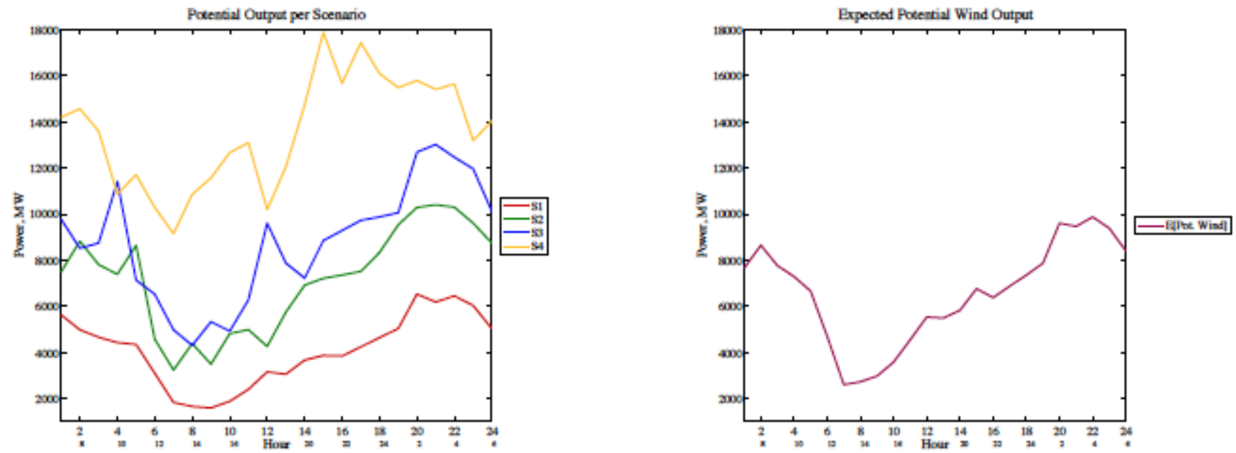
Case 3: Case 2 + 22GW of Deferrable Demand (DD) at five load centers

Case 4: Case 2 + 22GW of Energy Storage Systems (ESS) at the 16 wind farms

In all five cases, the cost of ramping and load following reserves are included as part of the optimization. The operating reliability of the system is represented by generator outages at Northfield (Bus 72926) and East Shore (Bus 73663) that provided ramping and base load capacity and are electrically close to the load centers. In Case 2u, the upgrade of transmission is represented by a network with unlimited capacity, implying there is no transmission congestion whatsoever. For Cases 3 and 4, the 22GW of DD and ESS represent the total power capacity and the total energy capacity is 22 x 6 = 132GWh. The total capacity values are identical in the two cases to make it easier to evaluate the effect of having storage at different locations.

6.3.2 Why Do the Stochastic Characteristics of Wind Generation Matter?

The procedures described in Section 6.2.2 characterize the stochastic characteristics potential wind generation in terms of a specified number of possible scenarios (four in these case studies). As a preliminary step before presenting the main analysis, this subsection demonstrates that the stochastic characteristics of wind generation affect the optimum dispatch and system costs. This is done by comparing the results for Cases 2 and 2u with stochastic wind with the same cases treating potential wind generation as a variable but deterministic resource equal to the expected value of potential wind generation for each hour. Figure 6.2a shows the values of potential wind generation in the four scenarios that represent stochastic wind (without the transition probabilities), and Figure 6.2b shows the values for deterministic wind.



6.2a Stochastic Wind **6.2b Deterministic Wind**

Figure 6.2 Input Values for Stochastic and Deterministic Potential Wind Generation

The horizontal axes show the hours of the day, starting at 7AM, and the values plotted indicate a decrease in the amount of potential wind generation during the peak demand period in the afternoon. Generally, the probabilities of realizing the low wind scenarios are relatively large and relatively low for the high wind scenarios. The range of potential wind generation between the high and low scenarios corresponds to roughly 50% of the total amount of installed wind capacity and 10% of the total generation capacity in the NYNE region.

The main results summarized in Table 6.4 report the three system criteria and the value of the objective function for four different cases. The first two cases, representing stochastic wind, were defined in the previous subsection and the last two are identical except that deterministic wind replaces stochastic wind. The four cases are:

Case 2: Wind, Case 1 + 29 GW of wind capacity at 16 locations

Case 2u: Case 2 + an upgrade of the transmission system

Case 2e, Case 2 with deterministic wind

Case 2eu, Case 2u with deterministic wind.

The total generating capacity in the system and pattern of demand are identical for all cases, and the locations and sizes of the wind farms are also the same.[15]

The main effects of eliminating all transmission constraints in Case 2u are to dispatch 1) the generators in economic merit order, and 2) 10GWh more of the potential wind generation, leading to savings in operating costs compared to

[15] In the two cases with upgraded transmission, the locations of facilities do not matter because transmission constraints will never bind.

Case 2. Since the cost of wind generation is zero, the only reason for not dispatching all potential wind generation is the need to provide reserve capacity for ramping to deal with the uncertainty of wind generation. Even though there is still uncertainty in the availability of wind in Case 2u, the lack of constraints on moving energy on the network allows wind to make a small positive capacity contribution that reduces the conventional generating capacity needed to maintain reliability.

Table 6.4 Summary of the Results for Stochastic and Deterministic Wind

	Case 2	Case 2u	Case 2e	Case 2eu
Operating Costs (k$/day)	41,932	41,469	36,692	35,252
GenCap (MW)	57,004	56,977	55,668	55,567
Wind Energy (MWh)	137,517	147,346	155,565	158,907
Objective Function (k)	-8,896,185	-8,897,412	-8,897,935	-8,899,321

A comparison of Case 2e to Case 2 reveals the same type of beneficial changes to Case 2u but the important difference is that these changes are much larger in Case 2e. By mitigating the stochastic characteristics of wind, the optimum amount of potential wind generation dispatched increases by 18GWh instead of 10GWh in Case 2u. Using more of the available wind drives down operating costs by $5 million/day compared to only $0.5 million/day in Case 2u. In addition, wind makes a greater capacity contribution, and the amount of conventional generating capacity needed falls by 1.3GW compared to less than 0.1GW in Case 2u. Combining the removal of transmission constraints with deterministic wind in Case 2eu makes it optimum to dispatch all of the potential wind generation with further modest decreases in operating costs and the amount of conventional generating capacity needed for reliability.

The optimum expected amounts of wind dispatched in the four cases are shown in Figure 6.3. The lowest amount of wind dispatched occurs in Case 2 with stochastic wind and the initial network, and the highest occurs in Case 2eu with deterministic wind and no transmission constraints. It is interesting to note that most of the wind spilled occurs towards the end of the planning horizon in the early morning hours, but there is no obvious explanation for why this happens

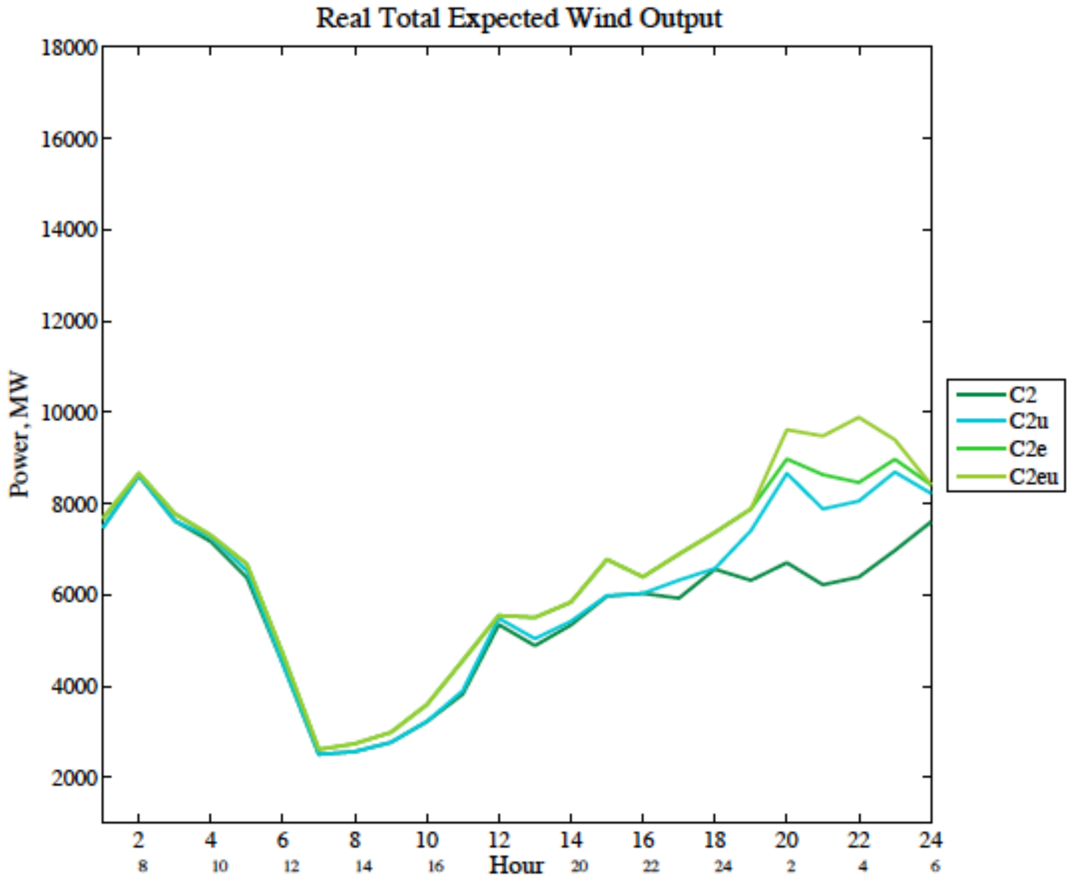


Figure 6.3 Expected Hourly Wind Dispatched for each Case

An important conclusion from the comparison of the four cases is that the economic benefits of upgrading transmission capacity are relatively small compared to the benefits of eliminating the stochastic characteristics of wind generation. In other words, dealing with the uncertainty of wind generation is likely to yield greater benefits than upgrading transmission capacity for this specific network. Deferrable demand and ESS represent two different ways to mitigate the wind variability. Although it is not possible to generalize this conclusion to other networks, it is reasonable to speculate that the conclusion is likely to hold for wind capacity that is installed on a meshed network and is relatively close to load centers, but it is less likely to hold for wind capacity installed in remote regions with limited network capacity. In the former situations, wind generation can displace some of the fossil generation that is already being transferred on the network to the load centers.

6.3.3 The Allocation of Total Costs and Payments in the Wholesale Market

Table 6.5 summarizes the main results for the five cases described in Section 6.3.1. Row 1 shows the operating (fuel) costs for each case, with sequential reductions associated with the adoption of wind (Case 2), upgrading transmission (Case 2u), adding deferrable demand at urban load centers (Case 3), and adding ESS at the wind farms (Case 4). These reductions in operating costs are caused largely by the corresponding increases in the dispatch of wind generation (Row 7), because the operating costs for this source are zero. Ramping costs (Row 2) are larger in Cases 2 and 2u than in Cases 3 and 4 because there is no storage capacity to mitigate the variability of the wind generation. The net revenues for generators (Row 3) are substantially lower than the value in the base case (Case 1) for all of the other cases because there is more wind capacity installed and this capacity displaces some of the fossil units dispatched in Case 1. The differences in net revenue among the four cases with wind capacity are relatively small compared to the large drop from Case 1 when wind capacity is added.

Table 6.5 A Summary of the Daily Results for Different Cases

	Case 1	Case 2	Case 2u	Case 3	Case 4
1. Operating Costs (k$/day)	50,279	41,932	41,469	40,908	40,513
2. Ramping Costs (k$/day)	499	1,385	1,571	1,080	1,166
3. Gen. Net Revenue (k$/day)	77,182	52,488	55,728	53,377	52,665
4. ISO Surplus (k$/day)	8,477	8,851	5,893	-5,124	7,956
5. Payments by Loads (k$/day)	135,939	113,385	115,272	101,423	113,229
6. Peak Gen. Cap. (MW)	58,550	57,004	56,977	50,778	60,360
7. Wind Energy (MWh)	718	137,517	147,346	147,401	150,957
8. Objective Function (k)	-8,885,103	-8,896,185	-8,897,412	-9,033,153	-8,902,031
9. Wind Revenue (k$/day)	0	10,112	12,182	12,262	12,094

The payments by loads (Row 5) correspond to all loads paying the real-time wholesale prices for their purchases from the grid. The ISO surplus (Row 4) is the difference between the payments by loads and the payments to generators (Sum of Rows 1, 2, 3 and 9) and it is a rough measure of congestion on the network. In practice, the ISO surplus would cover the cost of running the ISO and any remaining surplus would be treated as a partial payment to transmission owners. Additional revenue for transmission would be incorporated into the retail rate structures. The ISO surplus for the unmitigated wind case (Case 2) shows that congestion on the network increases compared to Case 1 caused by the accommodation of wind generation. The transmission upgrade, deferrable demand and collocated storage cases have reduced congestion, with negative values in Case 3. This negative value results from the relatively low payments made by loads after the daily pattern of purchases by loads from the grid and the corresponding daily pattern of nodal prices are flattened. In addition, reduced congestion during peak load periods leads to higher payments to some generating units that were previously cutoff from the high nodal prices in urban areas due to congestion.

Adding wind capacity to the system also implies additional payments for this source of generation. The payments to wind generators (Row 9), evaluated at the real-time nodal prices, show that even though less wind is dispatched in Case 3 (Deferrable Demand) than in Case 4 (ESS), the payments for wind generation are slightly higher in Case 3. A more detailed explanation of this finding will be given in the next Section 6.3.4. The amount of peak generating capacity (Row 6) measures the maximum amount of conventional generating capacity, including ESS in Case 4, needed to cover demand and provide the reserve capacity for reliability. The value for Case 3 is substantially lower than the values for the other cases because deferrable demand reduces the peak demand from the grid. In contrast, even though on-site ESS in Case 4 can do a better job at mitigating wind variability, the peak demand for power from the grid is just the same as it is in Cases 1, 2 and 2u. The lower peak demand in Case 3 reduces congestion on the network and this is reflected by the relatively low values for the ISO surplus and payments by loads in Case 3. This also explains why Case 3 has the lowest (best) optimum value of the objective function (Row 8).[16] In general, reducing congestion on a network in Case 3 should make the wholesale market more competitive. The relatively high levels of congestion for Cases 2, 2u and 4 with wind capacity but no deferrable demand are caused by the high demand in the urban areas. These urban areas have constrained transmission capacity and they become load pockets during peak demand periods. This situation raises the potential for local generators in the urban areas to exert market power that could further increase the payments by loads.[17]

While lower payments by loads are not indicative of increased net benefits for the system due to the missing money problem (Mount et al, 2010), all four wind cases clearly decrease wholesale payments compared to Case 1, and the use of deferrable demand in Case 3 leads to the lowest payments by loads.[18] The important conclusion is, however, that the additional wind generation in Cases 2-4 does reduce the real out-of-pocket expenses for generators (the sum of Rows 1 and 2). For Case 3 with deferrable demand, the amount of peak generating capacity needed for reliability is also substantially lower and this leads to additional cost savings that will be discussed further in Section 6.3.5.

In our previous research, we generally found that the peak amount of conventional generation capacity needed for reliability increased as more wind capacity was added. For this analysis, having 16 wind sites on the network provides some geographical averaging that gives wind generation a small positive capacity contribution and requires slightly less conventional generation for reliability purposes. The contribution of capacity from wind depends on the underlying characteristics of this resource, the locations and the interactions with the other factors on the network. This is an area of active research and while the results presented here are derived for a specific network, we believe that they do provide a realistic indication of how the effective quality of the wind resource in the different cases affects the amount of conventional generating capacity needed and the amount of potential wind generation that is dispatched. For example, the use of deferrable demand and ESS in Cases 3 and 4 makes it optimum to dispatch more wind generation compared to eliminating all congestion on the network in Case 2u. This result simply reiterates the conclusion made in Section 6.2 that the variability of wind generation represents a much more serious

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[16] The objective function minimizes the expected total daily cost, including the cost of shedding load, and is actually the negative value of net economic benefits.

[17] In this analysis, offers are equal to the true marginal costs and speculative behavior is not considered.

[18] A reduction in wholesale prices can lead to more ``missing money'' for the conventional generators that are needed for reliability purposes and higher payments to generators in a capacity market. For this reason, focusing on wholesale prices only is an incomplete measure of the real economic benefits of the system.

constraint on the dispatch of more wind generation than congestion on the network.

There is an apparent anomaly in the results for upgrading transmission in Case 2u. One might expect that eliminating all congestion on the network would lower wholesale prices for the urban buses compared to Case 2 but this is not the case (Row 5 in Table 6.5). The reason is that the network no longer has load pockets during peak demand periods and the whole network operates effectively as a single market with the nodal prices set by the most expensive source dispatched. Since the expensive natural gas and oil turbines in the urban regions are still dispatched in Case 2u to meet peak demand periods, this high price affects nodal prices for all generators throughout the network and increases the wholesale payments for importing power into the urban centers (but not the true costs). In Case 2, the expensive turbines only affect the nodal prices within the load pockets during peak demand periods and the prices in other parts of the network may be much lower. This situation is also reflected in the higher net revenues for all generators in Case 2u compared to Case 2 (Row 3 in Table 6.5).

6.3.4 Wholesale Payments to Wind Generators

A primary objective of this paper is to understand how the revenue streams for wind owners are affected by the different cases. As mentioned in the discussion of Table 6.5, the most interesting finding is that the wind revenue for Case 3 (deferrable demand) is the highest even though more wind is dispatched in Case 4 (ESS). Figure 6.4 illustrates how the revenue streams behave over the day for Cases 2, 3 and 4. For Case 2, the revenue stream exhibits two large drops from 10AM to 1PM and from 10PM to 4AM. The revenue for wind generators depends on two main factors: the amount of wind dispatched and the nodal prices at the wind buses. The underlying reason for the first drop in revenue is the reduction in the potential wind generation due to lower wind speeds, as illustrated in Figure 6.2. In this situation, the high nodal prices are not sufficient to offset the lower amount of wind dispatched. This phenomenon follows historical weather patterns, reflecting the lower average wind speeds during the daytime compared to the night. The second drop in revenue is caused by the very low nodal prices at night associated with the low load periods. In Case 2, wind generation is the marginal source of power at night that sets the lowest nodal prices of the day. Consequently, the wind revenue from 10PM to 4AM is low even though the potential wind generation and the amount dispatched are relatively high.

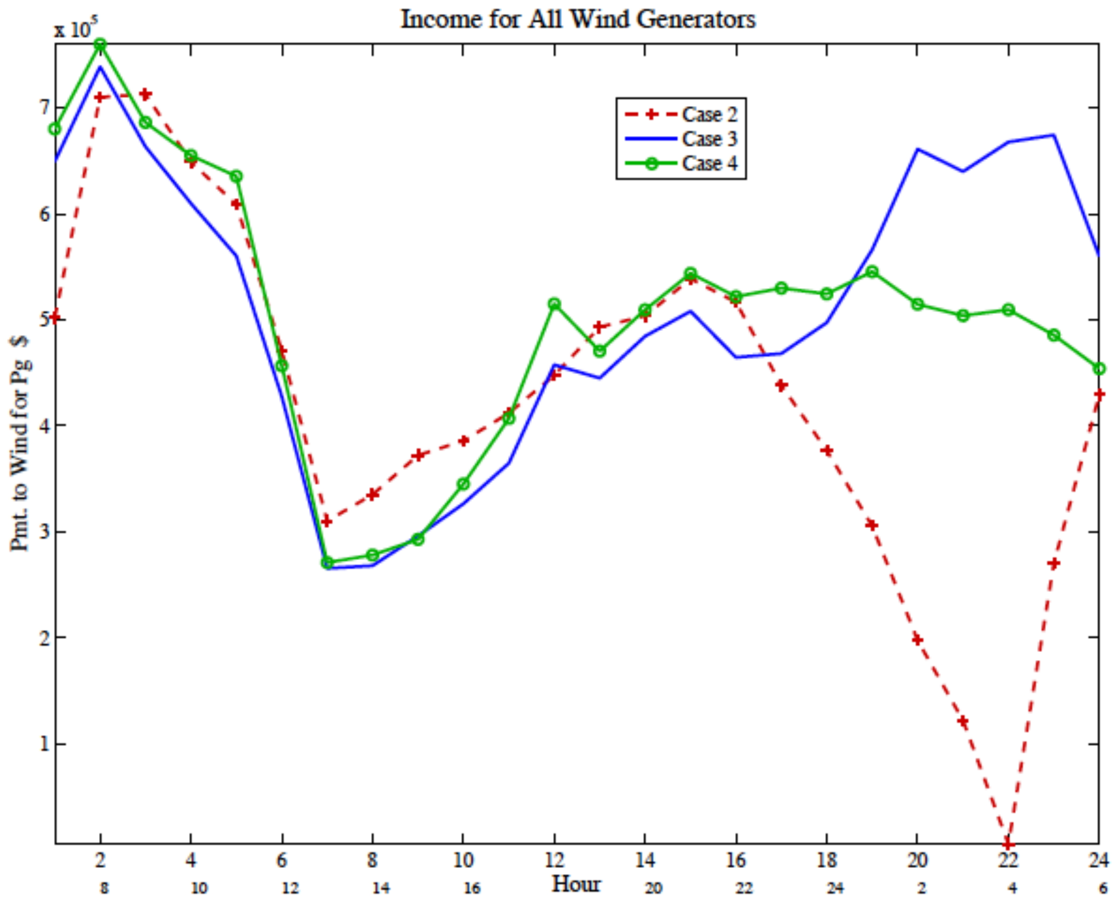

Figure 6.4 The Hourly Revenues for Wind Generators by Case

Contrasting this outcome in Case 2 with the wind revenues in Case 3 (deferrable demand) and Case 4 (ESS), the three revenue streams are quite similar during the daytime and all three exhibit the drop from 10AM to 1PM. The reason for this drop in all cases is that the potential wind generation is lower. The main differences are manifested at night during the second drop from 10PM to 4AM. Since the potential wind generation is the same and relatively high in all three cases, the reason for the differences is that more wind is dispatched in Cases 3 and 4 and the nodal prices for the wind buses (and in the overall system) are higher compared to Case 2. In Case 4, some of the wind dispatched is used to charge the ESS at night, and therefore, this generation does not depress the nodal price even though all generation is paid this price. In Case 3, the deferrable demand increases the load at night, and therefore, increases the nodal prices relative to Cases 2 and 4.

6.3.5 The Total System Costs of Generation

To turn to more general conclusions from the analysis, Table 6.6 summarizes the operating, ramping and capital costs of the conventional generators for the five cases. The operating and ramping costs are identical to the values shown in

Table 6.5 and the capital costs are proportional to the peak generating capacity in the same table. To determine a price for capacity, the same annualized capital cost from the EIA used in Mount et al (2010) for a peaking unit of $88,000/MW/year is adopted for all generating capacity. This simplification is justified because the focus of the evaluation is on how the total generating costs change from the Case 1 with no additional wind capacity, and it is reasonable to assume that the differences in the peak generating capacity affect primarily the number of peaking units needed. The next assumption is that the marginal peaking units are dispatched for only 100 hours during the summer peak load periods and that two of these hours occur during the particular day being analyzed. Hence, the price of capital is 2x88,000/100 = $1760/MW/day. Since the peak generating capacity in Table 6.5 includes the capacity of the storage in Case 4 with ESS, using this procedure for computing capital costs may underestimate the true cost because utility storage is relatively expensive compared to peaking units. On the other hand, storage would be used throughout the year to mitigate wind variability and not just for peak load periods.[19]

[19] In this analysis, the capital costs of deferrable demand are not considered explicitly. While not trivial in nature, these costs are witnessing steady reductions (EAC, 2008). In this paper, it is assumed that the savings in total system costs obtained from using deferrable demand will contribute to amortizing the capital cost of installation.

Table 6.6 The Total Daily System Costs by Case

	Case 1	Case 2	Case 2u	Case 3	Case 4
1. Operating Costs (k$/day)	50,279	41,932	41,469	40,908	40,513
2. Ramping Costs (k$/day)	499	1,385	1,571	1,080	1,166
3. Capital Cost (k$/day)	103,048	100,328	100,279	89,370	106,235
4. Total Costs (k$/day)	153,828	143,646	143,318	131,359	147,915
5. % Change from Case 1	-	-6.62	-6.83	-14.61	-3.84

Comparing the percentage reductions in the total cost from the base Case 1 shown in Table 6.6, adding wind capacity in Case 2 lowers the total cost by nearly 7%, and upgrading transmission in Case 2u leads to a similar percentage reduction from Case 1. Adding deferrable demand in Case 3, however, reduces the total cost by 15%, over twice as much as Cases 2 and 2u. Even though the operating and ramping costs are similar, the capital cost is much lower in Case 3 because the peak demand for power purchased from the grid and the non-wind capacity needed for reliability are much lower than the other cases. In contrast, adding ESS in Case 4 reduces the total cost by less than 4% from Case 1 because the non-wind capacity, including ESS, and the associated capital cost is higher than it is in Cases 2 and 2u.

The large reduction in total cost in Case 3 with deferrable demand is even more dramatic if the results in Table 6.6 are divided between the five buses that have deferrable demand and the other buses. These results are shown in Tables 6.7 and 6.8. For the deferrable demand buses in Table 6.7, the percentage reduction for Case 3 is now 24%, a value that is large enough to justify a more detailed analysis of the potential benefits of deferrable demand for urban customers. The reduction is also slightly larger in Cases 2 and 2u compared to the results in Table 6.6, but in Case 4, the reduction is actually smaller. The results for the other buses in Table 6.8 show that the percentage reductions in total cost are all similar and around 5% for Cases 2 - 4. It is interesting to note that the largest reduction of nearly 6% is for Case 2, the one that has no extra capabilities for mitigating wind variability.

Table 6.7 The Total Daily System Costs for the Deferrable Demand Buses by Case

	Case 1	Case 2	Case 2u	Case 3	Case 4
1. Operating Costs (k$/day)	23,122	18,653	17,323	17,416	19,152
2. Ramping Costs (k$/day)	285	452	561	275	434
3. Capital Cost (k$/day)	53,251	51,845	51,820	40,294	54,898
4. Total Costs (k$/day)	76,658	70,950	69,704	57,985	74,484
5. % Change from Case 1	-	-7.45	-9.07	-24.36	-2.84

Table 6.8 The Total Daily System Costs for the Other Buses by Case

	Case 1	Case 2	Case 2u	Case 3	Case 4
1. Operating Costs (k$/day)	27,158	23,280	24,145	23,492	21,362
2. Ramping Costs (k$/day)	215	934	1,010	806	733
3. Capital Cost (k$/day)	49,797	48,482	48,459	49,076	51,337
4. Total Costs (k$/day)	77,170	72,697	73,614	73,373	73,431
5. % Change from Case 1	-	-5.80	-4.61	-4.92	-4.84

6.4 Conclusions

The analysis in this paper uses a new multi-period version of the Cornell SuperOPF, a stochastic form of Security Constrained Optimal Power Flow (SCOPF). The important capabilities of this software for the analysis are that it is possible to 1) optimize the use of storage capacity over a planning horizon, 2) incorporate a realistic representation of the stochastic characteristics of wind generation, and 3) determine the optimum level of reserve generating capacity needed to cover equipment failures (contingencies) and ramping requirements. A preliminary analysis in Section 6.3.2 demonstrates that the optimum dispatch is very different if the stochastic properties of wind generation are ignored. If potential wind generation is assumed to be deterministic but still varies from period to period, system costs are lower and less wind is spilled. The main results presented in Section 6.3.3 show the allocation of total costs in the wholesale market for five different cases, a base (Case 1) and four cases with additional wind capacity for a highly simplified network topology representing New York State and New England. Case 2 has the extra wind capacity at 16 sites with no other features and the other three cases have one additional feature compared to Case 2. Case 2u adds unconstrained transmission capacity, Case 3 adds deferrable demand at five load centers, and Case 4 adds Energy Storage Systems (ESS) collocated at the 16 wind sites.

The policy debates of how to integrate more wind generation into the grid generally conclude that building additional transmission capacity is essential. The results in Section 6.3.2 show that it is also important to mitigate the inherent variability of wind generation effectively. Without some form of inexpensive mitigation, the ramping costs of using conventional generators to offset changes in wind speeds result in more wind being spilled. In other words, the least-cost dispatch uses less wind generation even though this source is offered at zero cost. The results show that adding storage capacity in Cases 3 and 4 leads to more wind being dispatched than upgrading transmission in Case 2u even though all congestion on the network is eliminated. The results also show in Section 6.3.3 that using deferrable demand in Case 3 as a form of storage at load centers actually provides a slightly higher revenue stream for the wind generators than Case 4 with collocated storage even though more wind is dispatched in Case 4.

The differences in costs between Cases 3 and 4 are, however, relatively small. In fact, the only obvious differences in comparing the composition of total wholesale costs for the five cases in Table 6.5 are 1) the lower fuel costs and payments to conventional generators in the four wind cases (Cases 2 - 4) compared to Case 1 (due to wind displacing fossil fuels), and 2) the lower ISO surplus and payments by loads in Case 3 compared to the other three wind cases (due to the lower peak load and less congestion). In terms of the out-of-pocket costs for generation in the wholesale market, there is little to choose among the four wind cases. The main difference in total costs among the four wind cases is that the amount of non-wind generating capacity needed and the associated capital cost are both much lower with deferrable demand in Case 3.

We have argued before that a successful smart grid must yield economic benefits for customers and this is exhibited in Case 3 in the sense that the system costs of supplying customers who have deferrable demand are 25\% lower than the base Case 1 (see Table 6.7). This reduction is much larger than it is in any of the other cases, including upgrading transmission in Case 2u and adding collocated storage in Case 4. The main reason is that deferrable demand can be used to lower a customer's purchase of power from the grid at the peak system load, and thereby, reduce the total amount of conventional generating capacity needed to maintain reliability. Deferrable demand also provides ramping services that mitigate the variability of wind generation and reduce the ramping by conventional generators. In fact, it is providing this service that makes deferrable demand in Case 3 a better option than upgrading transmission in Case 2u. Even though there is a substantial amount of congestion on the network when the system load is high that limits the transfer of wind generation to the load centers, eliminating all congestion in Case 2u does not deal with the uncertainty of wind generation effectively and the amount of wind dispatched is virtually the same in Cases 2u and 3. Case 3 is also a better option than installing ESS in Case 4. Even though ESS is a better way to mitigate the wind variability, it does not reduce the peak amount of power purchased from the grid by customers.

Paying a lower bill to the local utility in Case 3 is not a sufficient reason for increasing the net benefits for a customer. The reduction must be large enough to cover the extra cost of installing deferrable demand capabilities. This important issue is not considered in this paper but it will be addressed in a future paper. Our expectation is that deferrable demand will be less expensive than dedicated

ESS because the capital cost of deferrable demand is shared with the delivery of another energy service (e.g., transportation for electric vehicles and space cooling for thermal storage).

A very important barrier to deferrable demand is the current structure of the retail rates paid by most customers. These rates do not reflect the correct economic incentives. For example, getting the economic benefit of reducing one's demand at the peak system load requires that customers pay for their actual demand at the peak system load. This will require customers to have smart meters and real time pricing. At the present time, most customers do not pay a demand charge at all, and when the level of demand is measured with a traditional meter, this level is the maximum demand over a billing period even if it occurs at night when the system load is low[20]. To date, most state regulators have not shown much initiative in designing more appropriate rate structures or in educating the public in the potential benefits of the smart grid. Unless this situation changes, it seems unlikely that customers will see the economic benefits that they deserve from the smart grid and the utility industry will continue to depend on supply-side solutions for problems and assume that regulators will ensure that customers pay the bill.

[20] Given the complexity of the wholesale market, particularly if the demand-side can be paid for providing some ancillary services, it is likely that Aggregators of Residential Customers (ARC) will use the real-time price information and control some of their customers' appliances, such as deferrable demand, using wireless signals.

References

[1] Allen, E., Lang, J., & Ilic, M. (2008), "A Combined Equivalenced-Electric, Economic, and Market Representation of the Northeastern Power Coordinating Council U.S. Electric Power System," Power Systems, IEEE Transactions on, 23(3), 896–907.

[2] Chen, J., Mount, T. D., Thorp, J. S., & Thomas, R. J. (2005), "Location-based scheduling and pricing for energy and reserves: a responsive reserve market proposal," Decis. Support Syst., 40(3-4), 563–577.

[3] Condren, J., Gedra, T., & Damrongkulkamjorn, P. (2006), "Optimal power flow with expected security costs," Power Systems, IEEE Transactions on, 21(2), 541–547.

[4] Dorgan, C. (2000), Cool Storage Technology Guide, Technical report, EPRI, 7601 Ganser Way Madison, Wisconsin 53719-2074.

[5] EAC (2008), Bottling Electricity: Storage as a Strategic Tool for Managing Variability and Capacity Concerns in the Modern Grid, Technical report, Electricity Advisory Committee.

[6] Guojun Gan, Chaoqun Ma, J. W. (2007), "Data Clustering: Theory, Algorithms, and Applications".

[7] Mo, J. Y. (2011), Economic Analyses of Plug-in Hybrid Electric Vehicles, Carbon Markets and Temperature- Sensitive Loads, PhD thesis, Cornell University.

[8] Mount, T., & Lamadrid, A. J. (2010), Are existing ancillary service markets adequate with high penetrations of variable generation?, in PES General Meetings, pp. 1 –9.

[9] Mount, T., Maneevitjit, S., Lamadrid, A., Thomas, B., & Zimmerman, R. (2012), "The Hidden System Costs of Wind Generation in a Deregulated Electricity Market," The Energy Journal, 33(1), 161–186.

[10] NERC (2010), Long-Term Reliability Assessment, 116-390 Village Road, Princeton, NJ, 08540: North American Electric Reliability Corporation. URL: http://www.nerc.com/

[11] Norgaard, P., & Hottlinen, H. (2004), A Multi-Turbine Power Curve Approach, pp. 1–5.

[12] NREL (2010), Eastern wind integration and transmission study: Executive Summary and Project Overview, Technical report, EnerNex Corporation, The National Renewable Energy Laboratory, 1617 Cole Boulevard, Golden, Colorado 80401.

[13] Thomas, R., Murillo-Sanchez, C., & Zimmerman, R. (2008), An advanced security con- strained OPF that produces correct market-based pricing, in Power and Energy Society General Meeting - Conversion and Delivery of Electrical Energy in the 21st Century, 2008 IEEE, pp. 1–6.

[14] Zimmerman, R. D., Murillo-Sanchez, C. E., & Thomas, R. J. (2011), "MATPOWER: Steady-State Operations, Planning, and Analysis Tools for Power Systems Research and Education," Power Systems, IEEE Transactions on, 26(1), 12 –19.