Data-Dirven Method for Wake Effect Analysis on Nacelle Anemometer

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Abstract. For most wind turbines, blade wakes affect the measurement of nacelle anemometer, resulting in the inconsistency between nacelle wind speed (NWS) and free stream wind speed, which seriously affects the power forecasting and performance evaluation of wind turbine. This paper proposes a data-driven method to analyse the wake effect on nacelle anemometer. At first, we use Relevance Vector Machine to establish a site calibration model between Lidar wind speed (LWS) and NWS. After that, we can use the calibrated LWS to replace the free stream wind speed, and wake effect on nacelle anemometer can be evaluated by comparing the calibrated LWS and NWS. Then, Wind Turbine Power Curve (WTPC) is applied to make a detail analysis of wake effect on nacelle anemometer. The experimental results show that wake effect accelerates the air velocity behind the impeller. Therefore, WTPC fitted by NWS is “lower” than the real one. However, SCADA system overcorrects the wake effect, thus WTPC fitted by SCADA data is “higher” than the real power curve.

1. Introduction

Accurate wind speed measurement is critical for wind power forecasting, performance evaluation and condition monitoring [1, 2]. Ideally, wind speed measured by nacelle anemometer is equal to Free Stream Wind Speed (FSWS) for power generation. However, affected by blade wakes, nacelle wind speed (NWS) is inconsistent with the FSWS. Therefore, it is necessary to evaluate the wake effect on nacelle anemometer in order to obtain the correct NWS.

A majority of recent studies concentrate on wake effect between adjacent wind turbines, which can be divided into analytical wake model, numerical wake model and wind tunnel test [3]. Jensen wake model as a simple linear model for the calculation of velocity deficit is the most widely used analytical wake model [4]. Besides, several analytical wake models were proposed according to Jensen model [5, 6]. Numerical wake model mainly created by Computational Fluid Dynamics (CFD) theory. Based on CFD, Refs. [7, 8] used Large Eggy simulation to calculate the weak field of wind turbine. However, it is difficult to apply in actual wind farms due to the large amount of computation cost. Wind tunnel test can directly evaluate the wake effect and verify the performance of other wake models [9, 10]. However, limited by experimental conditions and costs, the application scope is narrow. Recent years, machine-learning techniques were applied for wake studies. Ref. [10] used Extreme Learning Machine and Wavelet Transform to predict the blade wake, Ref. [11] proposed a wake model by...
Adaptive Neuro-Fuzzy. In general, wake effect between wind turbines reduce the power production, and studying the wake effect helps wind farm designer optimize the arrangement of wind turbines.

However, few published literatures focus on the wake effect on nacelle anemometer. Ref. [12] considered the wind turbine rotor as an anemometer, thus the wind speed without wake effect can be estimated indirectly. Ref. [13] established a linear mapping model between NWS and meteorological mast wind speed to reduce the flow distortion by terrain, thus NWS can be replaced by the wind speed of meteorological mast, avoids the wake effect on nacelle anemometer. In addition, SCADA systems used simple linear method to correct the blade wakes. This paper proposes a data-driven method to evaluate the wake effect on nacelle anemometer. We use the measured data from a real wind turbine and Lidar for analysis, and the main contributions are: (1) an improved site calibration method is proposed based on Relevance Vector Regression (RVR). Compared with linear site calibration method [13], the calibrated LWS (CLWS) by RVR is closer to FSWS for power generation. (2) Wind Turbine Power Curve (WTPC) is applied to further evaluate the wake effect on nacelle anemometer. The results show that blade wakes accelerate the air velocity behind the impeller. On the one hand, WTPC fitted by NWS is “lower” than the real power curve. On the other hand, SCADA system overcorrects the wake effect, thus the WTPC fitted by SCADA data is “higher” than the real power curve.

The remaining parts are as follows. Section 2 introduces the experimental design and data sources. Section 3 makes a detailed description on the proposed method. Section 4 analyses and discusses the experiment results. Section 5 draws the conclusion.

2. Experimental Design and Data Source

2.1. Experimental Design

The test wind turbine is located in a hilly wind farm, Hunan province, China (111° 36’ 31” E, 25° 09’ 46” N). Besides, we installed a Molas B300 Lidar for the collection of meteorological information. Figures 1 and 2 show the specific information of the experimental site, and the main parameters of both wind turbine and Lidar are listed in table 1.

![Figure 1. Satellite image of the experimental site.](image1)

![Figure 2. Schematic chart of the experiment site.](image2)

| Equipment          | Parameter            | Value | Unit |
|--------------------|----------------------|-------|------|
| Wind turbine       | Hub height           | 80    | m    |
|                    | Impeller diameter    | 105   | m    |
|                    | Rated power          | 2     | MW   |
| Nacelle anemometer | Wind speed resolution| 0.1   | m/s  |
| Lidar              | Altitude range       | 40-300| m    |
|                    | Wind speed resolution| 0.1   | m/s  |
|                    | Wind direction resolution | 1   | degree |
As shown in figure 1, Lidar is installed on the main wind direction sector of the test wind turbine, according to IEC 61400-12-1 [13], the distance between Lidar and wind turbine base is set to 250 m (about 2.5 times the impeller diameter, 2.5D). In figure 2, the height difference between Lidar and wind turbine base is about 40 m.

The experimental process consists of two parts: 1) from 06/03/2017 to 06/13/2017, the test wind turbine stops working, and the impeller keeps braking. In this case, we train a mapping model between LWS and NWS for site calibration. 2) From 06/14/2017 to 06/26/2017, the test wind turbine starts working. Therefore, we can analyse the wake effect by CLWS and NWS.

2.2. Data Source
Figure 3 shows the selected parameters related to this study. As we can see, Lidar data includes wind speeds and wind directions at different altitudes, NWS is the wind speed directly recorded by nacelle anemometer, SCADA data includes wind speed corrected by SCADA system (SWS) and the power output. All the raw data is recorded at 1 Hz, and 1 min-average data is used in this study.

![Figure 3. Selected parameters related to this study.](image)

3. Methodology

3.1. Site Calibration
The aim of the site calibration is to establish a mapping model between LWS and NWS without wake effect (equal to FSWS). Therefore, when the wind turbine starts working, we are able to obtain the NWS without wake effect by the Calibrated LWS (CLWS). Figure 4 shows the structure diagram.

At first, according to the relative position of the test wind turbine and Lidar, data with wind direction from 315° to 360° is selected. Affected by surface roughness, wind farm topography and wind shear, wind speed in different altitudes has different features. Thus, selecting the one with strong correlation to the NWS from the LWS in different altitudes is important. This study uses both Pearson correlation coefficient (PCC) and Euclidean distance (ED) to choose the model inputs, expressed as [14]:

\[
PCC = \frac{\sum_{i=1}^{N} (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{N} (x_i - \bar{x})^2 \sum_{i=1}^{N} (y_i - \bar{y})^2}}
\]

(1)

\[
ED = \sqrt{\sum_{i=1}^{N} (x_i - y_i)^2}
\]

(2)

where \(x_i\) is the LWS point at specific altitude, \(y_i\) is the NWS, \(N\) the number of wind speed points. Table 2 lists the correlation results.
In Table 2, “all Dir.” is the wind speed selected from all wind directions, “selected Dir.” is the wind speed selected from 315° to 360°, [.] is the ranking of correlation between wind speed series. The results show that the correlation between NWS and LWS in selected wind direction sector is higher than that without considering the wind direction. On the other hand, with the increase of LWS altitudes, both PCC and ED present a trend of unimodal function. Among them, the value of PCC between NWS and LWS at 133 m is the highest while the value of ED between NWS and LWS at 120 m is the smallest. Accordingly, we choose the union of the optimal results of both PCC and WD as input parameters.

LWS in the selected wind direction sector is not continuous time series. Therefore, typical time series methods are not suitable for model training. This paper uses Relevance Vector Regression (RVR) to train the site calibration model.

RVR is Bayesian framework based regression method created by Michael E. Tipping [15]. Similar to SVR, the regressions based on the function:

$$y(x; w) = \sum_{i=1}^{N} w_i K(x, x_i) + w_0$$

where $K(x, x_i)$ is the kernel function. Assume that the prediction error of (2) obeys Gaussian distribution, and the likelihood can be written as:

$$p(t \mid w, \sigma^2) = (2\pi\sigma^2)^{-\frac{N}{2}} \exp\left(\frac{-\|t - \Phi w\|^2}{2\sigma^2}\right)$$

(4)

where $t$ is the expected vector, $\Phi$ is the design matrix of kernel function. Based on (4), Gaussian prior distribution is used to solve the over-fitting caused by model parameters, expressed as:

$$p(w \mid a) = \prod_{i=0}^{N} \frac{a_i}{\sqrt{2\pi}} \exp(-\frac{a_i w_i^2}{2})$$

(5)

where $a$ is hyperparameter vector. After a series of calculation in Ref. [15], we can derive the predictive distribution by:

$$p(t \mid \alpha) = \int p(t \mid \alpha, \sigma_{MP}^2) \cdot p(w \mid \alpha, \sigma_{MP}^2) \, dw$$

(6)
where $\alpha_{MP}$ and $\sigma_{MP}^2$ is the most-probable values of $\alpha$ and $\sigma^2$, solved by iterative calculation. Compared with SVR, RVR does not need to set margin parameter $C$ or insensitivity parameter $\epsilon$, thus it can significantly reduce the computation cost.

After model training, this paper uses Root Mean Square Error (RMSE) as the evaluation criteria to test the performance of site calibration, expressed as

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=0}^{N} (cv_i - n_i)^2}$$

where $cv_i$ is the CLWS point, $n_i$ is the measured NWS point.

### 3.2. Wake Effect Analysis

After site calibration, wake effect on nacelle anemometer can be evaluated by comparing the CLWS and the NWS under wake effect (when wind turbine starts working), as shown in figure 5.

![Figure 5. Time series of NWS and CLWS.](image)

As shown in figure 5, NWS is slightly higher than CLWS, and the average value of NWS is about 3% higher than CLWS. In order to make a detailed analysis on the wake effect on nacelle anemometer, we use LWS, CLWS and SWS to build WTPC separately. Among them, 9-order polynomial regression method is selected due to its good fitting performance [16]. In addition, Least Square is applied to estimate the model parameters. At last, this paper uses Relative Change Rate (RCR) to analyse the wake effect on WTPC, defined as:

$$RCR = \frac{\int [P_{SWS, NWS} - P_{CLWS}] \, dv}{\int P_{CLWS} \, dv} \times 100\%$$

where $P_{CLWS}$ is the WTPC fitted by CLWS, $P_{SWS, NWS}$ is the power curve fitted by NWS or SWS.

### 4. Results and Discussions

Data collected from 06/03/2017 to 06/13/2017 is used to test the performance of site calibration. Among them, 70% of data for model training, and 30% for testing. Table 3 lists the RMSE of several typical site calibration methods.

| Methods | N/A | Linear | SVM | RVM |
|---------|-----|--------|-----|-----|
| RMSE    | 1.184 | 0.783  | 0.763 | 0.765 |
| Training time (s) | N/A | 0 | 21.623 | 0.218 |
In Table 3, when directly using LWS instead of NWS, the result shows that the RMSE is 1.184, which is obviously higher than other three models. It can conclude that, site calibration effectively reduces the terrain impact. Besides, due to the nonlinear relationship between LWS and NWS, the RMSE of linear model [13] is higher than both SVR and RVR. At last, although SVR and RVR has the similar RMSE, the training time of SVR exceeds 100 times of SVR. In general, the proposed site calibration method has the best performance.

When test wind turbine starts working, we use CLWS, NWS and SWS to build WPTC separately, where data is collected from 06/14/2017 to 06/26/2017, and Figure 6 shows the fitting results.

![Figure 6. Power curves established by different types of wind speed.](image)

After site calibration, CLWS-WTPC can be regarded as the real power curve, because, the CLWS is close to FSWS for power generation. The results show that when the wind speed is higher than 6 m/s, blade wakes accelerates the air velocity behind the impeller, which causes the power curve established by nacelle anemometer (NWS-WTPC) is “lower” than the real one, and the RCR is -8.23%. On the contrary, SCADA system overcorrection of wake effect caused by nacelle anemometer, which caused an obvious deviation between SWS-WTPC and real WTPC, the RCR is over than 65%. However, limited by the weather condition during the experimental period, this paper only analyses the wake effect when the wind speed less than 8 m/s.

5. Conclusion
This paper proposes a site calibration model based on RVR, it has good performance compared with other typical site calibration methods. Accordingly, we can analyse the wake effect by comparing the CLWS and NWS. The experimental results show that when the wind speed exceeds 6 m/s, blade wakes accelerate the air velocity behind the impeller, thus the average value of NWS is about 3% higher than FSWS for power generation. Due to the wake effect on nacelle anemometer, WTPC fitted by NWS is 8% “lower” than the real power curve. On the contrary, SCADA system overcorrects the NWS, and WTPC fitted by SWS is about 60% “higher” than the real one. In the further study, we can use the same method to evaluate the wake effect in higher wind speed range.

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