# The Relationship between Wind Energy and System Operator Actions to Ensure Power Grid Reliability: Econometric Evidence from the 50Hertz Transmission System in Germany

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**Abstract –** This paper examines whether the integration of wind energy into a power system has any implications for the actions taken by a system operator to ensure reliability. The issue arises because the stability of an electricity control area requires that the supply of electricity match electricity demand at all times, not merely on average. Maintaining stability is greatly facilitated by having accurate forecasts of both supply and demand. Forecasts errors impose a "cost" on the power system because intervention by the system operator is required when actual energy levels are not equal to the forecasted levels. Large forecast errors also have implications for the level of operational uncertainty.

The analysis focuses on the 50Hertz transmission control area in Germany (formerly Vattenfall), a power system accounting for approximately 41% of Germany's installed wind energy capacity. Over the sample period of 1 November 2008 through 31 December 2009, wind energy in 50Hertz accounted for approximately 20.4 percent of consumption. Evidence that the errors in forecasting wind energy in this control area are very large relative to the errors in forecasting load is presented. An econometric model is formulated to evaluate the effect of wind energy on power system operations. The empirical analysis indicates that the wind energy forecasting errors have operational consequences. The results also suggest that the higher is wind energy's share of forecasted demand, the more likely it is that the system operator will need to undertake measures to ensure "safe, secure, and reliable operations." More specifically, the presence of wind energy raises the probability of such measures by a factor of 15 relative to the counterfactual case of no wind energy.

Keywords: Climate Change, Renewable Energy, Wind Energy, Wind Forecasting, 50Hertz, EnWG.

JEL Codes: Q2, Q4, Q5

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## 1. Introduction

Because of the environmental concerns associated with fossil fuel use, there is considerable support for increasing the share of electric power generation attributable to wind energy. In the United States, California has recently approved legislation which requires that one-third of the state's electricity come from renewable sources by 2020. Much of the increase is expected to come from wind, with wind energy capacity expected to be almost 13,000 MW, five times its 2007 level (Hawkins, 2008). The European Union has a goal of 20 percent renewable energy by 2020 with wind energy serving as a key source of the increase needed to meet the target. In particular, Denmark ambitiously plans to reach 100 percent renewable energy by 2050 with wind energy expected to play a key role in the transformation (Richardson, et al., 2011).

Heal (2010) has observed that the current renewable energy goals are not based on an economic analysis of the likely effects and he laments the lack of a comprehensive literature on the economics of renewable energy. Joskow (2010) has taken an impressive first step in remedying this deficiency by providing evidence that the "levelized cost" per MWh supplied is an inappropriate metric for comparing the cost of intermittent generating technologies with conventional dispatchable generating technologies. Of particular relevance to our research is Joskow's sense that though the current work on the operational challenges posed by large scale entry of wind generating capacity to meeting network reliability criteria "…is reasonably well advanced, …more needs to be done." (Joskow, 2010, p. 4)

In this paper, we formulate and estimate an econometric model to determine whether the integration of wind energy into a power system has any implications for power system reliability. Milborrow (2007, p 32, 36) and Delucchi and Jacobson (2011, p 1170-1171) have hypothesized that higher wind energy penetration levels may enhance the reliability of a power system by reducing the dependency on large conventional generating plants that could go offline with no advance notice. However, consistent with Heal's assessment of the current state of the literature, they offer no evidence to support their claim. Likewise, Moselle (2010) simply hypothesizes that concerns about renewables and adverse power system stability are …"probably exaggerated" (Moselle, 2010, p. 60).

The literature is particularly deficient in terms of assessing the accuracy of the wind forecasts. For example, Boyle (2010, p 25) reproduces a figure from Lange *et al*. (2007) that presents day-ahead forecasted and actual wind energy for one month in Germany and writes "As can be seen, the difference between the forecast and monitored power output is relatively small." But as almost all energy economists would attest, a simple graph of one month of data can be a poor means by which to evaluate the accuracy of a forecasting system.

Our research begins by pointing out that optimality in the production, transmission, and distribution of electricity requires that prices reflect all costs. In terms of power system reliability, the empirical evidence indicates that the costs of unmet electricity demand can be very high (Sanghvi, 1982; De Nooij *et al.*, 2007 ). We also remind readers that the stability of an electricity control area requires that electricity supply match electricity demand at all times, not just on average. Specifically, when electricity supply is not equal to demand, the observed level of system frequency will deviate from the established setpoint value which is 60 Hertz (Hz) in North America and 50 Hz in most of the rest of the world. Departures from this target value can compromise the stability of the transmission system. System frequency falls when demand exceeds supply and rises when demand is less than supply. Maintaining system frequency at its target value is greatly facilitated by having accurate load forecasts. However, maintaining frequency at its setpoint value can at times be a daunting challenge even when the load forecasts are reasonably accurate. National Grid, the system operator in the United Kingdom, has described it as "a bit like trying to keep a car at 50mph while driving up and down hills." In practice, system frequency varies around the target setpoint value with fairly strict "operational limits." For example, in the UK, the operational limits are 50 Hz +/- 0.2 Hz. When load forecasts are inaccurate, when generators unexpectedly go offline, or when actual electricity flows between control areas are not equal to scheduled flows, system frequency is kept within the operational limits by deploying balancing power. For example, in the synchronous power grid of Continental Europe, a system that serves most of the European Union, primary control reserves are expected to be fully activated following a quasi-steady state deviation of system frequency of +/- 200 mHz from the target value (European Network of Transmission System Operators for Electricity, 2009, p. 5).

Since wind energy is not fully dispatchable, system operators integrate it into operations by forecasting wind energy production levels. The accuracy of the forecasts is critical because of the system frequency considerations discussed above. We recognize that electricity storage may someday make the issue of electricity market balancing a trivial matter, but that day most likely remains in the distant future. Despite its ambitious plan, Denmark has concluded that energy storage considerations are likely to preclude achieving 100 percent wind energy by 2050 [Richardson, *et al*. (2011)].

We address the issue of wind energy's effect on power grid operations using high frequency data from the 50Hertz (formerly Vattenfall) transmission system operator (TSO) in Germany. All of the data were downloaded from 50Hertz's Website: http://www.50hertz-transmission.net/cps/rde/xchg/trm_de/hs.xsl/index.htm. In terms of granularity, the data are reported at 15 minute intervals for the period 1 November 2008 through 31 December 2009. Over this period, wind energy accounted for approximately 20.4 percent of electricity consumption in the 50Hertz control area. This makes the analysis particularly relevant since a 20 percent wind energy share is entirely consistent with the targets being set by regulators in both Europe and United States. The remainder of the paper is organized as follows.

Section 2 offers a discussion of wind energy and reliability actions in 50Hertz. The measurement and magnitude of forecasting errors are covered in section 3. Section 4 presents an econometric model of the likelihood of extraordinary balancing actions in the 50Hertz network. The multivariate regression results are reported and discussed in section 5. Section 6 offers a brief summary and concluding remarks.

## 2. Wind Energy and Reliability Actions in 50Hertz

50Hertz is the system operator of the 380/220 kilovolt transmission grid throughout the German Federal States of Thuringia, Saxony, Saxony-Anhalt, Brandenburg, Berlin, Mecklenburg-Western Pomerania, and Hamburg (Figure 1). It takes its name from the European system frequency's setpoint value of 50 Hz.

Within the 50Hertz network, wind farm capacity in October 2009 was about 10,000 MW and represented more than 40 percent of Germany's total wind energy capacity (50Hertz, 2010). Wind energy accounted for 20.4 percent of total electricity consumption and approximately 17.4 percent of total generation. According to the company's 2009 annual report, wind energy capacity in the control area is expected to increase to over 18,000 MW by 2017 with a substantial portion of the increase accounted for by the development of offshore wind resources (Vattenfall, 2010).

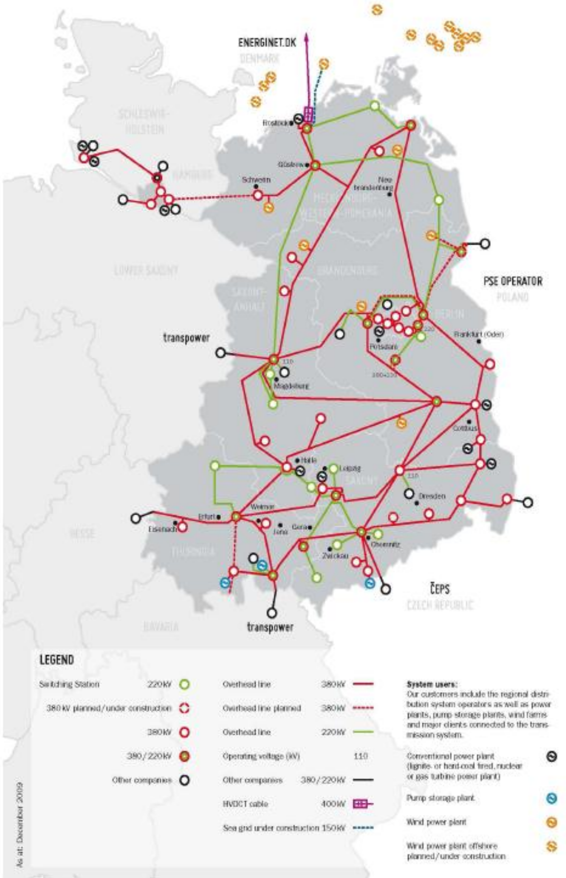
As system operator, 50Hertz is responsible for accepting and transmitting all fed-in energy in compliance with the German Renewable Energy Sources Act (EEG). 50Hertz is also obliged to maintain balance between power generation and demand within its control area. It traditionally meets this goal by scheduling generation on a day-ahead basis based on its load forecast as well as deploying balancing energy during the operating day. The three categories of balancing (or control) power include primary, secondary, and tertiary control. Primary and secondary control power are almost always activated. ". Control power is dispatched "up" when the system is short of generating resources and "down" when there is excess supply. Tertiary power is dispatched only when primary and secondary control power are insufficient to resolve the imbalance. In general, these forms of control power are non-locational in nature, and thus are less than ideal in managing transmission congestion within the control area. This can be an important issue with respect to wind energy integration since the wind farms in 50Hertz tend to be located in the northern portion of the control area while the major load centers are further south. Investments have been made in upgrading the transmission system but the growth in transmission capacity has lagged the growth in wind energy capacity. As a result, there are occasions when there is more wind energy than the transmission system can accommodate. For this reason, 50Hertz also takes actions under S.13.1 and S.13.2 of the German Energy Industry Act (EnWG). These actions are justified as necessary to ensure "safe, secure, and reliable operations." They include the re-dispatch of generating units, the modification of power feed-ins, electricity transits, and electricity off-takes from the transmission system. These interventions can be location specific and thus provide the system operator with the ability to manage transmission congestion within the control area. Details of one such intervention on 25-26 December 2009 are documented in "*Report of the Management System of Measures and Adjustments under Energy Act§ 13, during the Period of Strong Winds in the period 25/12/2009 to 26/12/2009*" (50Hertz, 2009). At one point during this event, the actual level of wind energy was more than 1,800 MW higher than forecasted and exceeded the level of electricity consumption in the entire control area by over 750 MW. To accommodate the oversupply of wind energy, significant levels of both secondary control power and minute reserves were dispatched down. For example, during hour 19 on 25 December 2009, a total of almost 1,100 MW of secondary and minute reserves were dispatched downward. During this same hour, 2,290MW of EnWG actions were implemented. Consistent with the aforementioned report, 50Hertz's discussion of its EnWG actions is couched in terms of the challenge of ensuring the stability of the power grid when the share of electricity consumption accounted for by wind energy is high. 50Hertz's 2009 annual report is remarkably candid on this point:

> "The installed capacity of wind power generation in the 50Hertz Transmission control area had reached approximately 10,500 megawatts (MW) at year-end2009. The installed wind power capacity had therefore risen 820 MW, or 8.5%, on the previous year by the end of December 2009. Against this backdrop, the principal challenge was to control the fluctuations in considerably increased wind power feeding such as to consistently guarantee system security. The maximum reached in terms of simultaneous feeding from wind power plants in the 50Hertz Transmission control area during the financial year was 9,081 MW on 18 November 2009. To guarantee safe and secure system operation in the control area of 50HertzTransmission, network- and market-related measures according to section 13, subsection 1 EnWG had to be resorted to ever more frequently. Ranging even to the point of re-dispatch and adjustments according to section 13, subsection 2 EnWG, these measures were necessitated by the growing discrepancy between the high installed wind generation capacity (approx. 41% of capacity installed in Germany) and the relatively low electricity consumption (approx. 20% of all-German consumption). Network extension projects have failed to keep pace with this development."(50Hertz, 2010, p 10)

The 25 December 2009 event is not unique with regard to wind energy production exceeding total consumption. Over the sample period, there were 304 market periods in which this occurred. While some might view these events as representing simply too much of a good thing, every one of these cases required EnWG actions and the downward dispatch of minute reserves. Over the period 1 November 2008 – 31 December 2009, EnWG actions were undertaken in about 22 percent of the 15 minute reporting periods. The median action was 1,000 MW. In five percent of the cases, the action by the system operator exceeded 3,180 MW; in one percent, the action exceeded 4,155 MW. In section 4 below, we offer an econometric model to examine the impact of high wind energy penetration levels on the likelihood of EnWG actions by 50Hertz.[2]

[2]Analysis of the magnitudes of the actions is deferred for future work. We also do not distinguish between actions undertaken under S.13.1 of the legislation as opposed to S.13.2.

**Figure 1. The 50Hertz Control Area in Germany**




## 3. Wind Energy Forecasting

It is widely believed that there have been many advances in forecasting wind energy. This view has been expressed explicitly by the North American Electricity Reliability Corporation (NERC), whose mission it is to ensure the reliability of the high voltage power system in North America. In NERC's own words:

> Forecasting the output of variable generation is critical to bulk power system reliability in order to ensure that adequate resources are available for ancillary services and ramping requirements. The field of wind plant output forecasting has made significant progress in the past 10 years. The progress has been greatest in Europe, which has seen a much more rapid development of wind power than North America." (NERC, 2009, p. 54)

Results reported by Lange, *et al*. (2006) seem consistent with NERC's assessment. According to their analyses, the root-mean-squared-errors (RMSE) of the day-ahead wind energy forecasts for the E.ON Netz control area (now TenneT) in Germany declined from approximately 10 percent of installed wind capacity in 2001 to approximately six percent of installed wind energy capacity in 2006. This finding has been cited by several studies including Cali, *et al*. (2006) and Giebel ,*et al*. (2011, p. 25), as well as by the European Wind Energy Association (2007) as evidence that wind power is a reliable source of electricity supply. Consistent with the reported decline in the RMSE relative to installed capacity, Milligan, *et al.* (2009), drawing on research from Germany, argues that it is a myth that wind energy is difficult to forecast.

Though we are certainly receptive to the proposition of substantial advances in wind energy forecasting, we remain at a complete loss to explain why any researcher would weight the RMSEs by installed wind energy capacity. An example is perhaps useful. Consider a control area with 10,000 MW of installed wind energy capacity and a mean level of wind energy production of 2,500 MW. Further, suppose that the root-mean-squared-error (RMSE) of the wind forecast equals 750 MW. Based on this hypothetical data, the capacity weighted RMSE equals 7.5 percent (0.075 = 750/10,000). In contrast, the energy weighted RMSE in this case would equal 30 percent (0.30 = 750/2500). In our view, the only purpose served by reporting a 7.5 percent capacity weighted RMSE for this hypothetical control area is to make the forecast error appear small. At a minimum, the practice is questionable since it precludes comparison of the accuracy of wind forecasts with that of load forecasts. In our view, it is far more relevant to evaluate the errors in terms of MW of energy since the energy market imbalance is in terms of MW of energy, not MW of energy weighted by capacity. Consider the relationship between actual and forecasted wind energy in November 2009 depicted in Figure 2. At first glance, the forecast accuracy may appear remarkable. However, closer inspection of the figure reveals instances in which the error in 50Hertz's day-ahead wind forecast was well over 1,000 MW. In terms of the need to balance exactly energy supply with demand, how large a 1,000 MW forecasting error is relative to installed capacity is irrelevant. The histogram of the day-ahead wind energy forecast errors for the period 1 November 2008 – 31 December 2009 shown in Figure 3 also indicates that the forecast errors in MW of energy can be quite large. For one percent of the 15 minute reporting periods, the actual wind energy produced was greater than the forecasted level by approximately 1860 MW; for another one percent, the actual wind energy produced was less than the forecasted level by approximately 1,475 MW. The RMSE of the wind forecasts over this period equals approximately 624 MW, approximately 34 percent of the average level of wind energy production. In a relative sense, this is considerably larger than the 11 percent error in forecasting load (Table 1). To be sure, the RMSE of the demand forecast in MW is larger than the RMSE of the wind forecasts (1190 MW vs. 624 MW). But unless the accuracy of the wind forecasts improves significantly, it is likely that the RMSE of the wind forecasts measured in MW will at some point exceed the RMSE of the demand forecasts measured in MW given the expected increases in wind energy penetration over the next few decades.

To the extent that a system operator receives and acts upon any revised forecasts, the forecasting errors may have little, if any, impact on operations. However, evidence from the ERCOT power grid in Texas indicates that the errors in wind forecasting are highly correlated across hours, i.e., the errors in the hour-ahead forecasts are highly correlated with the errors in the previous day-ahead forecasts [Forbes, *et al.* (2010)]. This finding is consistent with our preliminary analysis of the wind forecasts in the Republic of Ireland over the period 28 March 2008 through 15 August 2010 for which the correlation between the one-hour ahead and 24 hour ahead wind energy forecasts is approximately 0.94. Based on these findings, the day-ahead forecasts errors in 50Hertz may be an adequate proxy for any revised forecasts.

Before proceeding, we readily concede that there is some legitimacy to the claim that there have been significant advances in forecasting wind energy. As recently as 2005, the data from 50Hertz indicates that the RMSE of wind forecasting errors in 50Hertz was approximately 50 percent of the mean level of wind energy production. However, despite the decline to 34 percent by 2009, we believe that there exists room for improvement. Indicative of this, our preliminary analysis of the wind forecast errors in 50Hertz as well as in other control areas indicates that the errors have a systematic component. For example, the magnitude of the errors varies both by hour of the day and month of the year. There is also preliminary evidence that the errors are dependent on a number of variables including ambient temperature, relative humidity, air pressure, and other non-meteorological factors. Modeling the systematic component, a topic beyond the scope of this paper, may make it possible to generate revised forecasts that are more accurate.

**Figure 2. Forecasted and Actual Wind Energy Production Levels in 50Hertz, November 1 - 30, 2009**

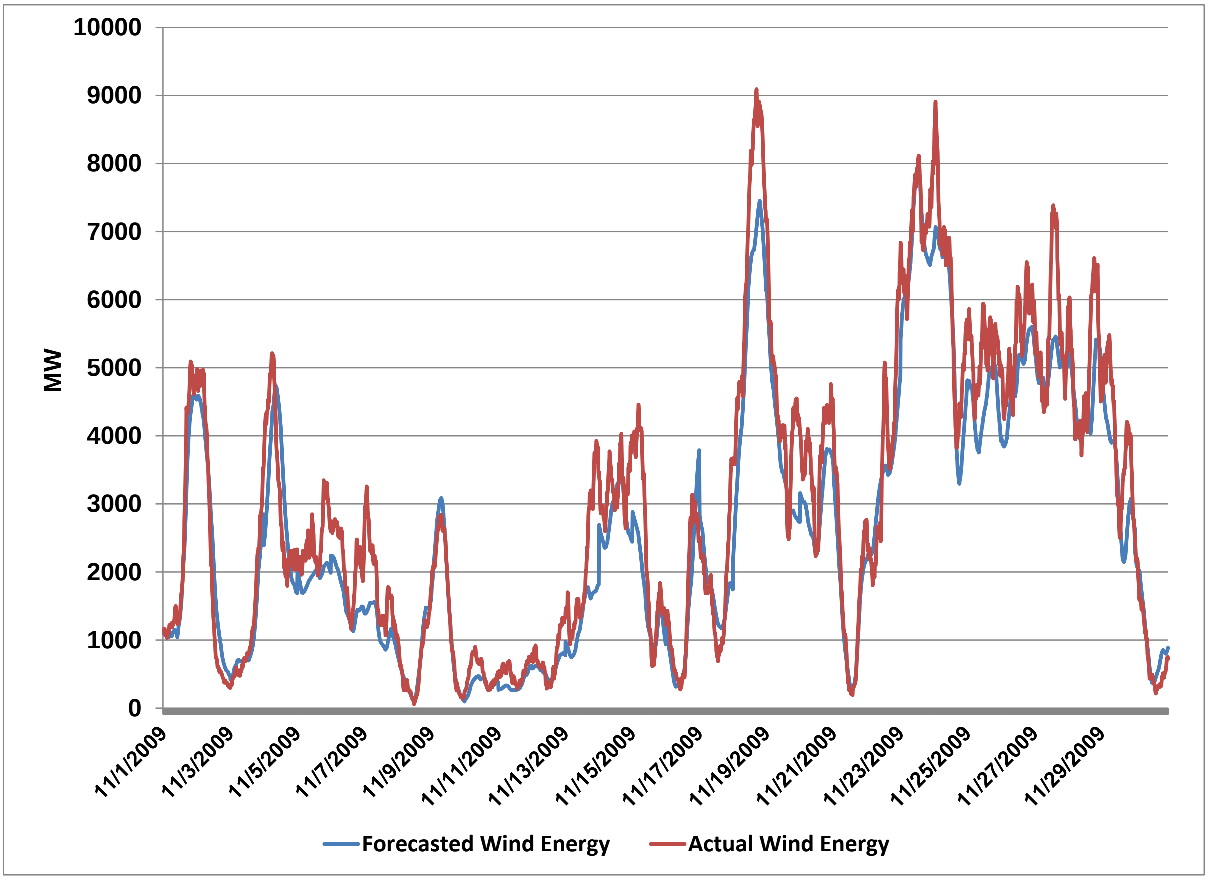


**Figure 3. A Histogram of the Day-Ahead Wind Forecasting Errors in the 50Hertz Power Grid in Germany, 1 November 2008 – 31 December 2009**

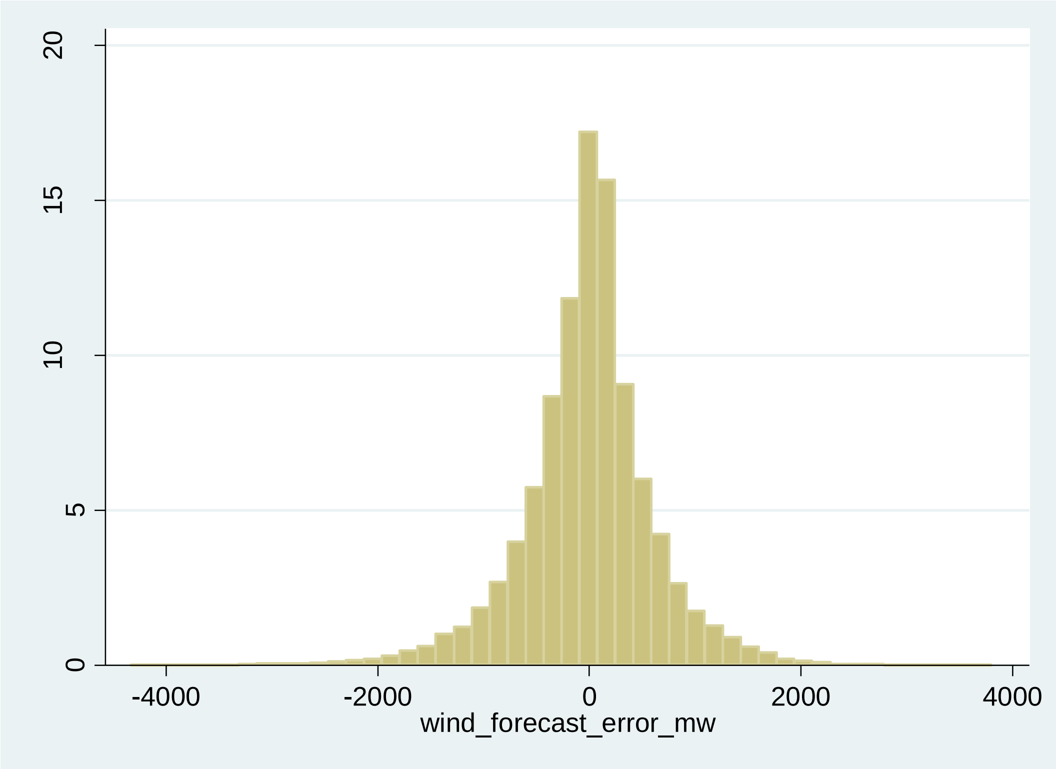



**Table 1 - Day-Ahead Forecasting Errors in 50Hertz, 1 November 2008 – 31 December 2009**

| | **Root Mean Squared Error in the Day-Ahead Forecast** | **Root Mean Squared Error of the Forecast as a Percent of the Mean Level of Activity** |
|---|---|---|
| Demand Forecasting | 1190 MW | 11.0 % |
| Wind Energy Forecasting | 624 MW | 34.2 % |
| Based on 40,601 observations. Source: 50Hertz | | |

## 4. Modeling the Likelihood of EnWG Reliability Actions

We hypothesize that the need for intervention by the system operator is largely a function of the expected activity levels and the deviation between actual and expected levels of both electricity demand and supply. Specifically, the probability of an EnWG reliability action by

50Hertz is hypothesized to be a function of forecasted load, the share of forecasted electricity demand accounted for by forecasted wind energy, the errors in load forecasts, and the errors in wind energy forecasts. Because of possible asymmetries, our model distinguishes between positive and negative forecasting errors. Since the dependent variable is binary, estimation using least squares is inappropriate. As Greene points out, the least squares specification could yield a predicted probability that is negative, a result that is obviously nonsensical [Greene, 2008, p. 773]

The functional form is presumed to be best represented by the binomial complementary log-log model, a nonlinear specification widely used in examining the contribution of factors that influence the probability of an uncommon binary event. Algebraically, the model is given by:

$$\begin{aligned} Ln(-\ln(1-p_t)) = c + \alpha_1 FDemand_t + \alpha_2 FWindshr_t \\ + \alpha_3 NegDemandError_t + \alpha_4 PosDemandError_t \quad (1) \\ + \alpha_5 NegWindError_t + \alpha_6 PosWindError_t \end{aligned}$$

where $p_t$ is the probability that the system operator will respond to a reliability challenge in reporting period t. The transformation on the left-hand side of (1), the complementary log-log, takes a number that is restricted to the (0, 1) interval and converts it into a value that has no upper or lower bound [Allison (1999), p. 3.10]. Consequently, the estimated equation is nonlinear, with the marginal impact of any single independent variable contingent on the values of the others. The variables on the right hand side of equation (1) are defined as follows:

- $\boldsymbol{FDemand_t}$ is the forecasted level of electricity demand for period t;
- $\boldsymbol{FWindShr_t}$ is the share of forecasted demand in period t accounted for by forecasted wind energy;

- ***NegDemandError$_t$*** equals the absolute value of the difference between the forecasted and actual level of demand when the forecasted level of demand is less than actual. It is zero otherwise;
- ***PosDemandError$_t$*** equals the absolute value of the difference between the forecasted and actual level of demand when the forecasted level of demand is greater than actual and zero otherwise;
- ***NegWindError$_t$*** equals the absolute value of the difference between the forecasted and actual level of wind energy in period t when the forecasted level of wind energy is less than actual and zero otherwise;
- ***PosWindError$_t$*** equals the absolute value of the difference between the forecasted and actual level of wind energy in period t when the forecasted level of wind energy generation is greater than actual wind energy and zero otherwise.

## 5. Estimation and Results

Equation 1 was estimated using maximum likelihood with robust standard errors. The results are reported in Table 2. Regarding the model's explanatory power, we note that it is not possible to calculate a meaningful conventional R-squared because the dependent variable is binary while the predicted values are probabilities. A number of alternative scalar fit measures have been introduced. According to Greene (2002, E15-28), these measures ''… share the flaw that none satisfactorily mimic the true measure of the proportion of variation explained given by $R^2$ in the linear regression context." McFadden's R-squared is one of the more commonly reported measures of scalar fit when the dependent variable is binary. Its value here is 0.508indicating that the log-likelihood function, the objective function whose maximization yields the estimated parameters, improves by almost 51 percent as compared to when the model is estimated with only a constant term as the explanatory variable. The percent of correct predictions is likely a more meaningful measure of the scalar fit. Using

0.5 as the threshold for a prediction, the percentage of correct predictions when EnWG actions are predicted equals 86.65% while the percentage of correct predictions when normal system status is predicted is 90.71%. With respect to the parameter estimates, the coefficient on the variable *FDemand* is positive indicating that the probability of an EnWG action is higher the higher is the level of forecasted demand. The coefficient on *FWindShr* is positive and highly statistically significant indicating that the probability of an EnWG action is higher the higher is the share of forecasted demand accounted for by forecasted wind energy. The coefficient on *PosDemandError* is negative and statistically significant. One explanation for this result is that the transmission system is less congested than expected when forecasted demand is greater than actual. Consistent with this view, the coefficient on *NegDemandError* is positive and statistically significant indicating that EnWG actions are more likely when forecasted demand is less than actual demand. This is consistent with expectations since the transmission system is more likely to be congested when actual demand exceeds the forecasts. The coefficient on *PosWindError* is negative and highly statistically significant indicating that EnWG actions are less likely whenever the forecasted level of wind energy exceeds actual wind energy production. This is consistent with expectations since a shortfall of wind energy reduces any wind energy induced transmission congestion within 50Hertz, making EnWG actions less necessary. The shortfall itself can be resolved by the traditional balancing instruments, the upward dispatch of primary, secondary, and tertiary control power. The coefficient on *NegWindError* is positive and highly statistically significant indicating that EnWG actions are more likely whenever the forecasted level of wind energy is less than actual wind energy production. Again, this is consistent with our expectations. When forecasted wind energy is less than actual there is likely more wind energy than the transmission system can safely accommodate inducing the system operator to respond by implementing EnWG actions. We suspect the balancing market is also impacted but defer our analysis of this for future work.

**Table 2**
**Estimation Results for Equation 1**

| Variable | Estimated Coefficient | T-Statistic | P-Value |
|---|---|---|---|
| **C** | -6.3545 | 54.8 | ~0 |
| **FDemand** | 0.0002 | 17.4 | ~ 0 |
| **FWindShr** | 10.0881 | 85.0 | ~ 0 |
| **PosDemandError** | -0.7459 | 5.5 | ~ 0 |
| **NegDemandError** | 4.7995 | 22.0 | ~ 0 |
| **PosWindError** | -0.0002 | 5.4 | ~ 0 |
| **NegWindError** | 0.0009 | 29.6 | ~ 0 |
| **Number of observations** | 40,594 | | |
| **Number of Nonzero Observations** | 8,912 | | |
| **McFadden's $R^2$:** | 0.508 | | |
| **Percentage of Correct Predictions when EnWG actions are predicted** | 86.65 % | | |
| **Percentage of Correct Predictions when normal system status is predicted** | 90.71 % | | |
| Reported t-statistics are robust to heteroskedasticity | | | |

One of the disadvantages of the complementary log-log functional form is that the estimated coefficients are difficult to interpret. Fortunately, one can readily calculate elasticities using STATA 12 (Table 3). Inspection of Table 3 indicates that the predicted probability of an EnWG event is elastic with respected to the levels of forecasted activity but inelastic with respect to the actual forecasting errors. Our interpretation of this result is that the EnWG actions are largely driven by the level of operational uncertainty which can be proxied by the levels of forecasted activity. The magnitudes of the estimated elasticities suggests to us that it may not be insurmountable to forecast the probabilities of EnWG actions on a day-ahead basis given the level of forecasted demand and the forecasted share of demand accounted for by (forecasted) wind energy.

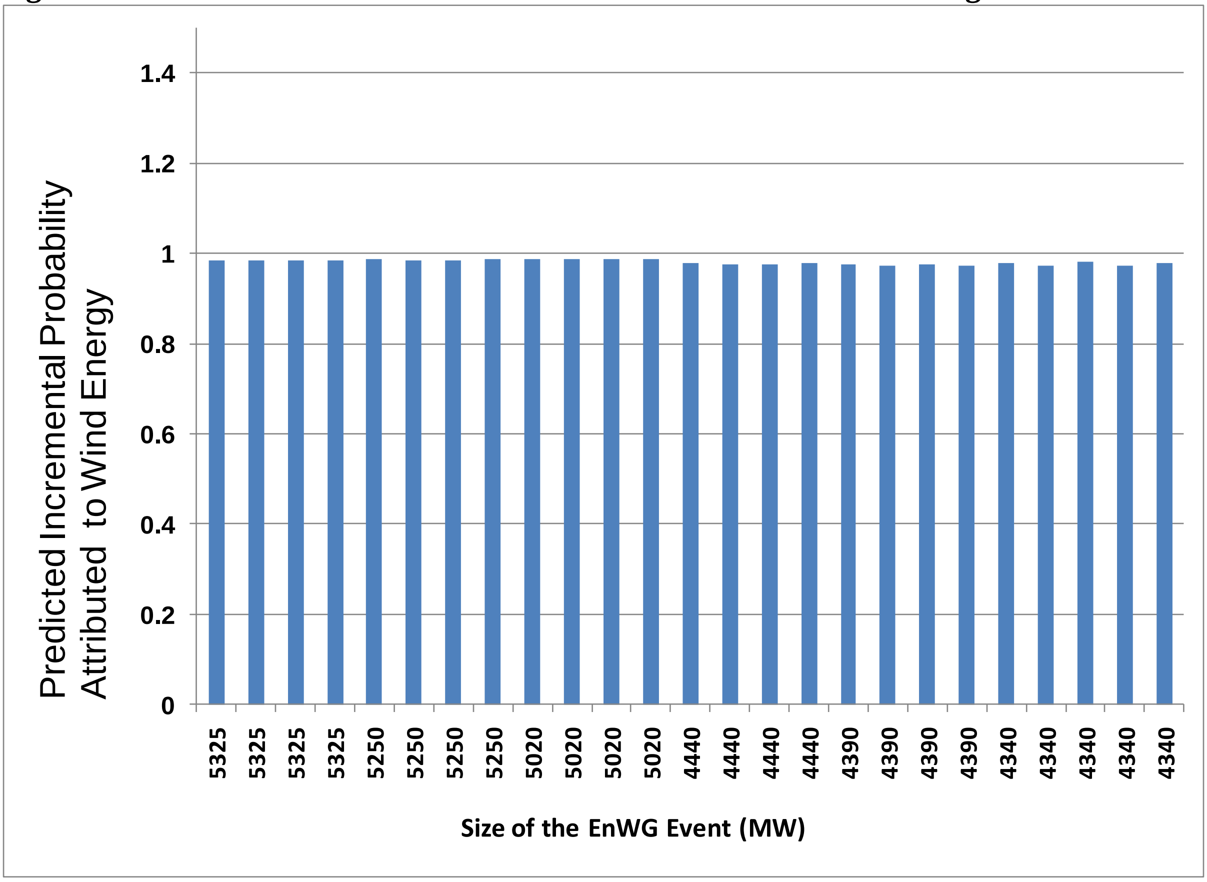
**Table 3**
**Estimated Elasticities Corresponding to the Coefficients Reported in Table 2**

| Variable | Estimated Elasticity | T-Statistic | P-Value |
|---|---|---|---|
| **FDemand** | 1.521 | 17.39 | ~0 |
| **FWindShr** | 1.260 | 102.48 | ~0 |
| **PosDemandError** | -0.035 | -5.46 | ~0 |
| **NegDemandError** | 0.201 | 22.88 | ~0 |
| **PosWindError** | -0.033 | -5.33 | ~0 |
| **NegWindError** | 0.150 | 33.25 | ~0 |

We use the estimated coefficients reported in Table 2 to simulate the probabilities of EnWG actions in the base case scenario (with variables at their observed values) and in the counterfactual of zero forecasted wind share and zero wind forecasting errors (with all of the other variables held equal to their actual values). The average predicted base case probability is 0.2164 while the average counterfactual likelihood is 0.0147. The difference represents the magnitude of wind's energy challenge to reliability, i.e., on average, wind energy in the 50Hertz system raises the probability of an EnWG event by a factor of about 15.

Figure 4 depicts the wind related incremental probabilities for 25 large EnWG events. For each of these events, the model's predicted probability of the event occurring was equal to 1.00. The predicted wind related incremental probability, the height of the bars for each of the EnWG events, is the portion of the predicted probability that the model attributes to wind energy. Note that for all of these events this incremental portion due to the presence of wind power is estimated to be over 90 percent. The EnWG actions on 25-26 December 2009 that were noted earlier are also correctly predicted by the model. For example, EnWG actions in hour 19 on 25 December 2009 were 2290 MW in magnitude. The model predicted the probability of these actions occurring to be 1.00. The predicted wind related incremental probability for each of the 15 minute intervals during this hour is approximately 0.988.

**Figure 4 - Predicted Wind Related Incremental Probabilities for25 Large EnWG Events**




Note: In each case in the above figure, an EnWG event occurred and the calculated probability of an EnWG event occurring is equal to 1.00.The predicted wind related incremental probability is the portion of the predicted probability that the model attributes to wind energy.

### 6. Conclusions

In response to Heal's call for more analysis of the economics of renewable energy, this paper has examined whether the integration of wind energy into a power system has any implications for the actions taken by a system operator to ensure reliability. The paper has presented evidence that the day-ahead wind forecasts by 50Hertz, a transmission system in Germany with approximately 20 percent wind penetration, are significantly less accurate than its day-ahead load forecasts. The econometric analysis indicates that the errors have operational implications. The analysis also indicates that the higher the level of forecasted demand and the higher the share of forecasted demand accounted for by forecasted wind energy, the more likely it is that the system operator will find it prudent to undertake nontraditional measures to maintain reliability. The estimates indicate that a wind energy penetration rate of approximately 20 percent raises the probability of such measures by a factor of 15, relative to a counterfactual of no wind energy penetration.

Based on this finding, it may not be unfair to conclude that ensuring power grid reliability in the 50Hertz power system over the sample period was significantly more challenging than "keeping a car at 50mph while driving up and down hills." Thus, even in the absence of Joskow's findings with respect to the market value of wind energy, it would seem that there is little merit in comparing the levelized cost of wind energy with conventional dispatchable energy unless the costs calculations include a rigorous treatment of reliability issues.

In terms of future research, it will be interesting to see whether these findings are consistent with the experiences of other control areas. It will also be interesting to see whether analysis of the wind energy forecasting errors may make it possible to construct revised wind energy forecasts that have lower errors. Based on the recent findings reported by Forbes and Zampelli (2011) with respect to load forecasting errors, we are cautiously optimistic that modest reductions are achievable. Given the elasticities reported in Table 3, we are also optimistic about the feasibility of forecasting reliability actions based on day-ahead information.

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