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Wind Power Plants and System Operation in the Hourly Time Domain

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WIND POWER PLANTS AND SYSTEM OPERATION IN THE HOURLY TIME DOMAIN

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ABSTRACT

Because wind is an intermittent power source, the variability may have significant impacts on system operation. Some studies have shown that this impact on regulation is not significant, but the impact on load following requirements has not yet received much attention. Part of the difficulty of analyzing the load following impact of wind is the inadequacy of most modeling frameworks to accurately treat wind plants and the difficulty of untangling causal impacts of wind plants from other dynamic phenomena. This paper presents a simple analysis of an hourly load following requirement that can be performed without extensive computer modeling. The approach is therefore useful as a first step to quantifying these impacts when extensive modeling and data sets are not available. The variability that wind plants add to the electricity supply must be analyzed in the context of overall system variability. The approach used in this paper does just that. The results show that wind plants do have an impact on load following, but when calculated as a percentage of the installed wind plant capacity, this impact is not large. Another issue is the extent to which wind forecast errors add to imbalance. Although load forecasts are generally more accurate than wind forecasts, they are also imperfect. The relative statistical independence of wind forecast errors and load forecast errors can be used to help quantify the extent to which wind forecast errors impact overall system imbalances. A case study is developed to illustrate the approach and to provide some quantitative results.

EXECUTIVE SUMMARY

Utility operations occur over several time scales. Regulation is the fast response of generators to changes in load from minute to minute. Over longer periods, such as 10 minutes to a few hours, generators must be controlled so that longer trends in load can be accommodated.

As more wind power plants are added to the electrical supply, there is more interest in the impact that these plants have on utility operations. This study analyzes the impact using hourly data for the state of Iowa, along with hourly estimates of wind power production from several sites in that state. The goal of this analysis is to determine the change in load following requirements that are induced by alternative wind plant configurations that represent different penetration rates of wind relative to annual system peak load. No attempt is made to determine which conventional generating units would compensate for the variable output of wind, nor do I develop any cost estimates of the load following impact. Instead, this analysis focuses on the physical requirements that wind would impose on the electrical supply.

It is important to realize that even without a wind plant, utilities have tremendous variability to contend with. Loads vary from day to day, hour to hour, and minute to minute. Utility operators have different procedures for handling these variations, and the existing portfolio of generating resources is divided unto units that can quickly respond to changing conditions and units that run at a more or less constant output. When analyzing load data, utilities can take advantage of the statistical correlation between loads, which can be high in the load following time frame and low during the regulation time frame. System operation does not require running all generators at a flat output. Instead, the mix of units must respond so that the total generation balances the total load, with a small error component.

This paper focuses on two aspects of the 1-hour time frame. The first aspect is the load following requirements that are imposed by different penetration rates of wind plants. In this part of the analysis, I calculate the 1-hour load following requirements with and without wind generation. Because there are already ramping requirements without wind, this approach recognizes whatever correlation appears in the data (wind power and load) to calculate the change in ramping requirements. In this first part of the analysis, no attempt is made to analyze the impact of forecasting loads or wind. The analysis therefore represents a backward-looking view of the impact of wind plants.

The second aspect of this analysis looks at the combined impact of wind forecast errors and load forecast errors. Load forecast errors cause an imbalance in the system that is added to the imbalances caused by generators that can't respond quickly enough to control signals. Although I ignore the impact of conventional plants, I analyze the combined impact of wind forecast errors and load forecast errors. These errors are largely uncorrelated, but the analysis method does not make any assumptions about this correlation. Using actual load forecast errors from the California Independent System Operator (ISO) and adapting this data to Iowa, the analysis focuses on several levels of wind forecast accuracy based on improvements to persistence forecasts. The load forecast errors are also varied so that I could develop a sensitivity analysis that compares the impact of wind forecast errors and load forecast errors, each with different levels of accuracy.

Table 1 summarizes some of the key results of this study. The table is arranged to show the impact of wind at increasing penetration levels, calculated with the ratio of rated wind capacity divided by annual peak. The first column contains the results from the backward-looking analysis that ignores forecast errors. The table contains the allocation of total standard deviation to the wind plant, and is then converted into a ratio of the wind plant capacity. For example, a 17% wind penetration rate changes the system load following requirement. The new load following requirement is allocated to the wind plant using the Oak Ridge vector allocation method, resulting in an impact of 2.0% of wind's rated capacity. If a utility were to apply a confidence band of three standard deviations, this would translate into a 6.0% allocation (of rated wind capacity) of variability to the wind plant.

TABLE 1. IMPACT OF WIND ON 1-HOUR LOAD FOLLOWING REQUIREMENTS AND IMBALANCE AT DIFFERENT PENETRATION RATES

Wind Penetration (Rated Capacity as Percent of Annual Peak Load)	Load Following Allocation as Percent of Rated Capacity (Standard Deviation)	Range of Imbalance Allocated to Wind Forecast (Persistence) as Percent of Rated Capacity (Standard Deviation)
5.68	0.78	1.13-1.53
8.52	1.10	1.63-2.17
11.36	1.41	2.08-2.72
14.20	1.71	2.50-3.19
17.04	2.00	2.86-3.57
19.88	2.27	3.19-3.88
22.72	2.53	3.47-4.13

The last column of the table reports wind's allocation of imbalance at different levels of load forecast accuracy and persistence forecasting for wind. This represents a very conservative estimate because wind forecasting can routinely improve upon persistence forecasting. At a penetration rate exceeding 22%, wind's allocation of imbalance ranges from 3.47%-4.13% of rated capacity. Converting this to a three standard-deviation band implies this range tops out at about 12.4% of the rated capacity of the wind plant. Further inspection of the table indicates that wind's allocation increases nonlinearly with penetration.

The implication of this analysis is that wind does indeed have an impact on load following requirements and imbalance. The magnitude of these impacts increases nonlinearly with wind penetration. The results in this paper suggest that when analyzed in the context of the existing ramping and imbalance characteristics of the system, the increase in load following requirements is a fraction of wind plant rated capacity and can be analyzed statistically. Similarly, the impact of wind on imbalances is noticeable, but it ranges from just more than 1% at low penetrations up to about 4% at a high penetration. Allowing for a 99% confidence interval implies that these quantities can be tripled, allowing for a low level of risk.

INTRODUCTION

As the use of wind power generators increases, more attention is now being directed at the operational impact that wind plants have on systems operation. One significant study looked at the impact of wind energy on various time scales, ranging from regulation (seconds-minutes), load following (10 minutes to a few hours), and unit commitment (many hours-days) [1]. PacifiCorp recently performed a wind analysis using a chronological electric production simulation model, but it was unable to precisely determine the impact of wind on load following and regulation. The California Energy Commission is embarking on a study to help determine the grid integration costs of wind. This study is expected to have a significant focus on load following and regulation impacts and costs. Interest in this type of study is motivated by concerns that fluctuations in wind power output may have a serious impact on grid operations and significantly increase costs. There are sometimes additional concerns that wind power fluctuations must be matched one-for-one by a compensating unit so that the resulting output is constant. Modern chronological production simulation models can help estimate cost impacts in the hourly time domain, but they are generally limited in the way they can represent wind power generators. That has precipitated the current interest in separate analyses of load following impacts of wind plants. Regulation impacts are also important to understand, but because regulation occurs in a shorter time scale, the production models won't see the fast variations in wind and load.

This paper presents a simple analysis of an hourly load following requirement that can be performed without extensive computer modeling. The approach is therefore useful as a first step to quantifying these impacts when extensive modeling and data sets are not available. The variability that wind plants add to the electricity supply must be analyzed in the context of overall system variability. This analysis focuses only on physical requirements that would be imposed on the system operator, and it does not make any assumptions about how these requirements would be met in practice. This analysis also ignores the market structure of the power system because these markets are not standard and are still evolving in the United States. For specific market structures, the results of this analysis or others like it can be used to estimate other market impacts or costs.

DATA AND CASE STUDY DESCRIPTION

Several alternative case studies are presented in this paper, all based on different scenarios of wind generation in Iowa. The data have been used in several previous studies and are described more fully in [2]. This previous work used an electricity production simulation model to select optimal locations to build 1,600 MW of wind capacity. Two alternative optimization targets were used: maximum economic benefit (reduction in conventional fuel cost plus a cost-based reliability benefit) and maximum reduction in expected unserved energy (EUE). The analysis utilized several different search patterns because the optimization is highly non-linear. Even though we were not able to guarantee that the algorithm found the very best solution, several promising wind capacity configurations were identified. Furthermore, many of these alternative configurations did not appear to provide significantly different economic or reliability benefits, so approximately 20 configurations were identified out of nearly 5 billion possibilities.

In some of the preliminary project work, we also ran a third set of optimizations that selected wind capacity levels in an attempt to provide the maximum wind output during peak load periods. This selection process did not address system economics or reliability. It was run for incremental percentages of the annual system peak, ranging from the top 1% of hourly loads to the top 30% of hourly loads. This method is called the peak-energy method.

For the analysis that appears below, I selected four cases from the economic optimization and four cases from the peak-energy method. Each of these cases contains 1,600 MW of wind capacity spread among six to seven sites throughout Iowa. These sites were selected from a total of 12 sites that were fed into the optimization processes. Table 2 shows each of the 8 cases.

Case 1 from the peak-energy method is unique in that almost all the wind capacity was selected from a single site. Because the peak-energy method ignores economics and reliability, we didn't find any similar combination of sites in the other two optimization processes. Case 1 illustrates potential load following impacts when the benefits of geographic dispersion are not fully taken advantage of. As will be seen in the simulation results below, the Case 1 results differ significantly from all the geographically disperse cases (numbered 2-8).

For many of the results, I also analyzed the load following impact at different wind penetration rates. The prior Iowa work was based on the possibility of a renewable portfolio standard in the state that would have resulted in 1,600 MW of wind, representing 22.7% of the annual peak load. This penetration rate is significantly higher than any that exists in the United States today and

TABLE 2. GEOGRAPHICALLY DISPERSE WIND CAPACITY (MW)

Case	Algona	Alta	Estherville	Forest City	Radcliffe	Sibley	Total
1	0	1,300	200	0	100	0	1,600
2	200	700	500	0	100	100	1,600
3	0	400	600	0	200	400	1,600
4	0	200	600	0	200	600	1,600
5	200	250	700	0	50	400	1,600
6	100	400	550	50	50	450	1,600
7	200	400	500	50	100	350	1,600
8	250	400	400	0	200	350	1,600

therefore is an extreme case. The wind power production data were calculated by convolving a wind turbine power curve with hourly average wind speeds, scaling up to the appropriate capacity and accounting for losses such as electrical and wake effects. It is likely that the resulting wind power time series data contain more variability than would be seen in practice, but that presents a conservative view of the effect of wind on load following. The alternative penetration rates used in this study scale the geographically disperse wind plant configurations, which is a weakness in this study.

LOAD FOLLOWING

Different utilities and control areas don't always run their systems in the same way. So that this analysis doesn't depend on specific operational practices, I look only at 1-hour load following requirements. The response of conventional generators to changes in system load or changes in wind output will depend on both of these operational practices and on the physical capabilities of generators that follow load. Larger control areas typically have several units that provide a fraction of total output and that can be called upon to either increase or decrease output. When this load following capability is spread among several units, the ramp rate becomes less of a constraint than if only a small number of units adjust to changing load conditions.

For this study, I define hourly ramp requirements without wind as

$$R_t = L_t - L_{t-1} \tag{1}$$

where L is the hourly load at hour t, and R is the ramp requirement in hour t.

Assigning a generator to follow each increase and decrease in wind output subjects the system (and the customers) to needless costs [3]. For example, if wind generation decreases by 100 MW during the same hour as load decreases 100 MW, ramping up a conventional unit to counter the wind decrease would not only be unnecessary, but it would also require that another unit back down by 100 MW. Because wind output is generally uncorrelated with hourly load, we would expect the load and wind to sometimes move in the same direction and sometimes move in the opposite direction. Power system operation does not require each generator or each load to maintain a balanced schedule. Instead, the overall system must be in balance (or nearly so) [4].

Load following units must move to achieve system balance. Ramping requirements of a system that includes wind generation can be defined as

$$N_t = (L_t - W_t) - (L_{t-1} - W_{t-1}) \quad (2)$$

where N is the ramping requirement of the system with wind, and the terms in parentheses are the load net of wind in the respective hour. To assess the impact of wind power on ramping requirements, I calculated equation (2) for each hour of the year, for each of the eight cases, and for various wind penetration rates. This section does not address forecast errors but assumes that both next-hour's load and wind output are known with certainty. In the following section, this omission is rectified.

Figures 1 and 2 illustrate the impact of wind on ramping for one week. Both graphs show the load following requirement without wind, with 800 MW of wind capacity (approximately 11% of annual peak load), and 1,600 MW of wind capacity (22.7% of annual peak load). Figure 1 is taken from the Case 1 scenario, which has most of the wind capacity at a single site, and Figure 2 represents Case 5, which is the first of the four economic optimization scenarios. These cases were selected to show as much difference as possible among the cases examined. Both graphs show that there can be relatively large differences in load following requirements between the wind and no-wind cases. At other times, there is a small difference.

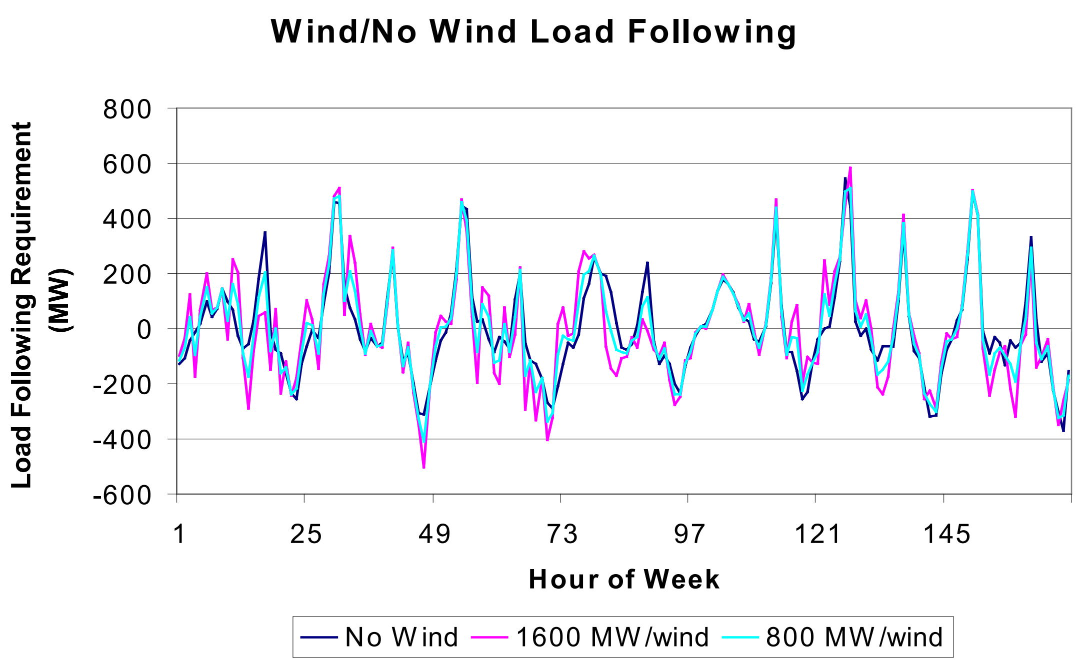

FIGURE 1. CASE 1: COMPARISON OF LOAD FOLLOWING WITH/WITHOUT WIND.

To get a better idea of the load following impact, we can compare the statistical distribution of the load following requirements over the entire year. Figure 3 is based on Case 1, and Figure 4 is based on Case 5. From these distributions, we can observe that the frequency of small ramps (at or near zero) declines when wind is added to the system. Although it is hard to see in the diagram, the tails of the distribution are a little wider as a result. We can also observe that the load following impact does not appear to be linearly related to penetration. This is most pronounced in Figure 4 in the middle of the distribution.

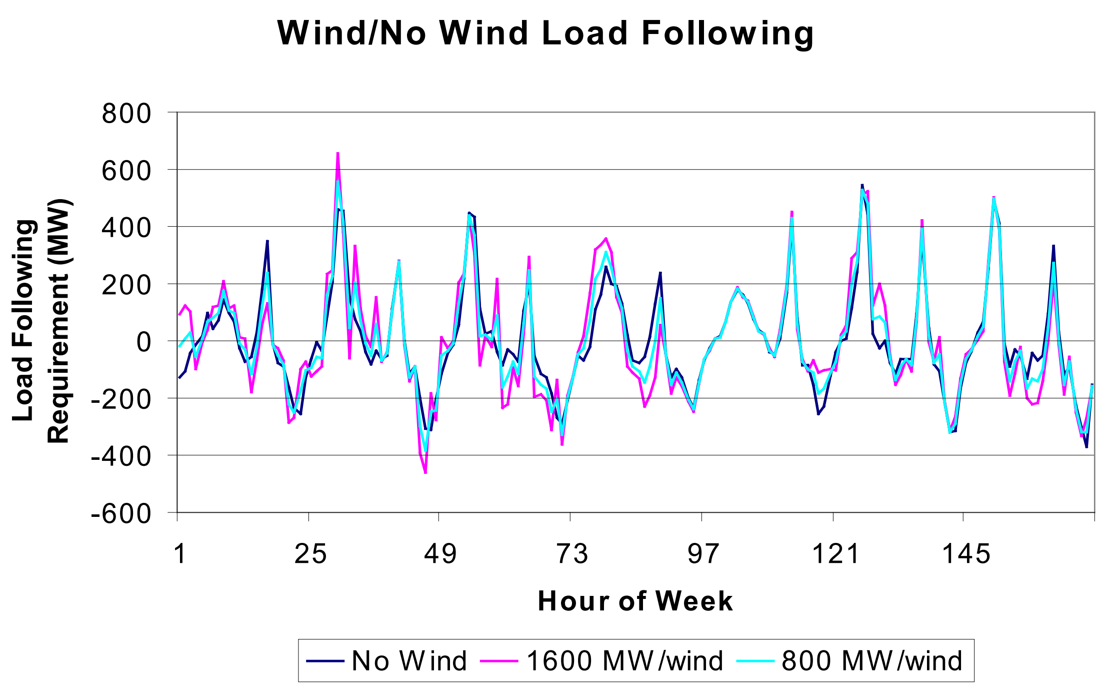

FIGURE 2. CASE 5: COMPARISON OF LOAD FOLLOWING WITH/WITHOUT WIND.

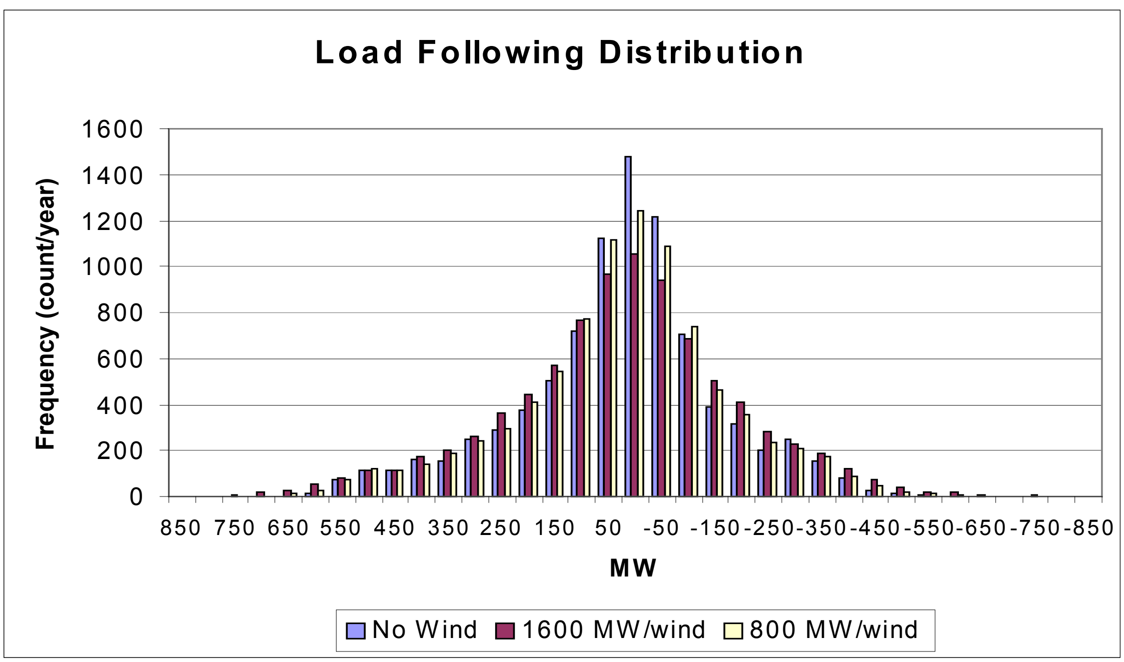

FIGURE 3. CASE 1: STATISTICAL DISTRIBUTION OF LOAD FOLLOWING REQUIREMENTS.

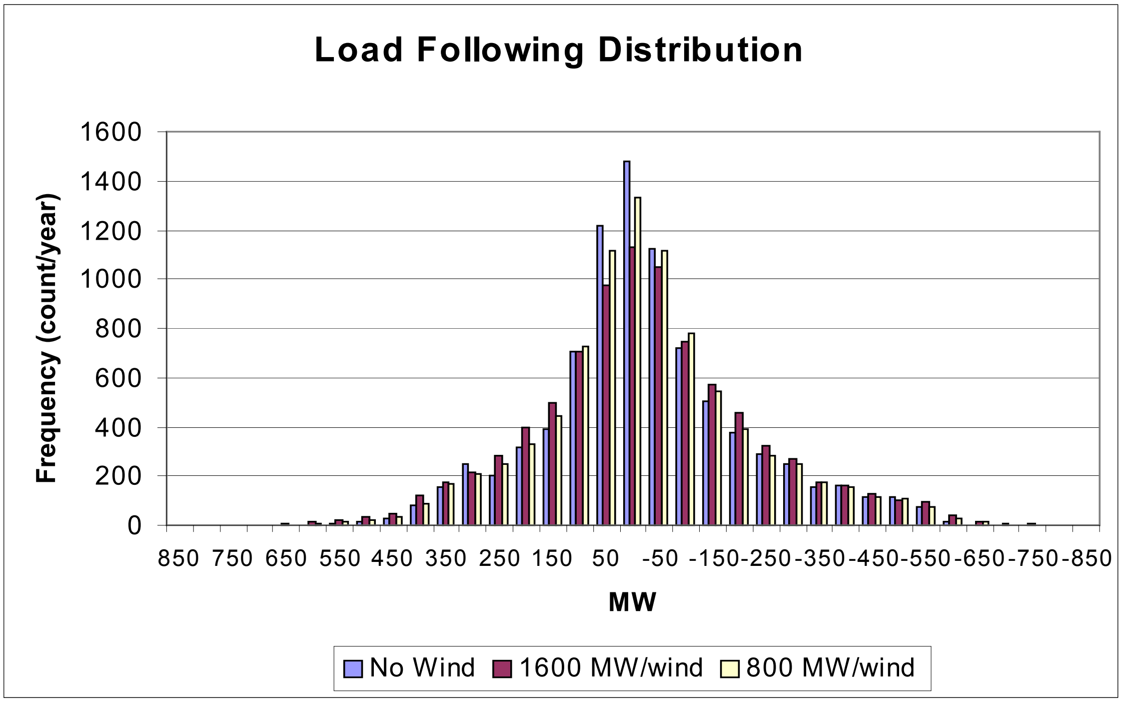

FIGURE 4. CASE 5: STATISTICAL DISTRIBUTION OF LOAD FOLLOWING REQUIREMENTS.

Extending our simple statistical investigation further, we can examine the standard deviation, σ, of the load following requirements of the eight cases. Figure 5 shows the standard deviation of load following requirements for the no-wind case, 800 MW of wind capacity, and 1,600 MW of wind capacity. It is again clear from examination of the graph that the load following impact does

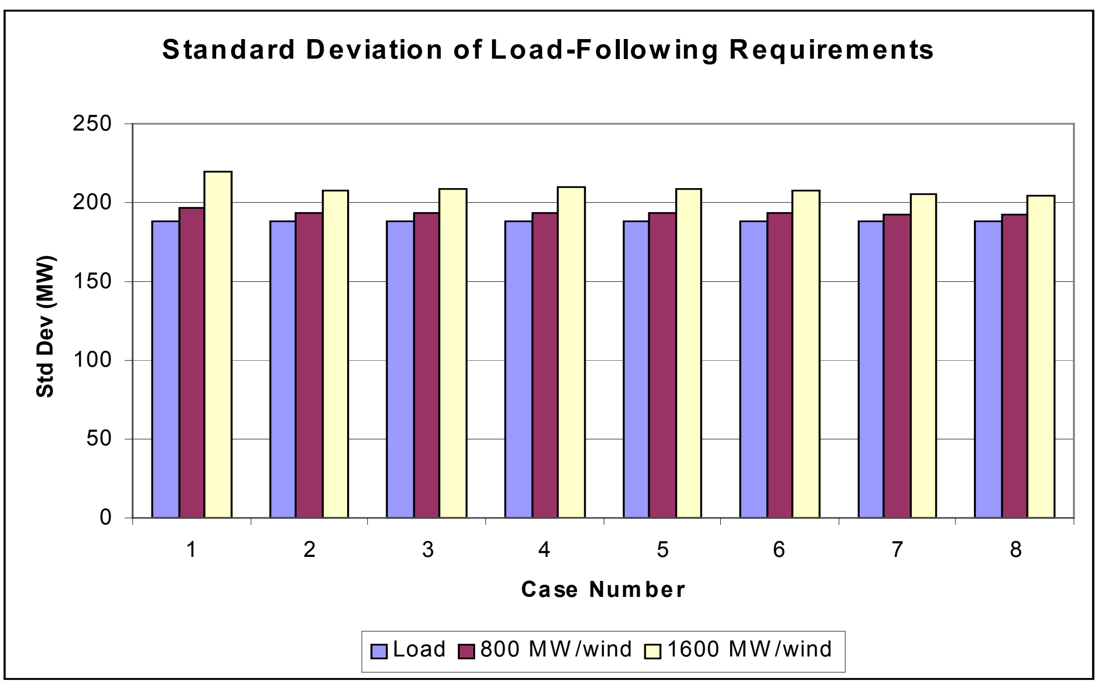

FIGURE 5. VARIATION (STANDARD DEVIATION) IN LOAD FOLLOWING REQUIREMENTS.

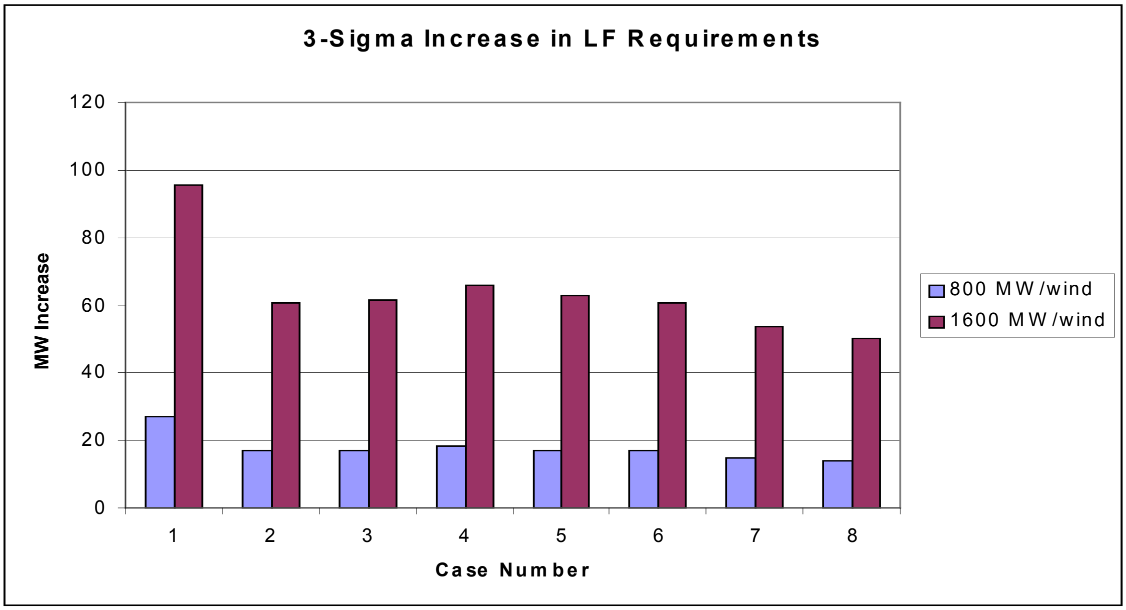

FIGURE 6. INCREASE IN HOURLY LOAD FOLLOWING REQUIREMENTS, 99% CONFIDENCE BAND.

not appear to be linear. However, this statement must be made with caution because of the scaling that was used to calculate hourly wind power output, which may not fully account for local smoothing within a wind farm. The graph does not show a large difference between the geographically disperse cases (2-8), but there is clearly a larger impact from Case 1. This is to be expected because most of the wind capacity in Case 1 is from a single site.

A risk-based analysis of the load following impacts of wind could assign a particular confidence interval (preferred risk level) and then calculate a multiple of σ corresponding to this risk level. Figure 6 was developed by taking 3σ based on a 99% confidence interval of the variability of load following requirements of wind. Case 1 shows a very large 3σ effect on load following, but the remaining cases appear to be quite different. The graph does show some variation among different wind combinations: Case 8 has a significantly smaller 3σ increase than Case 4, for example.

For a better look at the extremes, Figures 7 and 8 show the wind-induced change in maximum up-ramp and down-ramp requirements for the 800-MW and 1,600-MW penetration cases, respectively. In both graphs, Case 1 has very little geographic benefit, which can be seen in the figure. Even for this case, the largest down-ramp requirement of the year is approximately 8% of the wind plant capacity. For the remaining cases, the change in the annual maximum up-ramp requirement is higher than that of the annual down-ramp maximum requirement.

Although it might be tempting to use Figure 6 to allocate load following requirements to the wind plant, we instead use a vector allocation method that was first developed by Kirby and Hirst [5] at Oak Ridge National Laboratory (ORNL). This method has a number of attractive characteristics. It recognizes positive, negative, or zero correlation; is independent of the order that each variable is introduced to the analysis; and is independent of the level of aggregation. This method has been used extensively to analyze the regulation impact of non-conforming loads, and it appears to be ideal for examining the load following impacts of wind. The allocation of the load following impact of wind can be calculated as

$$LF_w = (\sigma_w^2 - \sigma_L^2 + \sigma_T^2) / (2\sigma_T) \qquad (3)$$

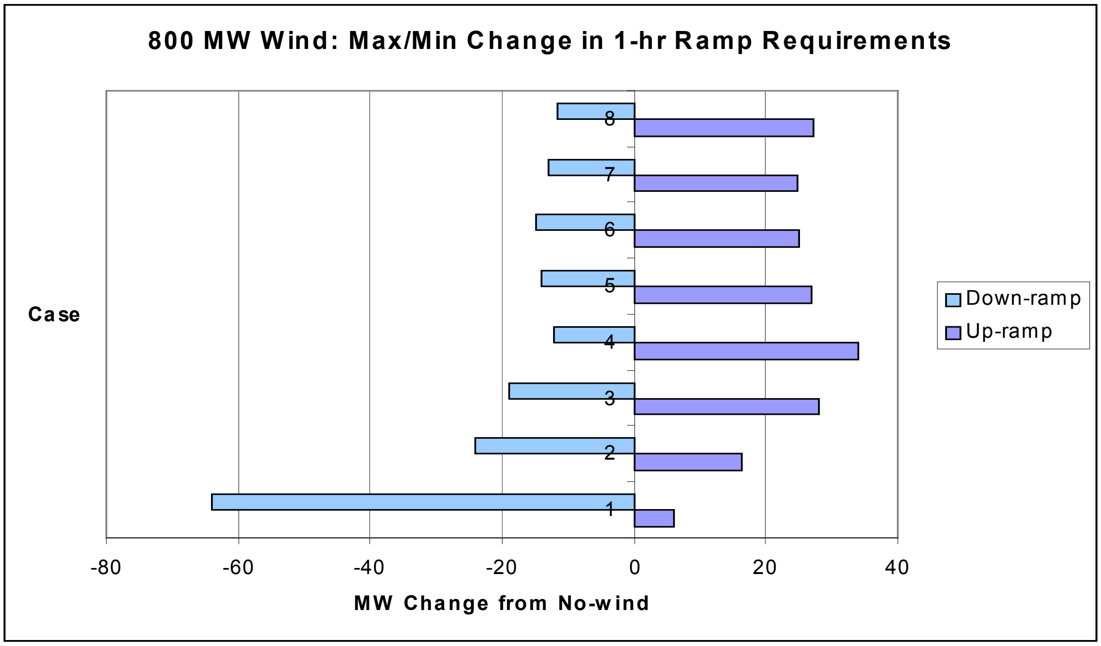

FIGURE 7. MAXIMUM CHANGE IN RAMPING REQUIREMENTS FOR 800 MW OF WIND CAPACITY.

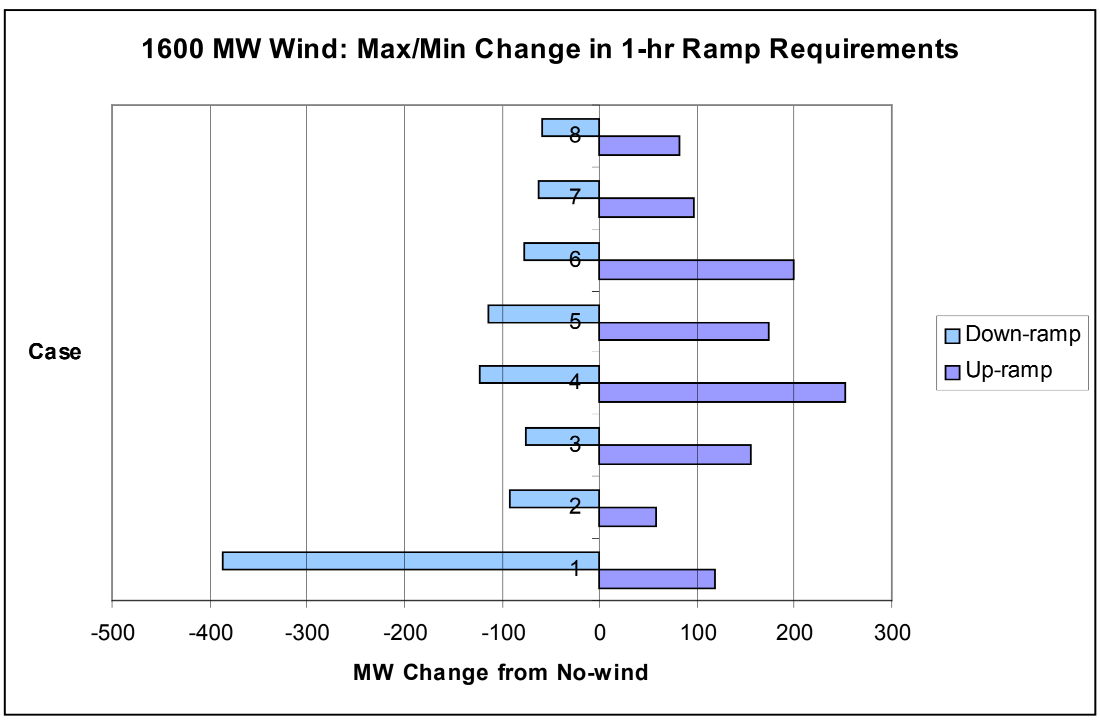

FIGURE 8. MAXIMUM CHANGE IN RAMPING REQUIREMENTS FOR 1600 MW OF WIND CAPACITY.

This allocation was applied to each of the eight cases at wind penetrations ranging from 200 MW to 1,600 MW. Because Cases 2-8 had similar results across all penetration rates, Figure 9 only shows the maximum wind allocation from Cases 2-8, in which one maximum is selected from each penetration case. Figure 9 also shows the allocation for Case 1. Once again we can see the benefits of geographic dispersion, because the allocation for Case 1 always exceeds the largest allocation for all other cases throughout the range of wind penetrations considered. For Cases 2-8, the load following share of wind is about 2.5% of the rated capacity of the wind plant. The allocation is expressed as a share of the total system, σ_T, and is therefore a standard deviation. Using a 3σ risk preference, we see that the load following impact of a 1,600-MW wind plant is about 7.5% of its rated capacity. This generally conforms to the ubiquitous 7.0%-7.5% reserve rule that is often applied to conventional reserves. Smaller penetrations of wind have correspondingly smaller load following allocations. For example, a 400-MW penetration (corresponding to just over 5% penetration) has a load following allocation of about 2.5% when using a 3σ risk preference.

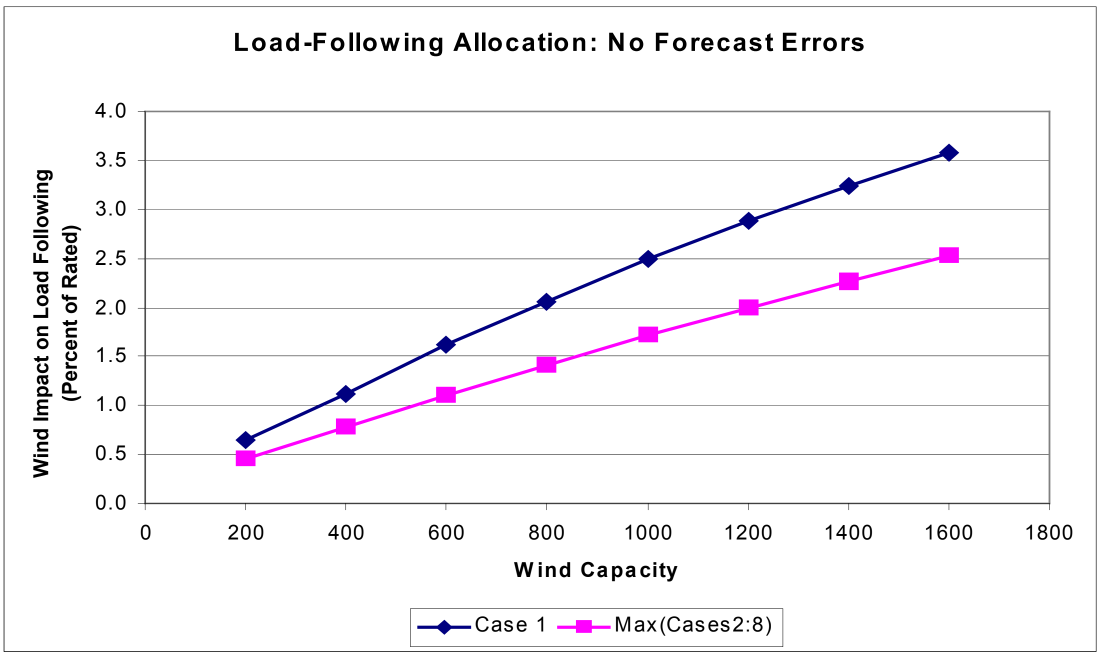

FIGURE 9. ALLOCATION OF LOAD FOLLOWING IMPACT USING THE OAK RIDGE VECTOR ALLOCATION METHOD.

LOAD FORECASTS AND WIND FORECASTS

Up to this point, the analysis has assumed that future load and wind power are known with certainty. That is clearly an unrealistic approach, so I rectify that in this section. Utilities invest significant resources to develop accurate load-forecasting models. Techniques often incorporate advanced mathematical and statistical models that use load data, weather data, and other factors as inputs. The short-term load forecasts are typically updated in various cycles from one day ahead to one hour ahead. Some markets, such as California, create 10-minute forecasts and recalculate optimal unit loading every 5-10 minutes, depending on changing demand conditions.

Load forecasting is a reasonably well-developed practice, but there can still be occasional surprises.

Wind forecasting tools are changing rapidly. The emerging wind forecasting technology often contains at least two components: a numerical weather model that is coupled to a statistical analysis tool, which may include neural network or standard time-series models. In spite of the advances in wind forecasting, a surprisingly simple and relatively powerful tool is the persistence model. Although the persistence model can be applied to several time scales, it is often used as a benchmark for hour-ahead forecasting models. The persistence model is

$$w_t = w_{t-1} \tag{4}$$

where t is the current time, and w can be either wind power output or wind speed. Generally the forecast models will estimate the average wind speed and use that as input to a wind farm estimator to calculate power output for the time period in question. Rather than utilize a specific wind forecasting method, I use the persistence model in equation 4 and examine the impact of improvements of wind forecasting relative to this model.

Wind power forecast errors can cause complications for the power system operator. If the forecast is too high, then additional units must be called on to make up the difference. If actual wind exceeds the forecast, then other units may need to be backed down. However, the same complications arise because of load forecast errors. Because load forecast errors and wind forecast errors are unlikely to be correlated, the errors may or may not occur in the same direction. If both the load forecast and wind forecast are too high, the reduction in actual wind may help the system operator by reducing the likelihood or magnitude of any change to the generation that is online. However, at other times the forecast errors may work against each other, requiring additional up-ramp or down-ramp from the dispatch stack. A simple statistical analysis of load forecast errors and wind forecast errors can give us an idea of the magnitude and frequency of occurrence of these scenarios.

System operators can compensate for forecast errors by moving units on the dispatch stack to a new loading point. If those units can't move fast enough, an imbalance might be created, which is handled differently in various power markets. I don't address imbalance markets or other adjustment mechanisms in this paper; rather, I simply calculate the magnitude of the imbalance that is created without wind and compare that to the imbalance with wind.

To calculate hourly load forecast errors, I started with hour-ahead forecasts from the California ISO for 2002. Hourly forecasts and actual load are publicly available on the ISO Web site[6]. For each hour of the year, I calculated the percentage forecast error and then applied these errors to the Iowa load data. It is not unusual for the standard deviation of load forecast errors (SLE) to be 2.0%-2.5% of the load. However, the ISO load forecasts are significantly better than that during 2002. To examine the effect of less accurate load forecasts, I developed several scenarios by increasing the load forecasting errors by 20%, 40%, and then 60%. This establishes a range of 1.1%-1.8% of SLEs, still less than many utilities experience.

I also developed a range of wind forecast improvements relative to persistence, ranging from a 10% improvement to 80% in 10% increments. Each load forecast error was convolved with each wind forecast error for wind penetrations of 400-1,600 MW in increments of 200 MW.

Figures 10-12 show the impact that 400 MW of wind capacity has on the standard deviation of imbalance at different levels of forecast accuracy. Figure 10 shows the standard load forecast case with varying levels of improvement in wind forecasting that is normalized to the persistence model (StdErr is the term used to indicate the standard deviation of the forecast error). The increase in total variation at this penetration rate of 5.7% is about 3 MW. As wind forecasting technology improves, this number becomes even less significant.

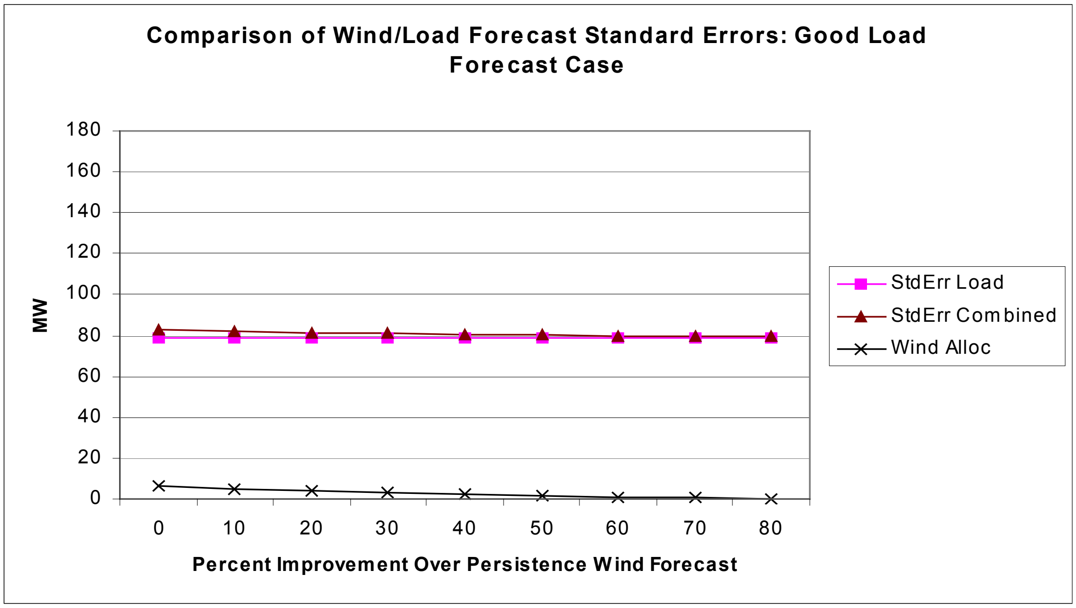

FIGURE 10. STANDARD DEVIATIONS FOR LOAD AND WIND FORECAST ERRORS COMPARED TO COMBINED FORECAST ERRORS. 400 MW WIND CAPACITY.

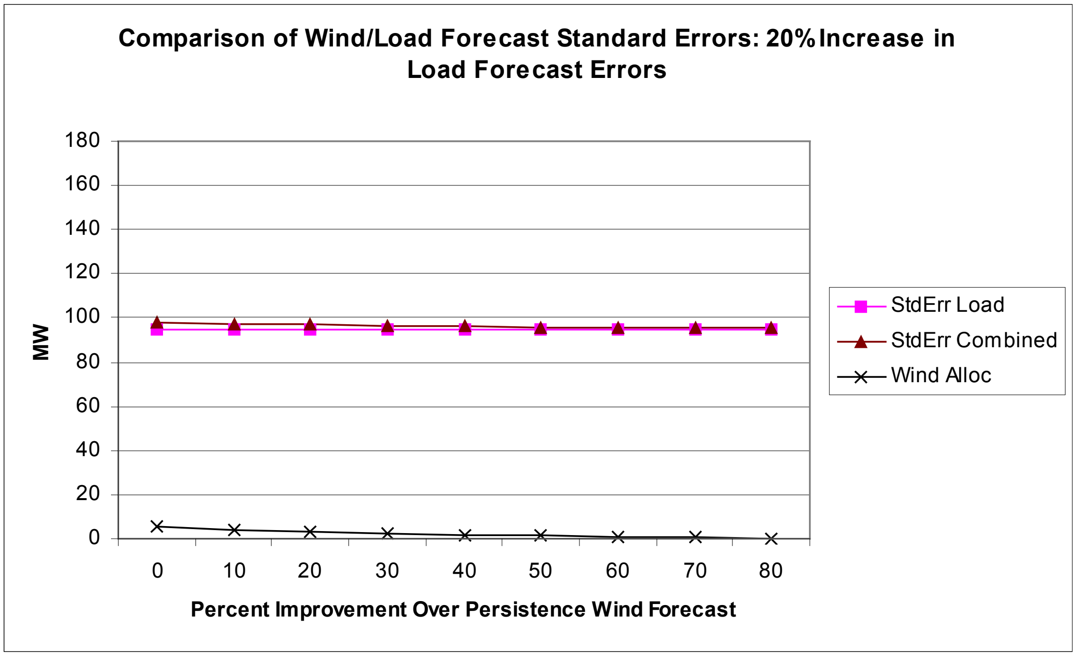

FIGURE 11. STANDARD DEVIATIONS FOR LOAD AND WIND FORECAST ERRORS COMPARED TO COMBINED FORECAST ERRORS WITH LESS ACCURATE LOAD FORECASTS. 400 MW WIND CAPACITY.

Figures 11-12 show the same patterns but assume somewhat worse load-forecasting capability. Figure 11 increases load-forecasting errors by 20%, and Figure 12 increases these errors by 60%. All of these scenarios are within ranges that can be observed in practice. As can be seen in the figures, the increase in variation is insignificant.

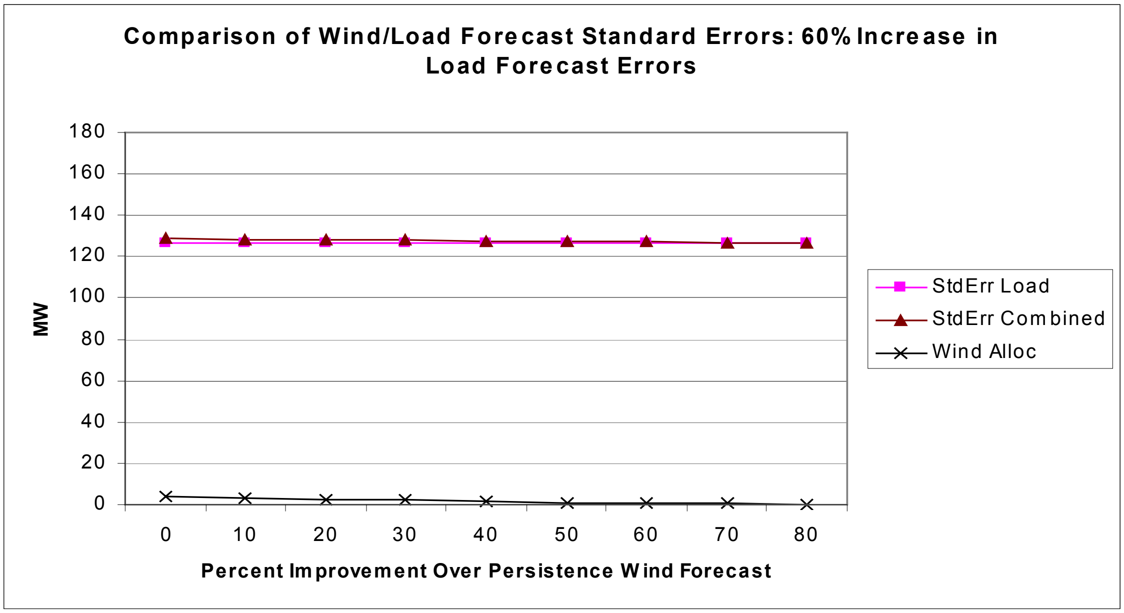

FIGURE 12. STANDARD DEVIATIONS FOR LOAD AND WIND FORECAST ERRORS COMPARED TO COMBINED FORECAST ERRORS WITH INACCURATE LOAD FORECASTS. 400 MW WIND CAPACITY.

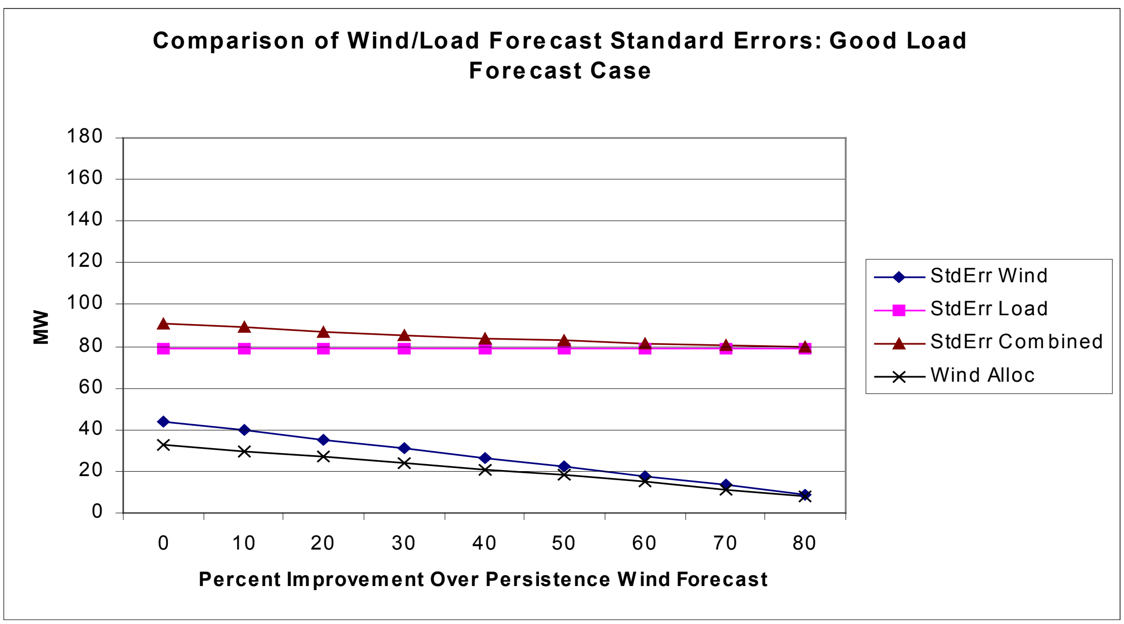

FIGURE 13. STANDARD DEVIATIONS FOR LOAD AND WIND FORECAST ERRORS COMPARED TO COMBINED FORECAST ERRORS WITH ACCURATE LOAD FORECASTS. 800 MW WIND CAPACITY.

Each of these figures also shows the allocation of variation to the wind plant, calculated by using the ORNL allocation method. In the worse case, the allocation to wind is 6 MW (base load forecast case, persistence wind forecast case). This allocation gradually declines as wind forecasting improves. When load forecasting becomes less accurate, the variation share of wind declines because load forecast errors contribute more to imbalance. If this allocation method were to be used in a power market, it would reward good forecasting for both wind and load, and assign higher allocation (cost) to poor forecasting.

The next series of graphs appear in Figures 13-14 and show the base load forecast case and the 20% degradation case. These graphs are analogous to Figures 10-11 except for increasing the wind penetration rate to 11.4%. Although this represents a doubling of wind capacity, the graphs show that the contribution that wind makes to total imbalance more than doubles. The base load forecast with persistence wind forecast results in wind's share increasing from 6 MW in the 400-MW case to 22 MW in the 800-MW case. As the load forecast degrades, Figures 13-14 show the wind allocation decline from 22 MW to 19 and 17 MW, respectively. This worse case additional variation represents 2.75% of the wind plant capacity.

The last series of graphs in this series are Figures 15-16, which are based on the extreme case of 1,600 MW of wind capacity, representing 22.7% of peak load. For the base load forecast case and persistence wind forecasting, the wind allocation nearly triples from the 800-MW case (to 66 MW). This represents about 4.1% of the wind capacity. It is clear that the impact appears to be nonlinear as wind penetration increases. As before, this series of graphs show declining wind allocations as a function of load forecast degradation, and as wind forecasting improves.

Figures 17-19 summarize all the base load forecast cases for all penetration rates. These graphs show the increase in total imbalance variation that is introduced by wind. Each line in each of the graphs shows a particular wind forecast accuracy, persistence, and persistence with 20% and 40% improvement.

The last series of graphs, Figures 20-22, show the allocation of imbalance to wind. Figure 20 shows the base load forecast case, and Figures 21-22 show 20% and 40% load forecast degradation cases, respectively. The results clearly show the nonlinear contribution that wind makes to imbalance as penetration increases. In the most challenging case for wind (22.7% penetration rate, good load forecast, persistence wind forecast), wind's allocation of the imbalance is 66 MW. If a 3σ risk level is used to determine the quantity of needed reserve, the wind portion of that would increase from 4.5% of wind capacity (400 MW) to 12.4% of wind capacity (1,600 MW) using the best load forecast and the worst wind forecast.

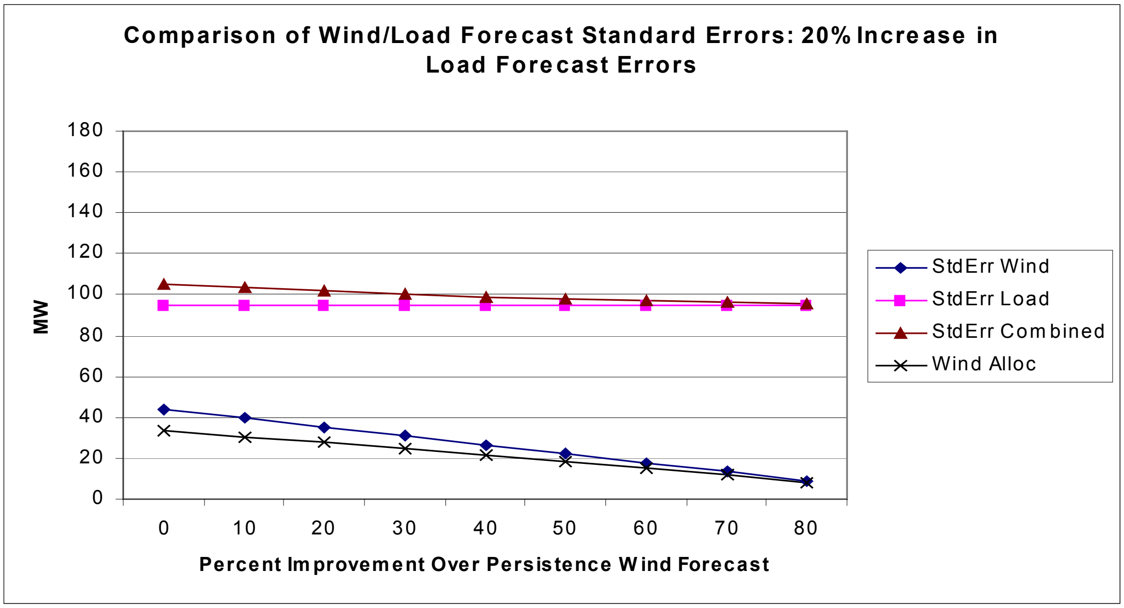

FIGURE 14. STANDARD DEVIATIONS FOR LOAD AND WIND FORECAST ERRORS COMPARED TO COMBINED FORECAST ERRORS WITH LESS ACCURATE LOAD FORECASTS. 800 MW WIND CAPACITY.

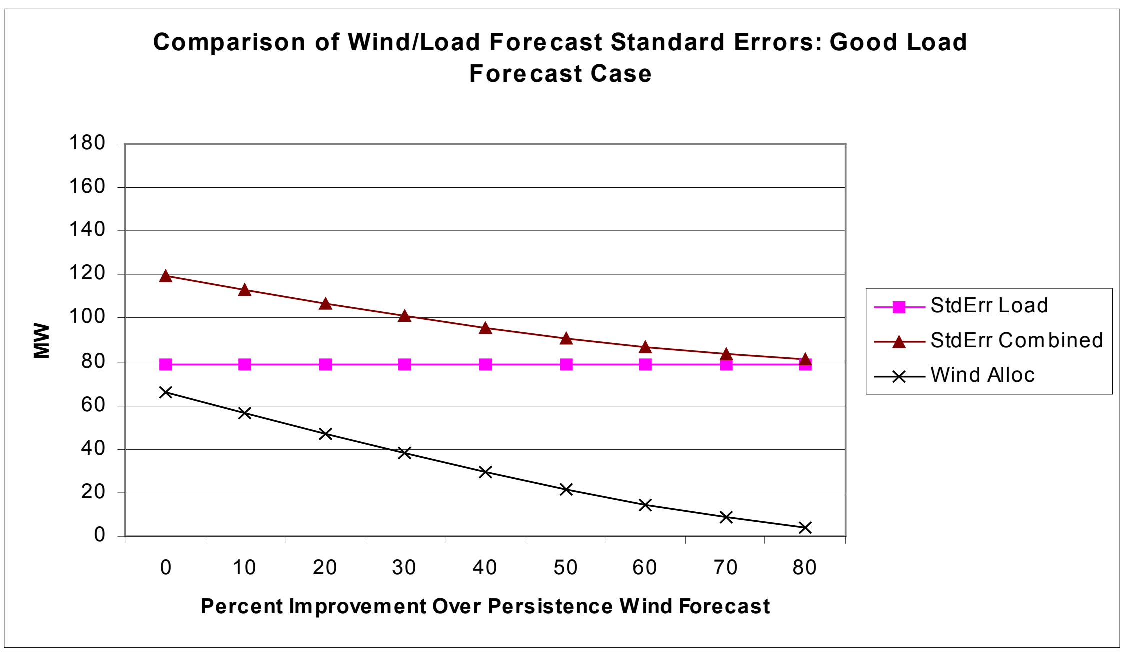

FIGURE 15. STANDARD DEVIATIONS FOR LOAD AND WIND FORECAST ERRORS COMPARED TO COMBINED FORECAST ERRORS WITH ACCURATE LOAD FORECASTS. 1600 MW WIND CAPACITY.

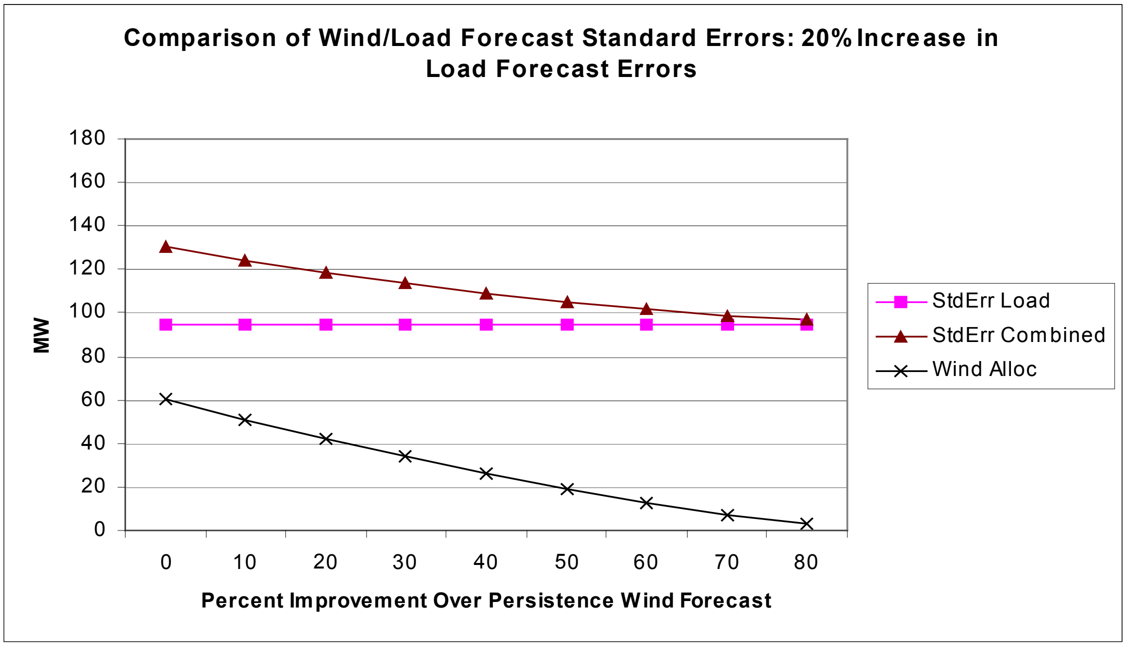

FIGURE 16. STANDARD DEVIATIONS FOR LOAD AND WIND FORECAST ERRORS COMPARED TO COMBINED FORECAST ERRORS WITH LESS ACCURATE LOAD FORECASTS. 1600 MW WIND CAPACITY.

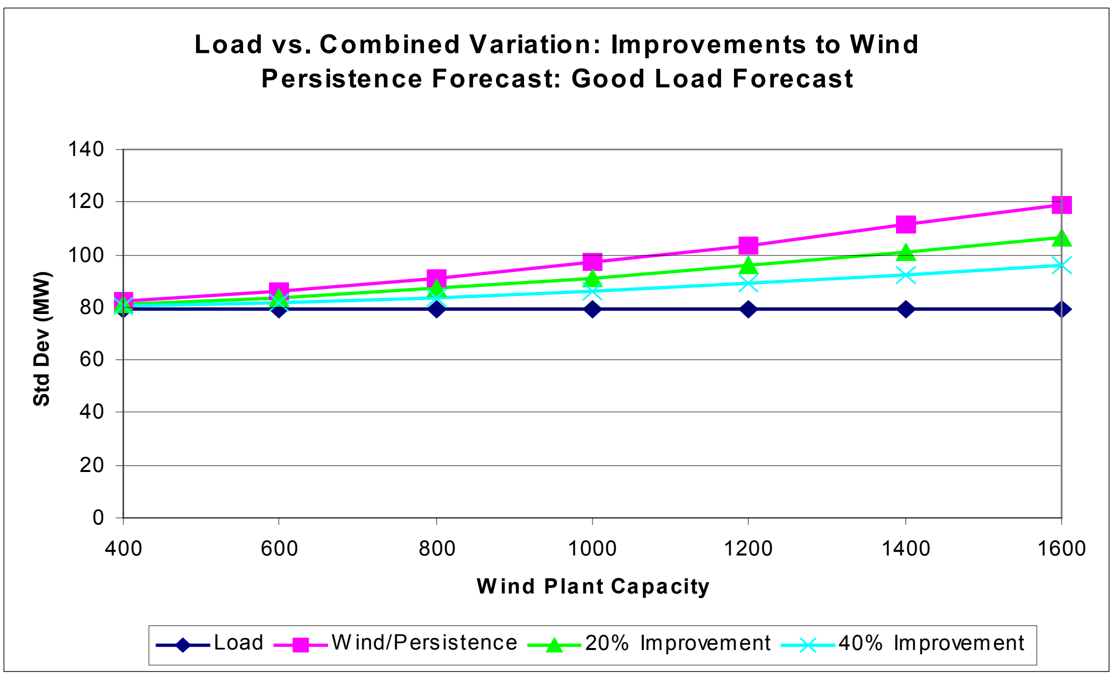

FIGURE 17. SYSTEM IMBALANCE IMPACTS OF WIND FOR VARIOUS LEVELS OF WIND FORECAST ACCURACIES AND PENETRATION RATES, ACCURATE LOAD FORECAST.

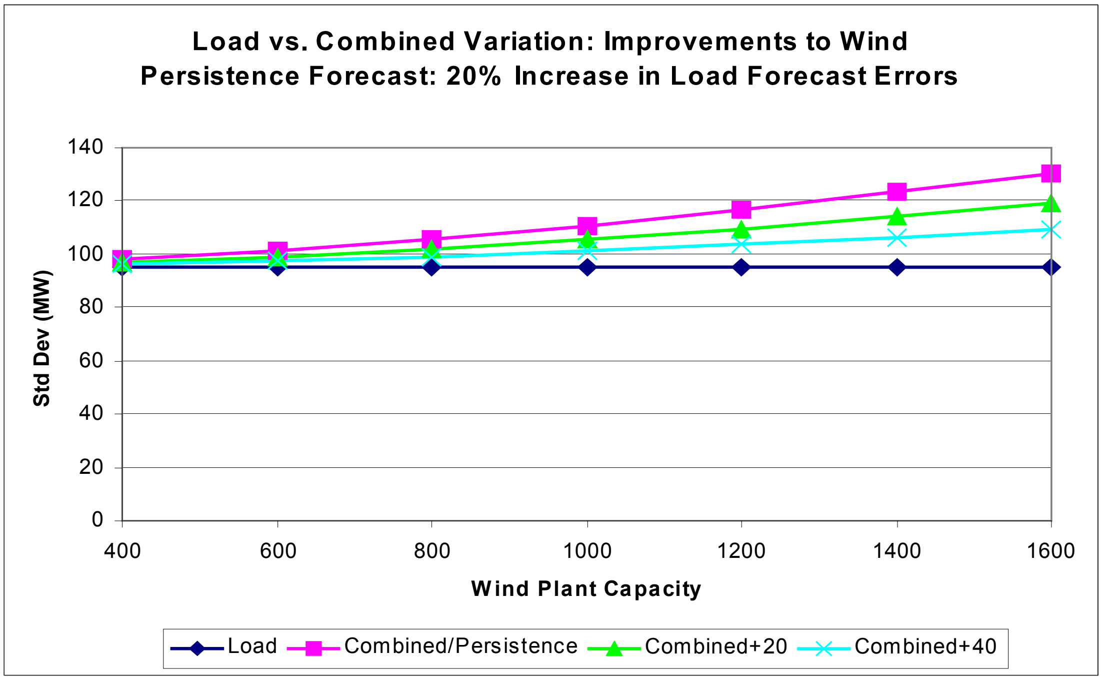

FIGURE 18. SYSTEM IMBALANCE IMPACTS OF WIND FOR VARIOUS LEVELS OF WIND FORECAST ACCURACIES AND PENETRATION RATES WITH 20% LOAD FORECAST DEGRADATION.

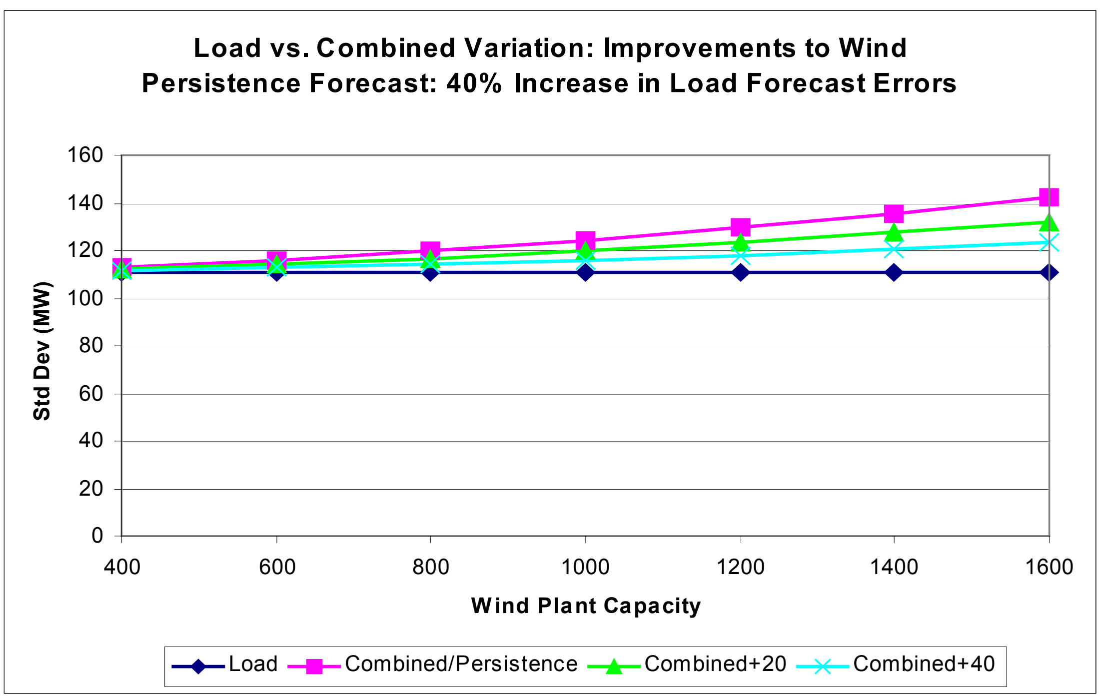

FIGURE 19. SYSTEM IMBALANCE IMPACTS OF WIND FOR VARIOUS LEVELS OF WIND FORECAST ACCURACIES AND PENETRATION RATES WITH 40% LOAD FORECAST DEGRADATION.

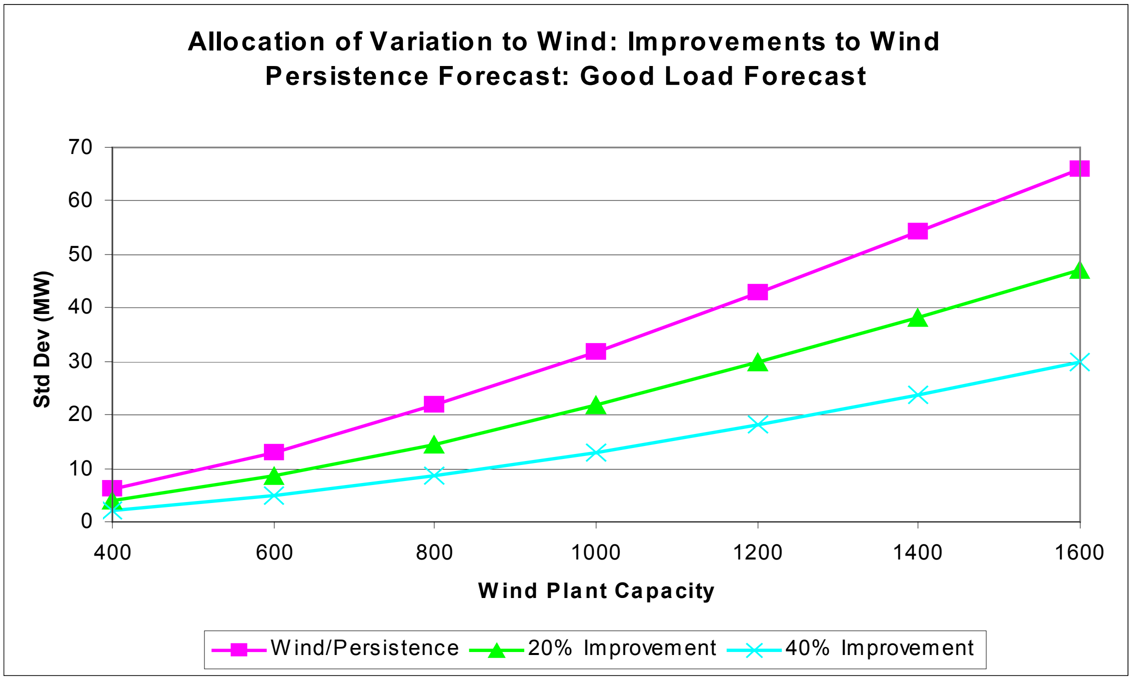

FIGURE 20. ALLOCATION OF SYSTEM IMBALANCE TO WIND FOR VARIOUS LEVELS OF WIND FORECAST ACCURACIES AND PENETRATION RATES USING ORNL VECTOR ALLOCATION METHOD. ACCURATE LOAD FORECAST.

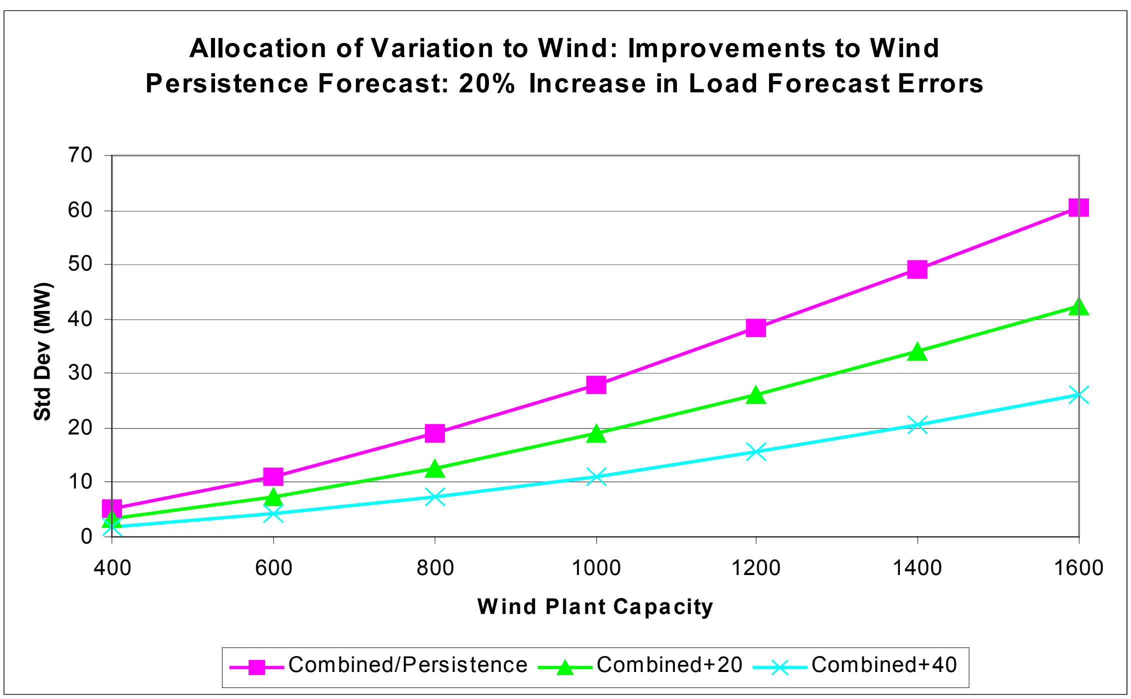

FIGURE 21. ALLOCATION OF SYSTEM IMBALANCE TO WIND FOR VARIOUS LEVELS OF WIND FORECAST ACCURACIES AND PENETRATION RATES USING ORNL VECTOR ALLOCATION METHOD. 20% DEGRADATION IN LOAD FORECAST ACCURACY.

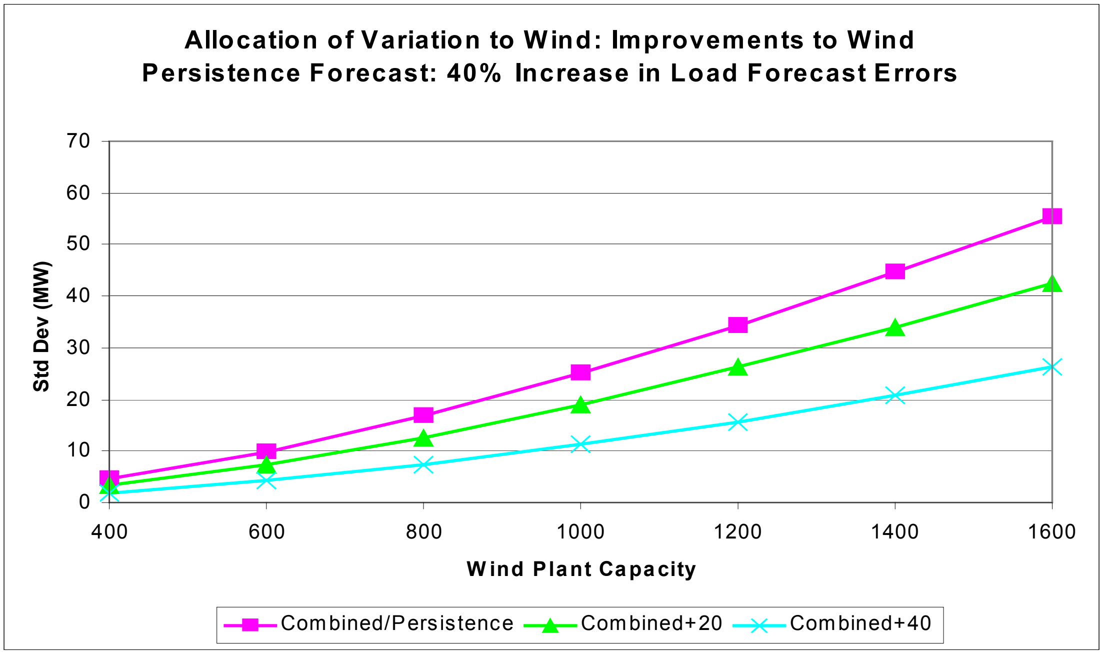

FIGURE 22. ALLOCATION OF SYSTEM IMBALANCE TO WIND FOR VARIOUS LEVELS OF WIND FORECAST ACCURACIES AND PENETRATION RATES USING ORNL VECTOR ALLOCATION METHOD. 40% DEGRADATION IN LOAD FORECAST ACCURACY.

CONCLUSIONS

Wind power plants can have a significant effect on load following and imbalance. However, the results in this paper indicate that those effects are very small at low wind penetration rates and increase nonlinearly with penetration. There may be times when the wind and load move in opposite directions, but the data used for this project never once suggested that a standby unit with the same capacity as the wind plant would be necessary to counter the swings in wind. In systems that do not have wind plants, there can be significant load following requirements. When wind is added to the mix, these load following requirements do change, but as a very small percent of the total at small penetration rates. Without considering the effects of forecast errors, and assuming very small geographic dispersion of the wind capacity, allocation of this impact ranges from just over 1% of wind plant rated capacity (at 400 MW, 5.7% of peak load) to about 3.6% (at 1,600 MW, 22.7% of peak load). Geographic dispersion of the wind capacity improves this, especially at higher penetration rates. These results are summarized in Figure 9.

Forecast errors for wind and load will cause very short run changes to the load following requirements. For U.S. utilities today, Figure 21 might represent a reasonable scenario of a moderately high level of load forecast accuracy. When wind output is predicted using a commercial forecasting model, a 20% improvement over persistence would appear to be possible to achieve. Depending on the load forecast and wind forecast accuracies, Figures 20-22 can suggest appropriate ranges of imbalance at various penetration rates.

In this paper, I use the ORNL vector allocation method to determine wind's share of impacts on load following and imbalance. This method is independent of the ordering of the individual components (load and wind in this case) and does not make any assumptions about whether the two signals are correlated. It recognizes that each individual load and each generator do not need to be balanced; rather, the total system must be in balance. When there is a reduction in both wind and load, it makes no sense to increase another unit to make the wind output look flat because that would require additional and needless down-ramp from another unit.

There are some caveats to this analysis. It would be better to use actual wind farm output from many locations to estimate the effect of geographic dispersion. Although data are available for some wind plants, this is the exception, so geographical dispersion can't now be analyzed in this framework. The analysis looks at a range of scenarios, but all are based in Iowa. Additional studies that look at other areas would have value.

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13. ABSTRACT *(Maximum 200 words)*

Because wind is an intermittent power source, the variability may have significant impacts on system operation. Part of the difficulty of analyzing the load following impact of wind is the inadequacy of most modeling frameworks to accurately treat wind plants and the difficulty of untangling causal impacts of wind plants from other dynamic phenomena. This paper presents a simple analysis of an hourly load-following requirement that can be performed without extensive computer modeling. The approach is therefore useful as a first step to quantifying these impacts when extensive modeling and data sets are not available. The variability that wind plants add to the electricity supply must be analyzed in the context of overall system variability. The approach used in this paper does just that. The results show that wind plants do have an impact on load following, but when calculated as a percentage of the installed wind plant capacity, this impact is not large. Another issue is the extent to which wind forecast errors add to imbalance. The relative statistical independence of wind forecast errors and load forecast errors can be used to help quantify the extent to which wind forecast errors impact overall system imbalances.

14. SUBJECT TERMS

wind energy; load following; system variability; wind forecasting; forecasting errors; wind power plants

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