A Temperature-Based Wind Power Model for System Reliability Analyses

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April 18, 2012

Abstract

Wind power models used in stochastic reliability analyses have previously been incorporated independent of load models. This has likely biased reliability metrics established for system planning. Northwest regional data show that load and wind fleet power generation are not independent and that when regional load center temperatures are extreme that the wind fleet power generation tends to be lower. This paper develops a model for wind power that is based on temperatures in the regional load centers. It is then demonstrated in a simulation based on IEEE-RTS that the reliability metrics are biased when independence is assumed.

1 Introduction

As the percentage of load served by wind generation increases in a power system, the ability to accurately assess and plan for the reliability implications becomes critical. Early work in the field incorporated wind generation into reliability assessment using a probabilistic approach to vary the forced outage rate to capture the stochastic nature of wind generation [5]. This approach was then expanded to include autocorrelation as part of the reliability assessment through the incorporation of ARMA or ARIMA wind speed models [2, 4, 12, 13] based on the well-established approximation of the distribution of wind speed using the Weibull distribution [8, 10, 16, 21]. For in-depth information about ARIMA models see Enders [7]. The wind-speed distribution is then translated through a power curve to give a simulated wind power generation. This can be extended to cross-correlated generation profiles for multiple wind sites [20]. Other alternatives for creating synthetic wind-generation time series include using Markov-Chain Monte-Carlo methods [22], using ARIMA methods on wind generation rather than wind speed with adjustments to limit the time series to not exceed the generation nameplate [6] and moving-block bootstrap methods [19].

The common element to all of these methods is that once a synthetic time series is created it is then used or intended for use in a Monte-Carlo simulation of system reliability [3, 18, 24]. The simulation often is then translated into reliability metrics such as Loss-Of-Load Probability (LOLP), Loss-Of-Load Expectation (LOLE) and Loss of Energy Expectation (LOEE). A good description of these metrics can be found in Billinton and Allan [3] or Li [18]. One of these metrics is then chosen to be held constant and a method of either incrementing load or decrementing generation is used to assess the contribution of the wind generation to the reliability of the system [4]. Often one of the stochastic elements in this calculation is a representation of load uncertainty. These

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models likely incorporate regional temperatures especially in population or load centers [11]. Recent observations have indicated that load and wind generation are not independent [15]. This paper further expands upon those observation in section 2.

Thus if the method for creating a sythetic wind power generation time series does not include an estimation of this relationship it could bias the traditional Monte-Carlo studies. One method of addressing this problem is examined. This is accomplished by applying the kth-Nearest-Neighbor or local bootstrap [23] methods that have been applied in water resource reasearch [14, 17, 26] and climate change research [27]. This paper describes this methodology in section 3.

Finally an example is given using the Northwest regional wind fleet generation and historical temperatures in regional load centers. This is then examined in an example generation system. This example is given in section 4.

2 The Relationship Between Regional Load and Wind Generation

The motivation behind the methods examined in this paper is that there is a statistical relationship between regional load and the generation of the regional wind fleet in the Northwest. While this paper focuses on this region, Keane et al. [15] indicates that this is also of concern in other regions. For comprability to that paper, the regional load as supplied by the Northwest Power and Conservation Council (NWPCC) is compared to the normalized wind fleet output reported by Bonneville Power Administration (BPA) in Fig. 1. This shows similar results for the Northwest as the Minnesota data that are examined in that paper and lends further support to the need for simulations of load and wind power generation in a dependent manner.

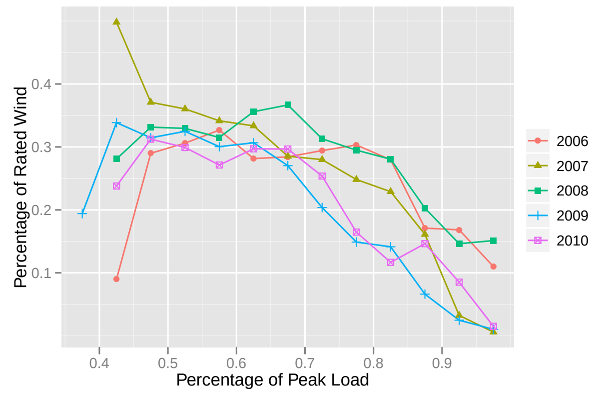

Figure 1: Average capacity by percentage of peak load vigiciles.

Further examination can show that this is in part related to the regional temperature sensitive load. In Fig. 2, the daily average regional load center temperatures are compared to the normalized wind fleet output. Note, the bin selection leaves a different number of observations in each temperature bin. There are fewer days with extreme regional temperatures as would be expected. This can be seen in Fig. 3.

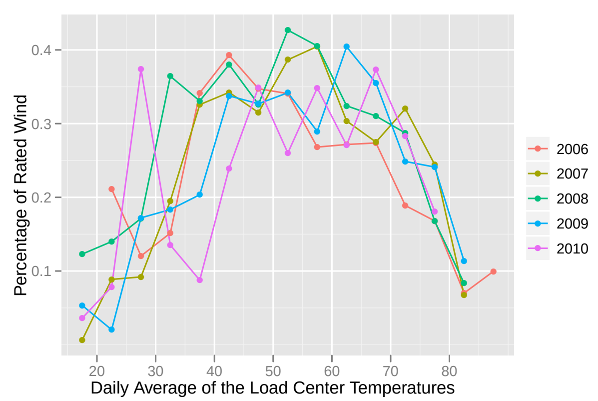

Figure 2: Average capacity by regional load center temperatures

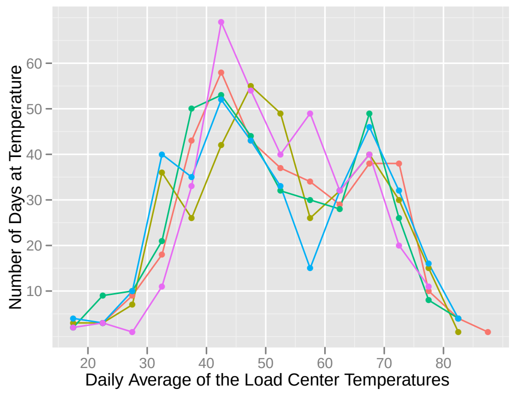

Figure 3: Number of days with observed regional temperature

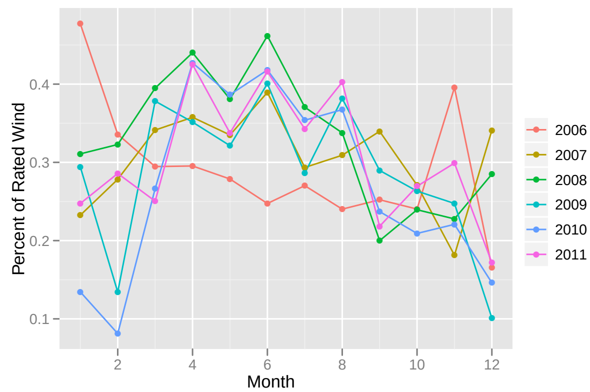

Figure 4: Regional normalized wind generation by month

Wind power generation in the region tends to be less when regional loads are higher. To capture this it is recommended that when a model is used to simulate wind power generation for reliability studies, the relationship between the regional load center temperatures be included as part of that model.

3 A Temperature-Based Wind Power Model

The K-nearest-neighbor (K-nn) bootstrap is based on assigning distances to a bootstrap data and restricting the bootstrap selection based on that distance. The strategy of this model is to select the distance in a manner that preserves the persistence characteristics of wind power generation and also bases the selection on load center temperatures. It is also important to preserve seasonal characteristics in wind power and diurnal characteristics. Fig. 4 shows the monthly characteristics in the observed record and Fig. 5 show the diurnal characteristics of the observed record.

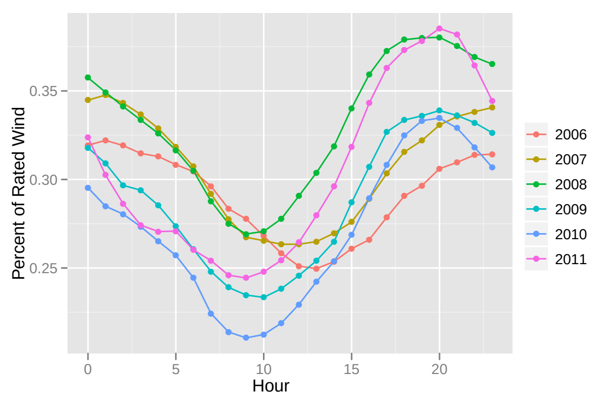

Figure 5: Regional normalized wind generation by hour

To keep the load and the wind generation forecast related, the temperatures that will be used must be established prior to generating the simulations with a model. The following algorithm assumes this choice has already been made. In the section 4 we will examine one manner in which to select the temperature record.

3.1 Model Algorithm

Suppose that daily temperature data indiced by t are established for P days and the first day corresponds to January 1st. Assume that the weather data that correspond to the wind generation record to be bootstrapped are available and any missing data have been estimated and filled in and that there are N years of corresponding daily temperature data and wind generation data to be bootstrapped.

1. Initialize the model for the first day by selecting at random one of historical years for December 31st and use this as the lagged observations of day $t-1$.

2. Restrict the bootstrap to a temporal window of length w centered day t.

3. Measure the distance between the wind generation of the prior day $t-1$ in the simulated record and each lagged day in the temporal window of the boostrap record. The metric used in this paper takes a weighted Euclidean distance with weights being heavier at the end of the day to create a realistic transition from one day to the next. The convenient choice of
$$h_j = \frac{j}{\sum_{i=1}^{24} i} \tag{1}$$
as a weight for hour j is made in this paper.

4. Measure the distance between the temperature established for day t and the temperatures that correspond to the bootstrap data in the temporal window. Mahalanobis distance as in Yates et al. [27] is used in this paper with the temperatures being the daily minimum and maximum observed temperatures for four load centers in the Northwest (Boise ID, Portland OR, Seattle WA, and Spokane WA).

5. Normalize these distances by dividing by the standard deviations.

6. Establish K the number of neighbors to be chosen. The choice of K is based on the number of observations in the temporal window. The choice of $K = \lceil\sqrt{w * N}\rceil$ as in Lall and Sharma [17] and Yates et al. [27] is made for this paper.

7. Weight these two distances and establish which days in the temporal window are the K closest based on this weight. An adaptive weighting scheme is used in this paper that weights the selection higher toward the temperatures when the temperatures establish for day t are further away from the average temperature in the temporal window. This is done to emphasize the selection for extreme temperature events and to adjust for the sparseness of extreme observations that can be seen in Fig. 3.

8. Select one of the K days based on the weight function
$$p_j = \frac{1/j}{\sum_{i=1}^{K} 1/i} \tag{2}$$
for all $j = 1$ to K as in Lall and Sharma [17] and Yates et al. [27]. This causes the day with the closest distance to have the highest probability of being selected and avoids having to recompute the weight each iteration since it is based on rank rather than distance.

9. Append the wind generation observed on the selected day to the simulated record.

10. Move to day $t+1$ and repeat steps 2 to 9 until P days are reached.

4 Simulation Example

For simplicity a two-state generation system (hierarchical level 1) is used that modifies the IEEE One

Area RTS-96 [9]. The loads are modified to be factored based on the load forecast from the NWPCC Sixth Northwest Conservation and Electric Power Plan [1]. These loads are forecast based on observed load center temperatures from 1929 to 1998 in the Northwest with the loads escalated to forecast levels for 2015. Thus there are 70 different load forecasts that are used for the simulation. In this study these loads are normalized and added into the RTS-96. To asses the impact of the temperature relation in the wind power model 20 records that did not depend on temperature were generated, i.e. the weight on the temperature component in the model was set to zero. Each of these records was run against each load forecast based on historical temperatures. To represent the wind fleet 2000 MW of wind generation was added to the system and the 2850 MW base peak load was increased by 110%. This is assumed to be the average peak load. Peak load is adjusted based on the ratio of the peak of each of the 70 forecasts to the average of all 70 forecasts. Since the observed wind generation in the data source includes outages for this analysis wind is treated as negative load. This system is purposefully unbalanced to emphasize the impact of the differing approaches to wind power modeling.

A sequential stochastic simulation was developed using R [25]. Planned outages are chosen to maximize the difference between the available capacity and average hourly load less wind generation. For simplicity hydro capacity is only modeled as capacity for this study, energy is not tracked. Thus the 90% rating [9] is applied for hydro units in the second half of the calendar year but restrictions on energy output were not modeled.

Using the algorithm described in section 3.1, w was chosen to be 61 and the weight was chosen to be 1 for the selection based on the lagged day wind power generation and zero based on the temperatures. The bootstrap data were the historical wind fleet generation from BPA from 2006 through 2011. This is to show a model that is not temperature-based for comparison sake. Using this setup the LOLP is 20.9%, the LOLE is 2.1 hours per year and the LOEE is 38.0 MWh per year.

When the algorithm is changed to the adaptive weighting as described in step 7 the observed temperatures from the load centers are used to generate wind records that correspond to the load forecast based on the same temperatures. The temperature data were taken from the National Climatic Data Center (NCDC) from 1929 through 2011 for sites located in or near the 4 regional load centers. In addition to the algorithm above, a couple of steps were taken to control for historical temperature vectors that are outside the general space defined by the temperature vectors associated with the bootstrap data. First, the temperatures were truncated to the minimum and maximum observed temperatures for each of the load centers in the temperature record associated with the bootstrap data. Second the extreme regional average temperatures as in Fig. 2 were examined and if the wind generation exceeded a threshold the record was rerun. This threshold was set well above the historical observations in the bootstrap data. For regional average temperatures below 20 degrees and above 85 degrees Fahrenheit the threshold was set to and average generation of 30%, below 30 degrees and above 75 degrees the threshold was set to 40% and between 30 degrees and 75 degrees the threshold was set to 60%. These thresholds were only violated if the average of all days within 5 degree bins exceeded these thresholds. In this setup the LOLP is 32.1%, the LOLE is 5.8 hours per year and the LOEE is 82.4 MWh per year.

Computation of the temperatures-related wind records for 70 years took approximately 2 days on an Intel(R) Core(TM)2 Duo CPU E8500 @ 3.16GHz, 2.98GB of RAM.

5 Conclusions

The assumption of independence between wind and load when running resource adequacy studies could potentially bias the estimate of the traditional system metrics downward, depending on the region. It is important to at least examine whether there is a relationship between wind generation and the load center temperatures in a region, especially if a high penetration of wind is expected.

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