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Forecastability as a Design Criterion in Wind Resource Assessment

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Abstract

This paper proposes a methodology to include the wind power forecasting ability, or "forecastability," of a site as a design criterion in wind resource assessment and wind power plant design stages. The Unrestricted Wind Farm Layout Optimization (UWFLO) methodology is adopted to maximize the capacity factor of a wind power plant. The 1-hour-ahead persistence wind power forecasting method is used to characterize the forecastability of a potential wind power plant, thereby partially quantifying the integration cost. A trade-off between the maximum capacity factor and the forecastability is investigated.

Keywords: Wind power plant design, wind forecasting, forecastability, layout optimization, turbine selection, wind resource assessment, grid integration.

1. Introduction

Wind power is gaining an increasing share of power production in the United States, producing 4% of U.S. electricity consumption as of August 2013 [1]. However, wind power is more variable and uncertain than power produced from traditional thermal power plants used to serve electricity demand. Load is also variable and uncertain, and at low levels of wind penetration the additional variability and uncertainty can be accommodated by the same mechanisms installed to accommodate load. As the amount of wind generation on the electric power system increases, new sources of flexibility will be required to help balance the variability and uncertainty at various timescales. Wind power forecasting is one such method that is used by utilities and independent system operators to reduce the uncertainty associated with wind power. At current levels of wind power penetration, wind can be effectively integrated wherever it may be installed; however, at higher penetration levels it might be more economically efficient to follow a design approach that chooses sites based on the correlation of their output to load, or their ability to be forecasted.

With the introduction of Federal Energy Regulatory Commission Order 764 [2], more of the responsibility for forecasting wind power plant output has shifted from the utilities and independent system operators to the wind power plant owner/operators. Not only do the operators have to provide meteorological information that can be used for forecasts, but they can also be assessed integration charges based on how well their forecasts match the actual wind power output. This makes a wind power plant site where the output can be well forecasted more valuable than a site where forecasting is

difficult—for example, perhaps because of complex terrain. This is especially important at the timescales that are most relevant to power system operations, namely those involved in the unit commitment and economic dispatch process. Day-ahead forecasts are typically used for unit commitment, and these forecasts are often based on numerical weather prediction models. Economic dispatch can utilize forecasts from 10 minutes up to 1 or 2 hours ahead. At these timescales, most models (weather physics-based or statistical) provide only slight improvements on the persistence method. Therefore, a measure of the 10-minute or 1-hour variability of a site corresponds well to its forecasting ability, or "forecastability," for the economic dispatch process. By examining the range of variability seen in a number of different wind power plant sites with a long time series of data, we can establish a measure of how well a potential site's power output will be able to be forecasted, and hence what sorts of integration charges can be expected. These integration charges can vary considerably by location (for example, depending on what utility or balancing authority area the wind will be integrated into), but the charges are on the order of $1/MWh to $10/MWh [3] and thus could have a significant impact on siting decisions.

2. Methodology Development

This paper develops a methodology to include forecastability in the stages of wind resource assessment and wind power plant design. The Unrestricted Wind Farm Layout Optimization (UWFLO) methodology is adopted here for wind farm layout optimization and turbine type selection. The wind power plant generation model in UWFLO is used to estimate the hourly power generation of the optimized wind power plant. The 1-hour-ahead wind power forecasts are synthesized using a 1-hour-ahead persistence approach.

2.1. UWFLO Methodology

The UWFLO methodology introduced by Chowdhury et al. [4, 5] avoids the assumptions presented by other methods that limit the layout pattern and the selection of turbines. In the UWFLO method, the turbine location coordinates are treated as continuous variables that allow all feasible arrangements of the turbines. The UWFLO method is applicable to both experimental-scale wind farms and full-scale commercial wind farms by:

i. Using the wake growth model proposed by Frandsen et al. [6],
ii. Implementing the wake superposition model developed by Katic et al. [7],
iii. Including the joint distribution of the wind speed and direction, estimated by the newly developed Multivariate and Multimodal Wind Distribution model [8],
iv. Modifying the power generation model to allow turbines with different hub heights and performance characteristics,
v. Evaluating the cost of the wind farm using an accurate response surface-based wind farm cost model [9, 10], and
vi. Implementing a newly developed mixed-discrete particle swarm optimization algorithm [11].

The objective of wind farm optimization here is to maximize the capacity factor (CF) for a given wind site (wind speed and direction). The variables in the optimization problem are the locations of each turbine (X_j ,Y_j) and the type of turbine (T) to be used—a total of 2N + 1 design variables for a N-turbine farm. A turbine type is defined by a unique combination of rated-power, rotor-diameter, hub-height, and performance characteristics. In this study, we allow turbines to be selected from a pool of thirteen 2-MW commercial turbines manufactured by Vestas and Gamesa. These turbine types are sorted in the order of their rotor diameters and their hub heights, and each turbine-type is then assigned an integer code between 1 and 13. The overall optimization problem is defined as

$$\begin{aligned} &\text{Max} \qquad f(V) = \frac{P_{farm}}{NP_{r0}} \\ &Subject\ to \\ &g_1(\mathrm{V}) \leq 0,\ g_2(\mathrm{V}) \leq 0 \\ &\mathrm{V} = \{X_1, X_2, \cdots, X_N, Y_1, Y_2, \ldots, Y_N, \mathrm{T}\} \\ &0 \leq X_i \leq X_{farm},\ 0 \leq Y_i \leq Y_{farm},\ T \in \{1,2,\cdots,T^{max}\} \end{aligned} \tag{1}$$

where P_{r0} is the rated power of the reference turbine (used for normalizing) and P_{farm} is the power generated by the farm; and f(V) represents the capacity factor. The parameters X_i and Y_i are the coordinates of the wind turbines on the farm. The parameters X_{farm} and Y_{farm} represent the extent of the rectangular wind farm in the X and Y directions, respectively. The inequality constraint g_1 represents the minimum clearance required between any two turbines. To ensure the placement of the wind turbines within the fixed-size wind farm, the X_i and Y_i bounds are reformulated into an inequality constraint, $g_2 \leq 0$. The parameter T^{max} represents the total number of commercial turbine types considered; $T^{max} = 13$ for the case study considered in this paper.

2.2. Wind Power Forecasting

Wind power forecast models can be broadly divided into two categories [12]: (1) data-driven models, such as forecasting based on the analysis of recent time series of wind; and (2) first principle models, such as forecasting based on numerical weather prediction models. The first type of forecast models generally use statistical approaches to provide reasonable results in the estimation of long-term horizons, such as mean monthly, quarterly, and annual wind speed. The second type of forecast models generally use explanatory variables (mainly hourly mean wind speed and direction) derived from a meteorological model of the wind dynamics to predict wind power.

Economic dispatch can utilize forecasts from 10 minutes up to 1 or 2 hours ahead, and at these timescales most statistical models provide only modest improvements on the persistence method. Numerical weather prediction models are much better at producing accurate day-ahead forecasts, but they often perform much worse than persistence at small timescales. Therefore, a measure of the 1-hour variability of a site corresponds well to its forecastability for the economic dispatch process. In this paper, the 1-hour-ahead forecasts were synthesized using a 1-hour-ahead persistence approach.

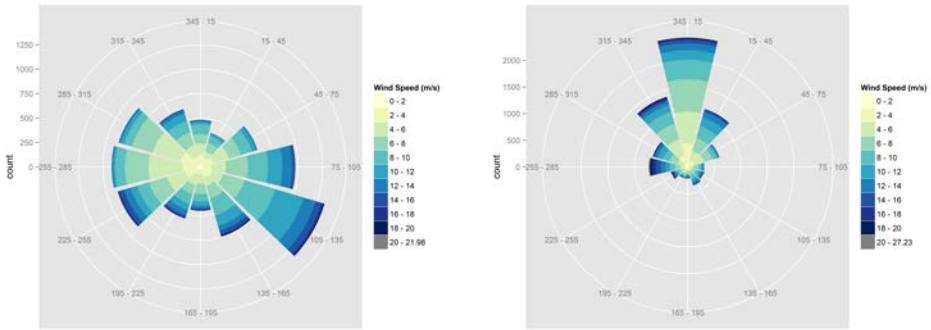
The root mean square error (RMSE) between the 1-hour-ahead wind power forecasts and the actual power outputs is used to represent the forecastability of a wind site. In the study, the RMSE is normalized by the nameplate capacity of the wind power plant to obtain the NRMSE, which is between 0 and 1. A smaller RMSE or NRMSE indicates a higher accuracy of forecasts and a better forecastability of the wind site.

3. Data Summary

In this paper, 5 potential wind power plant sites are evaluated and compared. Table 1 lists the locations, measured heights, and recorded years of these sites. Two sample wind rose diagrams at sites c and e are shown in Figure 1.

Table 1. Locations of Analyzed Wind Power Plants

Station	*Latitude*	*Longitude*	*Measured Height (m)*	*Year*
(a) Butler Grade	45.9501	-118.6830	62.5	2010
(b) Cedar Creek	40.9541	-104.0780	80.0	2010
(c) Jewell	39.7842	-98.1192	80.0	2004
(d) NWTC M2	39.9107	-105.2350	80.0	2010
(e) Prison Draper	40.4889	-111.8900	50.0	2004



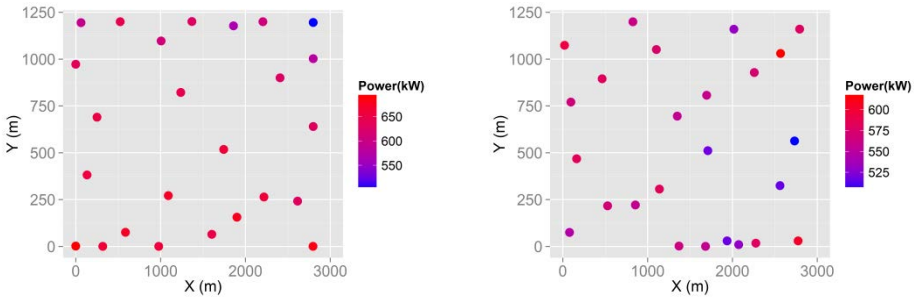
(a) Site d: NWTC M2 (b) Site e: Prison Draper

Figure 1. Wind rose diagrams at two potential sites

4. Results and Discussion

4.1. Optimal Wind Farm Layout and Turbine Selection

In this paper, 25 2-MW wind turbines comprise the fixed-size (land) rectangular wind farm that we consider. For all 5 wind power plant sites, 2-MW turbines with 90-m rotors were selected during the optimization. Different layouts were obtained at the 5 sites, and two sample optimal layouts are shown in Figure 2. The capacity factors for the 5 sites are 0.23, 0.33, 0.40, 0.42 and 0.37. In this paper, project-specific power loss factors (turbine downtime for operations and maintenance, extreme weather conditions, snow accumulation, and curtailments) are not considered, leading to an overestimation of the capacity factor.



(a) Site d: NWTC M2 (CF=0.42) (b) Site e: Prison Draper (CF=0.37)

Figure 2. Optimized wind power plant layouts

4.2. Wind Power Forecastability

The kernel density estimation [13, 14] is adopted in this paper to model the distribution of wind power forecast errors for different sites. Kernel density estimation is a nonparametric approach to estimate the probability density function of a random variable. Figure 3 shows the distribution of 1-hour-ahead wind power forecast errors at the 5 sites. It is important to note that the hour-ahead variability differs quite strongly among the sites.

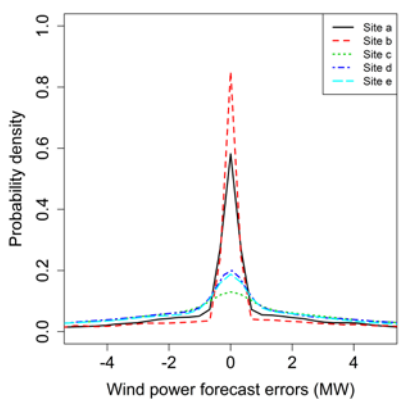


Figure 3. Distribution of 1-hour-ahead wind power forecast errors

4.3. Trade-Off Between Maximum Capacity Factor and Forecastability

In this paper, the forecastability of a site is measured by the NRMSE of 1-hour-ahead wind power forecast errors. The trade-off between the maximum capacity factor and the forecastability is illustrated in Figure 4. It is observed that some potential wind power plants sites (e.g., site d) have significantly larger capacity factors than others (e.g., site a). However, the capacity factors are relatively similar for some sites, e.g., sites c and e. When the capacity factors of potential wind power plants are similar, it would be very important to consider the forecastability of each wind power plant because of the larger integration costs that might be assessed to the less forecastable of the plants. Among the

5 potential wind plant sites, site d is considered to be a more suitable wind plant site, with the largest capacity factor and the smallest NRMSE.

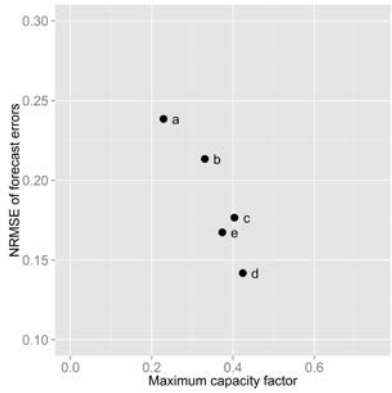


Figure 4. Trade-off between maximum capacity factor and forecastability

5. Conclusions

This paper investigated the effects of wind power forecasting on wind resource assessment and wind power plant design. To evaluate the forecastability of a potential wind power plant, the 1-hour-ahead wind power forecast errors were quantified and assessed. The UWFLO methodology was used to maximize the capacity factor of potential wind power plants. The trade-off between the maximum capacity factor and the wind power forecast errors indicates that the forecastability of the sites could make an economic difference for wind resource assessment and wind farm design, especially when the capacity factors of potential wind power plants are similar.

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