PREDICTION OF VARIABILITY

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1. Introduction

The variability and predictability of wind and solar power generation presents a great challenge for electric grid operators (ISOs, RTOs, LSEs). Aggregate electricity generation within a control area has to be adjusted in near real time to account for changes in electricity demand and variable generation, comprised mainly of wind and solar power. Sudden changes in output from wind or solar power facilities due to weather changes (i.e. wind speeds or cloud cover) must be balanced by adjusting output from dispatchable power plants to keep total generation equal to demand. For this reason, grid managers use forecasts to estimate the wind and solar generation. Unfortunately, forecasts are uncertain and must be used with caution. In round numbers, day-ahead load forecasts for an area the size of an ISO/RTO are accurate to about 5%, but wind power production forecasts are accurate to no better than 15%.

Large forecast errors potentially create big problems in electric grids. Unexpected increases in variable generation occasionally leads to curtailment of renewable power when these rapid generation changes cannot be balanced quickly enough. A more problematic occurrence is the unexpected loss of wind or solar power. An example of this occurred in Texas in February of 2008. A sudden change in weather occurred earlier than expected and dropped statewide wind generation by over 1 GW in a short time (O'Grady, 2008). Similarly, wind power production in all of BPA dropped from 1.5 GW to zero for a bit more than 11 days in January 2009. Although these are extreme examples, extremes drive the need for other resources, and illustrate the value of wind forecast accuracy. Grid managers use reserve generation to balance supply and demand. The amount of reserve generation needed for large scale wind and solar penetration is a question yet to be adequately answered. Without proper knowledge of forecast uncertainty, the amount of expensive reserve generation cannot be set to an optimal level. This paper focuses on wind generation, but similar conclusions can be made for solar or any other generation that is difficult to predict.

2. Forecast Models

Wind forecasts are created using statistical models, physical models or a hybrid of both. Some methods forecast wind power directly, while others forecast wind speeds and convert them to wind power. Statistical models rely on historical wind data from one or more wind farms to predict future values. These models vary greatly and generally employ time series or neural network analysis methods (Greibel, 2003). Physical models, often referred to as numerical weather prediction (NWP) models, use meteorological data to predict wind speeds (Landberg et al., 2003). Wind speed forecasts are then transformed to power forecasts using a transfer function to model wind farm output. In general, NWP models outperform statistical models for wind power predictions greater than 2 to 6 hours into the future depending on local conditions (Geibel et al., 2003; Landberg et al., 2003). The main drawback of NWP models is their complexity and expense due to large computational power needs. In a hybrid approach, NWP models are refined with statistical models.

3. Forecast Uncertainty

Forecasts are never exact, and the uncertainty of predicted values must be understood in order to effectively use forecasts. Forecast uncertainty is characterized using several calculations including mean average error (MAE), root mean square error (RMSE) and standard deviation of errors (SDE), which are shown below. If the average error, $\bar{e}$, is zero then the RMSE and SDE are equal. In general, forecasts are biased and the value of the average error ($\bar{e}$) is not zero.

$$MAE = \frac{\sum_{i=1}^{N} |e_i|}{N} \qquad RMSE = \sqrt{\frac{\sum_{i=1}^{N} e_i^2}{N}} \qquad SDE = \sqrt{\frac{\sum_{i=1}^{N} (e_i - \bar{e})^2}{N}}$$

The most common way to express the MAE, RMSE and SDE is to normalize it with respect to the wind farm capacity. The result is an indication of forecast accuracy as a percentage of maximum generation. At high wind penetrations, uncertainty indicators can provide a basis to determine how much non-wind generation is needed to balance forecast errors. These indicators are influenced by factors such as wind farm size, local terrain, model selection and weather fluctuations (Monteiro, 2009). Aggregating wind farm forecasts over a large region tends to reduce forecast errors due to spatial smoothing of generation output (Focken et al., 2002; Geibel et al., 2007).

A better understanding of forecast uncertainty is needed. Most forecasts provide point estimates of wind power. The uncertainty of these point estimates is difficult to characterize. Typically, errors from multiple forecasts over a large time period are used to calculate RMSE or MAE values. This method gives an overall indication of forecast uncertainty without considering the inter-temporal dependence of forecast errors between points in the time horizon. It also neglects the dependence of forecast accuracy on different weather conditions and seasons. Furthermore, RMSE and MAE values are insufficient to provide confidence intervals for forecast values.

A more appropriate approach to employing forecasts from the perspective of grid management might be to calculate RMSE or MAE values for different weather conditions. Another alternative would be to consider maximum errors instead of averaging many errors. The risk of blackouts is high during rapid changes in wind generation due to extreme weather conditions. It is during these times that forecast errors tend to be the greatest. Ideally, forecast error probability distribution functions (pdf) conditioned on different weather conditions would be used to determine reserve requirements for wind power. This not only gives an indication of the magnitude of errors but also the sign. Costs to the grid arising from positive forecast errors are not symmetrical to costs from negative forecast errors. Unfortunately, developing closed forms of these pdfs has proven to be a major challenge (Lange, 2005; Bludszuweit et al., 2008).

More analysis of forecast errors is needed to determine contributions of uncertainty. Uncertainty analysis might provide insight into costs and benefits of investments towards improving wind forecasts. It may also allow a better understanding of confidence intervals of point forecasts. This is especially important during times of highly variable winds where uncertainty is greatest. RenewElec can contribute in this area by developing statistical tools useful for estimating the reliability of wind power forecasts. A better understanding of forecast uncertainty would provide grid managers the ability to determine the probability of wind generation shortfall. Through the RenewElec project we will also review the current methods used to calculate reserve requirements based on wind forecasts. And, if necessary, we will propose methods that include probabilistic models used to develop wind forecasts. Finally, we will analyze the costs and benefits of improving wind power forecasts.

4. Conclusions

Although forecasting models are becoming better at predicting wind power, uncertainty will always exist. Good decision making requires a thorough understanding of the uncertainty. Forecast uncertainty needs to be understood over different seasons and weather conditions in order to improve forecasts and make optimal decisions based on forecasts. The ability to determine probabilities of wind shortfalls for different conditions and incorporating these probabilistic models into reserve requirement calculations, will allow more effective use of energy resources.

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