Wind Power Forecasting Error Distributions: An International Comparison

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Wind Power Forecasting Error Distributions

An International Comparison

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Abstract— **Wind power forecasting is essential for greater penetration of wind power into electricity systems. Since no wind forecasting system is perfect, a thorough understanding of the errors that may occur is a critical factor for system operation functions, such as the setting of operating reserve levels. This paper provides an international comparison of the distribution of wind power forecasting errors from operational systems, based on real forecast data. The paper concludes with an assessment of similarities and differences between the errors observed in different locations.**

Keywords-wind power forecasting; power system operation; power system reliability; power systems; wind power generation

I. Introduction

The amount of wind power being incorporated into power systems worldwide has been increasing dramatically over the past decade. Wind power has no fuel costs and zero emissions, which means that its increased presence in power generation portfolios provides great benefits to society. However, wind power is a variable and uncertain power resource, in contrast to traditional thermal power units. This has led to concerns from utilities and system operators about how increasing amounts of wind power will be handled in system operations [1]. One way to reduce the uncertainty surrounding wind power output is through wind power forecasting systems. Typical systems used in operational forecasting consist of one or more Numerical Weather Prediction models (NWP) that provide forecasts of wind speed on a grid over a geographic area, coupled with statistical techniques that translate the forecasts to local wind plant conditions and convert forecasted wind speed to power [2]. While these forecasts provide system operators with an expected wind power output level at future times, they are not perfect forecasts. Understanding the magnitude and frequency of the wind power forecasting errors can facilitate the integration of wind power through advanced operational techniques, for example, setting dynamic reserve levels [3, 4] or using stochastic unit commitment models [5, 6], or through simply increasing operator awareness. Power system operations are already designed to handle a certain degree of variability and uncertainty since load is itself both variable and uncertain [7]. Therefore it is the large and infrequent wind power forecasting errors with which we are most concerned. Large forecasting events can lead to major economic inefficiencies through non-optimal commitment schedules.

Wind power forecast errors are often a concern in wind integration studies and stochastic unit commitment models. Many of these studies assume that the forecast error distribution follows a normal distribution [3, 8, 9]. However, this is an overly simplistic assumption for most forecasting methods and timescales examined [10, 11]. Other distributions have been examined, including the Weibull [12] and beta [13] distributions, however in this work we utilize the hyperbolic distribution [10]. We analyze the forecast error distributions observed in a number of different countries and electrical systems, and at two different timescales that are important in the unit commitment and economic dispatch process. Comparisons are made between the different cases and conclusions on the importance of the differences for power systems operations with higher wind power penetrations are drawn.

II. Methods and Data

In this study statistical analysis techniques are applied to wind power forecasting data taken from seven different countries. Day-ahead wind power forecasts were supplied for six countries, or balancing areas within a country. Hour-ahead wind power forecasts were utilized for one country-wide system, and for one large wind plant in a balancing area. The hyperbolic distribution parameters were fitted to the data using a maximum likelihood method.

Mean, μ, and variance (represented here by the standard deviation), σ, the first two standardized moments, are frequently used in the characterization of wind forecasting error distributions. They provide important information about the distribution, however, considering the third and fourth statistical moments can provide additional information [10, 14, 15]. Skewness, γ, is the third moment and is a measure of the probability distribution's asymmetry. Kurtosis, κ, is the fourth moment and describes the magnitude of the distribution's peak. Conversely, kurtosis can also be thought of as a measure of the thickness of the tails of the distribution. A distribution with a high kurtosis value is leptokurtic and one with a low kurtosis value is platykurtic. Leptokurtic distributions have more pronounced peaks, slimmer shoulders, and longer tails than normal distributions with identical first two moments. In what follows we will refer to excess kurtosis, the kurtosis above that of the normal distribution, simply as kurtosis.

We utilize some standard statistical tools such as histograms, quantile-quantile (Q-Q) plots, and cumulative distribution function plots. It is important to note that the forecast errors have been normalized, based on the wind power capacity, for the sake of comparison. Therefore all of the forecast errors lie on the interval from -1 to 1. The Q-Q plots shown here are normal Q-Q plots that compare the observed distribution to a Gaussian distribution with the same mean and standard deviation as the observed distribution. They include a line that runs through the first and third quantiles of the observed distributions. If the two distributions are identical the line should pass through all of the points in the observed distribution. The cumulative distribution plots show how likely a random error from the distribution will be less than or equal to the magnitude selected.

III. System Operations with Forecasts

Wind power forecasting plays an important role in reducing the uncertainty of wind generation. Forecasts may be included directly in the unit commitment and economic dispatch scheduling process used to ensure that enough generation is available to meet forecast load, or they may simply provide situational awareness for the balancing authority. Day-ahead forecasts are often required for the unit commitment process, since the starting of large thermal units can often take 24 hours or more. The forecasted wind power output at this timeframe can be used to optimize the availability of other generation units over the course of the following day. The economic dispatch process sets the final power output for units that are online, and is performed closer to the time of realization, often one hour-ahead Variability and forecast errors at smaller timescales are often compensated with reserves held for that purpose. Since wind forecasts can be helpful to system operations in both the unit commitment and economic dispatch phases, we will examine the wind power forecasting errors that occur at these two timeframes, in this paper represented by day-ahead and hour-ahead forecasts.

IV. Error Distributions from Operational Systems

In this section we examine the wind power forecast error distributions observed in a total of seven countries at the day-ahead and hour-ahead timescales. In this work we follow the convention that the error is equal to the forecast minus the realized value.

A. Day-Ahead Forecasts

1) United States

Day-ahead forecasts for the United States are taken from the ERCOT interconnection in Texas for the year 2010, with an installed wind capacity of approximately 9,000 MW. As seen in Figure 1, the distribution is leptokurtic, though not dramatically so, with a significant negative skew. The distribution also has a fairly large spread, with minimum and maximum error values above half of the installed capacity. The red line represents a normal distribution with the same mean and standard deviation as the observed errors. Figure 2 shows that the distribution is poorly represented by the normal distribution. The observed error distribution has a more pronounced peak, slimmer shoulders and fatter tails than the corresponding normal distribution. This is shown as an example of the differences between the observed error and normal distributions, the other day-ahead forecasting Q-Q plots show similar features.

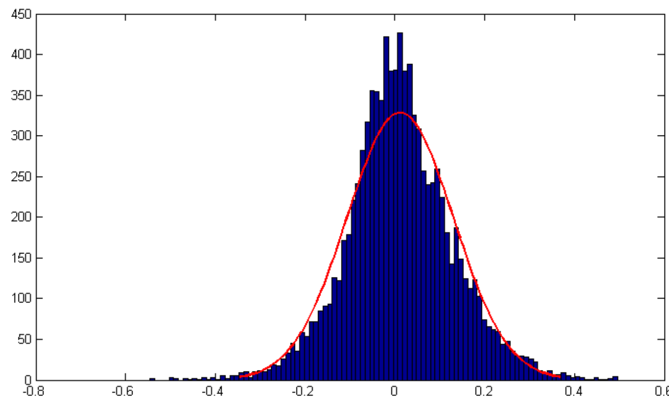

Figure 1. Histogram of the normalized day-ahead forecast errors for the ERCOT system. $\mu = 0.0117$; $\sigma = 0.1187$; $\gamma = -0.616$; $\kappa = 1.0308$.

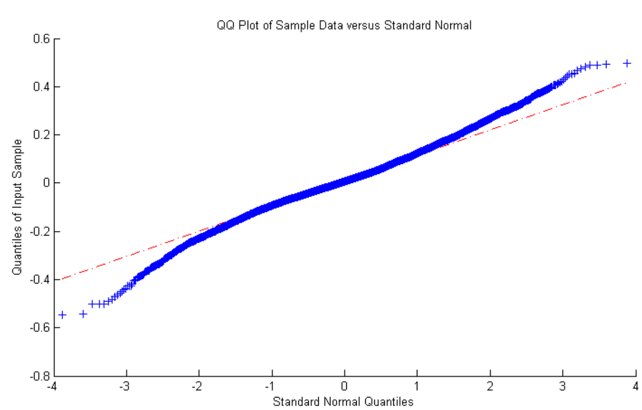

Figure 2. Normal Q-Q plot of the ERCOT day-ahead forecast errors. If the observed errors were well represented by a normal distribution, all observations would lie on the straight line.

2) Finland

The Finnish installed wind capacity is the smallest in the study, with 102 MW of rated power. However, the capacity is spread over 25sites (77 turbines) with the largest distance between the sites being 630 km. Figure 3 shows the slightly positively skewed and leptokurtic distribution of observed wind power forecasting errors for the Finnish system. The distribution includes a number of fairly large positive forecast errors (overforecasting), with a few exceeding half of the installed capacity. This may be the result of the smaller number of turbines included in this dataset, and possibly erroneous data used in producing the forecasts.

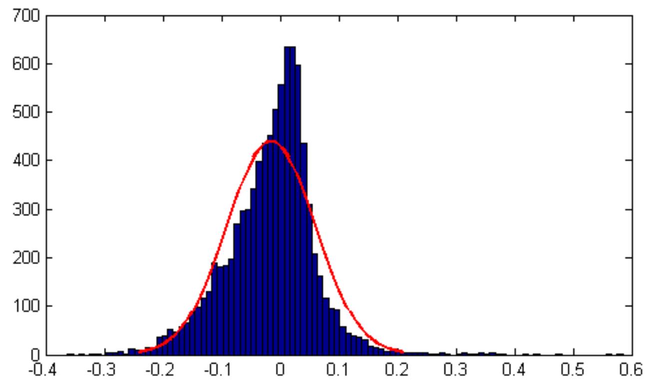

Figure 3. Histogram of the normalized day-ahead forecast errors for the Finnish system. $\mu = -0.0155$; $\sigma = 0.0751$; $\gamma = -0.0720$; $\kappa = 3.1036$.

3) Spain

The Spanish installed wind power forecasting error histogram is shown in Figure 4. This data is from the year 2010 and includes 19,300 MW of wind power capacity. The distribution is leptokurtic and fairly strongly positively skewed. The forecasts also display a notable bias, corresponding to over 15% of the installed wind power capacity. The distribution also has distinctly fat-tails in both the over and under forecasting directions.

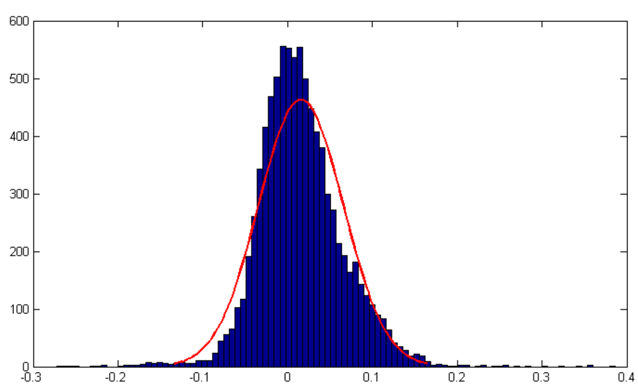

Figure 4. Histogram of the normalized day-ahead forecast errors for the Spanish system. $\mu = 0.0162$; $\sigma = 0.0514$; $\gamma = 0.3855$; $\kappa = 3.0180$.

4) Sweden

The day-ahead forecasts for the Swedish system (year 2011) include 2,899 MW of installed wind capacity. The distribution of forecast errors plotted in Figure 5 shows a slightly leptokurtic negatively skewed distribution. The Swedish errors are interesting for their fairly small spread, with the largest errors being less than 30% of the installed wind capacity. This is likely due to the large amount of geographic diversity stemming from the multiple sites over a large geographic area. It is also interesting to see that the normal distribution would under-represent the negative error tail, but over-represent the positive error tail, because of the skewness of the distribution. Figure 6 shows the cumulative distribution function of the observed errors, the normal distribution based on those errors, and a hyperbolic distribution fit to the observed errors. It is readily apparent that the hyperbolic distribution provides a superior fit to the data than does the normal distribution, with the hyperbolic line running on top of the observed errors line for much of the cumulative distribution function. The Swedish example was chosen to display the cumulative distribution plot due to the clear example it shows of the improved fit of the hyperbolic distribution. However, other cumulative distribution functions would have similar characteristics.

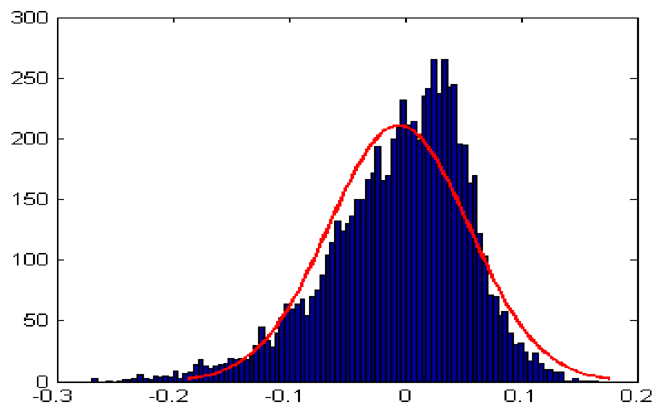

Figure 5. Histogram of the normalized day-ahead forecast errors for the Swedish system. $\mu = -0.0052$; $\sigma = 0.0603$; $\gamma = -0.7252$; $\kappa = 0.7757$.

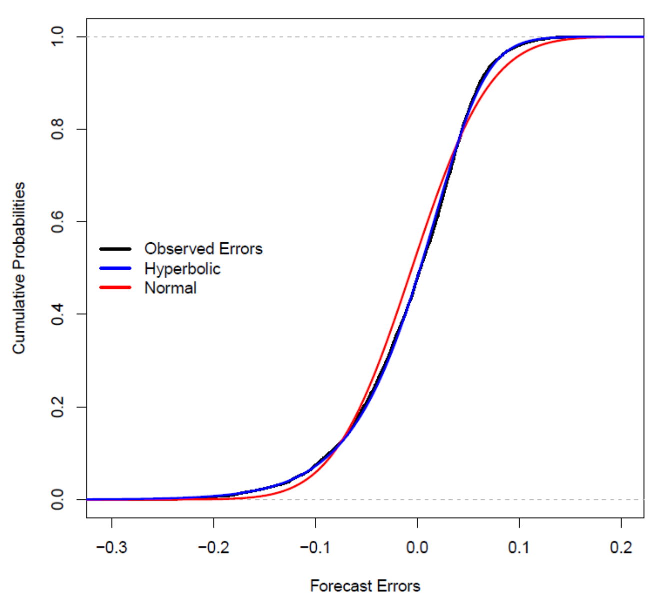

Figure 6. Cumulative distribution plot of the normalized Swedish day-ahead forecast errors.

5) Denmark

The Danish system data includes 3,871 MW of installed wind capacity for the year 2011. The distribution is more strongly leptokurtic than many of the other day-ahead forecast error distributions examined previously, as seen in Figure 7. Also in contrast to the other countries, the distribution is fairly symmetric, with only a slightly positive skew. The spread of the data is fairly small with relatively few errors greater than 25% of the total installed capacity. This is likely a result of the geographic diversity acquired from the turbines being spread throughout the country.

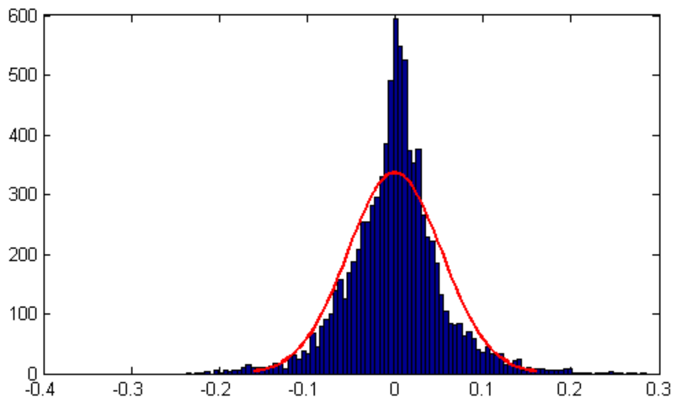

Figure 7. Histogram of the normalized day-ahead forecast errors for the Danish system. $\mu = -0.0005$; $\sigma = 0.0534$; $\gamma = 0.1378$; $\kappa = 2.3859$.

6) Ireland

The Irish data is from the year 2011 and includes 1,557 MW of installed wind capacity. The Irish day-ahead forecasting errors have a small positive skew, and are leptokurtic, as seen in Figure 8. There is a fairly large spread to the distribution with a significant amount of forecast errors approaching 50% of the installed wind power capacity. This is likely due to the small geographic area covered by the wind turbines. For reference, the total land area of Ireland is roughly 1/6th the land area of Sweden, and 1/5th that of Germany.

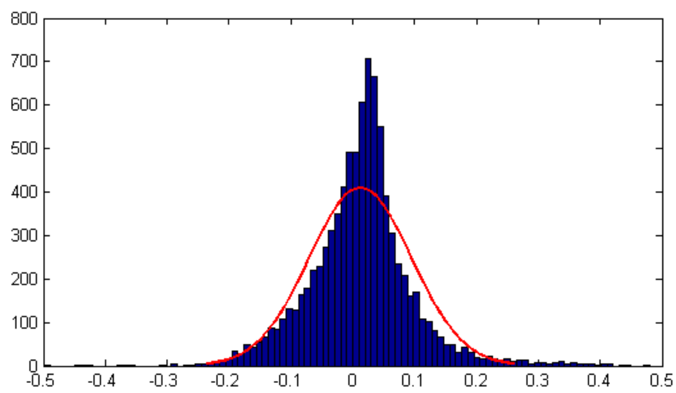

Figure 8. Histogram of the normalized day-ahead forecast errors for the Irish system. $\mu = -0.0123$; $\sigma = 0.0827$; $\gamma = 0.3063$; $\kappa = 3.0311$.

7) Germany

The German data is from the year 2010 and covers the total installed wind capacity in Germany ranging from 25.18 GW in January 2010 to 26.39 GW in December 2010. The power measurement is based on an up-scaling algorithm based on spatially distributed reference wind farms that include about 25% of the total capacity. The forecasts are used and published by the German TSOs and are based on combinations of power forecasts from different providers and on different NWP models. The day-ahead forecasting errors have a slightly negative skew, and are leptokurtic, as seen in Figure 9. The spread of the data is relatively small with all errors less than 30% of the installed wind capacity. This is due to the large number of turbines included in the analysis, as well as the geographic spread of the locations used.

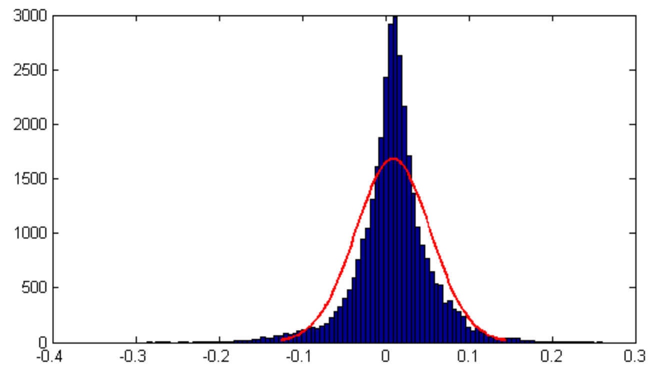

Figure 9. Histogram of the normalized day-ahead forecast errors for the German system. $\mu = 0.0092$; $\sigma = 0.0450$; $\gamma = -0.2891$; $\kappa = 3.5896$.

B. Hour-Ahead Forecasts

In power system scheduling short-term wind power forecasts are necessary to set the generating unit output levels in the dispatch process, which often coincides with intraday market timing. These shorter term forecasts are used to reduce the uncertainty from the day-ahead forecasts, and consequently, only these forecast errors must be balanced by reserve power [16]. While the dispatch interval may vary between systems, we will use a one hour interval as a representative example.

1) United States

The US hour-ahead forecast error distributions come from a single wind plant in the Xcel Colorado service territory with approximately 300 MW of capacity. As this data comes from a single plant, the benefits of geographic diversity will not be apparent. This is clear when looking at the extreme values seen in Figure 10. The maximum errors for the single plant are approximately 80% of the total capacity. It must be noted that these large values are likely due to the manual curtailment of wind plant output. These hour-ahead forecasts also have a much greater kurtosis value than the day-ahead forecasts observed in the previous section. The practical implication of this is that the forecasts are often more accurate, but have occasional instances when they are very inaccurate.

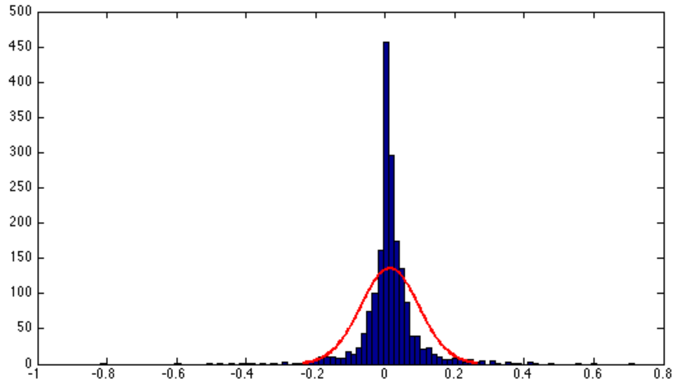

Figure 10. Histogram of the normalized day-ahead forecast errors for the Xcel Colorado wind plant. $\mu = -0.01$; $\sigma = 0.08$; $\gamma = -0.01$; $\kappa = 17.62$.

2) Spain

The hour-ahead forecasts for the Spanish system include 20,091 MW of wind power capacity, the second largest amount in this study. Figure 11 shows the histogram of the forecast errors. One important aspect to note is the smaller range of values seen in the Spanish data, with forecast errors over 10% of capacity being very rare. Part of the explanation is that the forecasts are hour-ahead instead of day-ahead forecast data; the smaller forecasting interval reduces the uncertainty in the forecast considerably. The fat tails seen in figure 11 result in a poor fit to the normal distribution. Further verification of this finding is provided by the normal Q-Q plot seen in the dramatic deviations in the tails seen in figure 12.

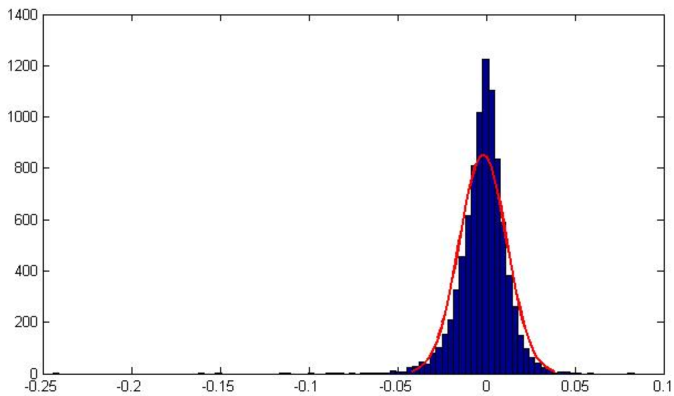

Figure 11. Histogram of the normalized hour-ahead forecast errors for the Spanish system. $\mu = -0.0018$; $\sigma = 0.0133$; $\gamma = -1.6585$; $\kappa = 20.2385$.

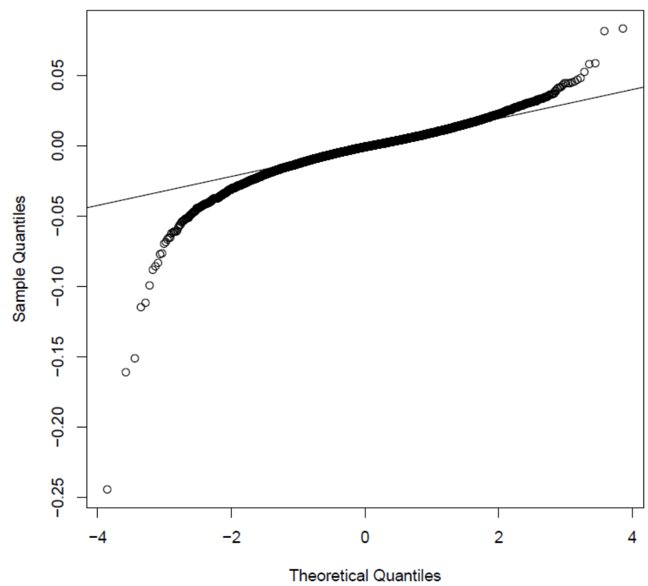

Figure 12. Normal Q-Q plot of the Spanish hour-ahead forecast errors. If the observed errors were well represented by a normal distribution, all observations would lie on the straight line.

3) Germany

The hour-ahead forecasts for the German system are for the same set of wind plants described in the day-ahead section. The histogram of the hour-ahead forecast errors can be seen in figure 13. The spread of the errors is very small with no errors above 10% of the installed capacity. As mentioned for the Spanish system, the large amount of wind turbines considered (~25 GW), with the resulting geographic diversity, is an important factor in the smaller spread of the error distribution, in addition to the usage of online power measurements that underlie a high quality data check. The distribution is leptokurtic and slightly negatively skewed.

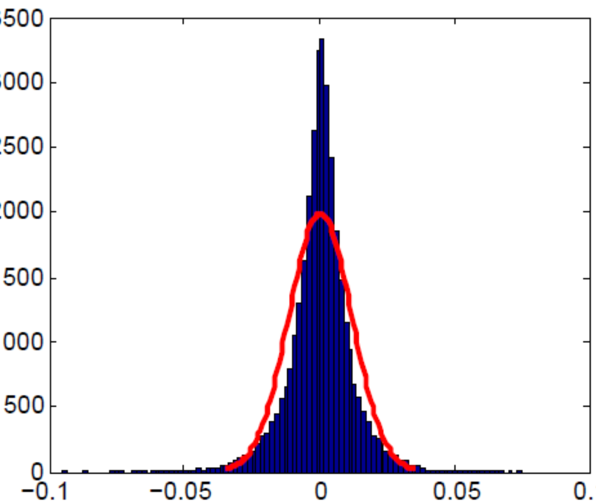

Figure 13. Histogram of the normalized hour-ahead forecast errors for the German system. $\mu = 0.0004$; $\sigma = 0.0116$ $\gamma = -0.2194$; $\kappa = 3.7389$.

V. Comparison

The wind power forecasting errors shown in this study follow at least one common theme, regardless of country, forecasting period, or amount of installed wind capacity considered: they are all leptokurtic distributions that are poorly represented by the normal distribution. However, the distributions shown do vary considerably based on each of the aforementioned criteria. As might be expected the hour-ahead forecasts have much higher kurtosis values than those made at the day-ahead timescale. This would be expected from the reduction in uncertainty that occurs between making a forecast in the day-ahead time frame, versus a single hour ahead. These distributions have many more very small forecast errors, but can still have large forecast errors in extreme cases with high power ramps, as represented by the relatively fat tails of the distributions. Generally speaking, the larger the installed wind power capacity, the smaller the spread of the distribution. This is related to the geographic diversity of having more turbines experiencing different weather conditions at the same time, though one exception of this is the ERCOT day-ahead dataset. Most of the wind capacity installed in Texas is found in a narrow corridor in the northwest panhandle of the state. Additionally, wind turbines in the United States tend to be built in clustered plants, with a high density of turbines in a small area. In some of the European countries considered, the turbines are built in smaller groups, with less dense clusters of wind power. This geographic distance means that the forecasting errors between individual turbines are not as well correlated.

TABLE I. Day-Ahead Forecast Summary

	US	Finland	Spain	Sweden	Denmark	Ireland	Germany
Installed Capacity (MW)	9,000	102	19,300	2,899	3,871	1,557	26,000
Dataset Length (Hours)	9,504	8,760	8,760	7,370	8,760	8,760	8,760
Forecast Horizon (Hours Ahead)	8-32	12-36	1-48	16-40	12-36	6-144	12-48

VI. Conclusion

This study has examined the day-ahead and hour-ahead wind power forecasting errors seen in operating practice in six different countries. The distribution of forecasting errors have been shown to be poorly represented by the normal distribution often assumed in wind integration studies. The distributions were found to be more leptokurtic, with an important distinction being the heavier tails seen in the operational forecast error distributions. These large errors that are not represented by the normal distribution can have a large impact on integration planning studies and system operations due to the greater economic impact of these extreme errors. It is recommended that in future integration studies, typical wind power forecasting error distributions are used to guide the process, instead of making the normal distribution assumption. The hyperbolic distribution has been found in this study to better represent the entire wind power forecasting error distribution. Further investigation is planned on the significance of the differences found in the country-to-country variations of wind power forecasting error distributions. Likely causes of such differences such as country-specific geographic features, forecasting methods, model input parameters, and long-term wind resource quality will be analyzed. In addition, the use of this information can be important in system operations, impacting operational and planning policies. An examination of how these country specific error distributions could impact issues such as wind power curtailment policies and thermal generator flexibility is planned. Additional work is planned on disaggregating the forecast error distributions based on time of day and prevailing weather patterns, in order to extract more useful information for system operations.

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