THREE ESSAYS ON THE EFFECT OF WIND GENERATION ON POWER SYSTEM PLANNING AND OPERATIONS

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ABSTRACT

Davis, Clay D. Ph.D., Purdue University, May 2013. Three Essays on the Effect of Wind Generation on Power System Planning and Operations. Major Professor: Paul V. Preckel.

In a report titled "20% Wind Energy by 2030" the United States Department of Energy assembled a group to assess the likely effects of wind generation providing 20% of electricity consumption by 2030 (DOE, 2008). While the benefits of wind generation are well known, some drawbacks are still being understood as wind power is integrated into the power grid at increasing levels. The primary difference between wind generation and other forms of generation is the intermittent, and somewhat unpredictable, aspect of this resource. The somewhat uncontrollable aspect of wind generation makes it important to consider the relationship between this resource and load, and also how the operation of other non-wind generation resources may be affected. The three essays that comprise this dissertation focus on these and other important issues related to wind generation; leading to an improved understanding of how to better plan for and utilize this resource.

The first essay addresses the cost of increased levels of installed wind capacity from both a capacity planning and economic dispatch perspective to arrive at the total system cost of installing a unit of wind capacity. This total includes not only the cost of the wind turbine and associated infrastructure, but also the cost impact an additional unit of wind capacity has on the optimal mix and operation of other generating units in the electricity supply portfolio. The results of the model showed that for all wind expansion scenarios, wind capacity is not cost-effective regardless of the level of the wind production tax credit and carbon prices that were considered. Larger levels of installed wind capacity result in reduced variable cost, but this reduction is not able to offset

increases in capital cost, as a unit of installed wind capacity does not result in an equal reduction in other non-wind capacity needs.

The second essay develops a methodology to better handle unexpected short term fluctuations in wind generation within the existing power system. The methodology developed in this essay leads to lower expected costs by anticipating and planning for fluctuations in wind generation by focusing on key constraints in the system. The modified methodology achieves expected costs for the UC-ED problem that are as low as the full stochastic model and markedly lower than the deterministic model.

The final essay focuses on valuing energy storage located at a wind site through multiple revenue streams, where energy storage is valued from the perspective of a profit maximizing investor. Given the current state of battery storage technology, a battery capacity of zero is optimal in the setting considered in this essay. The results presented in this essay are dependent on a technological breakthrough that substantially reduces battery cost and conclude that allowing battery storage to simultaneously participate in multiple wholesale markets is optimal relative to participating in any one market alone. Also, co-locating battery storage and wind provides value by altering the optimal transmission line capacity to the battery and wind site.

This dissertation considers problems of wind integration from an economic perspective and builds on existing work in this area. The economics of wind integration and utilization are important because wind generation levels are already significant and will likely become more so in the future. While this dissertation adds to the existing literature, additional work is needed in this area to ensure wind generation adds as much value to the overall system as possible.

CHAPTER 1: INTRODUCTION

In a report titled "20% Wind Energy by 2030" the United States Department of Energy assembled a group to assess the likely effects of wind generation providing 20% of electricity consumption by 2030 (DOE, 2008). Deployment of renewable energy resources, particularly wind generation, is growing at faster rates year over year, especially in the United States where wind generation increased 27% in 2011 over 2010 (EIA, 2012). While wind generation is increasing at a fast pace, it still makes up a relatively small portion of total electricity at 3% of total generation in 2011 (EIA, 2012). Even though wind generation comprises a small portion of the total, this small amount is having a significant impact on the functioning of the electricity system due to the intermittent nature of wind generation. The highly variable nature of wind generation (and solar generation in general) has resulted in the North American Electric Reliability Corporation (NERC) forming the Integration of Variable Generation Task Force (IVGTF), to study the integration of these variable resources (Lauby et al., 2011). Intermittent forms of generation pose many challenges to the power system, from system planning to system operations. One challenge system planners face is determining the effect of a unit of wind generating capacity on other capacity needs in order to maintain various reliability parameters, such as loss of load probability (LOLP). On a different scale, power system operators face the challenge of determining the level of wind generation that can be counted on over time periods ranging from the next five minutes to a few days.

The three essays in this dissertation address the aforementioned issues and add to the existing literature on integrating intermittent resources. The first essay addresses the cost of increased levels of installed wind capacity from both a capacity planning and economic dispatch perspective to arrive at the total system cost of installing a unit of wind capacity. This total includes not only the cost of the wind turbine and associated infrastructure, but also the cost impact an additional unit of wind capacity has on the optimal mix and operation of other generating units in the electricity supply portfolio. The second essay develops a methodology to better handle unexpected short term fluctuations in wind generation within the existing power system and aims to reduce expected unit commitment-economic dispatch (UC-ED) costs. The methodology developed in this essay leads to lower expected costs by anticipating and planning for fluctuations in wind generation in the unit commitment stage. The final essay focuses on valuing energy storage located at a wind site through multiple revenue streams and takes the perspective of a profit maximizing investor.

1.1 Essay 1: Determining the Impact of Wind on System Costs via the Temporal Patterns of Load and Wind Generation

Ambitious targets have been set for expanding electricity generation from renewable sources, including wind. The United States Department of Energy assembled a group to assess the likely effects of wind generation providing 20% of electricity consumption by 2030 (DOE, 2008). With only small amounts of large-scale energy storage currently in use, electricity must be generated as it is needed. Electricity demand (load) fluctuates throughout the day requiring generating units to follow these changes in order to satisfy demand. Wind generation also fluctuates throughout the day and other generating units must accommodate this additional variability. Therefore, it is the load net of wind generation that other generating units must satisfy. The variability in wind generation tends to increase system variability and alter the optimal mix of non-wind generating units. As states plan for increasing levels of wind generation in their portfolio of generation resources it is important to consider how this intermittent resource impacts the need for other generation resources.

In this essay three fossil fueled generation technologies are considered in addition to wind generation to make up the portfolio of generation resources. Baseload generation is characterized by high capital cost and low variable cost making this the lowest cost resource when the resource operates for the majority of hours during the year.

Alternatively, peaking generation is characterized by low capital cost and high variable cost making this resource the lowest cost form of generation for supplying power during a relatively small number of hours during the year. Cycling capacity is between baseload and peaking in terms of capital cost and variable cost making this resource economical when required to operate an intermediate number of hours during the year. Baseload, cycling and peaking generation assets are represented by different technologies (pulverized coal, natural gas combined cycle and natural gas combustion turbine, respectively).

A case study for Indiana estimates the value of wind capacity and demonstrates how to optimize its level and the levels of other generation resources. Changes are driven by temporal patterns of wind power output and load. System wide impacts are calculated for energy, capacity, and costs under multiple wind expansion scenarios which highlight the geographic characteristics of a systems portfolio of wind generation. The impacts of carbon prices, as proposed in the Bingaman Bill, are considered (Bingaman, 2011). Finally, calculations showing the effect increasing levels of wind generation will have on end use Indiana retail rates are included.

1.2 Essay 2: Modified Unit Commitment Due to Wind Forecasting Errors

The variable and intermittent nature of wind generation poses a number of challenges spanning many areas of electricity markets, with none more front and center than accurately forecasting this highly variable energy source. Forecasting wind power generation is difficult; historically weather models were not designed to predict wind speeds on the time scale required to accurately predict wind generation. Forecasts are able to predict there will be a storm tomorrow and this will have a dramatic impact on the variability of wind generation, but exactly what time of day a ramp event (necessary change in generation levels to match generation with load) will occur is difficult to predict (Burr, 2010). It is this inability to predict exactly when sudden changes in wind generation will occur that poses many challenges for schedulers and system operators. While this essay does not develop improved methods for forecasting wind generation, it modifies the traditional planning problems to reduce the cost of inaccuracies in forecasts.

This essay uses a modified unit commitment-economic dispatch (UC-ED) model to better account for wind generation uncertainty, as compared to a deterministic UC-ED model, while significantly reducing the computational burden of a full stochastic UC-ED model. The unit commitment (UC) stage is considered the strategic resource deployment planning stage and considers information on expected system conditions, such as the level of load and wind generation. In this stage, generating units are committed for each hour of a future operating day. On the other hand, economic dispatch (ED) takes place five to thirty minutes before real-time operations, where the actual realization of uncertain variables, such as load and wind generation occurs. Forecasts, especially for wind generation, can change dramatically between the UC and ED stages; as more accurate wind forecasts become available closer to the economic dispatch stage. To handle wind generation uncertainty stochastic models consider multiple possible wind generation levels, while deterministic models only consider one level for the uncertain wind generation. By considering multiple scenarios in the stochastic model these models are often able to achieve a lower expected cost by considering multiple possible wind generation realizations. However, the increased computational burden from considering multiple wind generation states for the stochastic model has limited its use in practice.

Comparisons using two test systems are made across three model types: deterministic, modified stochastic (developed in this essay), and full stochastic. A smaller, four bus, model is used to dissect the models to show how the models compare, while a larger, fourteen bus, model is used to show benefits are still achieved with a more realistic system using wind generation forecast errors derived from actual market data. The benefits of the modified stochastic model are apparent with both models, both in achieving costs savings comparable to the full stochastic model and markedly reducing problem size relative to the full stochastic problem.

1.3 Essay 3: Valuation of Battery Energy Storage with Wind Generation

In response to the dramatic increase in intermittent forms of electricity generation (wind and solar) an emphasis has been placed on the adoption of fast responding resources, such as battery storage, flywheels, and compressed air storage, which are capable of quickly responding to fluctuations in output from these intermittent resources. In a report titled "20% Wind Energy by 2030" the United States Department of Energy assembled a group to assess the likely effects of wind generation providing 20% of electricity consumption by 2030 (DOE, 2008). Denholm et al. (2010) concluded that wind penetrations at these levels would increase the flexibility requirements of the system: likely creating market opportunities for fast responding energy storage technologies. In order to determine the likely adoption of the various energy storage technologies, methods to accurately determine their value are required.

Energy storage is capable of simultaneously participating in the multiple markets that comprise wholesale electricity markets. As a result of the lack of storability, electricity must be generated as it is needed and has given rise to wholesale markets comprised of multiple markets focused on different time periods. Generating units require notice to start with some requiring longer lead times than others. On the demand side, utilities and other parties that purchase energy from these markets like to plan in advance of when the energy will be needed. The day-ahead market allows for transactions in advance of when the energy is needed and the majority of all energy sold in the wholesale markets is through this market. The day-ahead market clears one day in advance of when the energy is needed for each hour of the next operating day. The real-time market clears fifteen to thirty minutes before the energy is needed and is a much smaller market in terms of energy relative to the day-ahead market. The shortest term market is the market for ancillary services, which is used to procure generation to meet fluctuations in demand ranging from a matter of seconds to a few minutes. These markets will likely result in different market clearing prices at any given point in time.

This essay develops an approach to valuing battery energy storage technologies using a co-optimization framework to determine the value of storage serving multiple roles simultaneously. Four sources of value for energy storage are considered. Three of the four sources of value considered are supplying resources to wholesale markets and include: selling energy in the day-ahead energy market, selling energy in the real-time market, and selling capacity into the regulation market (i.e., one of the ancillary service markets). The fourth source of revenue is the potential for energy storage to alter the optimal transmission capacity to the wind site. In the United States, the best wind resources are located in the plains region of the country and are not near the coasts, which are the highest demand areas. Locating storage near a wind site may alter the optimal transmission capacity from the wind site to connect into the electric grid. The results of this essay show that battery cost is currently too high given current market conditions, but with lower battery costs this technology provides value through all four sources considered.

1.4 Overall Objective and Organization

These three essays address important aspects of wind generation and aim to increase understanding and improve decision making when it comes to considering the role wind generation will serve in meeting future energy needs. The benefits of wind generation (e.g. renewable, zero emissions, and near zero variable cost) are often used as reasons in favor of wind generation; however wind generation presents challenges which also deserve consideration. This research focuses on better understanding the tradeoffs related to wind generation and offering some solutions to better utilize this resource. In this dissertation the three essays are covered in chapters two through four and the final chapter offers general conclusions, discusses limitations of this research, and covers suggestions for future work.

CHAPTER 2: DETERMINING THE IMPACT OF WIND ON SYSTEM COSTS VIA THE TEMPORAL PATTERNS OF LOAD AND WIND GENERATION

2.1 Introduction and Literature Review

Increases in wind generation's share of states' generation portfolios, increase the need to understand how wind generation impacts needs for other generating resources. Due to its intermittency, increasing the level of energy generated from wind will alter the operational and capacity requirements of other generation resource types (e.g. baseload, cycling and peaking).

Wind generation is not dispatchable – that is, generation output cannot be increased at will to meet increases in electricity demand. Because it has zero fuel cost, wind generation is usually considered a price taker; so it is the combination of wind power variability in addition to load variability that the remaining generating units in the system must be able to meet (Wan, 2011). The temporal patterns of wind generation and electricity demand define the net load that must be served by other generation resources to meet demand at any given time (Wan, 2011). While wind generation may reduce the overall amount of energy needed from the other generation resources, it may also shift the needs among generation resource types. A load net of wind duration curve may be used to determine the optimal mix of non-wind generation resources and is created by sorting per period load minus per period wind generation in descending order. Doherty, Outhred, and O'Malley (2006) show increases in penetration of wind generation cause a steepening of the load net of wind duration curve and result in increases in peaking capacity needs and reductions in baseload needs.

Most of the existing work on valuing wind capacity has focused on reliability for serving peak load (see e.g. Milligan and Porter, 2008; Billinton and Bai, 2004). While this is an important dimension of the problem, it does not directly address the impact of investments in wind capacity on electricity prices. While there has been a fair amount of work on the cost of wind capacity (e.g Junginger, Faaij, and Turkenburg, 2005; Dale et al., 2004), work on the value of capacity – i.e. the impact of wind on the average cost of serving load – in the context of an existing generating system is more limited. Karki and Billinton (2004) use simulation modeling to estimate the cost savings due to varying levels of installed wind capacity finding that the offset fuel cost increases at a decreasing rate as wind turbines are added and that wind utilization efficiency declines as turbines are added.

Puga (2010) shows that large amounts of wind capacity will require increased levels of capacity with fast-ramping capabilities. He also shows that high levels of wind capacity can lead to increased cycling of baseload units, particularly during periods of low load and high wind. Increased cycling of baseload generation may lead to higher O&M costs and have implications for unit lifetimes.

Delarue et al. (2011) uses a portfolio theory approach to determine the optimal mix of generation resources by using a linear program to minimize the cost of meeting demand subject to ramping limits on generation, but does not allow for the possibility of wind curtailment. In this framework it may be beneficial to curtail wind generation if ramping of the load net of wind generation exceeds ramping capabilities of non-wind resources. Curtailing wind may result in lower system costs if it reduces the need to build more expensive, faster ramping units that will be used to meet infrequent large ramp events.

While these papers cover various aspects of wind generation, they do not consider both operational and planning aspects simultaneously and ultimately the impact this will have on retail electricity prices. Increasing levels of wind generation will not only impact operational decisions (economic dispatch), but also the optimal mix of generation resources determined during the resource planning period. Doherty, Outhred, and O'Malley (2006) determine capacity needs of non-wind generation resources as wind capacity is increased using a minimum cost economic dispatch framework, but their paper focuses on Ireland where characteristics of wind generation and the existing resource mix may be very different than the wind generation and resource mix in Indiana.

The model developed in section 2 reflects not only investment costs of wind capacity expansion and fuel savings, but also the impact on investment in other generation capacity. Capacity resource levels are determined relative to existing levels, so the optimal resource mix is not independent of the existing Indiana capacity levels. Section 3 considers various wind capacity expansion scenarios to determine the benefits from geographic diversification and section 4 covers the rate impact on retail customers in the state of Indiana as a result of increased levels of wind generation. This impact on retail rates is of value to policymakers as this paper shows how changes in system costs due to larger levels of wind generation will directly impact end use retail customers.

2.2 Methodology

This paper provides a framework for assessing the impact of wind generation on the need for other generation resources, using the state of Indiana as an example. Here, we use observed load data for 2004-2006 for the state of Indiana and estimated wind generation data from the National Renewable Energy Laboratory (NREL, 2010) to estimate the impact of wind generation on system costs and on the need for other generation types. Since Indiana is a regulated state it is important for capacity planning purposes to consider the effect of additional wind generation committed to serving Indiana load on other resources within the state. Baseload, cycling and peaking generation assets are represented by different technologies (pulverized coal, natural gas combined cycle and natural gas combustion turbine, respectively). Installed generation assets are based on existing 2007 Indiana capacity, and capacity additions to meet projected demand in 2025 are determined for alternative levels of wind generation capacity assuming a ten percent reserve margin. A reserve margin of ten percent is included to account for unit outages. Using a reserve margin of ten percent is an approximate method to limit the loss of load probability and is applied across all scenarios for comparability. Thus, our results reflect not only the investment costs of the wind capacity expansion and fuel savings, but also the impact on investment in other generation capacity.

The impacts of increased wind generation capacity on Indiana utilities' generation portfolios are calculated in four areas: changes in generating capacity needs for baseload, cycling, and peaking capacity; the change in energy (MWhs) supplied by baseload, cycling, and peaking generating units; changes in capital costs due to changes in capacity requirements; and changes in variable costs resulting from changes in energy requirements.

Hourly load data for the state of Indiana for 2004-2006 is used for the analysis (SUFG, 2009b). Wind generation data were acquired from the National Renewable Energy Lab's Eastern Wind Integration and Transmission Study (NREL, 2010). This study developed wind generation estimates at ten minute intervals for various sites throughout the eastern United States. The time period of the wind estimates coincides with the Indiana load data, which is important because wind speed affects both data types. (E.g. during the summer months higher wind speeds will lead to increased wind generation and reductions in air conditioning load.)

For this analysis, wind sites were chosen in close proximity to 2009 Indiana wind power purchase agreement (PPA) sites (SUFG, 2009a). The site capacities were initially scaled to the wind capacity agreed upon in the 2009 Indiana power purchase agreements, totaling 770 MW. The load data for each year were scaled from the respective year up to the forecasted load in 2025 (SUFG, 2009b). That is, each annual load profile was scaled such that annual energy consumption is equivalent to the projected consumption in 2025 (144,495 GWhs). The three years of load data were all scaled to the same year (2025) in order to generate three distinct annual load profiles. Impacts were calculated for each of the three years and averaged. The hourly load data were linearly interpolated to ten minute intervals, so as to correspond to the frequency of the wind generation data.

2.2.1 Capacity Impact Calculations

Capacity requirements were calculated for the three generation resource types (baseload, cycling, and peaking) as wind capacity was added relative to a base resource case, which includes existing 2007 capacities plus planned capacity changes. The base resource case capacity levels are: 16,426 MW baseload, 2,500 MW cycling, and 3,585 MW peaking.

Load net of wind duration curves (LDCs) were created using the load net of wind profiles at each level of wind generation capacity (see Figure 2.1). A load net of wind duration curve sorts the ten minute load minus the ten minute wind generation for each interval of the year from the highest to the lowest. The greater the difference between the highest and lowest load net of wind period of the year the more load net of wind varies throughout the year. In this analysis, there is no wind generation uncertainty, so that the analysis effectively assumes a perfect wind forecast. Since wind generation has near zero variable costs and wind power purchase agreement contracts are “take-or-pay” (i.e. the utility must pay for the wind generation regardless of whether it is used), all energy generated by wind units is used in the capacity planning stage.

Capacity levels for the three generation types were calculated using a break-even cost curve, in conjunction with the load net of wind duration curves. Murphy et al. (1988) uses this method of dispatching to a load duration curve in a capacity expansion planning model. This approach of dispatching to a load net of wind duration curve ignores some features of the economic dispatch problem, such as the possibility of wind curtailment, generator minimum up and down times, and the topology of the transmission network. Determining capacity requirements in this manner results in the least cost mix of generation resources to serve a given load net of wind duration curve. The break-even cost curve and load net of wind duration are shown below in Figure 2.1. The upper chart shows the break-even points of the three generation technologies. Where each line intersects the vertical axis represents the annualized per unit capital cost for each of the three technologies, with baseload having the highest capital cost and peaking generation the lowest capital cost. The slope of each line represents the variable cost of the three resource types. Peaking generation is characterized by low capital costs and high variable costs making this resource the lowest cost form of generation for serving the highest load portion of the LDC, due to peaking generation being the lowest cost form of generation when operating a small portion of the year. Similarly, baseload generation is the lowest cost resource to serve the lowest portion of the LDC, where this resource operates for the majority of hours during the year.

Capacity requirements for the three generation resources were calculated for the load net of wind duration curves. The new capacity requirements to meet 2025 demand were determined by subtracting the existing capacity levels (3,585 MW of peaking capacity, 2,500 MW of cycling capacity, and 16,426 MW of baseload capacity) from the levels resulting from these calculations. If the baseload capacity requirement is less than 16,426 MW, then no new baseload capacity is necessary and the excess base case baseload capacity is reclassified as cycling capacity. Similarly, if no new cycling capacity is needed then both excess baseload and cycling capacity are reclassified as peaking capacity. This reclassification may become more prevalent as wind capacity increases and is necessary to avoid idle baseload and cycling capacity. The 2025 new capacity levels calculated for each generation resource type were further increased by ten percent to account for forced outages. These capacity levels were used when dispatching the ten minute load, in order to calculate the energy impacts.

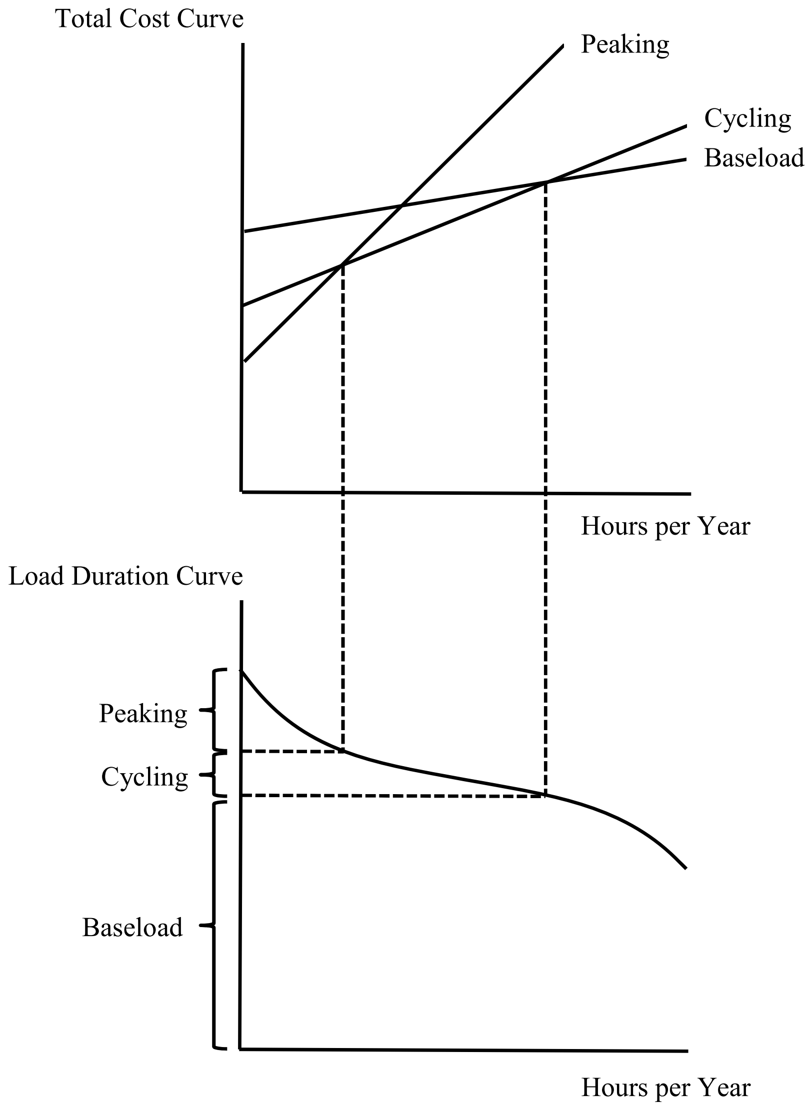

Figure 2.1 Break-even Cost and Load Duration Curves

2.2.2 Energy Impact Calculations

Energy impacts were calculated using a minimum cost economic dispatch model with wind generation being dispatched in addition to the other three non-wind generation technologies to meet load for each ten minute interval (shown below in (1)-(5)). The notation for the linear program formulation is shown in Table 2.1. The problem minimizes the cost (1) of meeting demand (2) in each time period. Wind generation may be dispatched up to the level of wind generation for a given ten minute interval (3), allowing for the possibility of wind curtailment when it is optimal. The other three generation technologies may be dispatched up to the capacity levels determined from the capacity planning stage for the various levels of wind capacity, shown in (4). If some wind generation is curtailed in the economic dispatch model it would alter the shape of the load net of wind duration curve and may have an impact on the optimal capacity. While wind curtailment would alter the load net of wind duration curve (and the optimal mix of generating capacities), this effect is expected to be minor. Absent any wind curtailment the energy impact from wind generation is equal to the total wind output for the year, although variations in impacts are likely across the three generation technologies. The final set of constraints (5) imposes ramping limits on baseload, peaking, and cycling generation. Ramping limits are shown by generation technology in Table 2.2 and are specified as a percent of installed capacity because the number of generating units is not determined in this analysis. In this problem wind curtailment will only take place to avoid violating a ramping limit. Other reasons wind curtailment may take place in a wholesale market, which were not modeled in this analysis, are to avoid violating transmission constraints, wind generation forecasting errors, or wind generation not having a lower offer price than the offer price of the marginal generation unit.

Energy impacts were calculated as the difference in generation for each technology between the base (no wind case) and generation at various levels of installed wind capacity. The difference in energy supplied by baseload capacity for the load and load net of wind profiles determines the change in energy that must be supplied by baseload generation at a given level of wind capacity. Similar calculations determine wind generation impacts on cycling and peaking generation. Again, these calculations were made for all three years and then averaged to arrive at an expected energy impact.

$$\min_{G_{t,i}} \sum_{t}^{T} \sum_{i}^{I} P_i G_{t,i} \tag{1}$$

$$s.t.$$

$$\sum_i G_{i,t} + W_t - L_t = 0 \quad \forall\, t \tag{2}$$

$$0 \le W_t \le W_t^{max} \quad \forall\, t \tag{3}$$

$$G_i^{min} \le G_{i,t} \le G_i^{max} \quad \forall\, i, t \tag{4}$$

$$-R_i \le G_{i,t} - G_{i,t-1} \le R_i \quad \forall\, i, t \tag{5}$$

Table 2.1 LP Notation

Notation	Definition
T	number of time periods
t	index of time periods
I	number of non-wind generating units
i	index for a non-wind generating unit
P_i	variable cost of generating unit i
$G_{i,t}$	generation level of unit i in time period t
G_i^{min}	minimum generation level of unit i
G_i^{max}	maximum generation level of unit i
L_t	load in period t
R_i	ramping limit of unit i
W_t	wind generation level in period t
W_t^{max}	maximum wind generation level in period t

Table 2.2 Generator Ten Minute Ramping Limits as a Percent of Installed Capacity[a]

Unit Vintage	Generation Type	Ramping Limit (% of capacity)
New Units		
	Baseload	40
	Cycling	70
	Peaking	100
	Wind	100[b]
Existing Units		
	Baseload	10
	Cycling	60
	Peaking	100

[a] Baseload ramping limits p.6 (Ihle, 2003); Cycling ramping limits Table 1 (NWPP, 2002); Peaking is assumed to have a ramping limit of 100 percent of installed capacity.

[b] Wind generation is capable of ramping between zero and the level of wind generation available for that ten minute period, as opposed to a percent of installed generation capacity.

2.2.3 Capital Cost Impact Calculations

Capital costs for this analysis are on an annual basis. Baseload capacity is modeled using characteristics representative of a pulverized coal plant, cycling capacity as a combined-cycle gas turbine unit, and peaking capacity as a combustion turbine unit. Per unit annualized capital costs of these technologies, as well as wind generation are shown below in Table 2.3. These costs include annualized capital costs plus fixed operating and maintenance costs associated with generation.

Table 2.3 Annualized Capital Costs and Variable Costs by Generation Type[c]

Unit Vintage	Generation Type	Annualized Capital Cost (2010 $/MW/Yr)	Variable Cost (2010 $/MWh)
New Units			
	Baseload	542,277	25.34
	Cycling	170,100	37.66
	Peaking	110,353	62.26
	Wind	403,430	0.00
Existing Units			
	Baseload	n.a.	24.65
	Cycling	n.a.	42.72
	Peaking	n.a.	67.27
	Wind	n.a.	0.00

[c] Fixed costs for baseload, peaking, cycling and wind units are from Tables 3-3, 9-2, 6-2 and 21-2 respectively, using Indiana specific costs (EIA, 2010). Capital costs for Base Case Units are sunk costs and hence, not used in the analysis. Fuel costs are 2025 projections for the East North Central Region in the EIA 2011 Annual Energy Outlook (EIA, 2011). Fuel prices are in 2010 dollars. Variable O&M costs and plant characteristics for existing generation are from personal communication with the State Utility Forecasting Group (2010). Variable costs for wind are treated as zero.

2.2.4 Variable Cost Impact Calculations

Variable costs were broken down by generation type and listed separately for new and existing capacity. This further distinction is made because newer technologies are generally more efficient due to lower heat rates, resulting in lower variable costs. Per unit variable costs are equal to per unit fuel costs plus per unit variable operations and maintenance costs. These costs are displayed in Table 2.3. Wind generation is assumed to have zero variable cost.

Total variable cost impacts for a given level of wind capacity were calculated relative to total variable costs by generation type without any wind generation. For example, the impact for new baseload variable cost is calculated as the difference between energy supplied by new baseload capacity without wind versus energy supplied by new baseload capacity given a specific level of wind generation, multiplied by new baseload variable cost. This calculation is performed for both new and base case units by type of generation and summed to arrive at the total impact. This is the annual impact for the year 2025, and it is calculated based on the data for each of the three years and then averaged to get the expected impact.

2.2.5 Modeling Scenarios

Four scenarios were chosen to show some key differences between adding wind at alternative locations in different regions. The results of the four scenarios chosen will show that location from which wind power is sourced is important, but also that the proportion of the wind capacity from a particular location in the overall wind portfolio is important, as well. The four scenarios modeled in order to further draw out these distinctions are: 1) scaling all power purchase agreements (PPAs) in proportion to their existing level, 2) scaling in-state PPAs in proportion to their existing levels while holding out-of-state PPAs constant, 3) scaling out-of-state PPAs in proportion to their existing levels while holding in-state PPAs constant, and 4) equally scaling all existing PPAs and the five sites in Indiana that are least correlated with the existing PPAs. All four scenarios were scaled from a total of 770 MW of wind capacity to a total of 6,000 MW in steps of 500 MW (i.e. 770, 1,000, 1,500, …, 6,000). The capacities were scaled to the same level for each scenario, in order to make the scenarios comparable.

The first scenario scales all existing power purchase agreements in proportion to their existing levels. This has the effect of adding more wind capacity at sites that currently have a higher level of wind capacity and less at sites that currently have a lower level of wind capacity. For example, if two sites currently have 100 MW and 300 MW of wind capacity, then adding 100 MW of wind capacity will result in adding 25 MW at the 100 MW site and 75 MW at the 300 MW site. If the sites that currently have the most capacity are more likely to have wind additions than sites that currently have less capacity, then this scenario models that reality.

The second scenario scales all in-state wind sites proportionally in the same manner as the first scenario, while holding out-of-state sites at their existing levels. The third scenario scales the out-of-state sites proportionally, while holding the in-state sites at existing wind capacity levels. Scaling the first three scenarios in this way shows the impacts resulting from changes in proportions of in-state and out-of-state sites.

The last scenario is intended to show the benefits from additional geographic diversification of the wind portfolio. Adding the five least correlated sites to the existing wind sites is intended to reduce the variability of the total wind portfolio. Reducing this variability should decrease the capacity needs of other resources. Instead of scaling all sites in proportion to their existing levels, the capacity levels of existing sites and five new sites are all increased equally in MW terms. Since the scaling was done in a manner that did not hold the proportion of each site in the overall portfolio constant, impacts are the result of diversification and a changing portfolio make-up.

Again, these scenarios are intended to show the importance of location when choosing new wind sites and the portion each site comprises of the state's overall wind portfolio. The scenarios presented here are indicative of the likely impacts of adding wind PPAs from in-state, out-of-state, or both, as well as the fourth scenario that opportunistically selects sites that are least correlated with existing wind sites. The next section will present the results of the analysis for these four scenarios.

2.3 Results

2.3.1 Scaling Existing PPA Scenario

This section details the impacts of scaling wind capacities at the sites of all existing power purchase agreements in proportion to their existing levels. Relative to 2007 capacity levels, total resource needs from non-wind resources decrease with increasing wind capacity, as is shown in Figure 2.2. However, there is a shift in the composition of resource needs with peaking capacity requirements increasing and baseload and cycling requirements decreasing with increasing wind capacity. The increase in peaking requirements as wind generation is added to the system is due to the increasing variation in the annual load net of wind generation profile. Increasing levels of wind generation cause the load net of wind duration curve to become steeper resulting in increasing levels of peaking capacity to become cost effective relative to cycling and baseload capacity. Beyond 2,500 MW of installed wind capacity new peaking capacity requirements begin to decrease as excess baseload and cycling capacity are dispatched as peaking capacity so as to avoid idling existing cycling and peaking capacity.

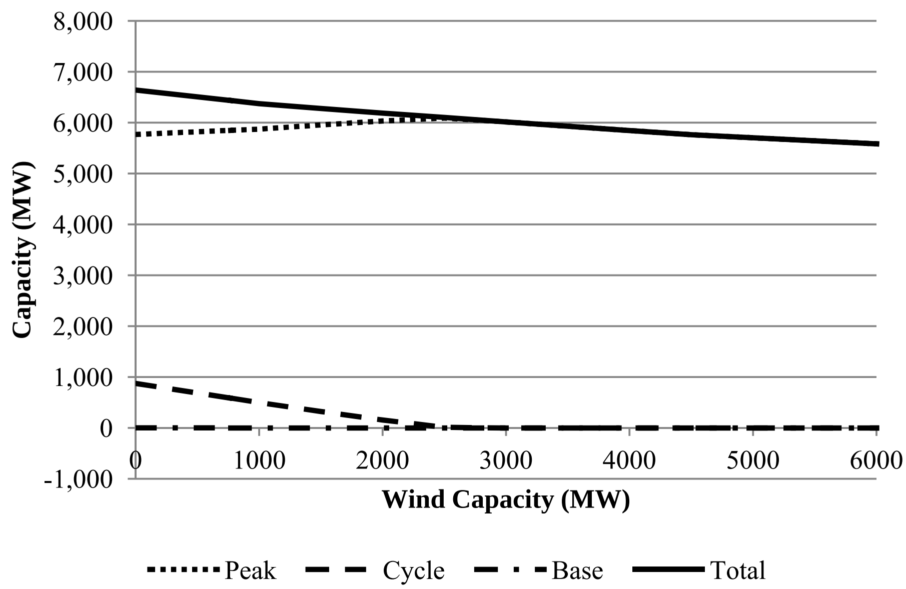

Figure 2.2 Change in Capacity Requirements (Relative to Base Case Capacity Levels)

The capacity planning stage results in no new baseload capacity being built as the cost curves for cycling and peaking capacity intersect well beyond 8,760 hours (the number of hours in a year). In a similar manner to baseload and cycling offsetting peaking needs beyond 2,500 MW of installed wind capacity, existing baseload is reclassified as cycling beginning at zero megawatts of installed wind capacity, leading to reductions in the level of new cycling capacity requirements.

Scaling wind capacity from the existing 770 MW to 6,000 MW, a net increase of 5,230 MW, offsets only 849 MW of capacity requirements from other resources, resulting in an increase in total capacity. Energy supplied by resources other than wind units decrease with increases in wind capacity. As with capacity requirements, energy that is supplied by baseload and cycling units are reduced as wind capacity increases, while energy supplied by peaking generation increases as wind capacity increases up to about 2,500 MW and then declines slightly with further increases in wind capacity (see Figure 2.3). Energy supplied by peaking capacity decreases beyond 2,500 MW of installed wind capacity due to the increases in energy supplied by existing cycling and baseload capacity which has been reclassified as peaking capacity. Energy supplied by baseload and cycling generation decreases as wind penetration increases due to additions in wind capacity causing a steepening of the load duration curve. Since additions in wind capacity are not able to offset non-wind resource needs on a one to one basis the system capacity factor declines (generation resources are less utilized). The capacity factor is the ratio of how much electricity is generated given a particular level of capacity divided by the amount of electricity that could have been generated if the unit was operating at full capacity continuously, with a larger number representing more generation per unit of capacity.

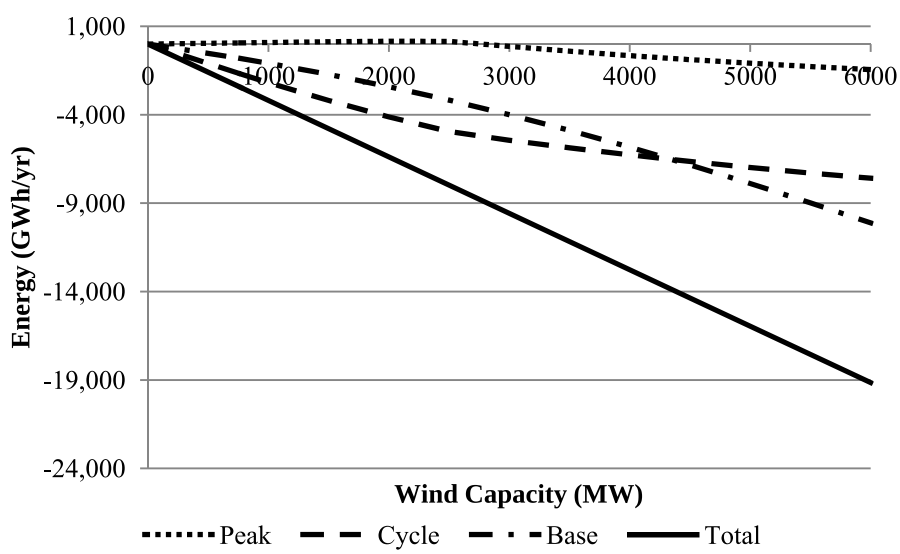

Figure 2.3 Change in Energy Requirements (Relative to 2025 with No Wind Generation)

Changes in annualized capital costs, in aggregate, increase with wind capacity. These costs are nearly completely driven by the capital costs of increasing wind capacity (see Figure 2.4). Incremental capacity costs mirror the pattern in Figure 2.2. No new baseload capacity is needed, so capital costs associated with baseload capacity are constant at all levels of wind capacity considered. Cycling capacity costs decrease due to a reduction in required additions. Capital costs associated with peaking capacity increase until about 2,500 MW of installed wind capacity and then decrease as existing baseload and cycling capacity is reclassified as peaking capacity.

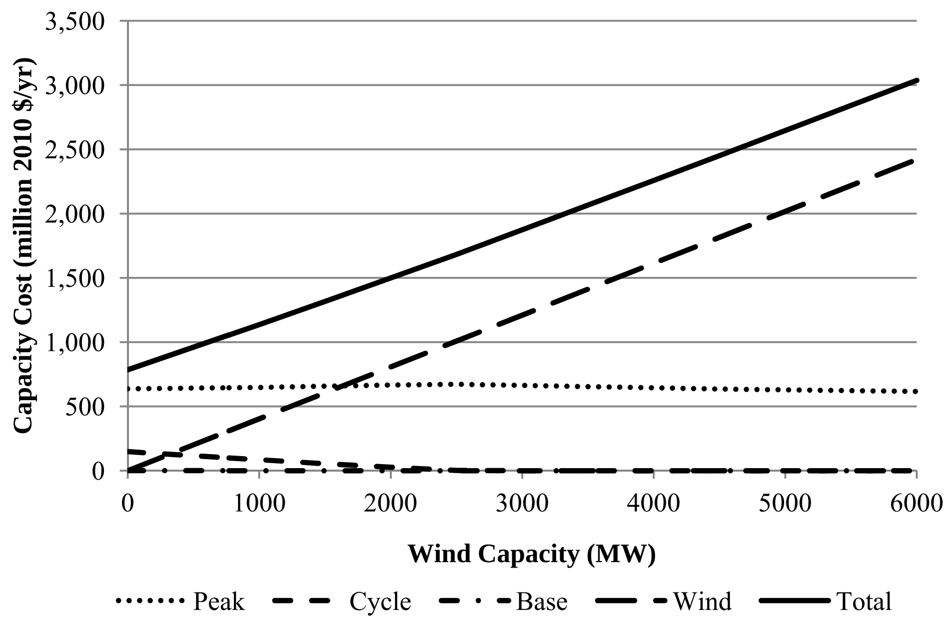

Figure 2.4 Change in Capital Costs (Relative to Base Case Capacity Levels)

Increasing wind capacity results in substantial decreases in variable costs because variable costs associated with wind generation are treated as zero in this analysis (see Figure 2.5). Thus, changes in energy requirements net of wind drive the changes in variable costs. Variable costs associated with baseload and cycling generation decrease with increasing wind capacity. Variable costs for peaking generation initially increase modestly and then decrease as some existing baseload and cycling capacity is reclassified as peaking capacity.

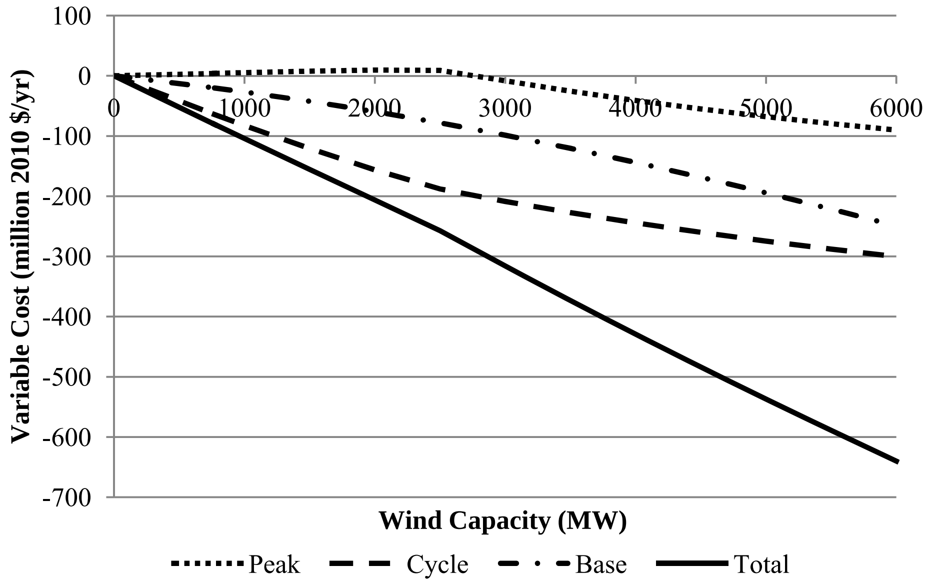

Figure 2.5 Change in Variable Costs (Relative to 2025 with No Wind Generation)

Table 2.4 summarizes impacts at varying levels of wind capacity. The capacity requirements impact represents total capacity needs, including existing capacity by resource in 2025 for a given level of wind capacity. The energy impact is energy that must be supplied by each resource type in 2025. The variable cost impact represents variable costs by resource type in 2025. Capital costs are annualized capital costs in 2025 for capacity needs relative to existing capacity.

Table 2.4 Annual Capacity, Energy, and Costs for Alternative Wind Capacity Levels

Impact Area	Existing (2010)[d] Capacity	0 MW Wind Capacity in 2025	1,000 MW Wind Capacity in 2025	3,000 MW Wind Capacity in 2025	6,000 MW Wind Capacity in 2025
Capacity					
Baseload (MW)	16,426	16,426	16,426	16,426	16,426
Cycling (MW)	2,500	3,375	3,000	2,500	2,500
Peaking (MW)	3,585	9,354	9,458	9,601	9,171
Total (MW)	22,511	29,155	28,884	28,527	28,097
Energy					
Baseload (GWh)	-	126,226	125,136	122,228	116,109
Cycling (GWh)	-	13,424	11,238	7,981	5,836
Peaking (GWh)	-	4,718	4,803	4,585	3,275
Total (GWh)	-	144,368	141,177	134,794	125,220
Variable Cost					
Baseload (million $)	-	3,111	3,085	3,013	2,862
Cycling (million $)	-	550	467	341	249
Peaking (million $)	-	295	300	286	205
Total (million $)	-	3,956	3,852	3,640	3,316
Capital Cost[e]					
Baseload (million $)	-	0	0	0	0
Cycling (million $)	-	149	85	0	0
Peaking (million $)	-	637	648	664	616
Wind (million $)	-	0	403	1,210	2,421
Total (million $)	-	786	1,136	1,874	3,037

[d] The existing capacity column represents existing 2007 capacity levels adjusted for planned capacity changes. Included in these planned capacity changes are certified, rate base eligible generation additions, retirements, and de-ratings due to pollution control retrofits. Existing capacity is taken from the Indiana State Utility Forecasting Group (SUFG, 2009b).

[e] Capital costs are the differences in annualized capital costs relative to the base resource case.

In order to determine what level of wind capacity is cost-effective, it is necessary to assess whether increases in capital costs are offset by decreases in variable costs. As calculated above, capital costs are relative to base case capacity levels. Comparing these capital cost increases to the reductions in variable costs would be inappropriate. The appropriate comparison is between increases in capital costs in 2025 without wind capacity and reductions in variable costs in 2025 without wind capacity. This comparison is analyzed in section 2.3.3.

2.3.2 Comparisons across Scenarios

This section compares the impacts of scaling up wind capacity across the four scenarios. The results show that while one scenario may result in a larger impact in one area, another may show a larger impact in another area. Also, while one scenario may result in the largest impact at a lower level of wind capacity another may show a larger impact at a higher level of wind capacity. This indicates that the locations of the wind capacity additions are important to the analysis.

At higher wind capacity levels, increasing all existing power purchase agreements by equal amounts while increasing the five least correlated sites by the same amount results in the largest reduction in the need for new non-wind generating capacity (see Figure 2.6). By scaling all sites by equal amounts (MWs), all sites are moving from their initial levels towards each site representing an equal portion of the overall wind portfolio. The results show that this scenario is slightly superior to the scenario where all PPA sites are scaled proportionally, showing that a larger impact is achieved due to the additional geographic diversification. The scenario where only in-state sites are scaled causes the in-state sites to dominate the portfolio at higher wind penetration levels. This negates some of the benefit from geographic diversification and is why this scenario results in the smallest impact on capacity requirements. The same reasoning explains the result for the scenario where only out-of-state sites are scaled. Scaling in-state sites results in the largest increase in peaking capacity needs and the smallest reduction to total capacity needs. This is because the load duration curve for the in-state scenario becomes steeper, relative to the other scenarios, at higher levels of wind capacity.

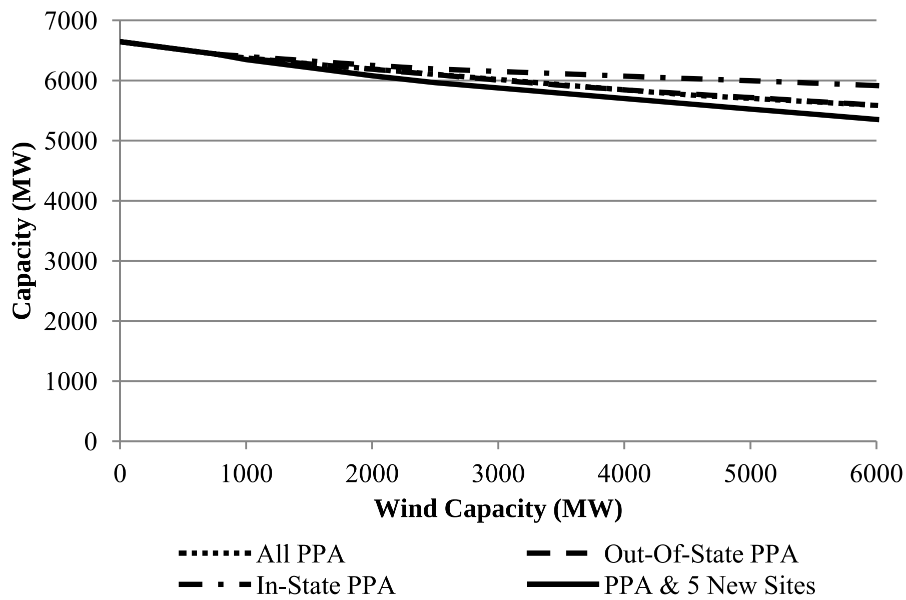

Figure 2.6 Total Non-wind Capacity Requirements Across Scenarios in 2025 (Relative to Existing 2010 Capacity Levels)

As shown in Figure 2.7, total energy impacts are similar across scenarios. The scenario where only out-of-state sites are scaled results in the largest energy impact, but the differences between the cases is small in terms of the change in energy requirements. This scenario exhibits the largest impact because the out-of-state sites have slightly higher capacity factors than the in-state sites. As this scenario is scaled up, the out-of-state sites make-up a larger portion of the overall wind portfolio. A larger capacity factor for the out-of-state sites means that a given level of wind capacity installed at an out-of-state site will result in a larger energy reduction than the same level of capacity installed at an in-state site. While the out-of-state scenario has the highest energy impact, it was shown earlier that it has the second lowest impact on capacity. This is because the out-of-state wind portfolio results in more wind generation, but during lower load periods, compared to the all PPA and PPA & 5 new sites scenarios. While wind curtailment was allowed in the economic dispatch model wind generation was not curtailed under any scenario or wind capacity level, therefore all differences in the impacts on total energy are the result of differences in capacity factors at the various wind sites.

Generally a wind site that is more highly correlated with load will have a larger impact on capacity, while a site with a larger capacity factor will result in a larger impact on energy, though this will not always be true. It would be possible for a site to have such a large capacity factor relative to another site that even if it was less correlated with load it could still lead to a larger capacity impact. This could happen if the capacity factor was sufficient to make the wind generation from the site higher during on-peak times despite being less correlated with load. Another way a site that is highly correlated with load could result in a smaller reduction in capacity would be if this site had a single, rather anomalous hour with very low output, which happened to be a relatively high load hour. As this discussion has shown, the impact of the correlation between wind generation and load and the wind site capacity factor cannot be considered entirely separate from each other.

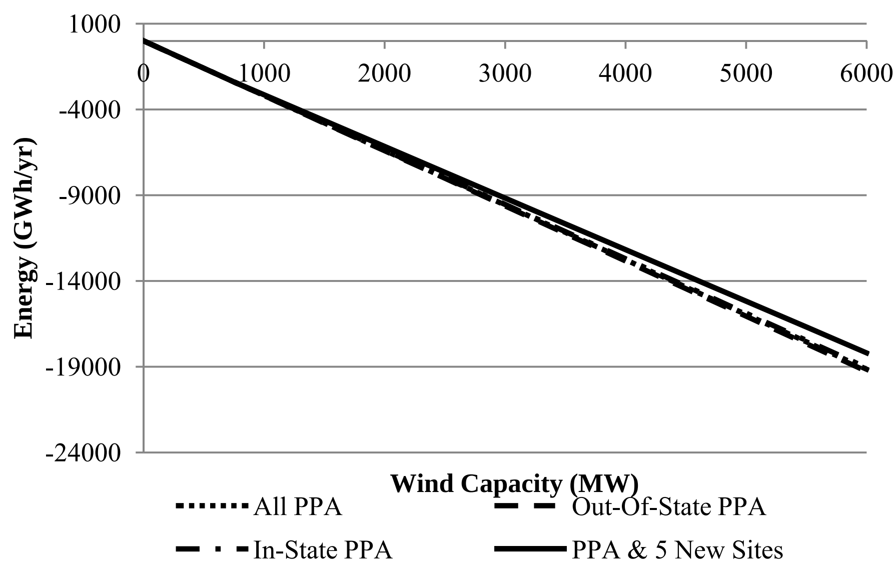

Figure 2.7 Change in Energy Requirements Net of Wind Across Scenarios

Figure 2.8 shows that changes in capital costs are nearly identical across scenarios and are driven by the increase in capital costs from additional wind capacity. For all scenarios, this is the result of additional wind capacity only offsetting a small amount of the capacity requirements for the other forms of generation. In other words, the incremental costs for installing wind capacity outweigh any other changes in capacity costs. The scenario where the capacity of PPA & 5 new sites are scaled proportionally results in the smallest increase in capital costs, a value of $3,011 million at 6,000 MW of wind capacity. It was shown earlier that the scenario where scaling existing PPA sites with the five least correlated sites resulted in the largest reduction in new capacity needs, therefore resulting in the smallest increase in capital costs. It may not always be the case that the scenario that has the largest impact on capacity requirements will result in the smallest increase in capital costs because both the resource mix and peak load are affected. While offsetting more capacity is generally better, it is also important to consider the type of unit the additional wind capacity is replacing.

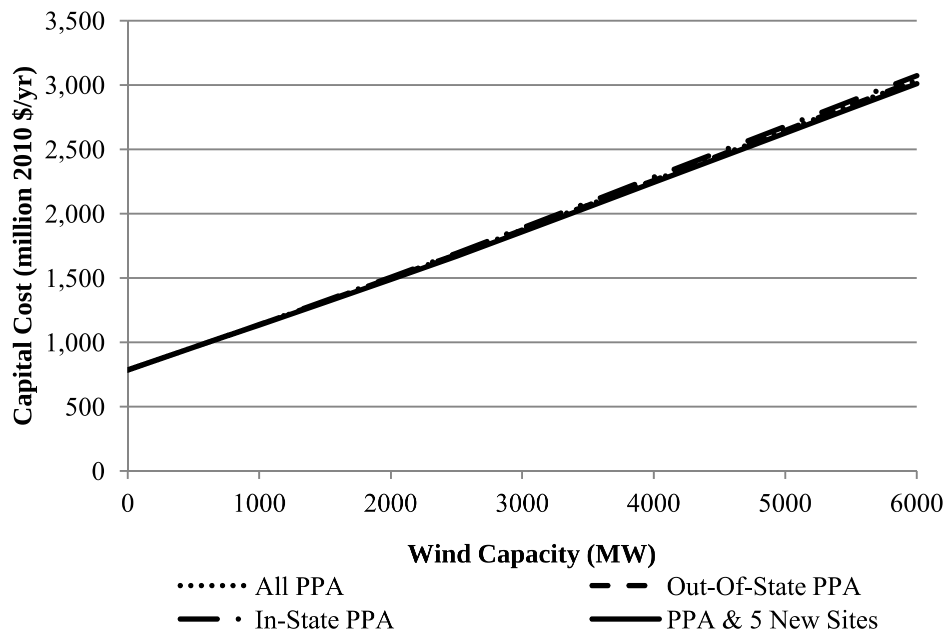

Figure 2.8 Change in Capital Costs Across Scenarios

The energy impacts have the most pronounced effect on variable costs. All scenarios, except for the PPA & 5 New Sites scenario, result in nearly identical energy impacts (see Figure 2.7), but show more variation in their impact on variable cost (see Figure 2.9). Two factors are driving the effect on variable cost. They are the reduction in total energy and the type of generation this reduction affects, because one MWh supplied by a baseload unit has a lower variable cost than one MWh supplied by a peaking unit. The first factor affects the energy impact, while both factors affect the variable cost impact. Thus, it is the change in composition of the generating units that makes the effect on variable costs different across scenarios while the effects on energy are quite similar.

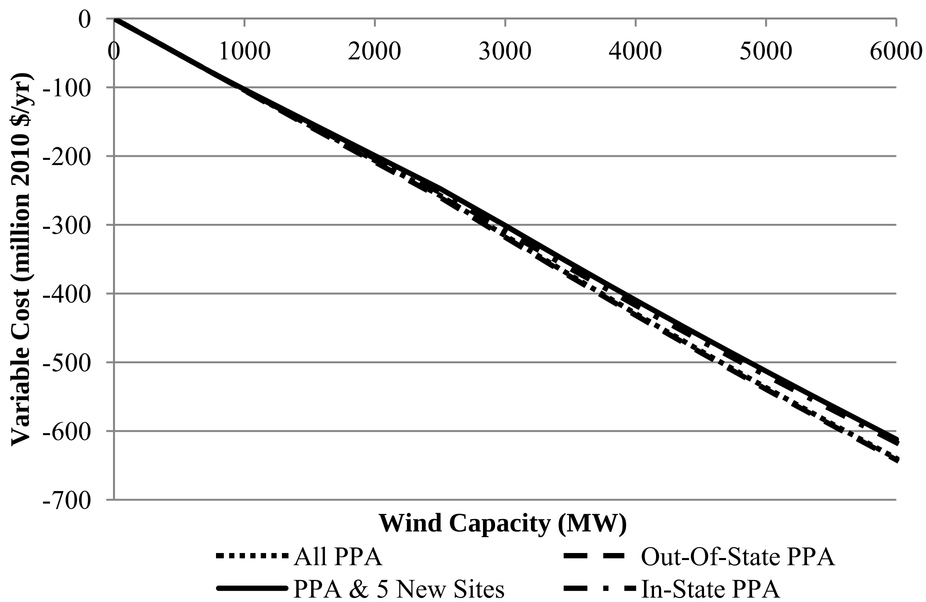

Figure 2.9 Change in Variable Costs Across Scenarios

These comparisons across scenarios highlight some key characteristics of wind generation. First, while one scenario may result in the largest impact in one area (e.g. capacity, energy, or cost) it may not in another area. This means that it is important to define the ultimate goal of the wind capacity that is being added to the system. However as a general rule, it will usually be most advantageous to add wind capacity at sites with high capacity factors and high correlation with load.

2.3.3 Cost-effectiveness of Additional Wind Capacity

This section addresses the cost-effectiveness of alternative levels of wind capacity, taking into account the variable cost and capital cost estimates presented in the previous section, as well as a wind production subsidy and an additional cost for carbon emitting technologies. As of July 2011, the Federal Production Tax Credit provided a wind energy production subsidy of 22 $/MWh. The wind production subsidy was not included in calculations to this point in the analysis because its existence and level in 2025 is uncertain.

Another important factor in determining the cost effectiveness of wind capacity additions relates to the value of reductions in carbon emissions. The carbon prices considered in this section were derived from the Bingaman bill proposed in the U.S. Senate (Bingaman, 2011). The bill proposes a price ceiling of $25/ton and a price floor of $10/ton for calendar year 2012, which were discounted to 2010 levels for this analysis. The price ceiling will increase each year by five percent in real terms. The carbon price ceiling of $25/ton in 2012, increasing at a rate of five percent per year in real terms, will result in a ceiling of 44.13 (2010 $)/ton in 2025. Similarly, the price floor will increase at a rate equal to three percent per year in real terms. This yields a carbon price floor of 10 (2010 $)/ton in 2012 that rises to 13.75 (2010 $)/ton by 2025. For modeling purposes, these low and high carbon prices were converted to dollars per megawatt hour based on heat rate, fuel type, and carbon emissions of the fuel, and are listed below in Table 2.5.

Table 2.5 Carbon Price by Type of Generation

Capacity Type	Low Carbon Price (2010 $/MWh)	High Carbon Price (2010 $/MWh)
New Capacity		
Baseload	15.47	49.65
Cycling	5.19	16.65
Peaking	7.86	25.24
Base Case Capacity		
Baseload	16.17	51.90
Cycling	6.31	20.24
Peaking	9.66	31.01

Baseload generation is modeled using the characteristics of a pulverized coal unit, which emits the highest levels of carbon dioxide. Cycling units, modeled using natural gas fired combined cycle technology, emit the lowest levels of carbon dioxide among the fossil fuel technologies. Cycling units have the lowest emission levels because this type of generation combines a gas turbine and steam turbine, where the exhaust heat from powering the gas turbine is then used to power the steam turbine, resulting in highly efficient generation. This highly efficient generation of combined cycle units uses less natural gas per MWh and ultimately emits less carbon dioxide per MWh. Peaking units are modeled as combustion turbine units, resulting in emissions per MWh between baseload and cycling units.

The optimal level of wind capacity is defined here as the capacity where the total cost of serving the load in 2025 with wind is lowest. For purposes of calculating the optimal level of wind capacity, the capacity cost impact is calculated relative to 2025 capacity requirements without any wind. (In previous sections, capacity impacts were calculated relative to base case capacity levels.) The goal in this section is to determine the optimal level of wind capacity in 2025, making the 2025 total cost without wind the relevant basis for comparison. Figure 2.10 below shows the impact on total costs from increasing wind capacity, without the inclusion of a production subsidy or carbon price. The decreases in variable costs are not able to offset the larger increases in capital costs at any level of wind capacity. Total costs from wind generation are always higher than in the no wind case. In terms of the optimal level of wind, zero wind capacity is optimal. In general, this answer may change in the presence of production subsidies or carbon costs.

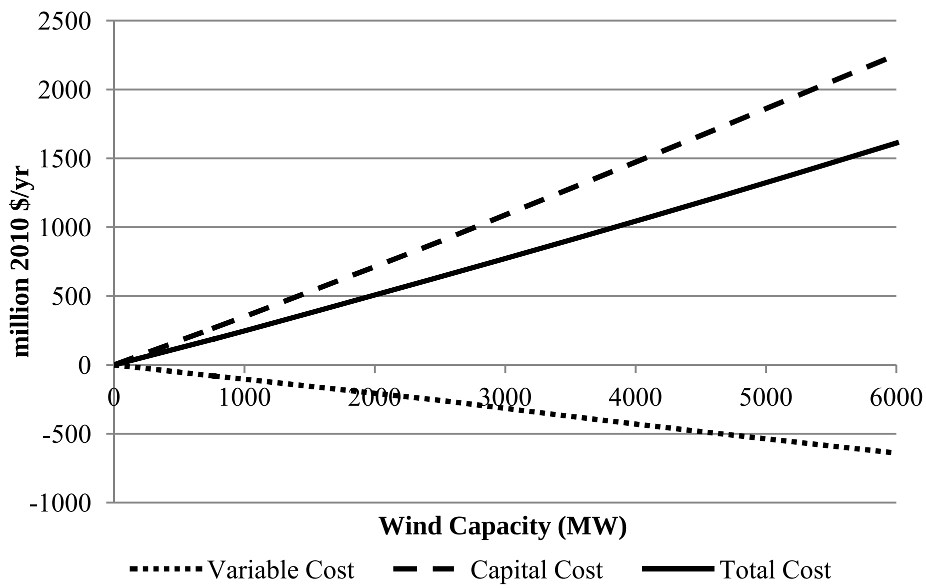

Figure 2.10 Breakdown of Cost Changes Across Levels of Wind Capacity Relative to No Wind (without Production Subsidy or Carbon Cost)

Including the wind production subsidy and/or the carbon prices makes wind more cost effective. Since both the production subsidy and the carbon price are in terms of dollars per unit of electricity generated, they will lead to further reductions in total variable costs with increases in wind generation and may alter the optimal mix of generation capacity. The impact on total cost is shown below in Figure 2.11 for all possible combinations of the wind production subsidy of 22 dollars per MWh and the high and low levels for the carbon price. While the wind production subsidy and carbon price both impact total system variable costs, the carbon price will also impact the optimal capacity mix of non-wind generation resources. The carbon price increases variable costs for the non-wind generation resources and has the effect of altering the intersection points of the breakeven cost curve used to determine the least cost generation capacity resource mix. Since no new baseload is added without considering the carbon price no new baseload capacity will be added to the mix when a carbon price is considered since the carbon price acts to increase the variable costs for baseload generation more than for other resources. The carbon price will tend to lead to a smaller increase in variable costs for cycling capacity as compared to variable costs for peaking capacity, therefore increasing the optimal level of cycling capacity relative to peaking capacity.

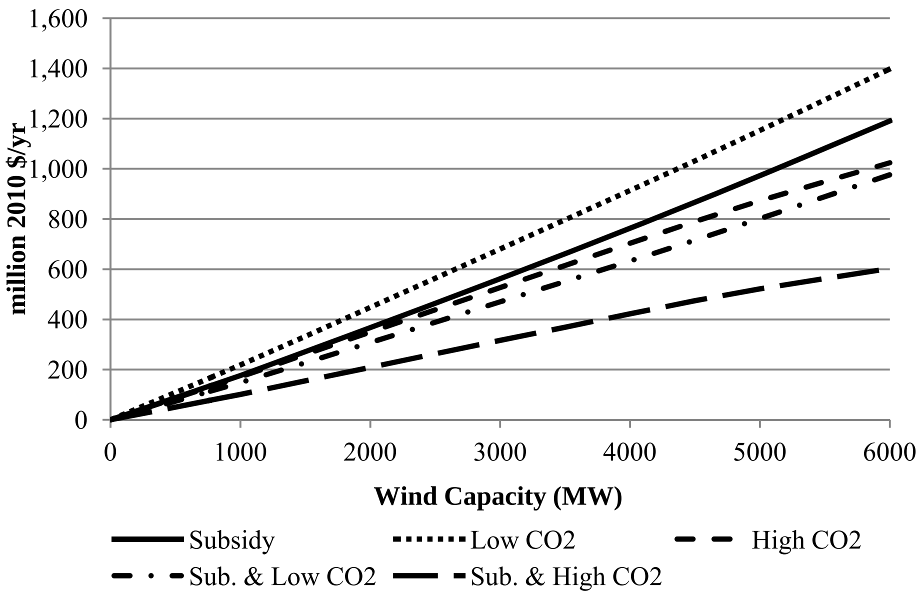

Figure 2.11 Breakdown of Cost Changes Relative to No Wind with Subsidy and Carbon Cost Alternatives

Total costs increase under all combinations of the subsidy and carbon price with any amount of wind capacity added to the system. In other words, zero wind capacity is optimal under all scenarios considered in this section. Capital costs increase faster than variable costs decline at all levels of wind capacity. The reduction in variable cost due to increases in wind generation is not able to offset the increases in capital costs even when the combination of the subsidy and high carbon price act to increase the reduction in variable costs. As no new baseload capacity is needed no matter what level of wind capacity is added to the system, additional wind capacity does not lead to reductions in baseload costs. (This result is driven in part by the initial capacity situation in Indiana which is relatively heavy on baseload and light on peaking. The results may be different in other study areas.) Although, additional wind capacity does lead to large reductions in cycling capacity needs and costs and increases in peaking capacity needs and costs.

Table 2.6 shows the impacts of various levels of wind capacity on 2025 average retail rates for all combinations of the subsidy and carbon prices. The values in this table are calculated by dividing the total cost quantities used in Figure 2.11 by 2025 projected retail energy sales of 144,495 GWh. For purposes of comparison, average Indiana retail rates in 2008 were 7.09 cents/kWh expressed in 2010 dollars. Thus, the 1,000 MW wind scenario with the federal subsidy and no CO2 costs represents a 1.7 percent increase in rates from their present level. As shown earlier, all combinations of subsidy and carbon price increase total cost and ultimately rates above the no wind case.

Table 2.6 Wind Capacity's Impact on Retail Rates in 2025 Under Various Scenarios (2010 dollars)

Program	1,000 MW Wind (cents/kWh)	3,000 MW Wind (cents/kWh)	6,000 MW Wind (cents/kWh)
Subsidy	0.12	0.39	0.82
Low CO2	0.15	0.47	0.97
High CO2	0.12	0.36	0.71
Subsidy & Low CO2	0.10	0.33	0.68
Subsidy & High CO2	0.07	0.22	0.42

2.4Conclusions

The primary distinguishing factor between wind generation and other forms of generation is the intermittency in output from wind generation. Since wind generation is not easily controlled, an important consideration is the relationship wind generation exhibits relative to load. Indiana's existing wind generation exhibits a strong negative correlation with Indiana load, and this relationship directly affects resource requirements for other forms of generation. Generally, though it is not always the case, a stronger negative correlation will lead to an increase in needs for peaking capacity because wind generation will typically not be available at full capacity during peak demand. The capacity factor of the wind will also have an effect on other resource needs.

This leads to the next important characteristic of a wind site. The capacity factor is the ratio of how much electricity is generated given a particular level of capacity divided by the amount of electricity that could have been generated if the unit was operating at full capacity continuously, thus a larger number represents more generation per unit of capacity. For the purpose of this paper the capacity factor indicates how much a given level of wind capacity will be able to reduce generation needs from other resources, with a higher factor reducing other resource needs by a larger amount. In addition to energy requirements, a higher capacity factor can affect capacity requirements, as well. Given two sites exhibiting the same correlation with load, the site with a higher capacity factor will typically be generating more electricity during the annual peak, which will have a direct effect on capacity requirements. In summary, when considering the addition of wind resources, sites that are more closely correlated with load and exhibit a higher capacity factor will generally lead to the largest reduction in capacity and energy needs from other generation resources.

Total costs increase with wind capacity because reductions in variable costs from additional wind capacity are not sufficient to offset the increases in capital costs for all scenarios. The results of the model showed that for all wind expansion scenarios, wind capacity is not cost-effective regardless of the level of the wind production tax credit and carbon prices that were considered. Since no positive level of wind capacity was deemed cost-effective, any level of positive wind capacity will lead to increases in retail rates, although these increases (sometimes small in percentage terms) may be determined by policymakers to be an acceptable price to pay to foster wind power development. Results may be affected by the existing mix of generation resources in Indiana. A state with a higher fraction of peaking capacity may be more suitable for siting wind capacity because the peaking units can be used to compensate for wind intermittency. While not considered in this paper, decommissioning existing generation capacity may be a viable option for older units. Wind expansion scenarios that consider alternative placement of wind capacity may result in wind generation looking more economically attractive. Other technologies to aid wind generation were not considered in this paper. For example, some form of energy storage could potentially make wind generation more cost-effective by shifting energy generated from wind from lower value, off-peak periods to higher value, on-peak periods, resulting in a larger reduction in capacity needs from non-wind generation sources.

CHAPTER 3: MODIFIED UNIT COMMITMENT IN RESPONSE TO WIND FORECASTING ERRORS

3.1 Introduction and Literature Review

The variable and intermittent nature of wind generation poses a number of challenges spanning many areas of electricity markets, with none more front and center than accurately forecasting this highly variable energy source. Forecasting wind power generation is difficult; historically weather models were not designed to predict wind speeds on the time scale required to accurately predict wind generation – which would ideally be hours, or even a day, in advance and a time scale of minutes. Forecasts are able to predict there will be a storm tomorrow and this will have a dramatic impact on the variability of wind generation, but exactly what time of day a ramp event will occur is difficult to predict (Burr, 2010). It is this inability to predict exactly when sudden changes in wind generation will occur that poses many challenges for schedulers and system operators.

While wind generation is not the only source of uncertainty in an electric system (unit outages and load are also uncertain), the degree of uncertainty is dramatically higher for wind generation. For instance, load forecast errors typically range from 1 to 4 percent, while forecasting errors for wind generation are on the order of 12 to 20 percent (Burr, 2010). Impacts of forced outages are likewise large, but very infrequent relative to wind fluctuations. Errors of this magnitude can have significant effects on real-time electricity market operations. Many papers have developed methods to mitigate the adverse effects of wind generation uncertainty on both the unit commitment (UC) and economic dispatch (ED) operational stages (Ummels et al., 2007; Bouffard and Galiana, 2008; Wang, Shahidehpour, and Zuyi, 2008; Tuohy et al., 2009; Wang et al., 2009; Wang et al., 2011). The unit commitment stage is considered the strategic resource deployment planning stage and considers information on expected system conditions, such as the level of load and wind generation. In this stage generating units are committed for each hour of a future operating day. On the other hand, economic dispatch takes place five to thirty minutes before real-time operations, where the actual realization of uncertain variables, such as load and wind generation occurs. Forecasts, especially for wind generation, can change dramatically between the UC and ED stages; as more accurate wind forecasts become available closer to the economic dispatch stage. There are two ways to handle wind generation uncertainty in the UC stage: 1) reserve requirements (i.e., spinning reserve) 2) stochastic programming (Ruiz et al., 2009). Stochastic programming has been shown to be an effective method to deal with wind forecasting uncertainty in the UC-ED program (Wang et al., 2009; Tuohy et al., 2009).

Tuohy et al. (2009) compare the results of a stochastic UC-ED model to two deterministic models: one using a perfect wind forecast for the UC stage and the other using the expected value of the wind forecast. As expected, the deterministic model which used the perfect wind forecast results in the lowest system costs; while the stochastic model shows higher system costs than the deterministic model with the perfect forecast, but lower costs than the deterministic model using the expected value of wind generation. The two models which did not use the perfect forecast resulted in costs 1.1 % and 1.7% higher for the stochastic and deterministic models, respectively, due to more frequent unit startups and more frequent use of higher cost peaking units. The stochastic optimization resulted in more frequent startups of lower cost units than the deterministic model with the imperfect forecast. The deterministic model which used the imperfect forecast had to use more quick start, higher cost peaking units to cope with unexpected changes in wind generation. By considering more possible wind scenarios the stochastic unit commitment program was better able to plan for the uncertain wind level by bringing on units with longer start times, which were lower cost. Their model did allow for wind curtailment when doing so resulted in a reduction to system costs. Wang, Shahidehpour, and Zuyi (2008) terms the day-ahead UC stage as the stage where preventative actions are taken, while the real-time ED stage is the stage where corrective actions take place. The stochastic program generally results in lower system costs by taking preventative actions to handle unforeseen variations in wind generation, usually by scheduling increased levels of ramping capability.

Wind site location can significantly impact which units respond to ramping associated with fluctuations in wind generation and may impact system costs. Including the transmission network in the UC-ED simulation plays an important role in determining the optimal planning of the UC and ED stages by considering potential transmission constraints, and may alter which units should respond to variations in wind generation. While many papers do not consider the transmission network (Ummels et al., 2007; Bouffard and Galiana, 2008; Wang et. al., 2009; Wang et al., 2011), Wang, Shahidehpour, and Zuyi (2008) showed the impact on both the UC and ED stages (and ultimately locational marginal prices or LMPs) are a direct result of the location of the wind site within the transmission network. The results of their paper concluded that LMP's changed markedly based on the location of the wind site within the transmission network. A paper by Mount and Lamadrid (2010) explicitly includes costs for ramping and shows that the variability of wind generation causes ramping costs to increase to a larger extent with the inclusion of the transmission network. This increase in costs is due to the transmission network restricting which units are able to respond to changes in wind generation, and further emphasizes the importance of including the transmission network in the UC-ED model.

While switching from a deterministic to a stochastic UC-ED model to handle wind generation uncertainty shows improvements in terms of lower system costs, this improvement comes at the expense of a marked increase in computational burden. Multiple papers note the dramatic increase in computation time (Bouffard and Galiana, 2008; Ruiz et al., 2009; Tuohy et al., 2009). The models used in a paper by Tuohy et al. (2009) resulted in computation times of approximately eight days for the stochastic program versus three hours for the deterministic program, using a perfect wind forecast for the deterministic program. Bouffard and Galiana (2008) notes, "…any practical implementation would require further investigation into the application of scenario reduction techniques." Ruiz et al. (2009) showed computation time increased by one to three orders of magnitude when going from the deterministic to the various stochastic programs considered in their paper.

In response to the large increase in computing time for stochastic programs several papers have proposed approximations to the full stochastic problem (Chen, 2008; Bouffard and Galiana, 2008). Chen (2008) uses a branch and bound technique to reduce the number of states to be examined in the unit commitment stage and implement a direct search method during economic dispatch to further reduce computation time. Bouffard and Galiana (2008) suggest using a solver preprocessor to reduce computation time. In their example the use of a mixed-integer linear programming solver preprocessor reduces the number of constraints by more than half.

The previous discussion concludes that stochastic UC-ED models are generally superior to deterministic models, but at the expense of increased computational time required to solve the stochastic model. This paper presents a modified stochastic UC-ED methodology which approaches the optimal solution achieved by the full stochastic framework while dramatically reducing the size of the full stochastic problem. In this paper a modified stochastic methodology is developed and compared to both deterministic and stochastic UC-ED models using a small four bus test system and a larger fourteen bus system that includes forecast error distributions derived from ISO market data.

3.2 Methodology

While the previous literature discussion highlights the potential benefits of using a stochastic model over a deterministic model, the significant increase in computational burden limits their use in practice. The model developed in this research is intended to capture a large portion of the benefits of stochastic optimization, while dramatically reducing the size of the full stochastic program and ultimately the computational burden. This model reduces the size of the full stochastic problem by focusing on the key transmission lines, which dramatically restrict the responses by other generators to variations in wind generation. Focusing the optimization on a small subset of transmission lines in the system dramatically reduces the number of constraints and variables, as compared to the full stochastic model.

An unexpected surge or drop in wind generation can significantly impact system costs, particularly when a transmission line that is located in close proximity to the wind site is constrained. In order to relieve congestion on the line either wind output will need to be curtailed, in the case of a wind surge, or other generating units, which impact the same transmission line, will need to alter their output to compensate for the unexpected wind shock. Stochastic unit commitment models lead to lower expected system costs by increasing the number of startups and generation for units with lower startup costs and higher variable costs, while reducing the number of unit startups for baseload units with lower variable costs, but higher startup costs (Tuohy et al., 2009). A stochastic UC-ED model minimizes expected system costs by balancing the tradeoff between committing a more expensive unit in the UC stage in the expectation that it will lead to lower system costs in the ED stage.

The unit commitment-economic dispatch is a two stage decision problem, shown below in Figure 3.1. Both the deterministic and stochastic optimization problems reflect a single optimization over both periods, but the deterministic optimization only considers one possible state for the level of wind generation in Stage 2. By only considering one possible realization of the wind generation level, the deterministic UC-ED problem does not account for the uncertainty associated with wind generation and will likely lead to a unit commitment that differs from the stochastic problem.

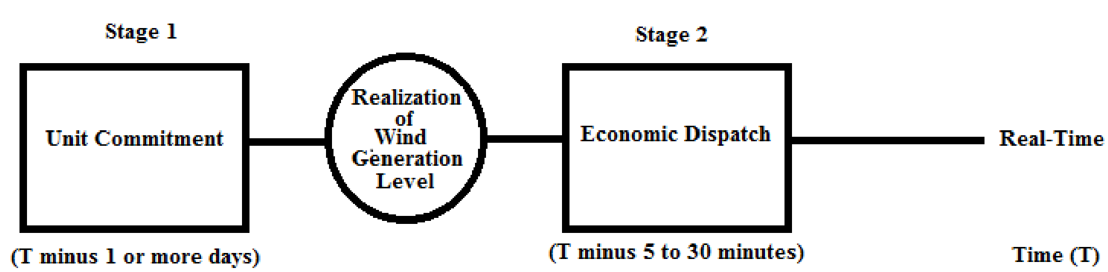

Figure 3.1 Two-stage Unit Commitment, Economic Dispatch Decision Layout

The formulation for the deterministic UC-ED problem is shown below in (1) through (4), with parameter and variable descriptions in Table 3.1. Units are committed in stage one considering a single realization for the wind generation in stage two. The problem minimizes the cost (1) of satisfying demand (2) subject to transmission constraints (3) and unit generation limits in (4). In contrast to the deterministic model, the stochastic problem, shown in (5) through (9c), minimizes the expected cost (5) of satisfying demand (6a,b) subject to transmission, unit ramping and unit generation constraints (7a)-(9c) for each state 's'. The upper and lower bounds on the level of wind generation for each state are shown in (9c). Parameter and variable descriptions for the full stochastic model are shown in Table 3.2.

$$\min_{G_i^0} \sum_i P_i G_i \tag{1}$$

$$\sum_i G_i - \sum_b D_b = 0 \tag{2}$$

$$-T_l \leq \sum_i F_{i,l} G_i - \sum_b E_{b,l} D_b \leq T_l \quad \forall\, l \tag{3}$$

$$G_i^{min} \leq G_i \leq G_i^{max} \quad \forall\, i \qquad (4)^1$$

[1] For purposes of this research lower bounds on generating units are set at zero MW. If a unit has a positive lower bound on generation, then a binary variable would be required to signify if the generating unit is committed. Binary variables would also be required on constraints 9a,b,c of the full stochastic problem and 14 and 15a,b of the modified stochastic problem.

Table 3.1 Parameters and Variables for Deterministic Formulation

Notation	Definition
i	index over generating units
b	index over loads
l	index over lines
P_i	offer price of unit *i*
G_i	generation level of unit *i* in unit commitment stage
G_i^{min}	minimum generation of unit *i*
G_i^{max}	maximum generation of unit *i*
$F_{i,l}$	power transfer distribution factor for unit *i* on line *l*
$E_{b,l}$	power transfer distribution factor for load *b* on line *l*
T_l	transmission capacity of line *l*
D_b	load *b*

$$\min_{G_i^0, G_{i,s}^1} \sum_i P_i \left(G_i^0 + \sum_s Pr_s G_{i,s}^1 \right) \tag{5}$$

$$\sum_i G_i^0 - \sum_b D_b = 0 \tag{6a}$$

$$\sum_i G_{i,s}^1 - \sum_b D_b = 0 \quad \forall\, s \tag{6b}$$

$$-T_l \le \sum_i F_{i,l} G_i^0 - \sum_b E_{b,l} D_b \le T_l \quad \forall\, l \tag{7a}$$

$$-T_l \le \sum_i F_{i,l} G_{i,s}^1 - \sum_b E_{b,l} D_b \le T_l \quad \forall\, l, s \tag{7b}$$

$$R_i^{down} \le G_{i,s}^1 - G_i^0 \le R_i^{up} \quad \forall\, i, s \tag{8}$$

$$G_i^{min} \le G_i^0 \le G_i^{max} \quad \forall\, i \tag{9a}$$

$$G_k^{min} \le G_{k,s}^1 \le G_k^{max} \quad \forall\, k, s \tag{9b}$$

$$G_j^{min} \le G_{j,s}^1 \le G_j^0 + W_{j,s}^{err} \quad \forall\, j, s \tag{9c}$$

Table 3.2 Parameters and Variables for Stochastic Formulation

Notation	Definition
i	index over all generating units
j	index over wind generating units as a subset of *i*
k	index over non-wind generating units as a subset of *i*
b	index over loads
l	index over lines
s	index over wind generation forecast error states
Pr_s	probability of state *s*
P_i	offer price of unit *i*
G_i^0	unit commitment generation level of unit *i*
$G_{i,s}^1$	economic dispatch generation level of unit *i* in state *s*
G_i^{min}	minimum generation of unit *i*
G_i^{max}	maximum generation of unit *i*
$F_{i,l}$	power transfer distribution factor for unit *i* on line *l*
$E_{b,l}$	power transfer distribution factor for load *b* on line *l*
T_l	transmission capacity of line *l*
D_b	load *b*
R_i^{up}	upward ramping capability of unit *i*
R_i^{down}	downward ramping capability of unit *i*
$W_{j,s}^{err}$	wind forecasting error for wind site *j* in state *s*

As can be seen in a comparison of the formulations, considering multiple states in the stochastic problem dramatically increases the number of variables and constraints. The previous section highlighted the potential gains from considering multiple wind generation states, so a method which is able to capture the benefits of the stochastic optimization while reducing the size of the problem would be very beneficial to both system planners and operators. The modified formulation, shown below in (10) through (15b), is carried out in addition to the deterministic optimization. Table 3.3 shows parameter and variable descriptions for the modified stochastic formulation. The optimal unit commitment levels (G_i) are treated as fixed parameters in the modified stochastic problem. Also, the set of binding transmission lines from the deterministic problem are indexed by *m* and are a subset of all the lines in the system, which is indexed by *l*.

$$\min_{DG_i, H_{i,s}} \sum_i P_i \left(DG_i + \sum_s Pr_s H_{i,s} \right) \tag{10}$$

$$\sum_i DG_i = 0 \tag{11}$$

$$\sum_i H_{i,s} = 0 \quad \forall\, s \tag{12}$$

$$-T_m \leq \sum_i F_{i,m}(DG_i + G_i) - \sum_b E_{b,m} D_b \leq T_m \quad \forall m \tag{13a}$$

$$-T_m \leq \sum_i F_{i,m}\left(G_i + DG_i + H_{i,s}\right) - \sum_b E_{b,m} D_b \leq T_m \quad \forall\, m, s \tag{13b}$$

$$G_i^{min} \leq G_i + DG_i \leq G_i^{max} \quad \forall\, i \tag{14}$$

$$\max\left(R_k^{down}, -\left(G_k + DG_k - G_k^{min}\right)\right) \leq H_{k,s}$$

$$\leq \min\left(R_k^{up}, G_k^{max} - G_k - DG_k\right) \quad \forall\, k, s \tag{15a}$$

$$\max\left(R_j^{down}, -\left(G_j + DG_j - G_j^{min}\right)\right) \leq H_{j,s}$$

$$\leq \min\left(R_j^{up}, G_j^{max} + W_{j,s}^{err} - G_j - DG_j\right) \quad \forall\, j, s \tag{15b}$$

Table 3.3 Parameters and Variables for Modified Stochastic Formulation

Notation	Definition
i	index over generating units
j	index over wind generating units as a subset of *i*
k	index over non-wind generating units as a subset of *i*
b	index over loads
l	index over lines
m	index over lines considered in modified problem as a subset of *l*
s	index over wind generation error states
Pr_s	probability of state *s*
P_i	offer price of unit *i*
DG_i	modification to deterministic dispatch in UC period for unit *i*
$H_{i,s}$	response of unit *i* in state *s* to wind error in state *s*
G_i	optimal unit commitment generation level of unit *i* from deterministic problem (a constant in this problem)
G_i^{min}	minimum generation of unit *i*
G_i^{max}	maximum generation of unit *i*
$F_{i,l}$	power transfer distribution factor for unit *i* on line *l*
$E_{b,l}$	power transfer distribution factor for load b on line *l*
T_l	transmission capacity of line *l*
D_b	demand at bus b
R_i^{up}	upward ramping capability of unit *i*
R_i^{down}	downward ramping capability of unit *i*
$W_{j,s}^{err}$	wind forecasting error for wind site *j* in state *s*

The modified formulation considers the same wind generation states as the full stochastic problem, while greatly reducing the number of variables and constraints by focusing on the portion of the transmission network where the impact of the wind generation is most pronounced. The objective (10) of the modified problem minimizes the expected cost of accounting for the uncertainty surrounding the wind generation level by altering the deterministic UC generation levels through the DG_i variables for each generation unit. The constraints on the $H_{i,s}$ variables ensure that the ramping capabilities of the generating units are sufficient to handle all wind states considered in the problem. The objective mimics the objective of the stochastic UC problem, but the number of variables and constraints are dramatically reduced in (11)-(15b). In (11), the DG_i's must sum to zero in order for the energy balance equality (2) to remain satisfied, since it was satisfied in the deterministic UC problem. Similarly, (12) satisfies the energy balance in

(6b) for every state of wind forecasting error. Constraints (13a) and (13b) are included to ensure that the constraints for the constrained (or nearly constrained) lines are not violated in either the UC or ED stages by altering the deterministic UC problem. The DG_i variables are restricted by the initial deterministic dispatch levels (A_i) and the units' maximum and minimum capacity in (14). Similarly, the $H_{i,s}$ variables are restricted by their ramping capability and the difference between their generation levels and their maximum or minimum capacity in (15a,b).

Constraint (15a) shows that by altering the DG_i variables the ranges for the $H_{i,s}$ variables are altered, as well. As noted earlier, the modified formulation accounts for the wind uncertainty through the various wind states, while largely reducing the size of the problem by ignoring transmission lines which are not constrained (or nearly constrained). Constraint (15b) restricts the response of the wind site and allows for wind curtailment when curtailment of wind generation is optimal.

While the modified stochastic program focuses on the constrained line, it is important to ensure that the optimal generation levels do not violate any of the other constraints in the transmission system. These constraints can be checked after the fact using (16) and (17) for each line not considered in the modified problem. If the modified UC or ED dispatch levels violate any of the transmission line constraints then these lines are added to the modified stochastic program and the program is recomputed. A flowchart (shown in figure 3.2) shows the process of checking and recalculating (if necessary) the modified stochastic model. As the flowchart shows, the deterministic UC model is calculated and any constrained (or nearly constrained) lines are determined. The modified stochastic model is calculated using these constrained lines and unit commitment generation levels from the deterministic UC model, then the solution generation levels are used to determine if any other transmission line constraints are violated; if so, these lines are added to the modified stochastic UC model and the problem is resolved. If none of the other line constraints are violated, then the process is complete and these are the unit commitment generation levels from the modified problem. For larger networks, it may be possible to reduce the set of lines which need to be checked for violations. Lines far from the constrained line (i.e., lines for which the wind site has small power transfer distribution factors (PTDFs)) may not need to be considered, since the generators responding to the wind generation deviation are likely to have a negligible effect on these lines, as well. Power transfer distribution factors are a measure of the sensitivity of power flow on a line resulting from an injection by a generator or withdrawal by a load. A PTDF with a larger absolute magnitude indicates power flow on a line is more sensitive to an injection or withdrawal from a generator or load. Further study is required to determine what the characteristics are for a sufficiently distant line to have a negligible effect on the problem.

$$Line\_Flow_l = \sum_i F_{i,l} * (A_i + DG_i) - \sum_b E_{b,l} * D_b \quad \forall\, l \tag{16}$$

$$Line\_Flow_{l,s} = \sum_i F_{i,l} * (A_i + DG_i + H_{i,s}) - \sum_b E_{b,l} * D_b \quad \forall\, l, s \tag{17}$$

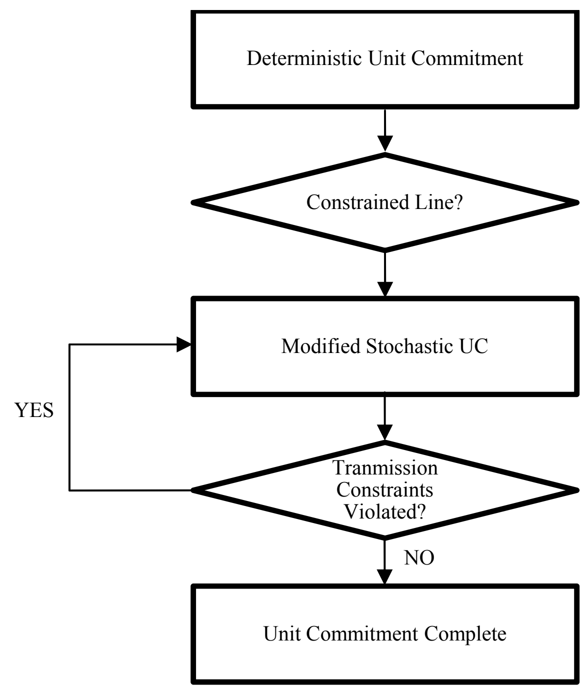

Figure 3.2 Modified Stochastic Unit Commitment Solution Approach

3.3 Results

3.3.1 Results of Four Bus Test System

The following example illustrates the potential benefits of using the modified stochastic problem relative to the deterministic problem in terms of expected cost and over the full stochastic program in terms of computational complexity. The test system (shown in figure 3.3) is a four bus model with five generating units, one of which is a wind unit (G2), and two loads located at buses B2 and B3. Parameter values for the system are shown in tables 3.4 and 3.5.

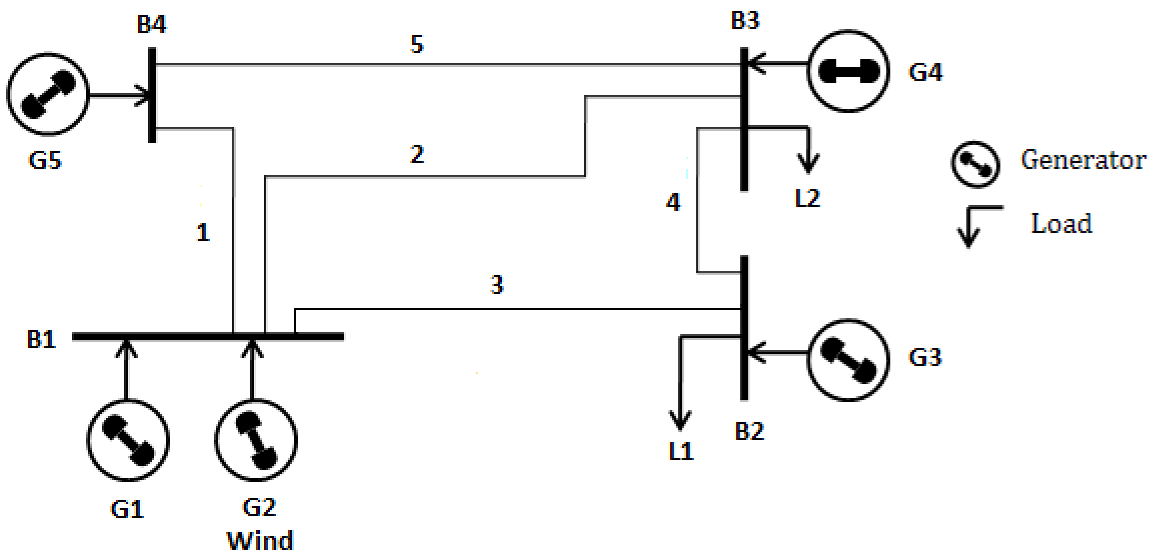

Figure 3.3 Four Bus Test System with Wind Site

Table 3.4 Test System Generator, Load and Line Parameters

Generator Offers

Generator	Price ($/MWh)	Capacity (MW)	Ramp Limits (MW/period)
G1	30	500	5
G2	1	100	0
G3	150	400	15
G4	25	150	16
G5	40	100	30

Load

Load	Load (MWh)
L1	253
L2	100

Line Capacity

Line	Capacity (MW)
1	150
2	150
3	146
4	110
5	100

Table 3.5 Test System Power Transmission Distribution Factors (PTDFs)

	Line				
Bus	1	2	3	4	5
1	0.2829	0.1405	0.1767	-0.0233	-0.0829
2	0.1100	-0.0648	-0.4452	0.3548	0.0900
3	-0.0728	-0.2818	-0.0454	-0.2454	0.2728
4	-0.6029	0.0656	0.1373	-0.0627	-0.1971

The wind unit (G2) and a low cost baseload unit (G1) are located at bus one (B1) and another low cost unit (G4) is located at bus three (B3). These units have more than enough capacity to satisfy the 253 MWhs of load. Unit G3 is the most expensive unit in the test system, therefore this unit would ideally be used as little as possible. Under the deterministic unit commitment model, line three is the only constrained line in the system (shown in table 3.6) and therefore it is the only line included in the first iteration of the modified stochastic model.

As can be seen in table 3.5, 17.67% of the generation from the wind site (located at bus one) flows onto line 3. A negatively signed PTDF indicates power flow in the opposite direction. For example, injections at bus 1 and bus 3 would result in power flowing on line 1 in opposite directions, due to these buses having PTDFs of opposite sign for this line. Therefore, transmission lines can bind in either direction and line flows are restricted to be between plus and minus line capacity. Since line three is already at capacity in the deterministic model any increase in wind generation will need to be met by a reduction in generation for a unit with a PTDF of the same sign as the wind site for line three, an increase in generation for a unit with a negative PTDF for line three, or the wind will need to be curtailed. In this test system, a reduction in wind generation does not have the adverse effect that an increase has, as a reduction does not increase the flow on line three in the binding direction. A reduction in wind generation actually causes the constraint to become non-binding. It is along this line of reasoning that focusing on positive wind deviations makes sense for this test system. If transmission line three were constrained in the other direction, then a decrease in wind generation would be problematic and the modified problem would focus on unexpected decreases in wind generation.

Table 3.6 Line Flow During the Unit Commitment Period for the Three Programs

	Line (Line Capacity)				
Program	1 (150 MW)	2 (150 MW)	3 (146 MW)	4 (110 MW)	5 (100 MW)
Deterministic	25.89	30.75	146.00	-106.62	-25.89
Modified Stochastic	16.64	30.38	146.00	-107.00	-27.51
Full Stochastic	24.23	28.77	140.01	-102.98	-24.23

The test system uses a positive wind surge, which for purposes of illustration is uniformly distributed over the interval zero to fifteen MWs, therefore the probability of each state is equal to one over the number of states or $\frac{1}{S}$ (0.01 in this analysis as there are 100 wind states). An unexpected surge in wind generation equal to the upper bound of fifteen MWs is fifteen percent of the wind site's expected output of 100 MW, therefore falling in the reasonable range of twelve to twenty percent mentioned in Burr (2010). The deterministic model does not account for the potential wind deviation from forecast and therefore results in the highest expected cost (shown in table 3.7). Both the modified and full stochastic models result in equal expected cost, which is lower than the deterministic model. The stochastic models are able to achieve a lower expected cost by altering the generation levels in the unit commitment stage, although these two models commit units at different levels.

Both stochastic models reduce the output from generator G1 and increase the commitment levels of G3 and G5 for the full stochastic and modified stochastic models, respectively (shown in table 3.8). While the two stochastic models arrive at different solutions for the unit commitment stage, they result in identical total economic dispatch cost for each wind error state and therefore identical expected cost. Units G3 and G5 are more expensive units than G1, so the deterministic model which does not account for the wind uncertainty commits G1 at a higher level than the stochastic models. The stochastic models find it advantageous to increase the output from either G5 or G3 and decrease the output from G1 due to the increase in ramping capability this brings into the system, and in particular for line three. Comparing the stochastic models reveals that it is very important to consider the location of ramping in the system. Remember the modified stochastic model only focuses on line three (the constrained line), and it is able to achieve an expected cost as low as the full stochastic program, which considers the entire transmission network.

Table 3.7 Expected Total Cost for Both Unit Commitment and Economic Dispatch

	Stage		
System Cost ($)	UC	E(ED)	E(UC-ED)
Deterministic	6,985.48	-120.84	6,864.64
Modified Stochastic	7,053.05	-283.11	6,769.94
Full Stochastic	8,140.48	-1,370.54	6,769.94

Table 3.8 Unit Commitment Generation Levels for the Three UC Problems

	Generating Unit				
Program	G1	G2	G3	G4	G5
Deterministic	102.62	100.00	0.38	150.00	0.00
Modified Stochastic	93.00	100.00	0.00	149.13	10.87
Full Stochastic	93.00	100.00	10.00	150.00	0.00

Table 3.9 highlights the importance of strategically locating ramping capability for line three, taken as the product of a unit's ramping capability and its distribution factor for line three and summing over all units with a distribution factor of the same sign for this particular line. The table shows the effective ramping on line three and the end of the line where the ramping is located. In the unit commitment stage, the stochastic models increase the effective downward ramping capability although on opposite ends of line three, whereas the deterministic model only allows for 0.88 MW of effective downward ramping capability on the same end of line three and 0.90 MW on the opposite end of line three with respect to the wind site. Bringing units G3 and G5 online, as is done in the stochastic models, increases the downward ramping capability to allow for the handling of larger potential upward deviations in wind generation. In the deterministic model, unit G1 is committed at a high level of capacity, but is only able to provide 5 MW of ramping per period, therefore limiting the system's overall ramping capability with respect to line three.

Table 3.9 Unit Commitment Directional Ramping Capability on Line 3 by Side of Line

	Ramping			
	Up	Down	Up	Down
Program	Positive	Positive	Negative	Negative
Deterministic	5.00	0.88	6.68	0.90
Modified Stochastic	5.00	2.38	6.72	0.73
Full Stochastic	5.00	0.88	6.68	5.18

Table 3.7 showed the deterministic model resulted in the higher expected cost, as compared to the two stochastic models. The impact on expected cost of locational-based ramping becomes more apparent as you look at the cost of economic dispatch for each of the three models (Figure 3.4). Economic dispatch costs by state are roughly the same until the unexpected wind surge exceeds 5 MW; at this point the deterministic model has used up all of the downward ramping capability (unit G1) on the side of line three where the wind site is located. This is in contrast to the two stochastic models that committed G1 at a lower level and increased the commitment level of other units which increase the system's downward ramping capability with respect to line three. The two stochastic models increase ramping capability with respect to line three using different generation units; the full stochastic model commits unit G3 at a higher level while the modified stochastic model commits unit G5 at a higher level, although both models result in the same cost for each wind error state and overall expected cost.

Beyond a wind surge of 5 MW, the deterministic model either has to start increasing output from the most expensive unit (G3) or curtail the wind generation in order to relieve the congestion on line three, therefore ED costs between the deterministic and stochastic models dramatically diverge beyond this point. Once the deterministic model runs out of downward ramping capability with respect to line three it is optimal to curtail wind generation, with costs leveling off for higher wind error states (see Figure 3.4). Similarly, the ED costs by state for both the modified and full stochastic models level off as excess wind is curtailed beyond a wind surge of 14.6 MW. In all three models ED costs stop falling and level off once all of the downward ramping capability has been used and the next least expensive way to relieve congestion on the line is to curtail excess wind generation. The results of the stochastic models show that some positive level of wind curtailment is optimal and it is not beneficial in terms of cost to completely eliminate wind curtailment. There is a tradeoff between altering the deterministic UC by bringing on a more expensive unit (G3 and G5 versus G1) in the unit commitment stage and curtailing excess wind generation to respond to the wind surge.

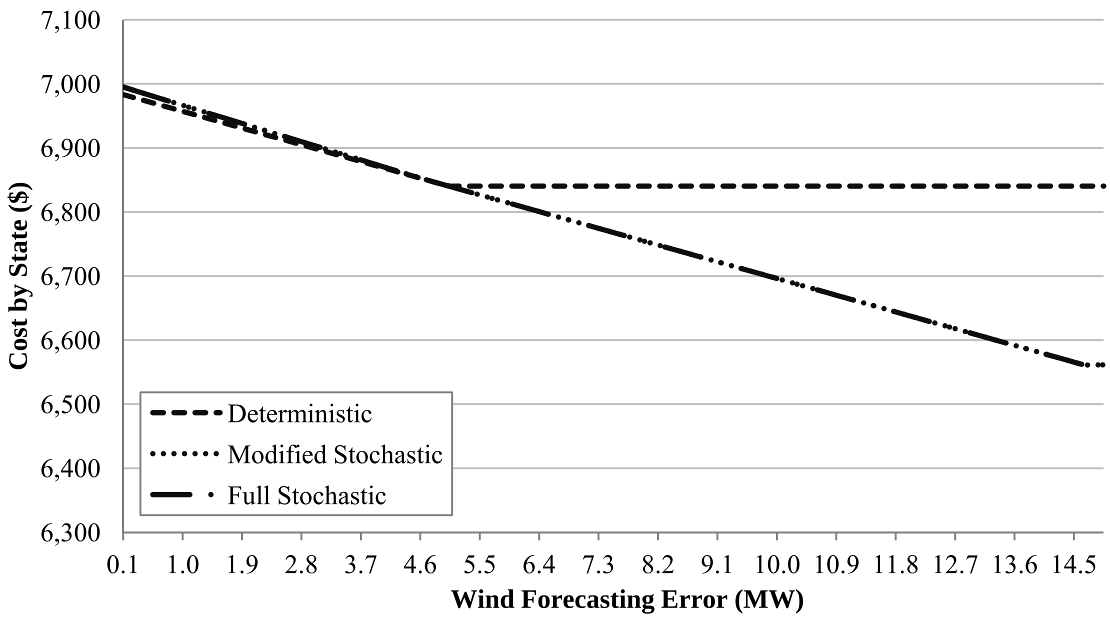

Figure 3.4 Dispatch Cost by State for the Three UC-ED Models

3.3.2 Fourteen Bus Test System

The previous section highlighted the benefits of stochastic models and in particular the modified stochastic model over the deterministic model through the use of a small four bus test system. This section compares a larger fourteen bus system, with the aim of comparing the three models in a more realistic system. While the previous section assumed a uniformly distributed wind forecasting error, in this section wind forecasting errors are approximated using actual wind forecasting and generation data from the Midwest Independent System Operator (MISO). The results of this section show that the cost benefits of the modified model equal the full stochastic model using a larger test system which incorporates wind error distributions approximated using actual generation and forecasting data.

3.3.2.1 Fourteen bus system and parameters

The parameters of the fourteen bus test system are from the University of Washington's power system test case archive, which houses the IEEE 14 bus test case used in this analysis (UW, 2012). A schematic of the test system is shown in figure 3.5. The system is comprised of ten generating units (G*), with the wind site (G9) located at bus thirteen (B13) and four loads (L*). Parameter values for generating units, loads, and transmission lines are shown in tables A1-A4 in the Appendix.

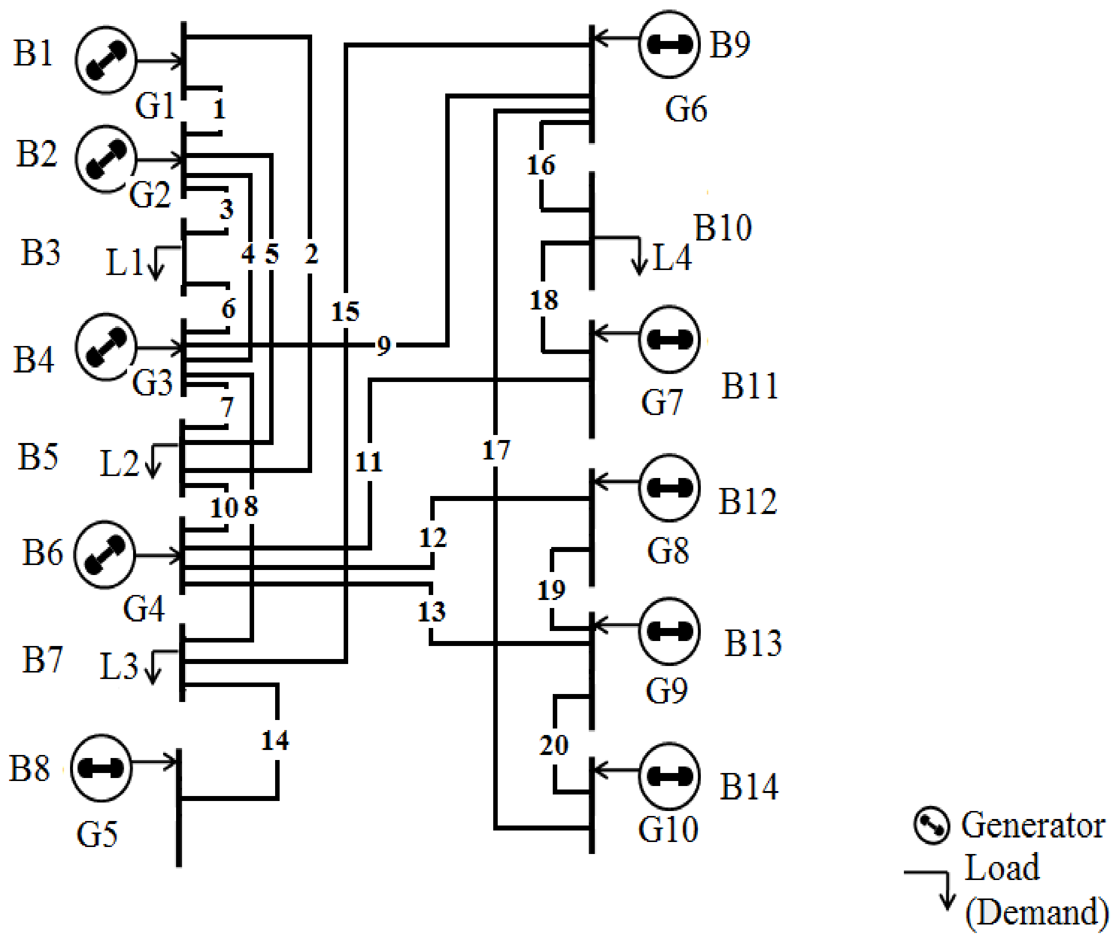

Figure 3.5 Schematic of Fourteen Bus Test System

3.3.2.2 Estimation of MISO Wind Forecasting Errors

Forecasts of wind generation continue to be updated as the operating hour approaches and ideally the forecast accuracy improves as the operating hour approaches. The forecast data used in this analysis is the day-ahead wind forecast and is in the range of the forecast that would be used during the unit commitment stage. In this section the distributions for wind forecasting errors are estimated using actual hourly aggregate wind generation and forecast aggregate wind generation data from MISO covering the time period of April 25th through August 29th of 2012, resulting in 3,072 hourly observations. MISO wind generation and wind forecast data were acquired through data request. Table 3.10 shows summary statistics of wind generation, wind generation forecast, and forecast error. Two factors may affect the accuracy of error measures used in this analysis as compared to actual forecast errors: 1) using aggregate data may result in less wind variability than a single wind site because variability at one wind site may be offset to some extent by variability at another wind site and 2) curtailment of wind generation may have an impact on error values, as curtailment is not observable in the actual wind generation data used in this analysis. Sensitivity analysis will be used to examine the impacts of increased variability in the wind forecast error. Total wind capacity in MISO is approximately 11,857 MW for the time period of the wind generation and forecast data used in this analysis, though mean wind generation is markedly less than this level (MISO, 2012). Mean forecast error is negative meaning on average the wind generation forecast is less than actual wind generation. Consistently under forecasting of wind generation is one method to increase the system reserve margin and will reduce the chance of under committing other generation resources, although it does not address the location of the ramping capability. Both actual wind generation and forecast are positively skewed, while skewness of the error is near zero. The distribution of the wind forecasting error is nearly symmetric about a mean of -25.47 MW.

Table 3.10 Summary Statistics of Wind Generation, Wind Generation Forecast, and Forecast Error

Summary Statistics	Wind Forecast	Wind Generation	Forecast Error[f]
Maximum (MW)	7,812.53	7,710.87	2,848.38
Minimum (MW)	70.89	47.63	-2,754.67
Mean (MW)	2,845.90	2,871.38	-25.47
Standard Deviation (MW)	1,785.33	1,866.13	669.39
Skewness	0.65	0.60	-0.07
Kurtosis	-0.51	-0.70	0.94

[f] Negative values are under forecast (actual wind generation is larger than forecast generation).

While the wind forecast error distribution appears to be approximately symmetric using all 3,072 observations, the conditional error distributions exhibit skewness values that deviate further from zero when the error is stratified based on the forecast level. In this analysis wind forecast errors are stratified into one of three bins depending on the wind forecast level. Bin widths are determined in order to have an equal number of observations in each of the three bins or 1,024 observations per bin. Summary statistics for each of the three bins are shown below in Table 3.11, with Bin 1 corresponding to wind forecast levels less than 1,691 MW, Bin 2 for forecast levels between 1,691 MW and 3,432 MW, and Bin 3 for forecast levels greater than 3,432 MW. The three bins are compared in this analysis to show the benefits of using the stochastic models over the deterministic model vary depending on the wind generation forecast level.

Table 3.11. Summary statistics of binned wind generation, forecast of wind generation, and forecast error

	Bin 1 (Forecast < 1691 MW)			Bin 2 (1691 MW < Forecast < 3432 MW)			Bin 3 (Forecast > 3432 MW)		
Summary Statistics	Wind Forecast	Wind Generation	Forecast Error	Wind Forecast	Wind Generation	Forecast Error	Wind Forecast	Wind Generation	Forecast Error
Maximum (MW)	1,691.00	3,089.90	1,022.20	3432.5	5976.7	1867	7812.5	7710.9	2848.4
Minimum (MW)	70.9	47.6	-1,625.10	2	1025	0	3434.8	1032.3	-2597.6
Mean (MW)	1,048.20	1,093.60	-45.4	2493.5	2554.8	-61.3	4996	4965.7	30.3
Std. Dev. (MW)	404.1	543.4	414.1	507.6	890.6	743.2	1078.1	1308.4	784.6
Skewness	-0.32	0.55	-0.7	0.2	0.51	-0.22	0.46	-0.28	0.09
Kurtosis	-0.94	0.05	1.44	-1.21	0.27	0.14	-0.72	-0.56	0.29

The previous section assumes the wind forecasting error is uniformly distributed, though this is not likely to be a very realistic assumption. Many papers assume the wind forecast error is normally distributed (Makarov et al., 2002; Castronuovo and Pecas-Lopes, 2004; Pinson and Kariniotakis, 2003; Milligan, Schwartz, and Wan, 2003), while other papers (Bofinger, Luig, and Beyer, 2002; Fabbri et al., 2005; Bludszuweit, Dominguez-Navarro, and Llombart, 2008) show wind forecast errors are more accurately described by a beta distribution. Using a persistence forecast for wind generation, Bludszuweit, Dominguez-Navarro, and Llombart (2008) show that the wind forecast error is well approximated by a beta distribution. In their paper the persistence forecast is calculated from the mean wind generation of the time interval two periods prior to the forecast interval. A two period delay between the calculation of the mean wind generation and the forecast interval is necessary to capture the market closure delay, typical in short-term energy markets. Their paper shows the kurtosis of the forecast error distribution varies widely depending on forecast horizon (how far in advance wind generation is being predicted) and wind generation level, making the beta distribution well suited due to its ability to approximate distributions over a wide range of kurtosis values.

In this section a maximum entropy method is used to approximate discrete distributions for each of the three bins (see Golan, Judge, and Miller, 1996). While other papers assume wind forecasting errors are specified by an assumed functional form, this method makes no assumption about the underlying data generating process for wind forecast error. The maximum entropy procedure used here selects probabilities for equally spaced points in a discrete distribution such that a specified list of moments of the distribution exactly match the analogous moments from the original distribution. In this analysis the first twenty moments are preserved for each of the three bins. Forty support points are estimated for each of the three distributions, which translates to forty wind error states considered by the two stochastic models. Wind forecast errors are specified as a percent of installed wind capacity so that the error distributions may be scaled to any level of installed wind capacity. Error distributions approximated using the maximum entropy method are displayed for each of the three bins in Figures 3.6-3.8. The figures show distributions that vary widely by wind forecast bin and are in agreement with the summary statistics shown in Table 3.11.

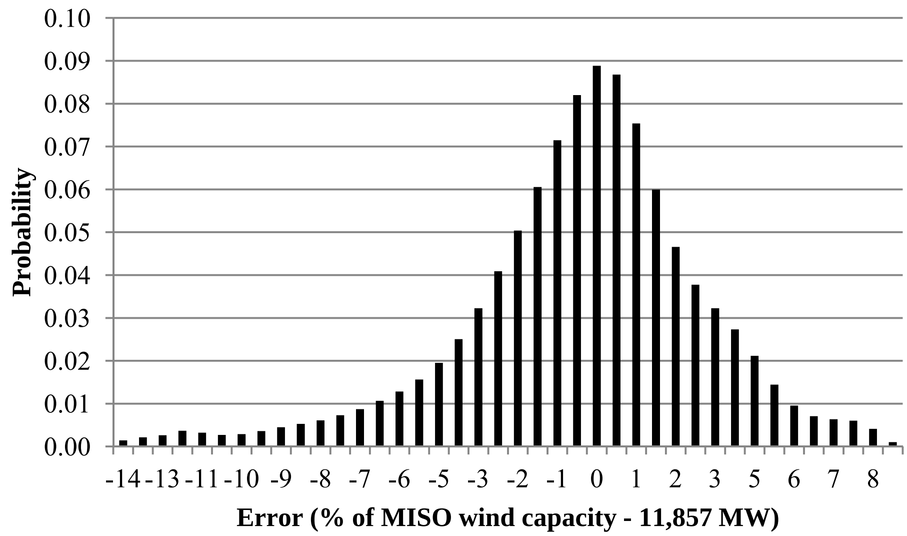

Figure 3.6 Wind Forecast Error Distribution for Bin One (Forecast<1,691 MW)

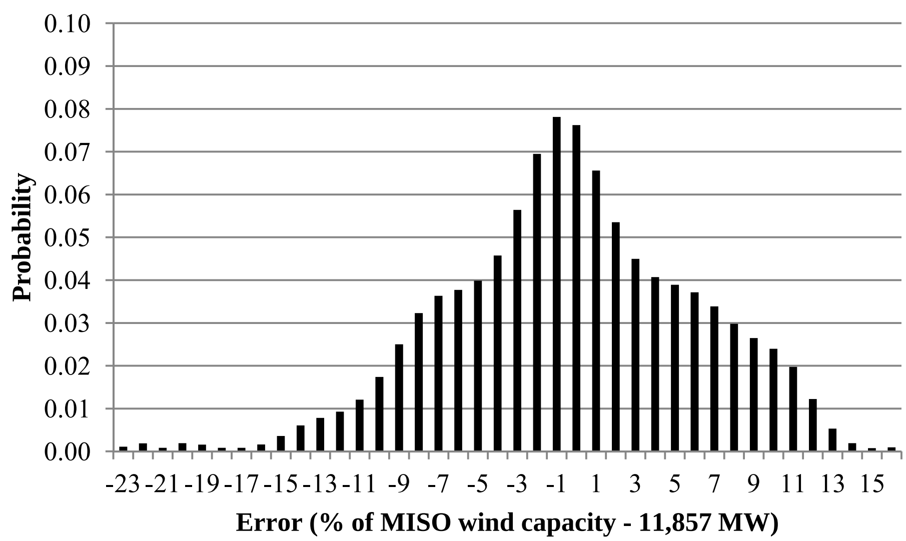

Figure 3.7 Wind Forecast Error Distribution for Bin Two (1,691 MW<Forecast<3,432 MW)

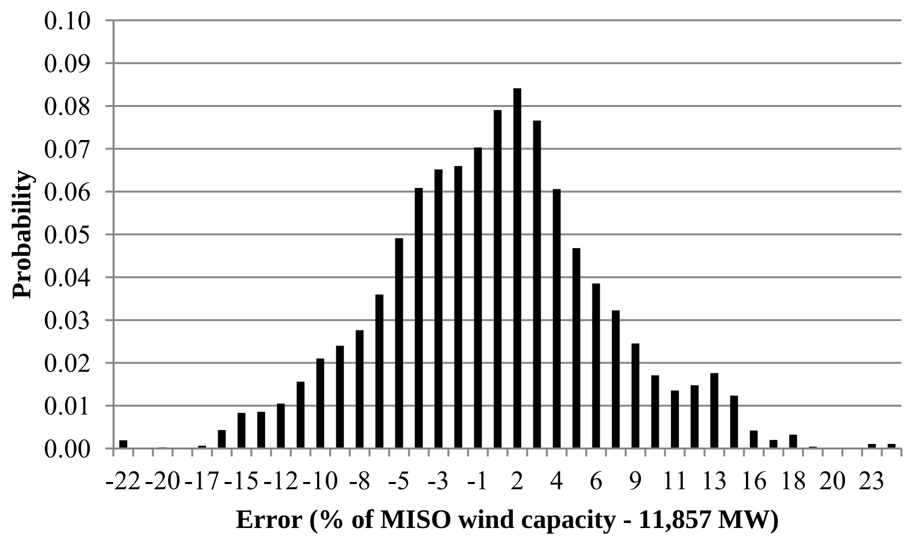

Figure 3.8 Wind Forecast Error Distribution for Bin Three (Forecast>3,432 MW)

3.3.2.3 Results of Fourteen Bus Test System

The results of the fourteen bus model show benefits of stochastic unit commitment models over deterministic models and in particular show the modified model achieves an optimal solution that is equal to the full stochastic model. In this section comparisons are made across the three wind forecast bins and at various levels of installed wind capacity. Installed wind capacity is scaled from 320 MW to a total of 6,400 MW or 50 percent of system load, in 320 MW increments. Wind forecast errors for the three bins are calculated as a percent of installed wind capacity, so errors increase in MW terms with the level of installed wind capacity. For each of the three bins the expected level of wind generation used in the unit commitment stage is the mean wind generation for each bin from the MISO data linearly scaled by the ratio of installed wind capacity to MISO wind capacity and is done so the mean wind generation for a particular bin increases with increasing levels of wind capacity.

Figures 3.9 through 3.11 show the cost reduction of the stochastic models as a percent of deterministic model expected cost. In all three figures the stochastic models achieve an expected cost no greater than the deterministic model and usually result in a lower cost solution. While reductions in expected costs are small in percentage terms they are large in dollar terms. For bin three a feasible solution does not exist beyond

3,840 MW of installed wind capacity, as insufficient levels of downward ramping requirements are available to meet the large unexpected reductions in wind generation. In an actual power system one method to accommodate the reduction in wind generation could be to shed load. Large unexpected increases in wind generation are not problematic as excess wind generation may be curtailed, leaving sufficient generation to meet load, but a large reduction in wind generation may result in insufficient upward ramping capability of non-wind generation and therefore no feasible solution.

The figures show that as the level of installed wind capacity is increased the benefits of the full and modified stochastic models over the deterministic model increase. In addition to benefits increasing with larger levels of installed wind capacity benefits also vary across bins with the stochastic models achieving larger cost reductions relative to the deterministic model for bins two and three relative to bin one. This is expected because figures 3.6 through 3.8 show forecast errors are larger for a given level of wind capacity both in percentage and MW terms for the higher wind forecast bins (i.e., Bins 2 and 3). The cost reduction benefits of the stochastic models increase for both higher levels of installed wind capacity and periods of higher forecasted wind generation.

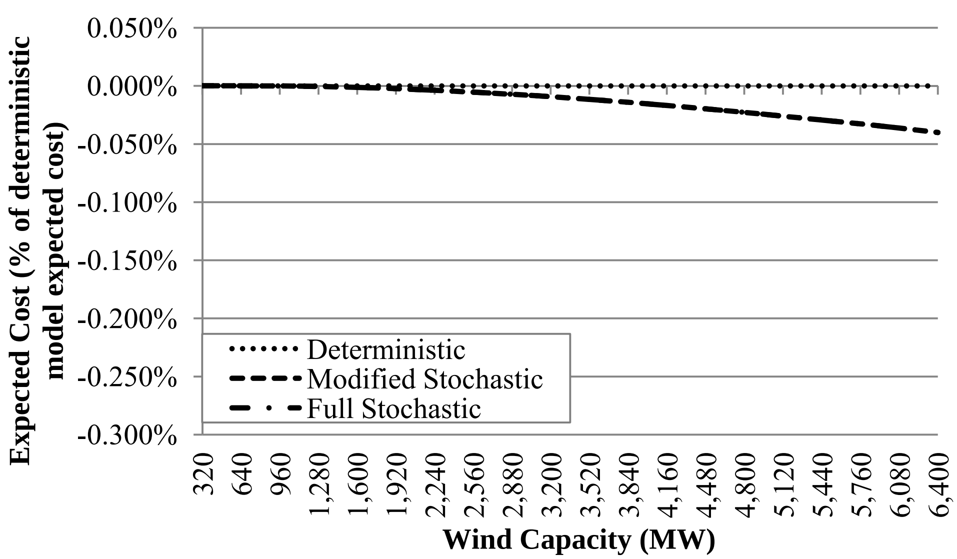

Figure 3.9 Bin One Expected Cost as a Percent of Deterministic Model Expected Cost

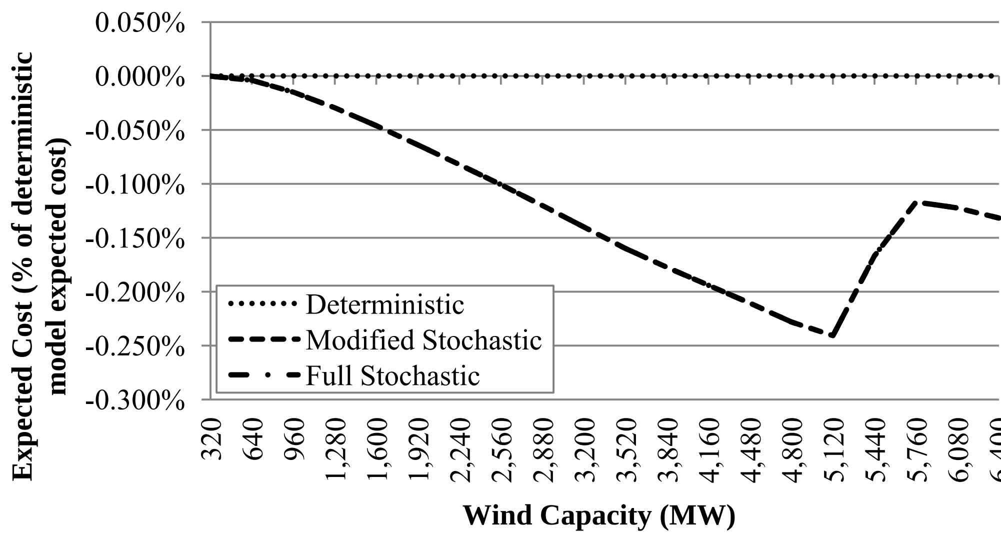

Figure 3.10 Bin Two Expected Cost as a Percent of Deterministic Model Expected Cost

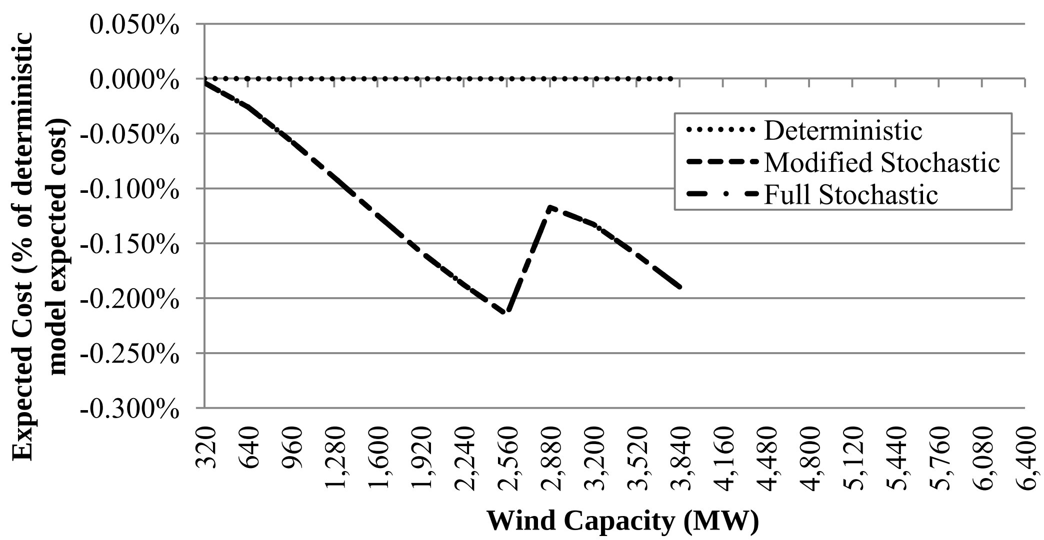

Figure 3.11 Bin Three Expected Cost as a Percent of Deterministic Model Expected Cost

The modified stochastic model is able to achieve a solution which is equal to the full stochastic solution for each of the three wind forecast bins and all levels of wind capacity considered at a marked reduction in problem size as compared to the full stochastic problem.

Table 3.12 shows a breakdown of the constraints considered by each of the three models for bin two and an installed wind capacity of 3,840 MW. The optimal solution of the deterministic model results in only four transmission lines being at their limit; line 11 is at its upper limit and lines 14, 15, and 18 are at their lower limits (binding in the opposite direction than specified). These four lines are the only lines considered by the modified stochastic model, leading to a reduction in the number of problem constraints of approximately 39.5 percent as compared to the full stochastic model. For this wind forecast bin and level of wind capacity the modified stochastic model achieves a solution which is identical to the full stochastic problem while considering 39.5 percent fewer constraints. The modified problem requires the solution to the deterministic problem as inputs, therefore adding the 61 constraints of the deterministic problem to the 2,009 constraints of the modified stochastic problem still results in a reduction of 37.7 percent as compared to the full stochastic model.

Table 3.12 Number of Constraints for the 14 Bus Model by Model Formulation

Constraints	Deterministic	Modified Stochastic	Full Stochastic
Load Balance	1	41	41
Maximum Generation	10	410	410
Minimum Generation	10	410	410
Transmission Line Up Limits	20	164	820
Transmission Line Down Limits	20	164	820
Generator Upward Ramp	0	410	410
Generator Downward Ramp	0	410	410
Total Constraints	61	2,009	3,321

Table 3.13 compares the problem sizes for a general formulation, using indices from the model formulations. The difference in the number of constraints between the full stochastic and modified stochastic problems for the general formulation is $2(s+1)(l-m)$, using indices from the model formulations. The reduction in problem size is a function of the number of lines considered by the two problems and the number of wind forecast error states considered. Figure 3.12 shows the reduction in problem size for the modified stochastic model relative to the full stochastic model changes with the number

of lines and binding transmission lines considered by the two stochastic problems. The modified problem becomes smaller relative to the full stochastic problem as the number of lines considered in the full stochastic problem (*l*) grows relative to the number of lines considered in the modified problem (*m*). Therefore, savings will likely increase in larger systems as the number of lines in the full stochastic model increases relative to the number of lines considered in the modified stochastic problem.

Table 3.13 Number of Constraints for a General Model by Model Formulation (using Indices from Model Formulations)

Constraints	Deterministic	Modified Stochastic	Full Stochastic
Load Balance	1	s+1	s+1
Maximum Generation	i	$i+i*s$	$i+i*s$
Minimum Generation	i	$i+i*s$	$i+i*s$
Transmission Line Up Limits	l	$m+m*s$	$l+l*s$
Transmission Line Down Limits	l	$m+m*s$	$l+l*s$
Generator Upward Ramp	0	$i+i*s$	$i+i*s$
Generator Downward Ramp	0	$i+i*s$	$i+i*s$
Total Constraints	$2(i+l)+1$	$(s+1)(4i+2m+1)$	$(s+1)(4i+2l+1)$

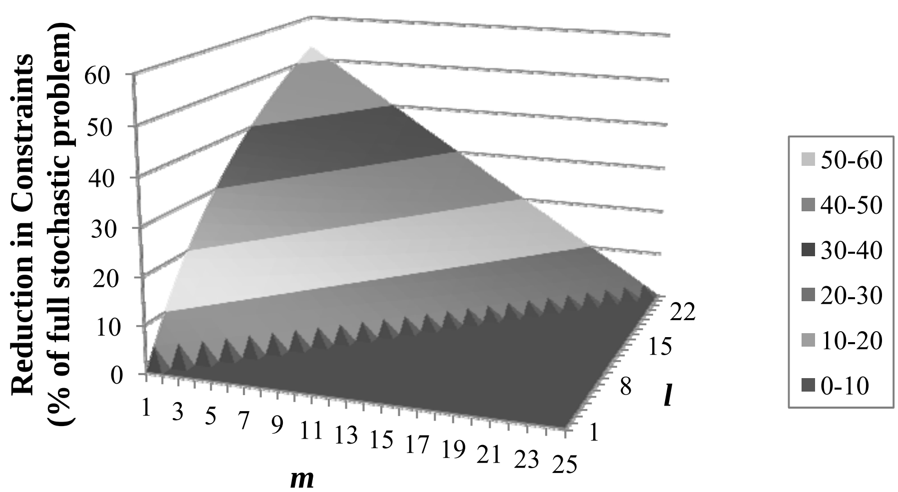

Figure 3.12 Reduction in the Number of Constraints Considered as a Function of Lines Considered in the Full Stochastic Problem (*l*) and the Modified Stochastic Problem (*m*)

The solution to the modified model is achieved through an iterative process where other transmission lines not binding in the solution of the deterministic model are checked for violations after the fact, therefore if other violations are found these lines are added to the original problem and resolved. In this regard, the modified stochastic problem size and solution times are somewhat uncertain and will increase with the number of iterations required to achieve an optimal solution that is feasible in terms of the entire system.

3.4 Conclusions

As installed wind capacity levels continue to increase in the United States and around the world methods are needed to improve the integration and utilization of this intermittent resource. Numerous papers have shown that stochastic models which account for the uncertainty in wind generation are superior to deterministic models in terms of cost, although at greater computational burden. This paper has demonstrated that a modified stochastic model (developed in this essay) is capable of achieving expected costs which are equal to the full stochastic model, while dramatically reducing the size of the model. The results of both the four and fourteen bus test systems highlight the importance of considering the location of the wind site within the transmission network and the effect the network has on the ramping capability provided by other units in the system. The modified stochastic model is able to capitalize on the use of key constraints in the system to achieve an expected cost for the UC-ED problem which is nearly as low as the full stochastic model and markedly lower than the deterministic model.

Comparisons across the three models are made using two test systems. While the magnitude of the benefits achieved in this paper are dependent on the underlying test systems, the cost reductions of the modified stochastic model relative to the deterministic model are equal to the full stochastic model for both test systems considered. Also, the reduction in problem size of the modified stochastic model relative to the stochastic model is dependent on the number of transmission lines included in the modified problem. The appropriate number of binding or near binding transmission lines to include in the modified problem will depend on the system and may require further simulation to determine an appropriate proximity for inclusion.

While the accuracy of wind forecasting techniques will continue to improve, more robust methods to plan for and incorporate higher levels of wind generation are also necessary. As a renewable resource wind generation has many benefits, but it also poses a number of challenges to both system planners and operators. This paper presents a methodology that helps improve decision making and will allow for better utilization of this intermittent resource at both the planning and operational stages.

CHAPTER 4: VALUATION OF ENERGY STORAGE WITH WIND GENERATION

4.1 Introduction and Literature Review

The dramatic increase in intermittent forms of electricity generation (wind and solar) increases the importance of development and adoption of fast responding energy storage resources, such as battery storage, flywheels, and compressed air storage, which are capable of quickly responding to fluctuations in output. In a report titled "20% Wind Energy by 2030" the United States Department of Energy assembled a group to assess the likely effects of wind generation providing 20% of electricity consumption by 2030 (DOE, 2008). Denholm et al. (2010) concluded that wind penetrations at these levels would increase the flexibility requirements of the system: likely creating market opportunities for fast responding energy storage technologies. A primary benefit of energy storage is its ability to serve the electricity system in multiple roles (arbitrage, ancillary services, congestion relief) simultaneously (Denholm et al., 2010). In order to determine the likely adoption of various energy storage technologies, methods to accurately determine their benefits are required.

Energy arbitrage (storing energy during low priced periods and selling during periods of high electricity prices) was one of the original uses for energy storage (see Sioshansi et al., 2009; Walawalkar, Apt, and Mancini, 2007). Due to the strong diurnal pattern exhibited by load, electricity prices tend to exhibit a similar daily cycle. Temporal arbitrage via energy storage capitalizes on this daily cycle by storing low priced energy during the late night and early morning hours for sale during the higher priced afternoon periods. It may also be possible for energy storage to profit from arbitrage on less than a daily time frame.

Participation in markets for ancillary services also shows promise for energy storage. Ancillary services are resources used to keep real-time supply and demand in balance and can be characterized by three types: regulation, spinning reserves, and non-spinning reserves (Xi, Sioshansi, and Marano, 2011). These three types of services are differentiated by the amount of time required to respond, with regulation requiring participants to respond in a matter of seconds, spinning reserves within ten minutes, and non-spinning reserves responding within the hour. Regulation is generally the most valuable of the three types due to the short response time required for resources providing this service. Energy storage is particularly well suited to providing regulation due to fast response times and generally low levels of energy delivered (Denholm et al., 2010). Tomic and Kempton (2007) utilize a metric called the “dispatch to contract ratio”, which is the amount of energy supplied for regulation divided by the amount of regulation services capacity supplied to the market during a given period of time. They estimated an average ratio of roughly 0.1 using data from the California Independent System Operator (CAISO), meaning that on average one-tenth of the available capacity sold into the market was called upon to supply energy during a given time period. A low level of actual energy being supplied is particularly beneficial to energy storage because it allows the device to use the majority of the energy stored for arbitrage purposes.

Providing congestion relief to existing transmission lines and backup power for line outages are potential additional sources of value for energy storage (see Denholm and Sioshansi, 2009; EPRI, 2010; Xi, Sioshansi, and Marano, 2011). Storage can relieve congestion on transmission lines and possibly postpone the need for transmission capacity additions. Using energy storage as a source of backup power also has the ability to reduce system damage due to outages.

In order to meet a 20% wind generation by 2030 goal, significant increases in transmission capacity will be required to deliver wind generation to load centers (DOE, 2008). While multiple studies (Denholm et al., 2010; Sioshansi et al., 2009) claim locating storage near the load (as opposed to at the wind site) results in higher system value, this may not be true when considering the potential reduction to new transmission capacity requirements due to locating storage at the wind site. Pattanariyankool and Lave (2010) show the optimal transmission line capacity to a distant wind site is less than the capacity of the wind site, due to the negative correlation between wind generation and load (and as a result, prices). Wind generation tends to produce its highest output of the day during the low value (night time) period and conversely its lowest output during the high value (afternoon) time of day. There is a direct tradeoff between installing a unit of transmission capacity and the value of energy this additional unit of transmission capacity is able to supply to the network. The negative correlation between wind generation and wholesale prices leads to further reductions in the optimal transmission line capacity. Siting energy storage at the wind site has the potential to further reduce the optimal transmission line capacity by shifting lower value (off-peak) energy to higher value (on-peak) periods. The additional reduction in transmission capacity (and ultimately costs) from energy storage is a potential source of value for this resource.

A number of papers have valued energy storage by using these fast responding resources to perform one or two of the functions covered above (Bathurst and Strbac, 2003; Garcia-Gonzalez et al., 2008; Denholm and Sioshansi, 2009; Sioshansi et al., 2009; Drury, Denholm, and Sioshansi, 2011). Bathurst and Strbac (2003) use battery storage in conjunction with wind generation to perform two functions: energy arbitrage and reduction of imbalance penalties from the wind site. They conclude that there is added value to jointly optimizing energy storage and wind site operation. Currently, wholesale electricity markets in the United States do not penalize wind generation for deviating from forecasted levels in real-time.

Garcia-Gonzalez et al. (2008) develop a stochastic revenue maximization model to jointly optimize wind generation and pumped hydro storage. In their paper, the joint optimization is compared to optimizing the use of the two assets independent from each other. Their paper shows benefits to joint optimization due to the wind site being responsible for deviations from generation the wind site cleared in the day-ahead market. As noted earlier, electricity markets in the United States do not hold wind sites accountable for deviations in generation from their forecast levels, so there is little incentive for owners of wind generation assets to reduce these deviations.

Papers by Denholm and Sioshansi (2009) and Drury, Denholm, and Sioshansi (2011) assess the economics of utilizing compressed air energy storage (CAES) with wind generation. The first paper by Denholm and Sioshansi looks at the economics of locating storage at the load versus at the wind site. In their paper, CAES is valued by performing two functions, arbitrage and transmission capacity reduction, when located at the wind site versus only arbitrage when storage is located at the load. Their paper uses a revenue maximization framework; the optimal transmission line capacity and energy storage capacity are determined by carrying out the maximization multiple times, iterating over various capacity combinations of these two parameters. Denholm and Sioshansi conclude that there are potential benefits to co-locating wind and storage, but these benefits may disappear if storage were able to participate in ancillary service markets in addition to being used for energy arbitrage. The paper by Drury, Denholm, and Sioshansi also uses CAES to value storage capable of participating in both energy and reserve markets. Unlike the previous paper, Drury, Denholm, and Sioshansi (2011) does not consider the joint operation of CAES and wind generation. Their paper concludes that using energy storage in both energy and reserve markets dramatically increases revenue for storage over participating in energy markets alone.

As the papers covered to this point show, energy storage is capable of simultaneously performing a multitude of functions. If energy storage were capable of serving only a single function at any given time, then valuing this resource serving in each role independently would be the correct method of valuation. As Sioshansi et al. (2009) notes, "…any analysis of energy storage that considers only one or a few attributes (such as energy arbitrage) and neglects the interplay among various sources of value is likely to significantly underestimate the value and social benefits of energy storage." In one of the more extensive analyses of valuing energy storage, Xi, Sioshansi, and Marano (2011) developed a stochastic dynamic programming model to value distributed energy storage in four areas: energy arbitrage, regulation, backup generation, and distribution relief. Their paper uses a co-optimization framework allowing battery storage to optimally serve in these four roles. Xi, Sioshansi, and Marano (2011) conclude there are tradeoffs between using the battery to perform these various functions. For example, using battery storage to provide both arbitrage and regulation (as opposed to strictly arbitrage) tends to reduce the revenues from arbitrage, although Xi et al. (2011)

conclude the additional revenues from providing regulation services more than offset the reduction in arbitrage revenue.

Multiple papers (e.g., Sioshansi et al., 2009; Drury, Denholm, and Sioshansi, 2011; Walawalkar, Apt, and Mancini, 2007) consider arbitrage via energy storage without considering wind generation, while other papers (e.g., Castonuovo and Pecas-Lopes, 2004; Benitez, Benitez, and Cornelis van Kooten, 2008; Garcia-Gonzalez et al., 2008; Denholm et al., 2010) consider energy arbitrage in conjunction with wind generation. The papers, which consider the joint optimization of wind generation and storage, generally conclude there is added value to the joint optimization of wind generation and storage primarily due to the negative correlation between wind generation and wholesale electricity prices. Denholm et al. (2010) argues that charging and discharging energy storage with respect to the entire system is optimal as compared to restricting the storage device to charge from a single generating unit. Co-locating wind generation and storage does not necessarily mean the operation of energy storage is directly tied to the wind site, and in the model developed in this paper energy storage is not operated solely considering the wind site. Operational decisions of the wind site and energy storage are tied through the transmission line constraint and charging of the battery using energy generated by the wind site, but participation of storage in the energy and regulation markets is not directly in response to the variability in output from the wind site.

A paper by Pattanariyankool and Lave (2010) uses a profit maximization framework to optimally size a transmission line to a distant wind farm. Their paper shows the optimal transmission line capacity to a distant wind site is less than the capacity of the wind site, largely due to average output from the wind site being dramatically less than the capacity of the wind site. There is a direct tradeoff between the additional revenue from increased energy sales from wind generation and the cost of installing a unit of transmission line capacity required to deliver the energy to the rest of the electricity network. While Pattanariyankool and Lave (2010) did not consider energy storage, introducing energy storage at the wind site may further reduce the optimal transmission line capacity and increase the capacity factor of the line by shifting energy generated at the wind site from times when the transmission line is at capacity to times when it is not.

This paper develops a method that values large-scale battery storage with intermittent wind generation by simultaneously considering multiple sources of revenue for the battery. Jointly considering multiple revenue streams allows for the possibility of all revenue generated by the battery coming from a single source of revenue and is therefore more robust than other methods which only consider one or two sources of revenue. Once the optimal levels of storage and transmission capacity are determined for a wind site of given capacity and transmission line of a given length, revenues and energy are broken down by market (i.e. day-ahead and real-time energy and regulation services) and sensitivities to modeling assumptions are analyzed.

4.2 Methodology

As the discussion of the previous section concluded, in order to correctly value energy storage it is necessary to consider all potential sources of revenue. The non-linear program developed in this section is used to determine the optimal levels of both energy storage and transmission line capacities for a wind site of given capacity. The model considers four potential sources of value for battery energy storage: day-ahead and real-time energy markets, the regulation market, and potential cost savings from optimal sizing of transmission line capacity. Each period the battery may sell energy into either the day-ahead or real-time energy markets or capacity into the regulation market (or perform any combination of these three functions). While the battery may sell its resources into multiple markets, it is restricted to charging from energy generated by the wind site.

The battery charging and discharging efficiency is specified by η^C and η^D, where the charging efficiency is the amount of energy stored in the battery per unit of charging and discharging efficiency is the amount of power supplied per unit of discharging. Round trip efficiency is the product of charging and discharging efficiencies. The remaining battery parameters are maximum charging and discharging rates (β^C and β^D, respectively) and maximum battery storage capacity (δ). These last three parameters are expressed in per MW of installed battery capacity and are increased by increasing the level of battery capacity installed at the wind site. Model parameters are listed below in Table 4.1.

Table 4.1 Battery Operations Optimization Model Parameters

Notation	Definition
η^C	battery charging efficiency
η^D	battery discharging efficiency
β^C	maximum battery charging rate (MWh/MW*hr)
β^D	maximum battery discharge rate (MWh/MW*hr)
δ	maximum battery storage capacity (MWh/MW)
p_t^{DA}	day-ahead LMP for time period 't' ($/MWh)
p_t^{RT}	real-time LMP for time period 't' ($/MWh)
p_t^{RG}	regulation market clearing price for time period 't' ($/MW)
κ	dispatch to contract ratio (MWh/MW)
W_t	quantity of wind generated by wind site in time period 't' (MWh)
C^B	per unit annualized battery cost ($/MW)
γ	lifetime round trip cycles for battery
A	annuity factor for transmission line cost
Z	miles per kilometer conversion factor (miles/km)
Θ	transmission line length (miles)
ψ	restriction on energy availability for regulation (MWh/MW)

Time granulation is set at one hour – i.e. a time period is an hour. This abstracts from charge/discharge cycles within the hour, which are assumed to be relevant only for regulation purposes. In each period decisions are made as to the level of battery charging and discharging and the level of capacity sold into the regulation market. The decision variable (q_t^{WB}) is the amount of energy stored in the battery from the wind site in period t. While one variable determines the level of energy stored in the battery, discharging of the battery may occur through three methods: selling energy into the day-ahead (q_t^{DA}) market, selling energy into the real-time market (q_t^{RT}), or energy supplied by selling capacity (q_t^{RG}) into the regulation market. Model decision variables are shown in Table 4.2.

Table 4.2 Battery Operations Optimization Model Decision Variables

Notation	Definition
q_t^{WB}	energy stored into the battery from the wind site in time period *t* (MWh)
q_t^{W}	energy sold from the wind site into the real-time market in time period *t* (MWh)
q_t^{DA}	energy sold into the day-ahead energy market in time period *t* (MWh)
q_t^{RT}	energy sold into the real-time energy market in time period *t* (MWh)
q_t^{RG}	capacity cleared in the regulation market in time period *t* (MW)
q_t^{B}	energy in the battery in time period *t* (MWh)
x_t^{C}	portion of time period spent charging the battery
x_t^{D}	portion of time period spent discharging the battery
Q^{B}	battery capacity (MW)
Q^{L}	transmission line capacity (MW)

The objective to be maximized, profit from operating the wind site and battery and determining battery and transmission line capacities, is shown below in (1). The objective considers the three sources of revenue for the battery and the wind site, where the wind site is only allowed to sell energy into to the real-time market, net of the annualized cost of the battery converted to a cost per MWh of use and the annualized cost of the transmission line. The dispatch to contract ratio (κ) is the level of energy supplied by a resource per unit of capacity cleared in the regulation market and remains constant for all periods. In actuality, the dispatch to contract ratio is a random variable because the amount of energy that is supplied for a given level of capacity sold in this market is not known in advance. Assuming a fixed level for the dispatch to contract ratio likely overstates the profitability of participation in the regulation market had uncertainty been considered.

$$\sum_{t=1}^{T} p_t^{DA}\eta^D q_t^{DA} + p_t^{RT}(q_t^{W} + \eta^D q_t^{RT} + \kappa q_t^{RG}) + p_t^{RG} q_t^{RG} - \frac{C^B}{\gamma\delta} Q^B \sum_{t=1}^{T} q_t^{WB} - \mathrm{C}^L(Q^L) \qquad (1)$$

The annualized cost of the battery is converted to a cost per unit of use by dividing the annualized cost by the product of the annual cycles of the battery and the storage capacity per cycle. Battery annual cycles are determined by spreading lifetime cycles evenly over the assumed life of the battery. Using a per unit of use cost for the battery does not ensure annual battery revenue is sufficient to cover annual battery cost, therefore another restriction is required and is defined as:

$$\sum_{t=1}^{T} p_t^{DA} \eta^D q_t^{DA} + p_t^{RT} \left(\eta^D q_t^{RT} + \kappa q_t^{RG}\right) + p_t^{RG} q_t^{RG} \geq C^B Q^B. \tag{2}$$

The restriction in (2) ensures annual battery revenue is sufficient to cover annual battery cost. Accounting for battery cost both as a per unit of use cost in (1) and annualized cost in (2) is necessary to ensure the battery is used during optimal times by (1) and frequently enough to cover annual battery costs by (2). The restriction in (2) may cause the battery to be used during periods when per unit revenue for the battery is not sufficient to cover the cost per unit of use, potentially resulting in a reduction in profit relative to the profit that would have occurred had the annual revenue restriction not been in place. From an investment perspective the annual revenue restriction is necessary to ensure annual revenue from the battery covers annual battery cost. Without this restriction the model may extend the battery life to an unrealistic period.

The form of the annualized transmission line cost per unit of capacity (Q^L) is specified in (3). Parameter estimates (β_1, β_2) were estimated by Pattanariyankool and Lave (2010) using linear regression techniques. The transmission cost function is non-linear due to certain components of transmission line cost, such as right-of-way and tower costs, that do not vary with the capacity of the transmission line. Transmission cost is an exponential function of line capacity and linear in line length.

$$\mathrm{C}^L(Q^L) = \frac{1}{A} e^{\beta_1} (Q^L)^{\beta_2} \mathrm{Z}\Theta \tag{3}$$

Since the battery charges from the wind site, the sum of energy sold from the wind site into the real-time market and energy stored in the battery can be no greater than the amount of energy generated by the wind site for a given period (shown in (4)).

$$q_t^W \leq W_t - q_t^{WB} \quad \forall t \tag{4}$$

Therefore, energy from the wind site (W_t) may be sold directly into the real-time market (q_t^W), used to charge the battery (q_t^{WB}), or curtailed.

An accounting equation is used to keep track of the level of energy in the battery during a given time period and is defined as:

$$q_t^B = q_{t-1}^B + \eta^C q_t^{WB} - \left(q_t^{DA} + q_t^{RT} + \frac{1}{\eta^D}\psi q_t^{RG}\right) \quad \forall t, \tag{5}$$

where q_t^B is the battery level in period *t*, $q_{t-1}^B$is the battery level in the previous period, $\eta^C q_t^{WB}$ is the energy stored in the battery from the wind site in period *t*, and $\left(q_t^{DA} + q_t^{RT} + \frac{1}{\eta^D}\psi q_t^{RG}\right)$ defines the energy supplied from the battery to each of the three markets in period *t*.

Since the battery may charge and discharge within a given hour, but not complete both tasks simultaneously, (x_t^C) and (x_t^D) are the portion of the hour spent charging and discharging, respectively. The sum of the portion of the hour spent charging and the portion spent discharging cannot exceed one (shown in (6)).

$$x_t^C + x_t^D \leq 1 \quad \forall t \tag{6}$$

The energy stored from the wind site into the battery during a given period is restricted by the lesser of the maximum charging rate times the proportion of the hour spent charging and the wind generated by the wind site (shown in (7a,b)).

$$q_t^{WB} \leq x_t^C \beta^C Q^B \quad \forall t \tag{7a}$$

$$q_t^{WB} \leq W_t \quad \forall t \tag{7b}$$

Similarly, the restriction on total energy supplied by the battery to each of the three markets during a given period *t* may be no greater than the product of the maximum discharge rate and proportion of the hour spent discharging and is defined as:

$$q_t^{DA} + q_t^{RT} + \psi q_t^{RG} \leq \; x_t^D \beta^D Q^B \quad \forall t. \tag{8}$$

The upper bound on the energy storage capacity for the battery is defined as:

$$q_t^B \leq \delta Q^B \quad \forall t, \tag{9}$$

where δ is the maximum battery storage capability per unit of capacity and Q^B is the battery capacity. Similarly, the upper bound on capacity sold into the regulation market is defined as:

$$q_t^{RG} \leq Q^B \quad \forall t. \tag{10}$$

The transmission line limits the total flow of energy from the combination battery and wind site and is defined as:

$$q_t^{DA} + q_t^{RT} + q_t^W + \kappa q_t^{RG} \leq Q^L \quad \forall t, \tag{11}$$

where total energy supplied to the three markets cannot exceed the transmission line capacity (Q^L).

The standard non-negativity constraints on the variables are shown in (12).

$$q_t^W, q_t^B, q_t^{DA}, q_t^{RT}, q_t^{RG}, q_t^{WB}, x_t^C, x_t^D \geq 0 \quad \forall t \tag{12}$$

4.2.1 Solution Method

The optimal transmission line and battery capacities are found by solving the above program treating both transmission line and battery capacities as exogenous parameters and iterating over a grid of possible transmission line and battery capacities, ranging from zero to the capacity of the wind site. This solution method results in solving multiple linear programs and choosing the combination of transmission line and battery capacities which results in the largest profit.

4.3 Data and Parameter Estimates

Modeling results are largely driven by electricity price data over time, parameter estimates for the battery and transmission line, and wind generation data. Prices for the day-ahead and real-time markets are from PJM Western Hub over the period September 2011 through August 2012 (PJM, 2012a,b). PJM Western Hub prices are chosen due to the relatively large amounts of existing wind capacity located in close proximity to this pricing point. Regulation market clearing prices are also from PJM during the same period September 2011 through August 2012 (PJM, 2012c). Summary statistics of prices in the three markets are shown below in Table 4.3. Mean prices in the day-ahead and real-time markets are nearly equal, although the standard deviation of real-time prices is dramatically larger. Using prices and/or wind generation from different locations may impact the profitability of energy storage. The results section includes sensitivities on parameters likely to have a large impact on the profitability of battery storage.

Table 4.3 Summary Statistics for DA and RT LMP at PJM Western Hub and PJM RMCP

	Day-Ahead ($/MWh)	Real-Time ($/MWh)	RMCP ($/MW)
Mean	34.41	34.12	14.81
Standard Deviation	13.99	21.30	14.14
Sample Variance	195.70	453.72	200.06
Kurtosis	65.47	92.32	242.52
Skewness	5.76	7.09	12.72
Minimum Value	0.00	-120.57	0.00
Maximum Value	284.04	457.83	414.23

Tomic and Kempton (2007) estimate a dispatch to contract ratio of roughly 0.1 using data from the California Independent System Operator (CAISO), meaning that one-tenth of the available capacity sold into the market is called upon to supply energy during a given hour. Their estimate is used throughout this analysis.

Actual wind generation data from PJM West covering the same time period as the price data, September 2011 through August 2012 is used throughout this analysis (PJM, 2012d). Over this time period wind capacity in PJM West was approximately 5,600 MW. For purposes of this analysis the wind generation data are linearly scaled to result in a wind site capacity of 1,120 MW or one-fifth the capacity of PJM West. Scaling of wind capacity is done in order to have a capacity which is more realistic for a single wind site. The capacity factor of the 1,120 MW wind site is 0.212. The capacity factor is the ratio of how much electricity is generated given a particular level of capacity divided by the amount of electricity that could have been generated if the unit is operating at full capacity continuously, with a larger number representing more generation per unit of capacity. Summary statistics of the scaled wind data are shown below in Table 4.4. The mean wind generation is markedly less than the capacity of the wind site and is positively skewed, meaning relatively more periods result in wind generation, which is less than the mean and relatively fewer periods of high generation further from the mean.

Table 4.4 Summary Statistics for Scaled Wind Site with a Capacity of Approximately 1,120 MW

	Wind Generation (MW)
Mean	237.83
Standard Deviation	172.10
Sample Variance	29,617.96
Kurtosis	-0.43
Skewness	0.69
Minimum Value	0.00
Maximum Value	1,089.80

Published battery costs and parameters vary widely by project and technology. This analysis considers sodium-sulfur (NaS) battery technology, as this technology is by far the most widely used to date (EPRI, 2010). Battery parameters used throughout this analysis are summarized in Table 4.5. Total battery cost of 3.1 million 2010 \$/MW is annualized assuming a lifetime of ten years and a discount rate of ten percent. This annualized battery cost is used in the battery revenue requirement, equation (2). Total lifetime cycles are assumed to be spread evenly over the ten year lifetime of the battery to convert the \$/MW-yr cost to \$/MWh. Battery cost is converted from \$/MW-yr to \$/MWh by dividing the annualized cost by annual cycles times MWhs stored per unit of battery capacity times battery capacity, for use in (1).

Table 4.5 Summary of Sodium-sulfur Battery Cost and Parameters[g]

Cost (million 2010 \$/MW)	3.1
Annualized Cost (2010 \$/MW-yr)	504,511[h]
Variable Cost (2010 \$/MWh)	186.86
Capacity (MWh/MW)	6
Charge/Discharge Rate (MWh/hr/MW)	1
Round trip efficiency	0.88
Total lifetime cycles	4,500

[g] Battery cost and technology parameters p.4-22 (EPRI 2010).
[h] Battery cost is annualized assuming a battery lifetime of 10 years and discount rate of 10 percent.

Pattanariyankool and Lave (2010) estimate transmission line cost per kilometer as a function of capacity (MW) using ordinary least squares regression. The function and parameter values estimated in their paper are used in this analysis and shown below in (13).

$$ln(cost) = 10.0841 + 0.5759 * ln(MW) \tag{13}$$

This analysis assumes a transmission line of ten-mile length is required to connect the wind site to the transmission network. Therefore the cost function estimated by Pattanariyankool and Lave (2010) is converted from cost per kilometer to cost per mile. For purposes of this analysis, the total cost function is annualized using a lifetime of 40 years and discount rate of ten percent. The non-linear shape of the cost function exhibits transmission line costs increasing with capacity, but at a decreasing rate (shown below in Figure 4.1). Therefore, each successive unit of transmission line capacity costs less than the unit before it.

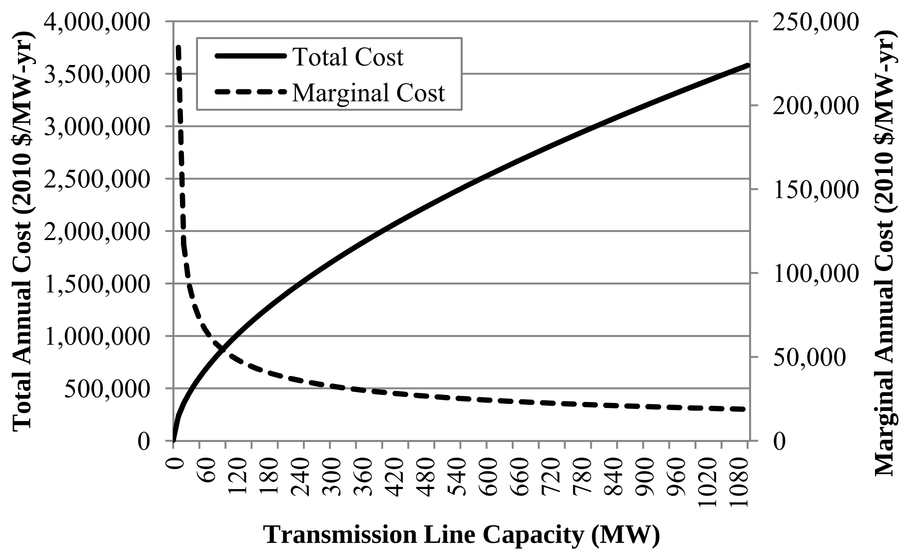

Figure 4.1 Annual Transmission Line Cost as a Function of Line Capacity for Line Length of Ten Miles

4.4 Results

For the model and parameter values considered in this paper, a battery cost of 3.1 million dollars per MW results in an optimal battery capacity of zero MW. In order for a positive level of battery capacity to be optimal a reduction in battery cost of 55 percent is required. This implies a cost per unit for the battery of 1.395 million dollars per MW. This reduced cost is used for the remainder of this analysis. Except for the reduction in battery cost, parameter values covered in the previous section define the base case. Changes in parameter values such as wind site characteristics, wholesale electricity prices, or transmission line cost will impact the optimal battery capacity. Changes in these parameters are considered through sensitivity analyses on battery efficiency, transmission line cost, and through increased variability in both wind generation and wholesale electricity prices.

4.4.1 Base Case

The profit level of the wind site and battery varies with both battery and transmission line capacity (see Figure 4.2). The optimal levels of battery and transmission line capacity for the 1,120 MW wind site are 151 MW and 741 MW, respectively. The profit level is increased by 979,898 2010 dollars with an optimally sized battery and transmission line, relative to no battery and a transmission line of optimal capacity. The optimal capacity of the transmission line is about 66 percent of the capacity of the wind site with an optimally sized battery, as compared to 60 percent with no battery. The transmission line restricts the amount of energy supplied to the markets by both the wind site and battery; therefore profit increases at lower levels of transmission capacity as the cost of each additional unit of transmission capacity is less than the value of energy that unit of capacity supplies to the market. For the optimally sized battery of 151 MW profit decreases beyond a transmission capacity of 741 MW.

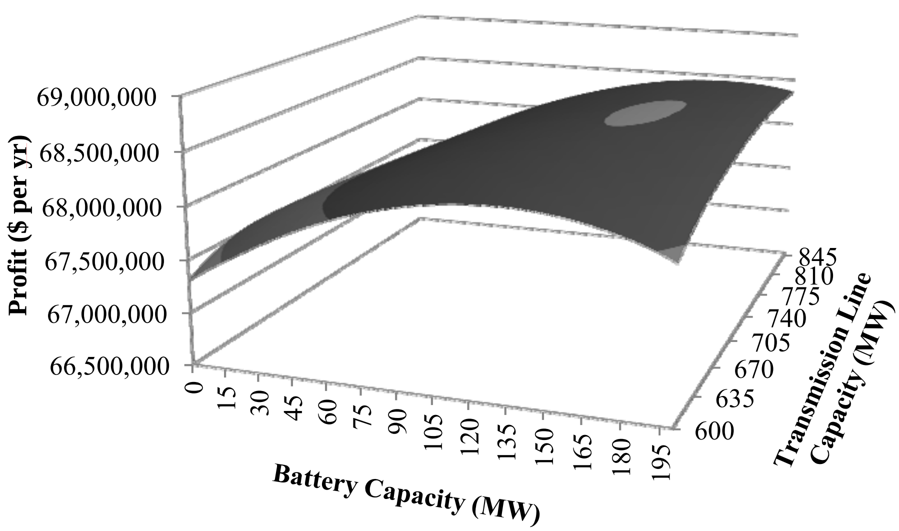

Figure 4.2 Profit as a Function of Battery and Transmission Line Capacity

Figure 4.3 shows the optimal transmission line capacity for a given level of battery capacity initially decreasing with increasing battery capacity, but increasing for battery capacity levels beyond 45 MW. At lower levels of battery capacity optimal transmission capacity initially decreases due to the relatively smaller battery not being able to shift enough energy to higher value periods to account for the additional cost required to make an increase in transmission capacity optimal. Conversely, at higher levels of battery capacity the cost of an additional unit of transmission capacity is less than the increase in revenue provided by the larger battery. The marginal cost of transmission capacity increases at a decreasing rate, meaning each additional unit of transmission capacity is less costly than the previous unit (see Figure 4.1). As the optimal transmission capacity increases, the increase in revenue required from the battery to make an additional unit of capacity profitable is reduced. The combined effects of transmission cost increasing at a decreasing rate and the capability of a larger battery to shift more energy to relatively higher value periods results in the optimal transmission capacity increasing with battery capacity beyond 45 MW.

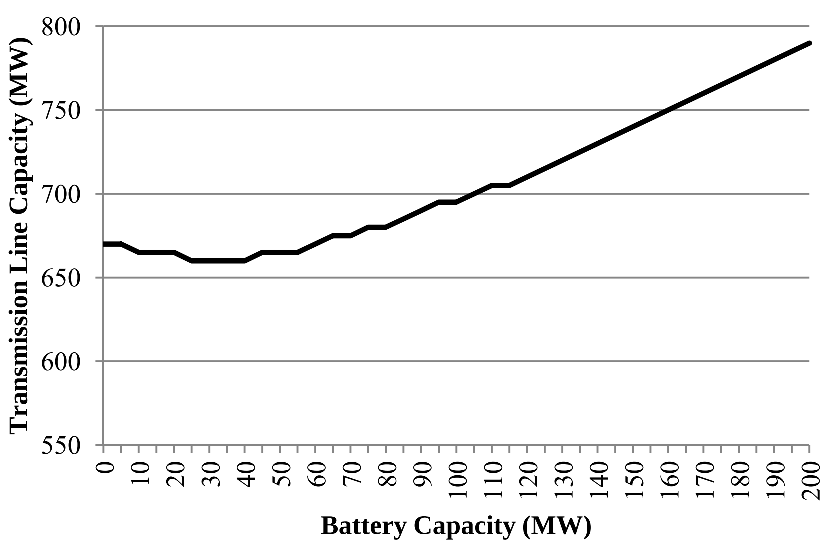

Figure 4.3 Optimal Transmission Line Capacity for a Battery of Given Size

Energy supplied to the real-time market directly from the wind site decreases as battery capacity is increased (see Table 4.6). With no battery, approximately 2,071 GWhs are supplied to the real-time market by the wind site out of a total of 2,083 GWhs generated by the wind site. For the no battery case, the optimally sized transmission line is 60 percent of wind site capacity and only results in wind curtailment of 12.5 GWhs (0.6 percent of total wind generation). Total energy supplied to the markets increases marginally as battery capacity is increased. Although, the energy sold with storage is sold at a higher average price than the no battery case causing total revenue to increase (see Table 4.7). With the optimally sized battery and transmission line, wind curtailment is reduced compared to the no battery case for two reasons: 1) the optimal transmission capacity is greater, and 2) the installed battery stores energy which would otherwise be curtailed. Installing storage at the wind site reduces the amount of wind curtailment, although total energy supplied to the markets decreases with increasing levels of battery capacity due to round trip efficiency losses of 12 percent. Even with losses the price differential between periods of charging and discharging the battery is large enough to make storage profitable.

Table 4.6. Total energy sold by market and source

	Battery Capacity (MW)									
	0		50		100		150		200	
Revenue Source	(MWh)	(%)	(MWh)	(%)	(MWh)	(%)	(MWh)	(%)	(MWh)	(%)
Wind (Real-Time)	2,070,819	100	1,974,325	95.7	1,876,655	91.4	1,778,100	87	1,678,149	82.6
Battery (Day-Ahead)	0	0	17,289	0.8	34,553	1.7	52,525	2.6	70,954	3.5
Battery (Real-Time)	0	0	26,942	1.3	54,212	2.6	81,335	4	108,975	5.4
Battery (Regulation)	0	0	43,640	2.1	87,280	4.3	130,920	6.4	174,580	8.6
Total	2,070,819	100	2,062,196	100	2,052,700	100	2,042,880	100	2,032,659	100

Table 4.7. Total revenue by market and source

	Battery Capacity (MW)									
	0		50		100		150		200	
Revenue Source	(million \$)	(%)	(million \$)	(%)	(million \$)	(%)	(million \$)	(%)	(million \$)	(%)
Wind (Real-Time)	69.201	100	66.732	85.5	64.14	73.9	61.422	64.3	58.559	56.3
Battery (Day-Ahead)	0	0	1.167	1.5	2.323	2.7	3.505	3.7	4.684	4.5
Battery (Real-Time)	0	0	2.212	2.8	4.435	5.1	6.633	6.9	8.832	8.5
Battery (Regulation Capacity)	0	0	6.482	8.3	12.963	14.9	19.445	20.4	25.927	24.9
Battery (Regulation Energy)	0	0	1.491	1.9	2.981	3.4	4.472	4.7	5.963	5.7
Total	69.201	100	78.084	100	86.843	100	95.476	100	103.964	100

The regulation market accounts for about 50 percent of the energy supplied by the battery (see Table 4.8) and approximately 70 percent of the revenue generated by the battery (see Table 4.9). This is in agreement with the belief that energy storage is well suited to providing regulation services as this market generally requires a small level of actual energy to be provided. Revenue from participating in the regulation market accounts for the largest share of battery revenue due to receiving the regulation market clearing price for clearing capacity in this market and the real-time energy price for any energy supplied for regulation purposes. This paper assumes a dispatch-to-contract ratio that remains constant at 0.1 MWh of energy is supplied to the real-time energy market for one MW of capacity cleared in the regulation market. Participation of the battery in the real-time market accounts for roughly 30 percent of the energy supplied by the battery and approximately 20 percent of revenue generated by the battery, while participation by the battery in the day-ahead market accounts for the smallest levels of energy and revenue at roughly 20 percent and 10 percent, respectively. The average prices in the day-ahead and real-time markets are nearly equal at approximately 34 $/MWh, although prices in the real-time market show a markedly larger level of volatility. The increased volatility of prices in the real-time market, as compared to the day-ahead market, results in more profitable opportunities to use the battery for arbitrage in this market. As Tables 4.8 and 4.9 show participation by the battery in each of the three markets remains relatively constant irrespective of the battery capacity, which is due to the model assuming the wind site and battery are price-takers and their behavior does not affect market prices.

Table 4.8 Percent of Battery Energy Sold by Market

	Battery Capacity (MW)				
Revenue Source	0	50	100	150	200
Battery (Day-Ahead)	0.0%	19.7%	19.6%	19.8%	20.0%
Battery (Real-Time)	0.0%	30.7%	30.8%	30.7%	30.7%
Battery (Regulation)	0.0%	49.7%	49.6%	49.4%	49.2%
Total	0.0%	100.0%	100.0%	100.0%	100.0%

Table 4.9 Percent of Battery Revenue by Market

	Battery Capacity (MW)				
Revenue Source	0	50	100	150	200
Battery (Day-Ahead)	0.0%	10.3%	10.2%	10.3%	10.3%
Battery (Real-Time)	0.0%	19.5%	19.5%	19.5%	19.5%
Battery (Regulation)	0.0%	70.2%	70.2%	70.2%	70.2%
Total	0.0%	100.0%	100.0%	100.0%	100.0%

The effect of the battery is to shift energy generated by the wind site from lower value periods to periods of relatively higher value. Figure 4.4 shows energy duration curves for the no battery case and the optimally sized battery (151 MW). The energy duration curves shown in this figure were created by sorting total energy supplied to the markets during a given hour from the highest value to the lowest value. The effect of the battery is to shift relatively small amounts of energy from the extreme low tail of the curve to the extreme high tail, resulting in a large impact on revenue (see Figure 4.5).

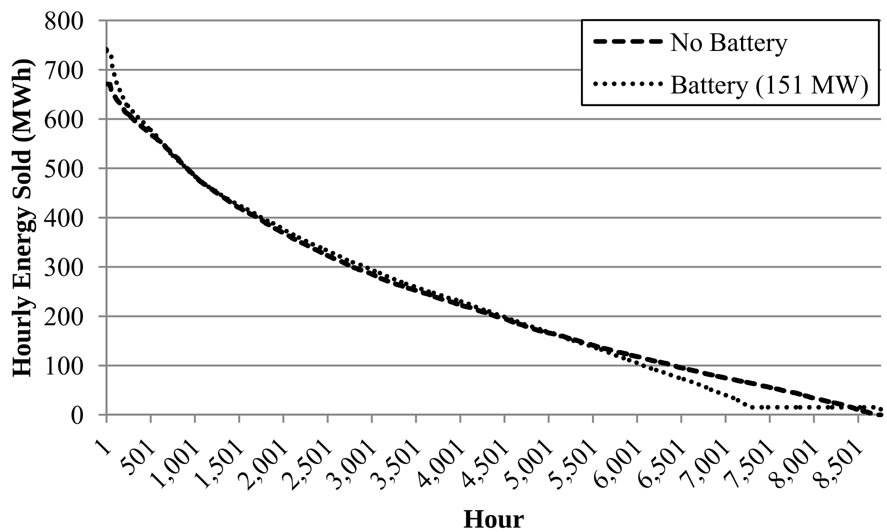

Figure 4.4 Energy Duration Curve

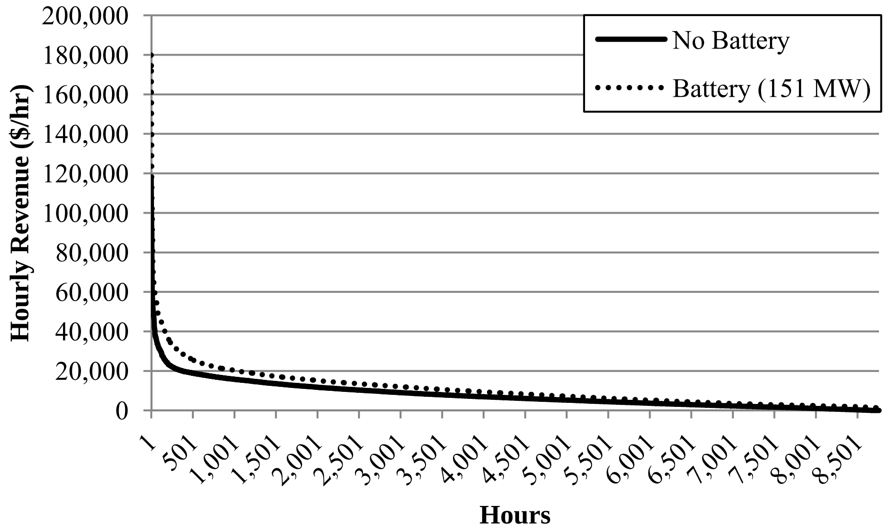

Figure 4.5 Revenue Duration Curve

A large share of the difference in revenue between the no battery case and the optimally sized battery is accumulated during relatively few hours during the year. Figure 4.6 shows that a large amount of the additional revenue added by the battery occurs during a small number of hours during the year and all hours result in higher revenue with the battery than without. The difference in accumulated revenue curve is increasing at a decreasing rate, with 33 percent of the additional revenue being generated during the top 10 percent of annual revenue hours and 50 percent of the additional revenue accumulating within the top 24 percent of annual hours.

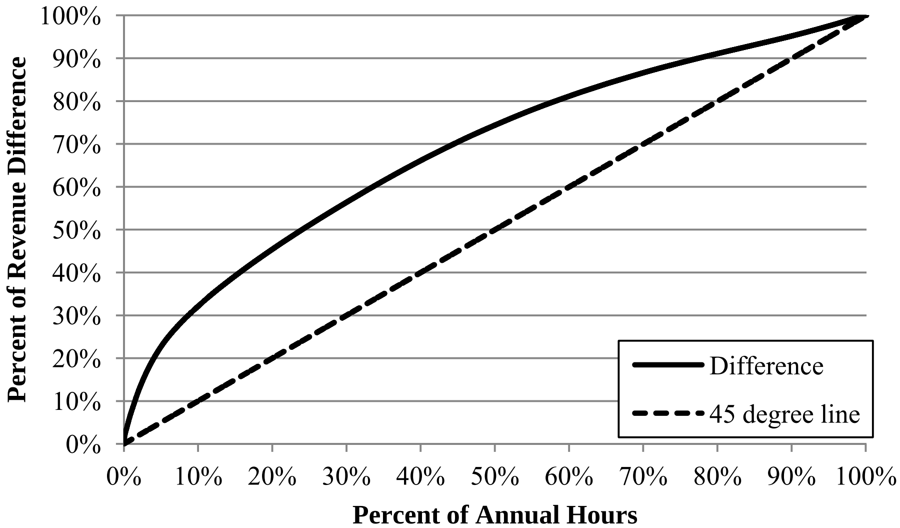

Figure 4.6 Percent of Revenue Difference Accumulated within a Given Percent of Annual Hours

It was initially thought that including energy storage would reduce the optimal transmission line capacity by shifting energy generated by the wind site from peak generation periods to periods of lower generation. This peak shaving and valley filling assumption would have the effect of reducing the volatility of the energy supplied to the market by the combination wind site and battery storage, further reducing the optimal transmission capacity relative to the no battery case. The previous results showed that optimal transmission capacity increases with increases in battery storage capacity due to additional revenue generated during a few high value periods more than offsetting the additional cost of increases in transmission capacity.

Figure 4.7 shows the capacity factor of the transmission line per unit of transmission capacity for both the no battery case and the optimally sized battery. Similarly, Figure 4.8 shows revenue per unit of transmission capacity. The capacity factors for the total transmission line are 0.35 and 0.31 for the no battery case and optimally sized battery case, respectively. The capacity factor for the optimally sized battery case shows a lower capacity factor due to a larger optimal transmission line capacity and charging losses associated with energy storage. The optimally sized battery case results in less wind curtailment, but not to a larger extent than the amount of charging losses.

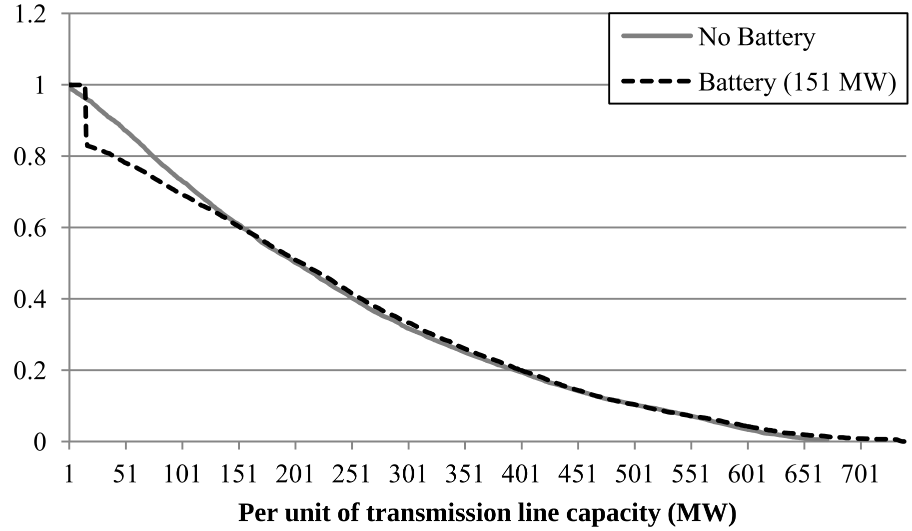

Figure 4.7 Capacity Factor of Transmission Line per Unit of Transmission Capacity

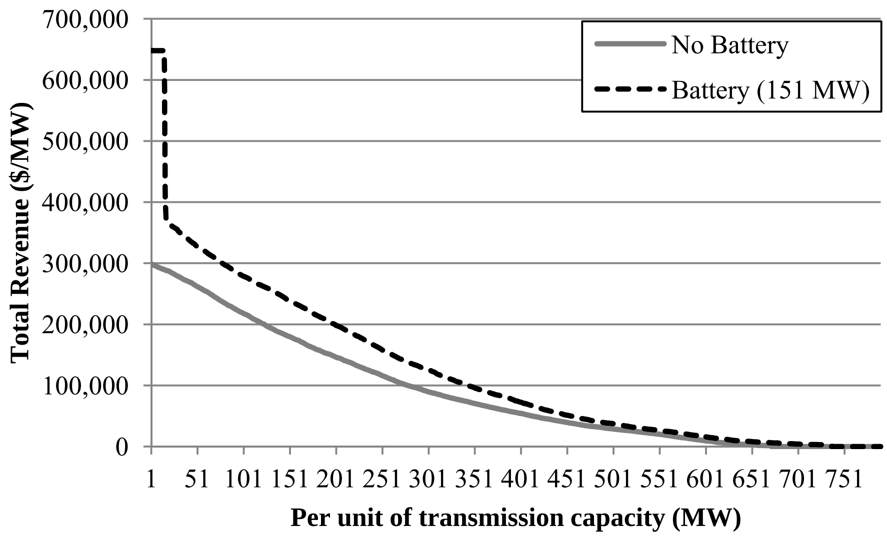

Figure 4.8 Revenue per Unit of Transmission Capacity

4.4.2 Sensitivities

This section aims to highlight the potential impacts of variation surrounding some of the key model parameters, as well as to investigate the impact of selection of alternative sites within the network that may have different patterns of wholesale electricity prices and wind generation. Specifically, this section focuses on uncertainty in transmission cost, battery charging efficiency, variability in wind generation, and variability in wholesale electricity prices. The impacts in these four areas are shown by varying each parameter over a reasonable range of values.

4.4.2.1 Transmission Cost

Transmission costs can vary dramatically by location as a result of costs of right of way, regulatory compliance, materials, and labor. Uncertainty in transmission cost is modeled by varying the transmission cost function (shown in (1)) over a range from 50 percent to 150 percent of base case cost. Scaling transmission cost in this manner also shows the effect of a longer (shorter) transmission line, which would increase (decrease) cost. Table 4.10 shows that optimal transmission capacity decreases moderately with increasing transmission cost, ranging from 779 MW to 703 MW for transmission cost ranging from 50 percent to 150 percent of base case cost. The results in this paper are less sensitive to variations in cost compared to the results of Pattanariyankool and Lave (2010) because their paper considers a distant wind farm requiring a much longer transmission line, where a small change in per capacity unit transmission cost would have a much larger impact on total transmission cost. The cost function used in this paper is in terms of MW per mile, therefore a longer transmission line linearly increases transmission cost for a line of given capacity. Like optimal transmission capacity, optimal battery capacity shows an inverse relationship to transmission cost. As transmission cost is decreased (increased) an additional unit of battery capacity needs to earn a smaller (larger) level of revenue in order to increase profit. A fifty percent change in transmission cost relative to the base case has a small (one percent) impact on combined profit of the battery and wind site.

Table 4.10 Sensitivity of Model Results to Transmission Line Costs

Scaling Factor	Optimal Transmission Capacity		Optimal Battery Capacity		Profit	
% of Base	MW	% of Base	MW	% of Base	thousand $	% of Base
Base	741	100	151	100	68,509	100
50	779	105	160	106	69,409	101
150	703	95	146	97	67,638	99

<u>4.4.2.2 Battery Efficiency</u>

There is considerable uncertainty in roundtrip battery charging losses. Multiple sources list roundtrip efficiencies ranging from 75 to 89 percent (Eyer and Corey, 2010; EPRI, 2010; Roberts, 2009). Losses in sodium sulphur batteries are comprised of battery operating temperature (300 ^{o}C) (Roberts, 2009) and round-trip ac-to-ac conversion (EPRI, 2010). The base case assumes a round trip efficiency of 88%, which is towards the upper end of the efficiency range. Sensitivity analysis shows that a relatively small change in efficiency has a dramatic impact on profits. Figure 4.9 shows how the profit maximizing level changes with charging efficiency. The profit maximizing level of battery capacity is zero for efficiency levels below 85%. At the other extreme efficiency of 100% is unrealistic, but shows the dramatic benefit of increased efficiency.

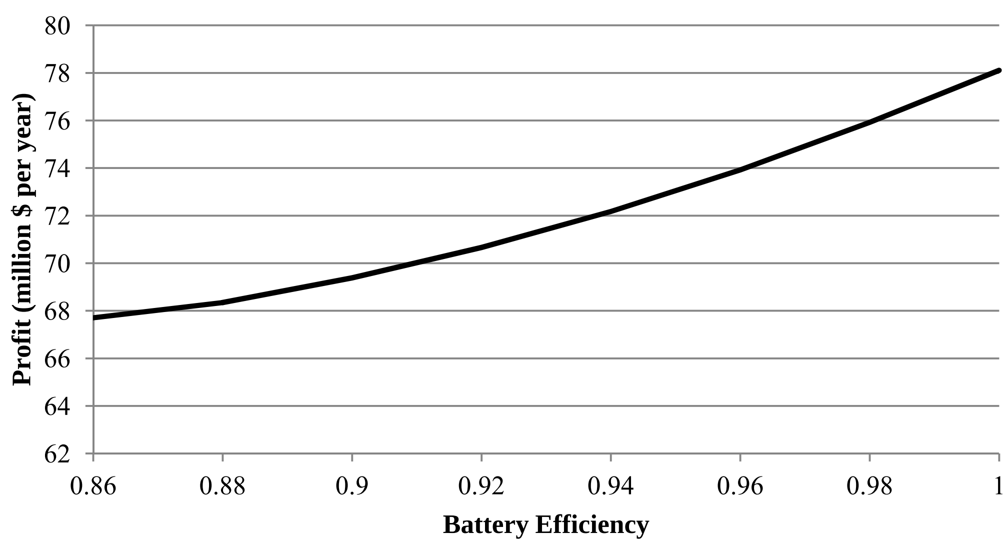

Figure 4.9 Profit of Wind Site and Battery in Relation to Battery Efficiency

Optimal battery and transmission line capacities change markedly with efficiency level (see Table 4.11). Both optimal transmission and battery capacities decrease with efficiency reductions, with battery capacity decreasing more in percentage terms. Optimal transmission capacity is much more affected by changes in efficiency, than even changes in transmission cost. A two percent reduction in efficiency relative to the base case reduces optimal transmission capacity by nine percent, while a 50 percent reduction in transmission cost relative to the base case leads to an increase in optimal transmission capacity of only five percent. Efficiency has such a profound impact on profitability because losses affect every MWh stored in the battery, which, similar to curtailed wind generation, are wasted MWhs. In the future technological advances in battery efficiency could have a dramatic effect on the competitiveness of this technology.

Table 4.11 Sensitivity of Model Results to Battery Efficiency

Battery Efficiency	Optimal Transmission Capacity		Optimal Battery Capacity		Profit	
Roundtrip	MW	% of Base	MW	% of Base	thousand $	% of Base
Base	741	100	151	100	68,509	100
0.86	674	91	65	43	67,707	99
1.00	1039	140	436	289	78,112	114

4.4.2.3 Wind Variability

Wind generation variability can differ dramatically by location. The data used in this paper are from the PJM Western Region, which is comprised of multiple wind sites. Aggregate wind generation data tends to exhibit reduced variability as compared to a specific wind site, due to wind sites not exhibiting a perfect positive correlation. A decrease at one wind site is not usually accompanied by an equal decrease at all other wind sites comprising the aggregate data. Using ERCOT wind data from 2004 through 2009 Wan (2011) showed variability in wind generation is reduced with increases in installed wind capacity. This section highlights the effects of increased wind site variability on both optimal transmission and battery capacities, and ultimately profitability.

A piecewise linear scaling of wind variability is done in a manner to preserve the mean wind generation and have all periods of wind generation remain non-negative. Two scaling factors were used – one for wind generation below the base case mean wind generation and used to further scale down wind generation for these periods and another for wind generation above the base case mean wind generation and used to scale up wind generation during these periods. The downward scaling factor was chosen to scale down periods below the base case mean wind generation in increments of 0.05. Given the downward scaling factor the upward scaling factor was chosen to preserve the mean wind generation. As Table 4.12 shows, downward scaling factors are larger in percentage terms than upward scaling factors, leading to equal total energy reductions for wind generation below the mean and total increases for wind generation above the mean.

Increasing wind generation variability leads to a marginal decrease in optimal transmission capacity and a more dramatic decrease in optimal battery capacity (see Table 4.12). Profit is reduced with increasing wind variability due to optimal transmission capacity and cost increases, while the capacity factor of the transmission line is decreasing. The decreasing transmission capacity factor is due to increasing optimal transmission capacity and increasing levels of wind curtailment. Optimal transmission capacity increases with increasing wind variability in order to capture higher levels of wind generation, which occur with increased frequency. The level of wind curtailment increases with wind variability as a result of the marginal unit of transmission capacity being less utilized. As mentioned earlier, there is a tradeoff between the cost of installing an additional unit of transmission capacity and the revenue that unit of capacity makes possible. Optimal battery capacity is reduced with increasing variability, as charging and discharging opportunities are reduced for the battery. Charging opportunities are reduced as increased variability results in more frequent periods of lower levels of wind generation.

Table 4.12 Sensitivity of Model Results to Wind Variability

Wind Variability Downward Scaling Factor	Wind Variability Upward Scaling Factor	Optimal Transmission Capacity		Optimal Battery Capacity		Profit	
		MW	% of Base	MW	% of Base	thousand $	% of Base
Base	Base	741	100.0	151	100.0	68,509	100.0
0.95	1.02	746	100.7	144	95.4	68,371	99.8
0.90	1.04	750	101.2	136	90.1	68,234	99.6
0.85	1.06	755	101.9	129	85.4	68,096	99.4
0.80	1.07	760	102.6	122	80.8	67,959	99.2
0.75	1.09	769	103.8	114	75.5	67,821	99.0

4.4.2.4 Price Variability

Sensitivity of model results to price variability is intended to show impacts from locations or time periods exhibiting higher levels of price volatility, as compared to the PJM Western Hub Data used in this analysis. PJM Western Hub is a highly traded pricing point and may exhibit less price volatility than other less frequently traded locations. One potential source of increased price variability in the future may be increases in the levels of wind generation, which has been shown to increase system variability. In this paper, prices for all three markets are scaled equally in percentage terms. Prices are scaled by adding the mean price level to the product of the scaling factor and the deviation from the mean price level in period *t*. This scaling method increases prices in periods having base case prices above the mean and decreases prices for periods with base case prices below the mean, while still preserving the mean price levels of the base case. A scaling method which preserves the mean base case price level is important, as it allows results to be driven by changes in variability and not changes in average price. This approach does not prevent negative prices, but these occur in the data before the scaling is performed.

Increased levels of price variability lead to increased arbitrage opportunities for the battery storage device and large increases in optimal battery capacity (see Table 4.13). While variability in wind generation impacts the ability of the battery to charge and discharge and ultimately reduces optimal battery capacity, increasing price variability does not impact the charging and discharging ability of the battery but increases the revenue per unit of energy sold. Revenue per unit of battery capacity increases with variability from increasing price spreads between charging and discharging. Optimal transmission capacity increases with price variability as revenue is increased from the battery. The additional revenue generated by the increased spread in prices increases the optimal transmission capacity as the additional revenue made possible from a marginal increase in transmission capacity exceeds the cost of that unit of capacity. Profitability of the wind site and battery is increased markedly with increased price variability.

Table 4.13 Sensitivity of Model Results to Price Variability

Price Variability Scaling Factor	Optimal Transmission Capacity		Optimal Battery Capacity		Profit	
	MW	% of Base	MW	% of Base	thousand $	% of Base
Base	741	100.0	151	100.0	68,509	100.0
1.05	789	106.5	197	130.5	69,492	101.4
1.10	840	113.4	240	158.9	70,661	103.1
1.15	874	117.9	274	181.5	72,005	105.1
1.20	919	124.0	316	209.3	73,515	107.3
1.25	958	129.3	355	235.1	75,211	109.8

4.4.2.5 Summary

The results of the sensitivity section show some model parameters resulting in markedly larger impacts in percentage terms, while others do not. Sensitivity on model parameters is important as it shows which parameters result in relatively larger impacts on optimal transmission and battery capacity levels and ultimately project profitability. Conducting sensitivity analysis on technological parameters, such as battery efficiency, can show which areas of research into battery technology may make batteries more competitive with other forms of energy storage or generation. Market parameters, such as price variability, show it is not only important to consider average wholesale price when locating wind sites, but also price variability and the potential benefits of including some form of energy storage when a wind site is located at a relatively more volatile pricing point. Ultimately, it is important to understand both technological and economic drivers of project analysis when considering investment decisions.

4.5 Conclusions

Simultaneously considering multiple sources of value for energy storage not only more accurately determines the value of this resource, but also shows the tradeoffs between multiple revenue streams competing for the device's limited resources (i.e. capacity, charging rate, etc.). This paper has developed and analyzed a methodology to value battery storage considering multiple sources of value, by locating storage at an intermittent form of generation. This is only one use for energy storage. Comparison across functions is necessary in order to determine the best use for energy storage and the tradeoffs among the various uses.

The results of this paper show that allowing battery storage to simultaneously participate in multiple markets is optimal relative to participating in any one market alone. This paper is in agreement with others that using battery storage in regulation markets is a valuable use of this resource. Participation of the energy storage device in the regulation market was modeled using PJM Interconnection's previous regulation market pricing framework. In response to Federal Energy Regulatory Commission (FERC) Order 755, as of October 1, 2012 PJM Interconnection implemented a new framework to compensate market participants for providing frequency regulation. Participants providing this resource are now compensated through a two part payment system, one part compensates for providing capacity and another for providing movement within a time periods known as a "mileage" component (PJM, 2012e). This two part compensation system was implemented because it was determined that the old framework discriminated against resources which offered small capacities, but were capable of providing a large amount of ramping or "mileage" (FERC, 2011). Due to a lack of available data the new framework was not modeled in this paper, but it would be of value to compare the economics under the new framework to the old.

An additional source of value for storage could be participation in PJM Interconnection's capacity market. This source of revenue was not considered in this paper, but may improve the economics of storage and offer some interesting tradeoffs with the other markets if a certain minimum level of energy is required to remain in the battery in order to receive capacity credit. While not believed to be allowed under PJM's current market rules, allowing the combination wind generation and storage device to participate as a single unit may markedly improve the economics of battery storage.

Sensitivity on certain key parameters showed the impacts these parameters have on modeling results and is an important part of any modeling where variation in parameter values is concerned. While given the current state of battery storage technology no level of battery capacity is optimal in the setting considered in this paper, wind site characteristics (wind variability) and market conditions (price variability) had non-trivial impacts on profitability and the optimal level of installed battery storage. Sensitivity analysis highlights the importance of project specific characteristics when determining the optimal level and profitability of large scale battery storage.

In this essay a few assumptions abstract from reality. In particular, perfect foresight is assumed for prices, wind generation, and the dispatch to contract ratio. In reality these model parameters are random variables and are not known before supply and storage decisions are made. Assuming perfect foresight for these parameters provides an upper-bound on profitability and is a baseline for future comparisons with models that do not assume perfect foresight. Assuming perfect foresight for wind generation, prices, and the dispatch to contract ratio likely overstates the value of energy storage. In particular, the assumption of perfect foresight for the dispatch to contract ratio overstates the profitability of storage by allowing the battery to reserve the exact amount of energy that will be called for each unit of capacity sold into this market. If the dispatch to contract ratio were uncertain the battery would likely store some level in excess of the 0.1 used in this analysis and would reduce storage capacity and energy for use in the other markets. Additionally, the assumption of perfect foresight likely leads to a larger optimal transmission capacity than would be optimal without this assumption because the revenues achieved assuming perfect foresight would not be achievable.

The results of this essay conclude that given the current state of battery technology, both in terms of cost and technology, and wholesale electricity market conditions battery storage is too expensive to be competitive. In the future a breakthrough in battery technology may lead to large reductions in cost or market conditions may change to benefit energy storage. In the model developed in this paper, improvements in battery charging and discharging efficiency and increased variability in market prices resulted in the largest impact on profit.

CHAPTER 5: CONCLUSIONS

Wind power has emerged as the preferred choice for non-hydro renewable capacity to meet states' Renewable Portfolio Standards (RPS), accounting for 94% of RPS capacity additions from 1998 through 2009 (Wiser, Barbose, and Holt, 2010). If this trend continues, wind power will likely comprise a larger share of electricity generation portfolios. While the benefits of wind generation are well known, some drawbacks are still being understood as wind power is integrated into the power grid at increasing levels. The primary difference between wind generation and other forms of generation is the intermittent, and somewhat unpredictable, aspect of this resource. The majority of research on wind generation technology has been focused on this difference. The research completed through this dissertation is no exception, with the intermittent aspect of wind power playing a role in the outcomes of each of the three essays.

5.1 Summary of Essays

This dissertation improves the understanding of how to better plan for and utilize wind power. The somewhat uncontrollable aspect of wind generation makes it important to consider the relationship between this resource and load, and also how the operation of other non-wind generation resources may be affected. The first essay is focused on planning for increased levels of installed wind capacity and the impact it has on the optimal mix of other non-wind generation resources. The second essay develops a framework to better plan the commitment and implement the dispatching of non-wind generation resources while considering the unpredictable nature of wind generation and the computational burden of considering the entire power system. The final essay values battery energy storage coupled with wind generation through a co-optimization framework which simultaneously values the combination wind site and battery considering multiple sources of revenue.

5.1.1 Conclusions for Essay One: Determining the Impact of Wind on System Costs via the Temporal Patterns of Load and Wind Generation

The first essay shows the importance of considering the relationship wind generation exhibits relative to load and how this impacts the optimal mix of non-wind resources. Using Indiana as a case study it is shown that wind generation exhibits a strong negative correlation with Indiana load, and this relationship directly affects resource requirements for other forms of generation. The first major conclusion from this research is a stronger negative correlation (as wind capacity expands) will lead to an increase in needs for peaking capacity because wind generation will typically not be available at full capacity during peak demand. A higher capacity factor of the wind site will also reduce other resource needs.

This leads to the next important characteristic of a wind site. In addition to energy requirements, a higher capacity factor can affect capacity requirements, as well. The capacity factor is the ratio of how much electricity is generated given a particular level of capacity divided by the amount of electricity that could have been generated if the unit was operating at full capacity continuously, with a larger number representing more generation per unit of capacity. Given two sites exhibiting the same correlation with load, the site with a higher capacity factor will typically be generating more electricity during the annual peak, which will have a direct effect on capacity requirements. In summary, when considering the addition of wind resources, sites that are more closely correlated with load and exhibit a higher capacity factor will generally lead to the largest reduction in capacity and energy needs from other generation resources.

In this essay, total costs increase with wind capacity because reductions in variable costs from additional wind capacity are not sufficient to offset the increases in capital costs for all scenarios. The results of the model showed that for all wind expansion scenarios, wind capacity is not cost-effective regardless of the level of the wind production tax credit and carbon prices that were considered. Since no positive level of wind capacity was deemed cost-effective, any level of positive wind capacity will lead to increases in retail rates, although these increases (sometimes small in percentage terms) may be determined by policymakers to be an acceptable price to pay in order to foster wind power development.

The analysis does not consider the transmission network, which would likely negatively impact optimal capacity and generation levels. Other technologies to aid wind generation were not considered in this paper. For example, some form of energy storage could potentially make wind generation more cost-effective by shifting energy generated from wind from lower value, off-peak periods to higher value, on-peak periods, resulting in a larger reduction in capacity needs from non-wind generation sources. This aspect is addressed in essay three.

5.1.2 Conclusions for Essay Two: Modified Unit Commitment in Response to Wind Forecasting Errors

The second essay demonstrates that a modified stochastic model (developed in this essay) is capable of achieving expected costs, which are in the range of the full stochastic model, while dramatically reducing the size of the model. An important conclusion of this essay is the importance of considering the location of the wind site within the transmission network and the effect the network has on the ramping capability provided by other units in the system. The modified stochastic model is able to capitalize on the use of key constraints in the system to achieve an expected cost for the UC-ED problem, which is nearly as low as the full stochastic model and markedly lower than the deterministic model.

Comparisons across the three models are made using two test systems. While the magnitude of the benefits achieved in this paper are dependent on the underlying test system, the cost reductions of the modified stochastic model relative to the deterministic model are in the range of the full stochastic model for both test systems considered. Also, the reduction in problem size of the modified stochastic model relative to the stochastic model is dependent on the number of transmission lines included in the modified problem. The appropriate number of binding or near binding transmission lines to include in the modified problem will depend on the system and may require further simulation to determine an appropriate proximity for inclusion.

5.1.3 Conclusions for Essay Three: Valuation of Energy Storage with Wind Generation

The third essay developed and analyzed a methodology to value battery storage considering multiple sources of value, by locating storage in close proximity to an intermittent source of generation. Given the current state of battery storage technology, no level of battery capacity is optimal in the setting considered in this paper. The results presented in this paper are dependent on a technological breakthrough that substantially reduces battery cost. Tradeoffs are shown between the multiple revenue streams competing for the devices limited resources (i.e. capacity, charging rate, etc.). Sensitivity on certain key parameters showed the impacts these parameters have on modeling results and is an important part of any modeling where parameter value uncertainty is a concern. The results show wind site characteristics (wind variability) and market conditions (price variability) have non-trivial impacts on profitability and the optimal level of installed battery storage. Sensitivity analysis highlights the importance of project specific characteristics when determining the optimal level and profitability of large scale battery storage. Volatility of wholesale market prices and battery losses had the largest impact on profit and the optimal battery and transmission line capacities.

This essay only considers one setting for energy storage (i.e., locating storage near a wind site), though comparison across settings (i.e., locating storage somewhere else in the network) is also necessary in order to determine the best location for energy storage and the tradeoffs among the various locations. For example, energy storage could participate in the three markets considered in this paper, but be located near a load center. An additional source of value for storage could be participation in PJM Interconnection's capacity market. This source of revenue was not considered in this paper, but may improve the economics of storage and offer some interesting tradeoffs with the other markets if a certain minimum level of energy is required to remain in the battery in order to receive capacity credit. This essay only considers a perfect forecast for wind generation and prices in the three markets, while not considering perfect foresight would likely impact optimal battery capacity and use. Hence, the estimates of storage value are an upper bound on the true value.

5.2 Future Work

Future work could improve the first and third essays by not assuming a perfect wind forecast, although assuming perfect foresight for wind generation provides a valuable baseline for comparison. The second essay which focused on the impact of the wind forecasting error shows that considering the error will likely alter the results of the perfect foresight case in these models.

In the first essay the transmission network is not considered. Including the transmission network in future models may show some additional tradeoffs between adding wind capacity in-state versus outside of Indiana, in addition to the capacity factor effects and the correlations among wind sites. Also, results may be affected by the existing mix of generation resources in Indiana. A state with a higher fraction of peaking capacity may be more suitable for siting wind capacity because the peaking units can be used to compensate for wind intermittency.

The unit commitment models used in the second essay may be expanded to more than two periods and approach a more realistic rolling type model which covers many periods. The unit commitment stage usually commits units a day in advance for each hour of the next operating day, so considering the impact of the wind forecasting error on multiple periods may provide a more accurate cost of this error.

While the models used in the three essays leave room for further expansion, they have provided a valuable contribution and provide a good baseline for comparison. If wind power continues to be the preferred renewable technology, then resources will need to continue to be directed towards understanding and utilizing this resource.

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LIST OF REFERENCES

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APPENDIX

APPENDIX

Table A1. Generator Offers and Operational Parameters

Generating Unit	Price ($/MWh)	Capacity (MW)	Ramp (MW/period)
G1	201	770	50
G2	200	1,100	55
G3	202	2,200	100
G4	75	3,000	10
G5	49	2,000	200
G6	248	1,000	300
G7	250	1,000	15
G8	20	820	15
G9	0	1,000	.
G10	26	900	50

Table A2. System Load

Load	Load (MWh)
L1	400
L2	1,500
L3	2,500
L4	2,000

Table A3. Transmission Line Limits

Line	Capacity (MW)
1	300
2	2,000
3	500
4	1,000
5	500
6	200
7	400
8	1,500
9	1,600
10	800
11	850
12	1,500
13	1,300
14	600
15	700
16	900
17	1,800
18	1,200
19	800
20	1,000

Table A4. Power Transfer Distribution Factors (PTDFs) used in 14-bus Test System

	Bus													
Line	B1	B2	B3	B4	B5	B6	B7	B8	B9	B10	B11	B12	B13	B14
1	0.666	-0.172	-0.081	-0.002	0.055	0.036	0.008	0.008	0.014	0.018	0.027	0.034	0.033	0.022
2	0.334	0.172	0.081	0.002	-0.055	-0.036	-0.008	-0.008	-0.014	-0.018	-0.027	-0.034	-0.033	-0.022
3	0.228	0.256	-0.304	0.077	0.125	0.109	0.086	0.086	0.090	0.093	0.101	0.107	0.106	0.097
4	0.235	0.292	0.092	-0.082	0.019	-0.015	-0.064	-0.064	-0.054	-0.047	-0.031	-0.018	-0.021	-0.040
5	0.202	0.280	0.131	0.003	-0.089	-0.058	-0.014	-0.014	-0.022	-0.029	-0.043	-0.055	-0.053	-0.036
6	-0.022	0.006	0.446	-0.173	-0.125	-0.141	-0.165	-0.165	-0.160	-0.157	-0.149	-0.143	-0.144	-0.153
7	-0.148	-0.068	0.159	0.355	-0.450	-0.176	0.211	0.211	0.135	0.080	-0.046	-0.151	-0.132	0.018
8	0.261	0.264	0.272	0.279	0.250	0.044	-0.373	-0.373	-0.190	-0.149	-0.054	0.025	0.011	-0.102
9	0.100	0.102	0.107	0.111	0.094	-0.024	-0.066	-0.066	-0.159	-0.135	-0.081	-0.035	-0.043	-0.108
10	0.139	0.134	0.121	0.110	0.156	-0.520	-0.061	-0.061	-0.151	-0.216	-0.365	-0.490	-0.468	-0.289
11	0.101	0.099	0.091	0.084	0.112	0.307	-0.019	-0.019	-0.073	-0.183	-0.434	0.277	0.254	0.070
12	0.008	0.008	0.007	0.006	0.010	0.039	-0.009	-0.009	-0.017	-0.007	0.015	-0.512	-0.160	-0.080
13	0.029	0.028	0.024	0.020	0.035	0.135	-0.033	-0.033	-0.060	-0.026	0.053	-0.256	-0.561	-0.279
14	0.000	0.000	0.000	0.000	0.000	0.000	0.000	-1.000	0.000	0.000	0.000	0.000	0.000	0.000
15	0.011	0.014	0.022	0.029	0.000	-0.206	0.377	0.377	-0.440	-0.399	-0.304	-0.225	-0.239	-0.352
16	0.149	0.152	0.159	0.166	0.138	-0.057	0.269	0.269	0.323	-0.567	-0.316	-0.027	-0.004	0.180
17	-0.038	-0.036	-0.031	-0.026	-0.044	-0.174	0.042	0.042	0.078	0.033	-0.068	-0.233	-0.279	-0.641
18	-0.101	-0.099	-0.091	-0.084	-0.112	-0.307	0.019	0.019	0.073	0.183	-0.566	-0.277	-0.254	-0.070
19	0.008	0.008	0.007	0.006	0.010	0.039	-0.009	-0.009	-0.017	-0.007	0.015	0.488	-0.160	-0.080
20	0.038	0.036	0.031	0.026	0.044	0.174	-0.042	-0.042	-0.078	-0.033	0.068	0.233	0.279	-0.359

Essay 1: GAMS Code for Capacity Planning Model

```
option lp = cplex;
option Limrow = 0;
option Limcol = 0;

* Create a .gdx file from the .xlsx file '2004_10_min_indiana_load.xlsx'
* Parameter 'load_04(r)' is Indiana ten minute load for 2004 scaled to 2025
$CALL GDXXRW.EXE 2004_10_min_indiana_load.xlsx set=t rng=D2:D52525 rdim=1
par=load_04 rng=D2:E52525 rdim=1
* Loads the .gdx file into GAMS
* Creating parameter 'load_04'
$GDXIN 2004_10_min_indiana_load.gdx
set t(*);
$LOAD t
parameter load_04(t);
$LOAD load_04
$GDXIN

* Create a .gdx file from the .xlsx file '2005_10_min_indiana_load.xlsx'
* Parameter 'load_05(r)' is Indiana ten minute load for 2005 scaled to 2025
$CALL GDXXRW.EXE 2005_10_min_indiana_load.xlsx par=load_05 rng=D2:E52525
rdim=1
* Loads the .gdx file into GAMS
* Creating parameter 'load_05'
$GDXIN 2005_10_min_indiana_load.gdx
parameter load_05(t);
$LOAD load_05
$GDXIN

* Create a .gdx file from the .xlsx file '2006_10_min_indiana_load.xlsx'
* Parameter 'load_06(r)' is Indiana ten minute load for 2006 scaled to 2025
$CALL GDXXRW.EXE 2006_10_min_indiana_load.xlsx par=load_06 rng=D2:E52525
rdim=1
* Loads the .gdx file into GAMS
* Creating parameter 'load_06'
$GDXIN 2006_10_min_indiana_load.gdx
parameter load_06(t);
$LOAD load_06
$GDXIN

* Create a .gdx file from the .xlsx file '2004_10_min_wind_gen.xlsx'
$CALL GDXXRW.EXE 2004_10_min_wind_gen.xlsx set=w rng=E1:K1 cdim=1
par=wnd_gen_04 rng=D1:K52525 cdim=1 rdim=1
* Loads the .gdx file into GAMS
```

```
$GDXIN 2004_10_min_wind_gen.gdx
set w(*);
$LOAD w
parameter wnd_gen_04(t,w);
$LOAD wnd_gen_04
$GDXIN

$CALL GDXXRW.EXE 2005_10_min_wind_gen.xlsx par=wnd_gen_05
rng=D1:K52525 cdim=1 rdim=1
* Loads the .gdx file into GAMS
$GDXIN 2005_10_min_wind_gen.gdx
parameter wnd_gen_05(t,w);
$LOAD wnd_gen_05
$GDXIN

$CALL GDXXRW.EXE 2006_10_min_wind_gen.xlsx par=wnd_gen_06
rng=D1:K52525 cdim=1 rdim=1
* Loads the .gdx file into GAMS
$GDXIN 2006_10_min_wind_gen.gdx
parameter wnd_gen_06(t,w);
$LOAD wnd_gen_06
$GDXIN

* Create a .gdx file from the .xlsx file 'Wind_Data_Existing_PPA_Sites.xlsx'
* Set 'k' / 2004 2005 2005 /
* Set 'm' wind capacity levels
* Set 't' hour of year
$CALL GDXXRW.EXE wnd_expnsn_scnrs.xlsx dset=n rng=A3:A54 rdim=1 dset=m
rng=B3:B54 rdim=1 par=wnd_scnrs rng A2:I54 rdim=2 cdim=1
* Loads the .gdx file into GAMS
* Creating sets 'k','m','t' and parameter 'wnd_scnrs'
$GDXIN wnd_expnsn_scnrs.gdx
set n(*),m(*);
$LOAD n m
parameter wnd_scnrs(n,m,w);
$LOAD wnd_scnrs
$GDXIN

set k /y2004,y2005,y2006/;

parameter load(t,k)
          wind(t,w,k);

load(t,'y2004')=load_04(t);
load(t,'y2005')=load_05(t);
```

```
load(t,'y2006')=load_06(t);

wind(t,w,'y2004')=wnd_gen_04(t,w);
wind(t,w,'y2005')=wnd_gen_05(t,w);
wind(t,w,'y2006')=wnd_gen_06(t,w);

option clear=load_04;
option clear=load_05;
option clear=load_06;
option clear=wnd_gen_04;
option clear=wnd_gen_05;
option clear=wnd_gen_06;

alias(t,tt,ttt);

set i types of generation        / peak,cycle,base,wind /
   ii(i) generation technologies / peak,cycle,base /
   y generation vintage          / new,exstng /;

parameter cap_cst(ii)          annualized capital cost by type of generation
        var_cst(ii,y)          variable cost by type of generation
        exst_cap(ii)           existing capacity levels by type of generation
        hl_1                   breakeven hour between peak and cycle cap
        hl_2                   breakeven hour between cycle and base cap
        ldnw(t)                hourly load net of hourly wind generation
        ldnw2(t)               hourly load net of hourly wind generation
        ldnw3(t)               hourly load net of wind duration curve
        rlnw(t)                rank of hourly load net of wind
        a                      index variable
        b                      index variable
        c                      index variable
        cap_lnw(ii)            capacity needs by generation type for load net of wind
        clnw_1                 capacity corresponding to breakeven hour between peak
                               and cycle for lnw curve
        clnw_2                 capacity corresponding to breakeven hour between cycle
                               and base for lnw curve
        new_cap_lnw(ii)        new capacity needs by generaton type for lnw curve
        tot_cap_lnw(ii)        total capacity existing plus new for load net of wind
        ramp_lim_lnw(ii,y)     ramping limit for generator 'ii'
        ramp_lim_wind(t)       ramping limit for wind generation
        ramp(ii,y)             ramping limit on generation by type (MW per period)
        disp_cst(k,m,n)        total dispatch cost for LDC cap levels
        disp_cst2(k,m,n)       total dispatch cost for endogenous cap levels
        load2(t)               hourly load
        wind_gen(t,k,m,n)      indiana wind generation
```

```
        unit_gnrtn(k,m,n,ii,y)      annual unit generation by technology and vintage
        unit_gnrtn2(k,m,n,ii,y)     annual unit generation by technology and vintage
        unit_cap(ii,k,m,n)          unit capacity by technology
        unit_cap2(ii,k,m,n)         unit capacity by technology
        tot_var_cst(ii,y,k,m,n)     total annual variable cost by technology
        tot_var_cst2(ii,y,k,m,n)    total annual variable cost by technology
        tot_cap_cst(ii,k,m,n)       total annual capital cost by technology
        tot_cap_cst2(ii,k,m,n)      total annual capital cost by technology
        wnd_crtlmnt(k,m,n)          level of wind curtailment by period
        wnd_crtlmnt2(k,m,n)         level of wind curtailment by period;

cap_cst("peak")  = 110353.33;
cap_cst("cycle") = 170100.00;
cap_cst("base")  = 542276.67;
*cap_cst("wind")  = 403430.00;
var_cst("peak","new")     = 62.26;
var_cst("cycle","new")    = 37.66;
var_cst("base","new")     = 25.34;
var_cst("peak","exstng")  = 67.27;
var_cst("cycle","exstng") = 42.72;
var_cst("base","exstng")  = 24.65;
exst_cap("peak")  = 3585*0.9;
exst_cap("cycle") = 2500*0.9;
exst_cap("base")  = 16426*0.9;
ramp("peak","new") = 1;
ramp("cycle","new") = 0.7;
ramp("base","new") = 0.4;
ramp("peak","exstng") = 1;
ramp("cycle","exstng") = 0.6;
ramp("base","exstng") = 0.1;

* calculate breakeven hours for generation cost per MW *
hl_1 = round((cap_cst("peak")-cap_cst("cycle"))/(var_cst("cycle","new")-
var_cst("peak","new")));
hl_2 = round((cap_cst("cycle")-cap_cst("base"))/(var_cst("base","new")-
var_cst("cycle","new")));

* equations used in economic dispatch
equations cost                  total cost
          cost2                 total cost endogenous capacity
          enrgy_bal(t)          supply meets demand in period 't'
          ramp_up(ii,y,t)       ramping up limit for generator 'i' in period 't'
          ramp_dn(ii,y,t)       ramping down limit for generator 'i' in period 't'
          enrgy_bal2(t)         supply meets demand in period 't'
          ramp_up2(ii,y,t)      ramping up limit for generator 'i' in period 't'
```

```
        ramp_dn2(ii,y,t)       ramping down limit for generator 'i' in period 't'
        cpcty(ii,y,t)          capacity level by type of generation;

variables tot_cost     total cost of meeting demand
          gen(ii,y,t)  generation supplied by unit 'i' in period 't'
          wgen(t)      wind generation in period 't'
          cap(ii,y)    generation capacity for endogenous capacity model
          gen2(ii,y,t) generation supplied by unit 'i' in period  't';

cost..  tot_cost =e= sum(t,sum(ii,sum(y,var_cst(ii,y)*gen(ii,y,t))));
enrgy_bal(t)..  sum(y,sum(ii,gen(ii,y,t)))+wgen(t) =g= load2(t);
ramp_up(ii,y,t)$(ord(t) ne 1).. gen(ii,y,t)-gen(ii,y,t-1) =l= ramp_lim_lnw(ii,y);
ramp_dn(ii,y,t)$(ord(t) ne 1)..  gen(ii,y,t)-gen(ii,y,t-1) =g= -ramp_lim_lnw(ii,y);

cost2..  tot_cost =e=
sum(ii,cap_cst(ii)*cap(ii,"new"))+sum(t,sum(ii,sum(y,var_cst(ii,y)*gen2(ii,y,t))));
enrgy_bal2(t)..  sum(y,sum(ii,gen2(ii,y,t)))+wgen(t) =g= load2(t);
ramp_up2(ii,y,t)$(ord(t) ne 1)..  gen2(ii,y,t)-gen2(ii,y,t-1) =l= cap(ii,y)*ramp(ii,y);
ramp_dn2(ii,y,t)$(ord(t) ne 1)..  gen2(ii,y,t)-gen2(ii,y,t-1) =g= -(cap(ii,y)*ramp(ii,y));
cpcty(ii,y,t)..  gen2(ii,y,t) =l= cap(ii,y);

model dispatch /cost,enrgy_bal,ramp_up,ramp_dn/;

*****************************************************
* create load and load net of wind duration curves *
*****************************************************
parameter Ld_Index(t);
parameter Ld_Index2(t);
parameter Ld_Sorted(t);

loop(n,
loop(k,
* create load net of wind duration curve
loop(m,
wind_gen(t,k,m,n)=sum(w,wind(t,w,k)*wnd_scnrs(n,m,w));
ldnw(t) = load(t,k) - wind_gen(t,k,m,n);
ldnw2(t)=ldnw(t);
* write symbol A to gdx file
execute_unload "rank_in.gdx", ldnw;
* sort symbol; permutation index will be named A also
execute 'gdxrank rank_in.gdx rank_out.gdx';
* load the permutation index
execute_load "rank_out.gdx", Ld_Index=ldnw;
Ld_Index2(t) = card(t) - Ld_Index(t) +1;
* create a sorted version
```

```
Ld_Sorted(t + (Ld_Index2(t)- Ord(t))) = ldnw(t);

***************************************************
* determine optimal capacity levels                 *
***************************************************
loop(t,
clnw_1$(ord(t) eq 6*hl_1) = Ld_Sorted(t);
clnw_2$(ord(t) eq 6*hl_2) = Ld_Sorted(t);
);
* total capacity requirements for load and load net of wind curves
cap_lnw("peak")  = max(0,Ld_Sorted("1")-clnw_1);
cap_lnw("cycle") = max(0,clnw_1-clnw_2);
cap_lnw("base")  = max(0,clnw_2);
* new capacity requirements calculated by net of total requirements and existing levels
new_cap_lnw("base")  = max(0,cap_lnw("base")-exst_cap("base"));
new_cap_lnw("cycle") = max(0,cap_lnw("cycle")-exst_cap("cycle")-
max(0,exst_cap("base")-cap_lnw("base")));
new_cap_lnw("peak")  = max(0,cap_lnw("peak")-
exst_cap("peak")+min(0,cap_lnw("cycle")-exst_cap("cycle")-max(0,exst_cap("base")-
cap_lnw("base"))));
* total capacity by generation type for economic dispatch
tot_cap_lnw("peak")  = exst_cap("peak")+new_cap_lnw("peak");
tot_cap_lnw("cycle") = exst_cap("cycle")+new_cap_lnw("cycle");
tot_cap_lnw("base")  = exst_cap("base")+new_cap_lnw("base");

***************************************************
* economic dispatch for load and load net of wind  *
***************************************************
ramp_lim_lnw(ii,"new") = new_cap_lnw(ii)*ramp(ii,"new");
ramp_lim_lnw(ii,"exstng") = exst_cap(ii)*ramp(ii,"exstng");
ramp_lim_wind(t) = wind_gen(t,k,m,n);
gen.lo(ii,y,t) = 0;
gen.up(ii,"new",t) = new_cap_lnw(ii);
gen.up(ii,"exstng",t) = exst_cap(ii);
wgen.lo(t)   = 0;
wgen.up(t)   = wind_gen(t,k,m,n);
load2(t)=load(t,k);
solve dispatch using lp minimizing tot_cost;
disp_cst(k,m,n) = tot_cost.l;
unit_gnrtn(k,m,n,ii,y) = sum(t,gen.l(ii,y,t));
unit_cap(ii,k,m,n) = tot_cap_lnw(ii);
tot_var_cst(ii,y,k,m,n) = sum(t,gen.l(ii,y,t)*var_cst(ii,y));
tot_cap_cst(ii,k,m,n) = new_cap_lnw(ii)*cap_cst(ii);
wnd_crtlmnt(k,m,n) = sum(t,wind_gen(t,k,m,n)-wgen.l(t));
); ); );
```

Essay 2: GAMS Code for 4-Bus Unit Commitment Models

```
Option LP = CPLEX;
Option limrow = 0;
Option limcol = 0;

*set of nodes n
Set n /1*4/;
*set of generators
Set g /1*5/;
alias(g,gg);
*set of lines l
set l /1*5/;
*set of time periods
set t /1*2/;
*set of states of nature
Set s /1*100/;
*set of models (1=naive,2=modified,3=full dsp)
Set r /1*3/;

Parameter offer(g) Offer Prices different Generators /1 30,2 1,3 150,4 25,5 40/;
Parameter ql(g,n) Lower MW limit of the generators /2.1 100/;
Parameter qu(g,n) Upper MW limit of the generators /1.1 500,2.1 100,3.2 400,4.3 150,5.4
100/;
Parameter d(n) Demand at Node n (MW)
/
2   253
3   100
/;

Parameter PTDF(n,l) Distribution factors for node n on line l;
Table PTDF(n,l)
      1        2        3        4        5
1     0.2829   0.1405   0.1767  -0.0233  -0.0829
2     0.1100  -0.0648  -0.4452   0.3548   0.0900
3    -0.0728  -0.2818  -0.0454  -0.2454   0.2728
4    -0.6029   0.0656   0.1373  -0.0627  -0.1971
;

Parameter PTDF2(g,l) Distribution factors for generator g on line l;
Table PTDF2(g,l)
      1        2        3        4        5
1     0.2829   0.1405   0.1767  -0.0233  -0.0829
2     0.2829   0.1405   0.1767  -0.0233  -0.0829
3     0.1100  -0.0648  -0.4452   0.3548   0.0900
```

```
4    -0.0728   -0.2818   -0.0454   -0.2454    0.2728
5    -0.6029    0.0656    0.1373   -0.0627   -0.1971
;

Parameter T_Cap(l)
/
1   150
2   150
3   146
4   110
5   100
/;

Parameter Ramp(g)
/
1  5
2  10000
3  15
4  16
5  30
/;

Parameter  Gen_Out1(r,g)
           Gen_Out2(r,s,g)
           Tot_Cost1(r)
           Tot_Cost2(s,r)
           Tot_Cost(s,r)
           Line_Lvl1(r,l)
           Line_Lvl2(r,s,l)
           Ramp_Up_Pos_Line(r,l)
           Ramp_Dn_Pos_Line(r,l)
           Ramp_Up_Neg_Line(r,l)
           Ramp_Dn_Neg_Line(r,l)
           LMP_ED(r,s,n);

*************************************************
* Create the set of wind forecast errors        *
*************************************************
Scalar   WL lower bound of wind forecast error / 0 /
         WU upper bound of wind forecast error / 15 /
         ETC2 expected total cost;
Parameter w_err(s) realizations of the wind forecast error;
w_err('1') = WL;

loop(s,
```

```
w_err(s) = w_err(s-1)+((WU - WL)/card(s));
);
w_err(s) = w_err(s) - (w_err(s)-w_err(s-1))/2;


**************************************************
* The naive period 1 dispatch problem                  *
**************************************************
Variable  Z1;
Positive Variable p(g,n) power output of generator g in period 1;
p.up(g,n) = qu(g,n);
p.lo(g,n) = ql(g,n);

Equations
OBJ         Objective function
LB          supply equals demand in MW at bus n
TL_UP(l)    the upper capacity bound on transmission line n
TL_LW(l)    the lower capacity bound on transmission line n
;

OBJ..        Z1 =e= sum(g,offer(g)*sum(n,p(g,n)));
LB..         sum(n,sum(g,p(g,n))-d(n)) =e= 0;
TL_UP(l)..   sum(n,PTDF(n,l)*(sum(g,p(g,n))-d(n))) =l= T_Cap(l);
TL_LW(l)..   sum(n,PTDF(n,l)*(sum(g,p(g,n))-d(n))) =g= -T_Cap(l);

Model dispatch1 /OBJ,LB,TL_UP,TL_LW/;
Solve dispatch1 using LP MINIMIZING Z1;

Tot_Cost1('1')=Z1.l;
Line_Lvl1('1',l)=sum(n,PTDF(n,l)*(sum(g,p.l(g,n))-d(n)));
Ramp_Up_Pos_Line('1',l)=sum(g$(PTDF2(g,l)>0),PTDF2(g,l)*min(sum(n,qu(g,n)-
p.l(g,n)),Ramp(g)));
Ramp_Dn_Pos_Line('1',l)=sum(g$(PTDF2(g,l)>0),PTDF2(g,l)*min(sum(n,p.l(g,n)-
ql(g,n)),Ramp(g)));
Ramp_Up_Neg_Line('1',l)=sum(g$(PTDF2(g,l)<0),PTDF2(g,l)*min(sum(n,qu(g,n)-
p.l(g,n)),Ramp(g)));
Ramp_Dn_Neg_Line('1',l)=sum(g$(PTDF2(g,l)<0),PTDF2(g,l)*min(sum(n,p.l(g,n)-
ql(g,n)),Ramp(g)));

**************************************************
* Modification to naive dispatch using DSP             *
**************************************************
Parameter a(g) generation levels from initial problem;
a('1') = p.l('1','1');
a('2') = p.l('2','1');
```

```
a('3') = p.l('3','2');
a('4') = p.l('4','3');
a('5') = p.l('5','4');
Gen_Out1('1',g) = a(g);

Variables Z2  expected total cost
        dg(g)   generation modification to initial dispatch
        h(g,s)  response of generator g to wind error in state s;

dg.up(g) = sum(n,qu(g,n))-a(g);
dg.lo(g) = -(a(g)-sum(n,ql(g,n)));
dg.up('2') = qu('2','1')-a('2');
h.up(g,s) = ramp(g);
h.lo(g,s) = -ramp(g);

* allowing for wind curtailment
*h.up('2',s) = w_err(s);
*h.lo('2',s) = -(a('2')-ql('2','1'));

Equations
obj2                objective function
sys_bal1            generation and load remain equal in period 1
sys_bal2(s)         generation and load remain equal in each state of period 2
tline_constrt1      transmission line capacity constraint is not violated in period 1
tline_constrt2(s)   transmission line capacity constraint is not violated in each state of
                    period 2
h_up(g,s)           upper bound on the response in the second period from generator g in
                    state s
h_lo(g,s)           lower bound on the response in the second period from generator g in
                    state s
h_up_wnd(g,s)       upper bound on the response in the second period from wind site in
                    state s
;

obj2..                        Z2 =e= sum(g,offer(g)*dg(g)) +
                              sum(s,sum(g,(1/card(s))*offer(g)*h(g,s)));
sys_bal1..                    sum(g,dg(g)) =e= 0;
sys_bal2(s)..                 sum(g,h(g,s)) =e= 0;
tline_constrt1..              sum(g,PTDF2(g,'3')*dg(g))+sum(g,PTDF2(g,'3')*a(g))-
                              sum(n,PTDF(n,'3')*d(n)) =l= T_Cap('3');
tline_constrt2(s)..           sum(g,PTDF2(g,'3')*h(g,s))+sum(g,PTDF2(g,'3')*a(g))-
                              sum(n,PTDF(n,'3')*d(n)) =l= T_Cap('3');
h_up(g,s)$(ord(g) ne 2)..     h(g,s) =l= sum(n,qu(g,n))-a(g)-dg(g);
h_lo(g,s)..                   h(g,s) =g= -(a(g)+dg(g)-sum(n,ql(g,n)));
h_up_wnd(g,s)$(ord(g) eq 2).. h(g,s) =l= sum(n,qu(g,n))+w_err(s)-(a(g)+dg(g));
```

```
Model dispatch2
/obj2,sys_bal1,sys_bal2,tline_constrt1,tline_constrt2,h_up,h_lo,h_up_wnd/;

solve dispatch2 using lp minimizing Z2;

Gen_Out1('2',g)=a(g)+dg.l(g);
Gen_Out2('2',s,g)=Gen_Out1('2',g)+h.l(g,s);
Tot_Cost1('2')=sum(g,offer(g)*(a(g)+dg.l(g)));
Tot_Cost2(s,'2')=sum(g,offer(g)*Gen_Out2('2',s,g));
Line_Lvl1('2',l)=sum(g,PTDF2(g,l)*Gen_Out1('2',g))-sum(n,PTDF(n,l)*d(n));
Ramp_Up_Pos_Line('2',l)=sum(g$(PTDF2(g,l)>0),PTDF2(g,l)*min(sum(n,qu(g,n)-
p.l(g,n))-dg.l(g),Ramp(g)));
Ramp_Dn_Pos_Line('2',l)=sum(g$(PTDF2(g,l)>0),PTDF2(g,l)*min(dg.l(g)+sum(n,p.l(g,
n)-ql(g,n)),Ramp(g)));
Ramp_Up_Neg_Line('2',l)=sum(g$(PTDF2(g,l)<0),PTDF2(g,l)*min(sum(n,qu(g,n)-
p.l(g,n))-dg.l(g),Ramp(g)));
Ramp_Dn_Neg_Line('2',l)=sum(g$(PTDF2(g,l)<0),PTDF2(g,l)*min(dg.l(g)+sum(n,p.l(g,
n)-ql(g,n)),Ramp(g)));

*************************************************
* Full discrete stochastic program              *
*************************************************
Parameter a3(g)
        a4(s,g)
        a5(g,n);

Variable  Z3;
Positive Variable p2(g,n,t,s) power output of generator g in period t and state s;

p2.up(g,n,t,s) = qu(g,n);
p2.lo(g,n,t,s) = ql(g,n);
p2.up('2','1','2',s) = qu('2','1') + w_err(s);
p2.lo('2','1','2',s) = 0;

Equations
OBJ3                objective function
LB3(t,s)            supply equals demand in MW at bus n
TL_UP3(l,t,s)       the upper capacity bound on transmission line n
TL_LW3(l,t,s)       the lower capacity bound on transmission line n
RAMP_UP3(g,t,s)     generator upward ramping limits
RAMP_DN3(g,t,s)     generator downward ramping limits
GEN_PER_1(g,n,t,s)  restricts generation in period one to be equal across states
;
```

```
OBJ3..  Z3 =e= sum(s,sum(g,sum(n,(1/card(s))*offer(g)*(p2(g,n,'2',s)))));
LB3(t,s)..  sum(n,sum(g,p2(g,n,t,s))-d(n)) =e= 0;
TL_UP3(l,t,s)..  sum(n,PTDF(n,l)*(sum(g,p2(g,n,t,s))-d(n))) =l= T_Cap(l);
TL_LW3(l,t,s)..  sum(n,PTDF(n,l)*(sum(g,p2(g,n,t,s))-d(n))) =g= -T_Cap(l);
RAMP_UP3(g,t,s)$(ord(g) ne 2 and ord(t) ne 1)..  sum(n,p2(g,n,t,s) - p2(g,n,t-1,s)) =l=
Ramp(g);
RAMP_DN3(g,t,s)$(ord(g) ne 2 and ord(t) ne 1)..  sum(n,p2(g,n,t,s) - p2(g,n,t-1,s)) =g= -
Ramp(g);
GEN_PER_1(g,n,t,s)..  p2(g,n,'1',s) =e= p2(g,n,'1','1');

Model dispatch3
/OBJ3,LB3,TL_UP3,TL_LW3,RAMP_UP3,RAMP_DN3,GEN_PER_1/;

Solve dispatch3 using lp minimizing Z3;

a3('1')=p2.l('1','1','1','1');
a3('2')=p2.l('2','1','1','1');
a3('3')=p2.l('3','2','1','1');
a3('4')=p2.l('4','3','1','1');
a3('5')=p2.l('5','4','1','1');

Gen_Out1('3',g) = a3(g);
Line_Lvl1('3',l)=sum(g,PTDF2(g,l)*Gen_Out1('3',g))-sum(n,PTDF(n,l)*d(n));
Ramp_Up_Pos_Line('3',l)=sum(g$(PTDF2(g,l)>0),PTDF2(g,l)*min(sum(n,qu(g,n))-
a3(g),Ramp(g)));
Ramp_Dn_Pos_Line('3',l)=sum(g$(PTDF2(g,l)>0),PTDF2(g,l)*min(a3(g)-
sum(n,ql(g,n)),Ramp(g)));
Ramp_Up_Neg_Line('3',l)=sum(g$(PTDF2(g,l)<0),PTDF2(g,l)*min(sum(n,qu(g,n))-
a3(g),Ramp(g)));
Ramp_Dn_Neg_Line('3',l)=sum(g$(PTDF2(g,l)<0),PTDF2(g,l)*min(a3(g)-
sum(n,ql(g,n)),Ramp(g)));

a4(s,'1') = p2.l('1','1','2',s)-p2.l('1','1','1',s);
a4(s,'2') = p2.l('2','1','2',s)-p2.l('2','1','1',s);
a4(s,'3') = p2.l('3','2','2',s)-p2.l('3','2','1',s);
a4(s,'4') = p2.l('4','3','2',s)-p2.l('4','3','1',s);
a4(s,'5') = p2.l('5','4','2',s)-p2.l('5','4','1',s);

Gen_Out2('3',s,g)=a4(s,g);
Line_Lvl2('3',s,l)=sum(g,PTDF2(g,l)*Gen_Out2('3',s,g))-sum(n,PTDF(n,l)*d(n));
Tot_Cost1('3')=sum(g,offer(g)*a3(g));
display Tot_Cost1;
LMP_ED('3',s,n)=card(s)*(LB3.m('2',s)+sum(l,PTDF(n,l)*(TL_UP3.m(l,'2',s)+TL_LW3.
m(l,'2',s))));
```

```
***********************************************
* Naive period 1 generation levels in dsp                *
***********************************************
p2.lo(g,n,'1',s)=p.l(g,n);
p2.up(g,n,'1',s)=p.l(g,n);
p2.up('2','1','2',s) = qu('2','1') + w_err(s);
p2.lo('2','1','2',s) = 0;

Solve dispatch3 using lp minimizing Z3;

a4(s,'1') = p2.l('1','1','2',s)-p.l('1','1');
a4(s,'2') = p2.l('2','1','2',s)-p.l('2','1');
a4(s,'3') = p2.l('3','2','2',s)-p.l('3','2');
a4(s,'4') = p2.l('4','3','2',s)-p.l('4','3');
a4(s,'5') = p2.l('5','4','2',s)-p.l('5','4');

Gen_Out2('1',s,g) = a4(s,g);
Line_Lvl2('1',s,l)=sum(g,PTDF2(g,l)*Gen_Out2('1',s,g))-sum(n,PTDF(n,l)*d(n));
LMP_ED('1',s,n)=card(s)*(LB3.m('2',s)+sum(l,PTDF(n,l)*(TL_UP3.m(l,'2',s)+TL_LW3.
m(l,'2',s))));

***********************************************
* Modified period 1 generation levels in dsp             *
***********************************************
a5('1','1') = dg.l('1');
a5('2','1') = dg.l('2');
a5('3','2') = dg.l('3');
a5('4','3') = dg.l('4');
a5('5','4') = dg.l('5');
p2.lo(g,n,'1',s) = p.l(g,n)+a5(g,n);
p2.up(g,n,'1',s) = p.l(g,n)+a5(g,n);
p2.up('2','1','2',s) = qu('2','1') + w_err(s);
p2.lo('2','1','2',s) = 0;

Solve dispatch3 using lp minimizing Z3;

a4(s,'1') = p2.l('1','1','2',s)-p2.l('1','1','1',s);
a4(s,'2') = p2.l('2','1','2',s)-p2.l('2','1','1',s);
a4(s,'3') = p2.l('3','2','2',s)-p2.l('3','2','1',s);
a4(s,'4') = p2.l('4','3','2',s)-p2.l('4','3','1',s);
a4(s,'5') = p2.l('5','4','2',s)-p2.l('5','4','1',s);

Gen_Out2('2',s,g) = a4(s,g);
Line_Lvl2('2',s,l)=sum(g,PTDF2(g,l)*Gen_Out2('2',s,g))-sum(n,PTDF(n,l)*d(n));
```

```
LMP_ED('2',s,n)=card(s)*(LB3.m('2',s)+sum(l,PTDF(n,l)*(TL_UP3.m(l,'2',s)+TL_LW3.
m(l,'2',s))));
Parameter Gen_Out3;
Gen_Out3(r,s,g)=Gen_Out1(r,g)+Gen_Out2(r,s,g);
Tot_Cost2(s,r)=sum(g,offer(g)*Gen_out2(r,s,g));
Tot_Cost(s,r)=sum(g,offer(g)*Gen_out3(r,s,g));;
Parameter Expected_TC2(r);
Expected_TC2(r)=sum(s,(1/card(s))*Tot_Cost2(s,r));
Parameter Expected_TC(r);
Expected_TC(r)=sum(s,(1/card(s))*Tot_Cost2(s,r))+Tot_Cost1(r);
Parameter mod_dsp(s,g);
mod_dsp(s,'1')= p2.l('1','1','2',s)-p2.l('1','1','1',s);
mod_dsp(s,'2')= p2.l('2','1','2',s)-p2.l('2','1','1',s);
mod_dsp(s,'3')= p2.l('3','2','2',s)-p2.l('3','2','1',s);
mod_dsp(s,'4')= p2.l('4','3','2',s)-p2.l('4','3','1',s);
mod_dsp(s,'5')= p2.l('5','4','2',s)-p2.l('5','4','1',s);
Parameter Opt_dg(g);
Opt_dg(g)=Gen_Out1('3',g)-Gen_Out1('1',g);
```

Essay 3: GAMS Code for Battery Energy Storage Valuation Model

```
option limrow=0;
option limcol=0;

$CALL GDXXRW.EXE PJM_DA_RT_LMP.xlsx set=t rng=C2:C9505 rdim=1 set=r
rng=D1:E1 cdim=1 par=DA_RT_LMP rng=C1:E8761 rdim=1 cdim=1
$GDXIN PJM_DA_RT_LMP.gdx
set t(*),r(*);
$LOAD t r
parameter DA_RT_LMP(t,r);
$LOAD DA_RT_LMP
$GDXIN

$CALL GDXXRW.EXE PJM_RGLTN_2.xlsx set=s rng=D1:E1 cdim=1 par=RGLTN
rng=C1:E8761 rdim=1 cdim=1
$GDXIN PJM_RGLTN_2.gdx
set s(*);
$LOAD s
parameter RGLTN(t,s);
$LOAD RGLTN
$GDXIN

$CALL GDXXRW.EXE PJM_Wind_Gen_2.xlsx par=WND_GEN rng=C2:D8761
rdim=1
$GDXIN PJM_Wind_Gen_2.gdx
parameter WND_GEN(t);
$LOAD WND_GEN
$GDXIN

set   b set of battery capacities /1*41/
      y set of transmission capacities /1*51/;

scalar  c_eff maximum charge rate per MW of capacity (MW per period) /0.94/
        d_eff maximum discharge rate per MW of capacity (MW per period) /0.94/
        C_B   annualized capacity cost for battery ($ per MW) /504511/
        batt_lf annual battery cycles /450/
        km_pr_ml kilometers per mile /1.60934/
        tln_lf life of transmission line /40/
        lngth length of transmission line (miles) /10/
        strg  battery storage per MW of battery capacity (MWh per MW) /6/
        c_rt  battery charge rate (MWh per MW per hour) /1/
        d_rt  battery discharge rate (MWh per MW per hour) /1/
        dcr   regulation dispatch to contract ratio /0.1/
        batt_cap /0/
```

```
        i /0/
        j /5/
        A     annuity factor for annualized cost
        scl_wnd wind generation scaling factor /0.2/
        cap_l
        t_cost
        scl_bcost /0.45/;

A = (1-1/power(1.1,40))/0.1;

parameter   p_da(t)  day-ahead energy price
            p_rt(t)  real-time energy price
            p_a(t)   ancillary services price;
p_a(t) = RGLTN(t,'RMCP');
p_da(t) = DA_RT_LMP(t,'DA_LMP');
p_rt(t) = DA_RT_LMP(t,'RT_LMP');

positive variables  qb(t)  the quantity of energy in the battery (MWh)
                    q_a(t)  capacity sold from battery into ancillary services market (MW)
                    qb_da(t)  energy sold from battery into day-ahead energy market
                              (MWh)
                    qb_rt(t)  energy sold from battery into real-time energy market (MWh)
                    qw_rt(t) energy sold from wind site into real-time energy market
                              (MWh)
                    qb_w(t)  energy stored into the battery from the wind site (MWh)
                    x_c(t)  portion of the hour spent charging
                    x_d(t)  portion of the hour spent discharging;
x_c.up(t) = 1;
x_d.up(t) = 1;

variables z profit maximizing level of wind gen and battery site;

equations   obj  objective of profit maxinization ($)
            obj_II  objective of profit maxinization ($)
            wnd_lmt(t)  upper limit on wind generation sold into real-time market (MWh)
            wnd_lmt_II(t)  upper limit on wind generation sold into real-time market
                           (MWh)
            batt_lvl(t)  level of energy stored in the battery in period 't' (MWh)
            chrg(t)  upper limit on battery charging per period
            chrg_II(t)  upper limit on battery charging per period
            dchrg(t)  upper limit on battery discharging per period
            b_cap(t)  upper limit on energy stored in the battery
            t_cap_up(t)  upper limit on energy flow on transmission line
            t_cap_up_II(t)  upper limit on energy flow on transmission line
            t_cap_lw(t)  upper limit on energy flow from the market to the wind site
```

```
              int_var(t)
              reg_up(t)
              batt_lfe  restriction on battery revenue;

obj..           z =e= sum(t,p_da(t)*d_eff*qb_da(t) +
                p_rt(t)*(qw_rt(t)+d_eff*qb_rt(t)+dcr*q_a(t)) + p_a(t)*q_a(t))
                - t_cost - scl_bcost*C_B/(batt_lf*strg)*sum(t,qb_w(t));

wnd_lmt(t)..  qw_rt(t) =l= scl_wnd*wnd_gen(t) - qb_w(t);
batt_lvl(t)..   qb(t) =e= qb(t-1) + c_eff*qb_w(t) - (qb_da(t) + qb_rt(t) +
                (1/d_eff)*dcr*q_a(t));
chrg(t)..       qb_w(t) =l= c_rt*batt_cap*x_c(t);
chrg_II(t)..    qb_w(t) =l= wnd_gen(t);
dchrg(t)..      qb_da(t) + qb_rt(t) + dcr*q_a(t) =l= x_d(t)*d_rt*batt_cap;
b_cap(t)..      qb(t) =l= batt_cap*strg;
reg_up(t)..     q_a(t) =l= batt_cap;
t_cap_up(t)..  qb_da(t) + qb_rt(t) + qw_rt(t) + dcr*q_a(t) =l= cap_l;
int_var(t)..    x_c(t) + x_d(t) =l= 1;
batt_lfe..
                 sum(t,p_rt(t)*d_eff*qb_rt(t)+p_da(t)*d_eff*qb_da(t)+p_rt(t)*dcr*q_a(t)+
                p_a(t)*q_a(t)) =g= scl_bcost*C_B*batt_cap;

obj_II..        z =e= sum(t,p_rt(t)*qw_rt(t)) - t_cost;
wnd_lmt_II(t)..   qw_rt(t) =l= scl_wnd*wnd_gen(t);
t_cap_up_II(t)..   qw_rt(t) =l= cap_l;

model battery /obj,wnd_lmt,batt_lvl,chrg,chrg_II,dchrg,b_cap,reg_up,t_cap_up,int_var/;
model battery2
/obj,wnd_lmt,batt_lvl,chrg,chrg_II,dchrg,b_cap,reg_up,t_cap_up,int_var,batt_lfe/;
model wind /obj_II,wnd_lmt_II,t_cap_up_II/;

set w
/tot_prft,line_cap,bttry_cpcty,rev_wnd,rev_batt_da,rev_batt_rt,rev_batt_rg_cap,rev_batt_
rg_rt,

enrgy_wnd,enrgy_batt_rt,enrgy_batt_da,enrgy_batt_rg,cap_batt_rg,avg_lmp_chrg,avg_l
mp_dchrg,
    tline_cpcty_fctr,bttry_lftm,line_cst,crtld_wnd/
   u /wnd,batt_da,batt_rt,batt_reg_cap,batt_reg_rt/;

parameter   results(b,y,w)
            batt_chrg_lvl(t,b,y)  level of storage in the battery
            tline_flow(b,y,t)  power flowing on the transmission line
            enrgy(t,b,y,u)  energy sold per period by wind site and battery
            rvne(t,b,y,u)  revenue per period by wind site and battery
```

```
                opt_enrgy(t,b,u)  energy sold per period by wind site and battery for optimal
                                  tcap
                opt_rvne(t,b,u)  revenue per period by wind site and battery;

parameter results_optml(b,w);

loop(b,
cap_l = 600;
loop(y,
 t_cost = ((1/A)*exp(10.0841)*exp(0.5759*log(cap_l+.0001))*km_pr_ml*lngth);
 batt_cap = i;
if(ord(b) eq 1,
  solve battery using lp maximizing z;
else
  solve battery2 using lp maximizing z;
);

tline_flow(b,y,t) = qw_rt.l(t)+d_eff*qb_da.l(t)+d_eff*qb_rt.l(t)+dcr*q_a.l(t);
batt_chrg_lvl(t,b,y) = qb.l(t);

* account for discharge losses in revenue and regulation energy sold in RT market
results(b,y,'tot_prft') = z.l;
results(b,y,'line_cap') = cap_l;
results(b,y,'bttry_cpcty') = i;
results(b,y,'rev_wnd') = sum(t,p_rt(t)*qw_rt.l(t));
results(b,y,'rev_batt_da') = sum(t,p_da(t)*d_eff*qb_da.l(t));
results(b,y,'rev_batt_rt') = sum(t,p_rt(t)*d_eff*qb_rt.l(t));
results(b,y,'rev_batt_rg_cap') = sum(t,p_a(t)*q_a.l(t));
results(b,y,'rev_batt_rg_rt') = sum(t,p_rt(t)*dcr*q_a.l(t));
results(b,y,'enrgy_wnd') = sum(t,qw_rt.l(t));
results(b,y,'enrgy_batt_rt') = sum(t,d_eff*qb_rt.l(t));
results(b,y,'enrgy_batt_da') = sum(t,d_eff*qb_da.l(t));
results(b,y,'enrgy_batt_rg') = sum(t,dcr*q_a.l(t));
results(b,y,'cap_batt_rg') = sum(t,q_a.l(t));
results(b,y,'avg_lmp_chrg')$(ord(b)>1) =
sum(t$(qb_w.l(t)>0),p_rt(t))/sum(t$(qb_w.l(t)>0),1);
results(b,y,'avg_lmp_dchrg')$(ord(b)>1) =
(sum(t$(qb_da.l(t)>0),p_da(t))+sum(t$(qb_rt.l(t)>0),p_rt(t)))/(sum(t$(qb_da.l(t)>0),1)+su
m(t$(qb_rt.l(t)>0),1));
results(b,y,'tline_cpcty_fctr')$(cap_l > 0) = sum(t,tline_flow(b,y,t))/(cap_l*card(t));
results(b,y,'bttry_lftm')$(ord(b)>1) = (batt_lf*strg*batt_cap)/sum(t,qb_w.l(t));
results(b,y,'line_cst') = t_cost;
results(b,y,'crtld_wnd') = sum(t,scl_wnd*wnd_gen(t) - qb_w.l(t)- qw_rt.l(t));
cap_l=cap_l+j;
);
```

```
results_optml(b,'tot_prft') = smax(y,results(b,y,'tot_prft'));
i=i+5;
);

results(b,y,'tot_prft')$(not results(b,y,'tot_prft')) = EPS;
results(b,y,'line_cap')$(not results(b,y,'line_cap')) = EPS;
results(b,y,'bttry_cpcty')$(not results(b,y,'bttry_cpcty')) = EPS;
results(b,y,'rev_wnd')$(not results(b,y,'rev_wnd')) = EPS;
results(b,y,'rev_batt_da')$(not results(b,y,'rev_batt_da')) = EPS;
results(b,y,'rev_batt_rt')$(not results(b,y,'rev_batt_rt')) = EPS;
results(b,y,'rev_batt_rg_cap')$(not results(b,y,'rev_batt_rg_cap')) = EPS;
results(b,y,'rev_batt_rg_rt')$(not results(b,y,'rev_batt_rg_rt')) = EPS;
results(b,y,'enrgy_wnd')$(not results(b,y,'enrgy_wnd')) = EPS;
results(b,y,'enrgy_batt_rt')$(not results(b,y,'enrgy_batt_rt')) = EPS;
results(b,y,'enrgy_batt_da')$(not results(b,y,'enrgy_batt_da')) = EPS;
results(b,y,'enrgy_batt_rg')$(not results(b,y,'enrgy_batt_rg')) = EPS;
results(b,y,'cap_batt_rg')$(not results(b,y,'cap_batt_rg')) = EPS;
results(b,y,'avg_lmp_chrg')$(not results(b,y,'avg_lmp_chrg')) = EPS;
results(b,y,'avg_lmp_dchrg')$(not results(b,y,'avg_lmp_dchrg')) = EPS;
results(b,y,'tline_cpcty_fctr')$(not results(b,y,'tline_cpcty_fctr')) = EPS;
results(b,y,'bttry_lftm')$(not results(b,y,'bttry_lftm')) = EPS;
results(b,y,'line_cst')$(not results(b,y,'line_cst')) = EPS;
results(b,y,'crtld_wnd')$(not results(b,y,'crtld_wnd')) = EPS;

batt_chrg_lvl(t,b,y)$(not batt_chrg_lvl(t,b,y)) = EPS;

loop(b,
loop(y,
if(results(b,y,'tot_prft')=results_optml(b,'tot_prft'),
results_optml(b,'line_cap') = results(b,y,'line_cap');
results_optml(b,'bttry_cpcty') = results(b,y,'bttry_cpcty');
results_optml(b,'rev_wnd') = results(b,y,'rev_wnd');
results_optml(b,'rev_batt_da') = results(b,y,'rev_batt_da');
results_optml(b,'rev_batt_rt') = results(b,y,'rev_batt_rt');
results_optml(b,'rev_batt_rg_cap') = results(b,y,'rev_batt_rg_cap');
results_optml(b,'rev_batt_rg_rt') = results(b,y,'rev_batt_rg_rt');
results_optml(b,'enrgy_wnd') = results(b,y,'enrgy_wnd');
results_optml(b,'enrgy_batt_rt') = results(b,y,'enrgy_batt_rt');
results_optml(b,'enrgy_batt_da') = results(b,y,'enrgy_batt_da');
results_optml(b,'enrgy_batt_rg') = results(b,y,'enrgy_batt_rg');
results_optml(b,'cap_batt_rg') = results(b,y,'cap_batt_rg');
results_optml(b,'avg_lmp_chrg') = results(b,y,'avg_lmp_chrg');
results_optml(b,'avg_lmp_dchrg') = results(b,y,'avg_lmp_dchrg');
results_optml(b,'tline_cpcty_fctr') = results(b,y,'tline_cpcty_fctr');
results_optml(b,'bttry_lftm') = results(b,y,'bttry_lftm');
```

```
results_optml(b,'line_cst') = results(b,y,'line_cst');
results_optml(b,'crtld_wnd') = results(b,y,'crtld_wnd');
);
);
);
```