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Analyzing Effects of Turbulence on Power Generation Using Wind Plant Monitoring Data

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In this paper, a methodology is developed to analyze how ambient and wake turbulence affects the power generation of a single wind turbine within an array of turbines. Using monitoring data from a wind power plant, we selected two sets of wind and power data for turbines on the edge of the wind plant that resemble (i) an out-of-wake scenario (i.e., when the turbine directly faces incoming winds) and (ii) an in-wake scenario (i.e., when the turbine is under the wake of other turbines). For each set of data, two surrogate models were then developed to represent the turbine power generation (i) as a function of the wind speed; and (ii) as a function of the wind speed and turbulence intensity. Support vector regression was adopted for the development of the surrogate models. Three types of uncertainties in the turbine power generation were also investigated: (i) the uncertainty in power generation with respect to the published/reported power curve, (ii) the uncertainty in power generation with respect to the estimated power response that accounts for only mean wind speed; and (iii) the uncertainty in power generation with respect to the estimated power response that accounts for both mean wind speed and turbulence intensity. Results show that (i) under the same wind conditions, the turbine generates different power between the in-wake and out-of-wake scenarios, (ii) a turbine generally produces more power under the in-wake scenario than under the out-of-wake scenario, (iii) the power generation is sensitive to turbulence intensity even when the wind speed is greater than the turbine rated speed, and (iv) there is relatively more uncertainty in the power generation under the in-wake scenario than under the out-of-wake scenario.

Keywords: surrogate modeling, uncertainty quantification, turbulence, wind plant, turbulence intensity, wind distribution

I. Introduction

During the past decade, notable progress has been made in developing renewable energy resources. Among them, wind energy has taken a lead; it currently contributes approximately 2.5% of worldwide electricity consumption.[1] Wind energy comes from wind power plants that consist of multiple wind turbines distributed throughout a substantial stretch of land (onshore) or water (offshore). The power generated by a wind plant is an intricate function of the configuration and location of the individual wind turbines. The flow pattern inside a wind plant is complex, primarily due to the wake effects and the highly turbulent flow. Wake loss leads to significant energy loss, especially in large-scale wind plants. The average wake loss is approximately 5% to 20%, depending on

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turbine placement and site climatology.[2] The offshore average ambient turbulence is typically between 6% and 8% at heights of approximately 50 m; the onshore average is between 10% and 12%.[3] Within a wind plant, turbulence is characterized by ambient and wake turbulence. Ambient turbulence is defined as the normal turbulence at the site that would be experienced by a single, stand-alone, turbine. Wake turbulence is caused by upwind turbines shading those downstream.[4] In the past years, a number of experimental and computational studies have been performed to investigate different wake characteristics within a wind plant, such as velocity deficit, turbulence intensity, multiple wake interactions, and the wake width and trajectory at various distances downwind.[3–10] In the presence of turbulence, with the same wind speed condition, the same turbine might generate different power: (i) under ambient turbulence (when the turbine is out of the wakes from other turbines), and (ii) under wake turbulence (when the turbine is in the wake of other turbines). The research question in this paper is: under the same wind condition, how does the ambient and wake turbulence affect the power generation of a wind turbine within a wind plant?

A methodology is developed in this paper to analyze effects of ambient and wake turbulence on the power generation of a wind turbine. The remainder of the paper is organized as follows: a brief summary of the wind plant monitoring data is provided in Section II; the methodology for turbulence analysis is developed in Section III; and Section IV presents the results and discussion of the case study.

II. Wind Plant Monitoring Data

The monitoring data from the Xcel Cedar Creek Phase One wind plant were analyzed in this paper. The wind plant is located in northeast Colorado.[11] Two-hundred seventy-four turbines, including 221 Mitsubishi 1-MW turbines and 53 GE 1.5-MW turbines, comprise the first phase. The turbines are spread throughout an area of approximately 17 km by 17 km. There are two meteorological towers at this site. The site map in Fig. 1 shows the relative distances among turbines and meteorological towers. The blue, yellow, and red dots represent GE turbines, Mitsubishi turbines, and meteorological towers, respectively. The GE turbines are 80 m and the Mitsubishi turbines are 69 m. The turbines are generally lined up in rows that are perpendicular to the prevailing wind direction (northwest) at the site. The average distance between two turbines in the same row is approximately 320 m, or roughly 5 rotor diameters. The distance among rows ranges from approximately 530 m to more than 8,900 m. The two meteorological towers measure wind speed (in m/s) and direction (from 0° to 359°) at 50 m and 80 m at meteorological tower MET01 and at 50 m and 69 m at meteorological tower MET02.[11]

A plant information (PI) system is installed at the wind plant to collect detailed operating information. For each turbine, the collected data include turbine status (availability and online status), rotor speed (rpm), power output (kW), nacelle position (degree), and wind speed from the anemometer on top of each nacelle (m/s). The output of the entire plant is monitored by the utility's supervisory control and data acquisition (SCADA) system and transmitted to its PI system. The wind speed, direction, barometric pressure, and temperature data from the two meteorological towers is also stored by the PI system.[11]

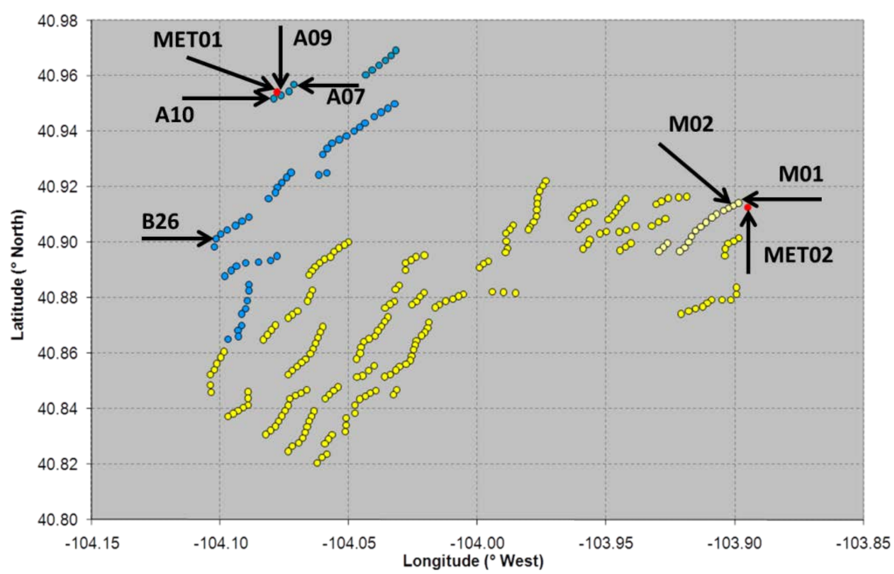


Figure 1. Cedar Creek turbine and met tower locations[11]

III. Methodology Development for Turbulence Analysis

With monitoring data from the wind plant, a methodology was developed to analyze the effects of ambient and wake turbulence on the power generation of a wind turbine by observing the following sequence:

i. Selecting one turbine on the edge of the wind plant, and determining two groups of wind and power generation data: (i) out-of-wake scenario, a set of data (wind speed, wind direction, and wind turbine power generation) when the turbine directly faces incoming winds; and (ii) in-wake scenario, a set of data when the turbine is in the wake of other turbines.

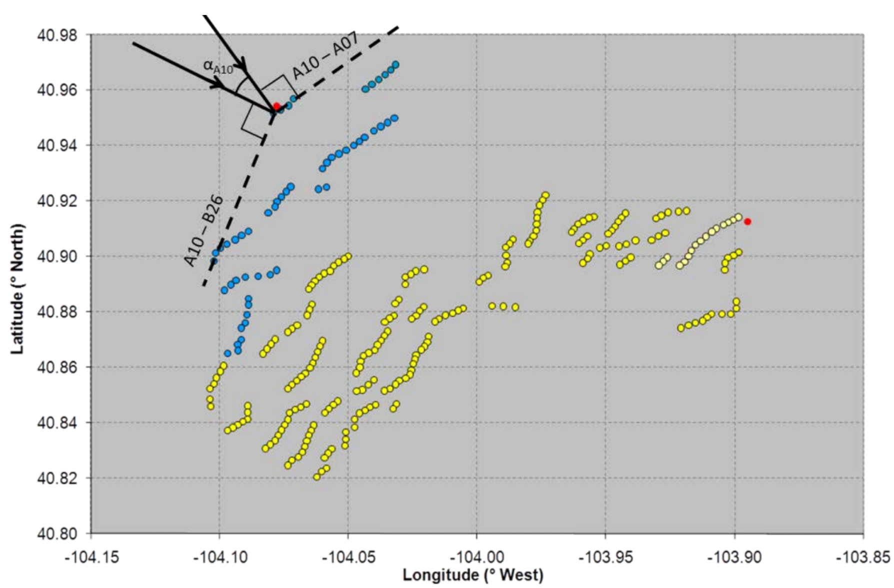
ii. For each group of data, two surrogate models were developed to represent the power generation (i) as a function of the wind speed; and (ii) as a function of the wind speed and turbulence intensity. Regression methods can be used for this purpose, and support vector regression (SVR) was adopted in this paper.

iii. Quantifying the uncertainty in the surrogate models, thereby quantifying the uncertainty in turbulence effects on wind power generation.

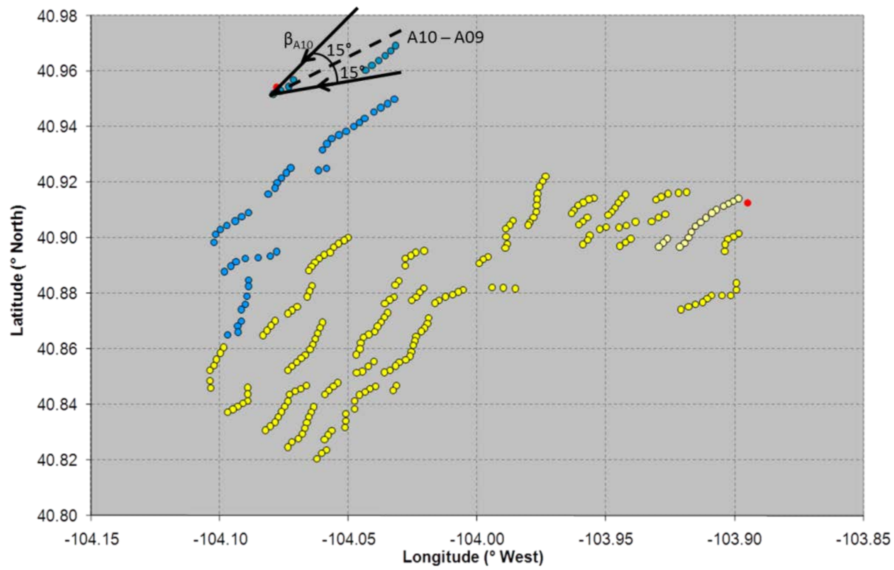
A. Determining Two Groups of Wind and Power Generation Data: In-Wake and Out-of-Wake Scenarios

With the Xcel Cedar Creek wind plant monitoring data, the analysis of the in-wake and out-of-wake scenarios could be performed for a single wind turbine. To investigate the effects of ambient turbulence (out-of-wake scenario), a turbine on the edge of a wind plant was selected. To this end, a GE 1.5 MW turbine (A10 in Fig. 1) was analyzed in this study to perform the turbulence analysis. This turbine A10 is mainly in the wake of turbine A09 in certain wind direction conditions. The data used in the paper included (i) 10-minute wind speed, direction, and power generation data from A10 during the whole year 2011; (ii) 10-minute wind speed and direction data from the meteorological tower (MET01) during the whole year 2011; and (ii) 1-minute wind speed and direction data from the meteorological tower during the summer of 2011 (July, August, and September).

Two sectors of wind data were determined to ensure that the turbine faces incoming winds directly or is in the wake of other turbines. This is illustrated in Fig. 2. Figure 2(a) shows the out-of-wake scenario; A10 faces incoming winds directly when the wind direction is within the angle of α_{A10}. To determine α_{A10}, two dashed lines (A10–A07 and A10–B26) were created by connecting A10 to turbines A07 and B26. Figure 2(b) illustrates the in-wake scenario; A10 is in the wake of other turbines when the wind direction is within the angle of β_{A10}. The angle β_{A10} is 30 degrees, which was determined based on the dashed line A10–A09. For A10, (i) the turbine is only in ambient turbulence when the incoming wind direction $331° < \theta < 354°$; and (ii) the turbine is in the wake of other turbines when $69° < \theta < 99°$. The parameter θ is the wind direction; the values 0°, 90°, 180°, and 270° indicate incoming winds from the North, East, South, and West, respectively.



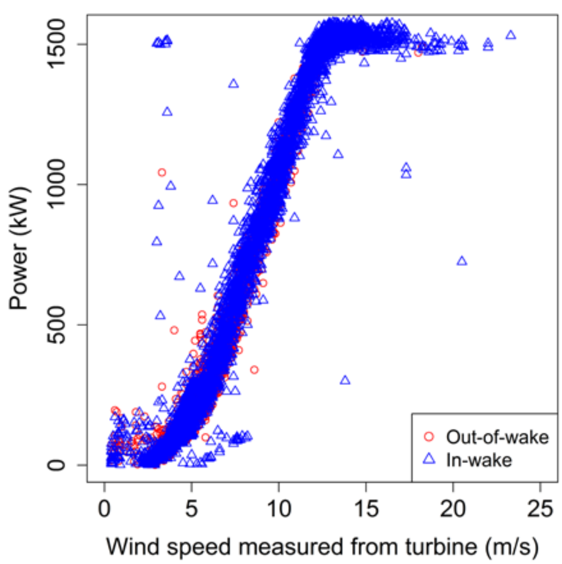
(a) Determining α_{A10} (out-of-wake scenario)



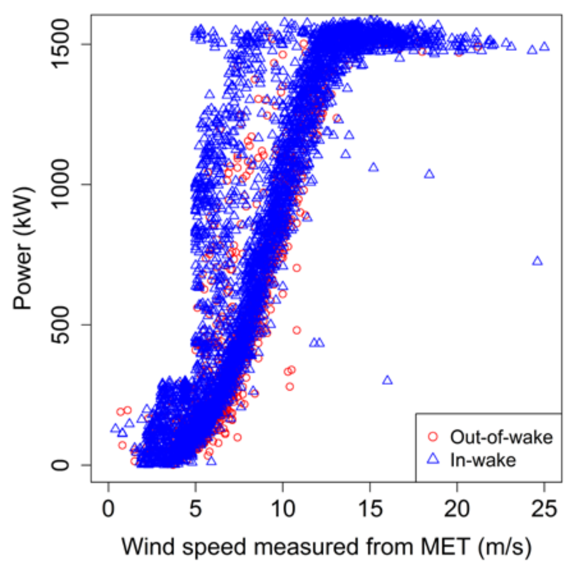
(b) Determining β_{A10} (in-wake scenario)

Figure 2. Determining the two groups of data for turbulence analysis

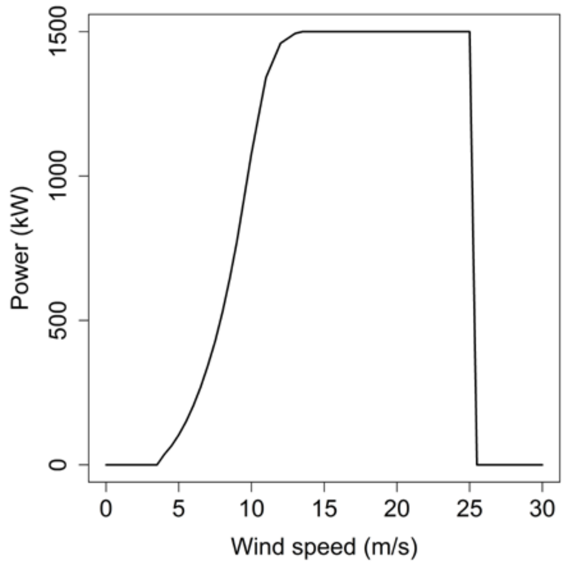
Figure 3 shows the scatter plot of recorded wind speed and turbine power generation for the in-wake and out-of-wake scenarios. Figures 3(a) and 3(b) represent wind speed measured from A10 and the meteorological tower MET01, respectively. Circle points represent the power and speed relationship when the turbine is only in ambient turbulence, and triangle points represent the power and speed relationship when the turbine is in the wake of other turbines. The reported power curve from the manufacturer is provided in Fig. 3(c). A wind rose is a graphical tool used by meteorologists to provide a succinct illustration of how the wind speed and the wind direction are distributed. Figure 4 shows wind rose diagrams from the whole year 2011 at the wind plant. The wind roses were generated from the 10-minute recorded wind data at MET01. It was observed that winds from the northwest and the southeast dominated throughout the year.



(a) Wind speed measured from turbine

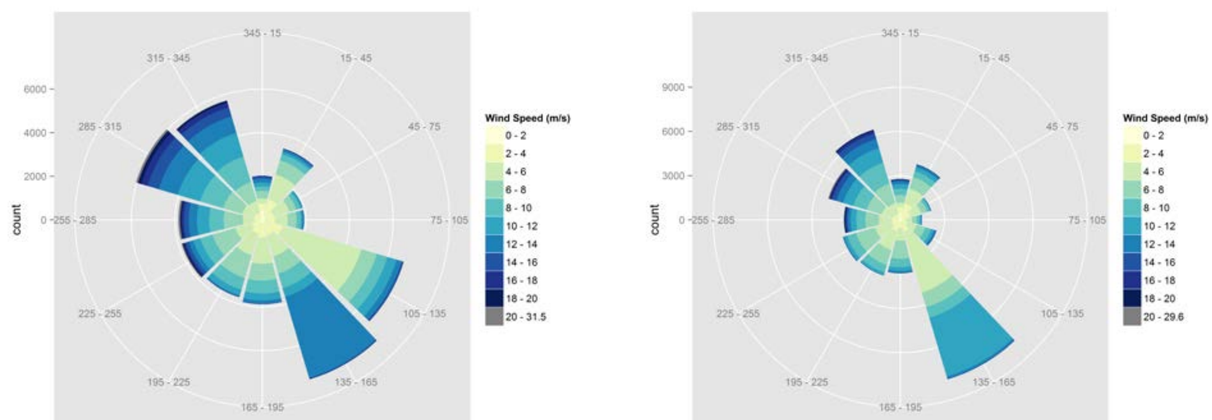


(b) Wind speed measured from MET01



(c) Power curve reported by the manufacturer[12]

Figure 3. Power output and wind speeds for the turbine A10



(a) 80 meters

(b) 50 meters

Figure 4. Wind rose diagrams at the meteorological tower MET01

B. Surrogate Modeling: Wind Power as a Function of Wind Speed and Turbulence Intensity

For each set of data (in-wake and out-of-wake), two surrogate models were developed to represent the turbine power generation (i) as a function of the wind speed and (ii) as a function of the wind speed and turbulence intensity. The first type of surrogate models were expressed as

$$P_a = \tilde{f}(U) \qquad \text{and} \qquad P_w = \tilde{f}(U) \tag{1}$$

where P_a and P_w were the estimated wind power of A10 in the cases of out-of-wake and in-wake scenarios, respectively; and U was the wind speed measured from the anemometer on top of the nacelle (or from the meteorological tower). The second type of surrogate models represented the turbine power generation as a function of the wind speed and turbulence intensity (TI), given by

$$P_{aI} = \tilde{f}(U, TI) \qquad \text{and} \qquad P_{wI} = \tilde{f}(U, TI) \tag{2}$$

where P_{aI} and P_{wI} were the estimated wind power of A10 in the out-of-wake and in-wake scenarios, respectively.

1. Turbulence Intensity

The characteristic turbulence standard deviation was used to determine the characteristic turbulence intensity. The turbulence intensity (TI) is defined as the standard deviation of the wind speed within a short time period divided by the mean wind speed during that time period. In this study, 10-minute turbulence intensity was estimated using the 1-minute wind data recorded at the meteorological tower.

$$TI = \frac{\sigma_U}{\overline{U}} \tag{3}$$

where σ_U is the standard deviation of the 1-minute wind speed within a 10-minute period, and $\overline{U}$ represents the mean wind speed at the same location during the same time period.

2. Support Vector Regression

A wide variety of surrogate modeling techniques have been developed in the literature, including[13]: (i) the polynomial response surface model, (ii) Kriging, (iii) radial basis functions, (iv) extended radial basis functions, (v) artificial neural networks, and (vi) support vector regression (SVR). Regression methods are desired to represent the power generation of a wind turbine as a function of the wind speed (and turbulence intensity). To this end, the SVR was adopted in this study.

The SVR has gained popularity both within the statistical learning community[14,15] and within the engineering optimization community.[16,17] The SVR approach provides a unique way to construct smooth, nonlinear regression approximations by formulating the surrogate model construction problem as a quadratic programming problem. The SVR approach can be expressed as[18]

$$\tilde{f}(x) = \langle w, \Phi(x) \rangle + b \tag{4}$$

where $\langle \cdot,\cdot \rangle$ denotes the dot product; w is a set of coefficients to be determined; and $\Phi(x)$ is a map from the input space to the feature space. To solve the coefficients, we can allow a predefined maximum tolerated error ε (with respect to the actual function value) at each data point, given by[18]

$$\left| \tilde{f}(x_i) - f(x_i) \right| \le \varepsilon \tag{5}$$

where $f(x)$ is the actual function to be approximated. The flatness of the approximated function can be characterized by w. By including slack variables x_i to the constraint and a cost function, the coefficient w can be obtained by solving a quadratic programming problem given by[18]

$$\begin{aligned} &Min \quad \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{n_p}\left(\xi_i + \xi_i^*\right) \\ &subject \quad to \\ &\qquad f(x_i) - \tilde{f}(x_i) \le \varepsilon + \xi_i \\ &\qquad f(x_i) - \tilde{f}(x_i) \le \varepsilon + \xi_i^* \\ &\qquad \xi_i, \xi_i^* \ge 0 \end{aligned} \tag{6}$$

where n_p is the number of sample points. The parameter $C > 0$ is user-specified and represents the trade-off between flatness and the amount up to which errors larger than ε are tolerated. Figure 5 shows a typical cost function, the ε-insensitive loss function. The above formulation is the primal form of the quadratic programming problem. In most cases, the dual form with a fewer number of constraints is easier to solve, and it is widely used to define the final form of the approximation. It can be shown that the dual form is convex and therefore has a unique minimum. The typical mapping functions allowed are radial basis functions, such as the Gaussian function.

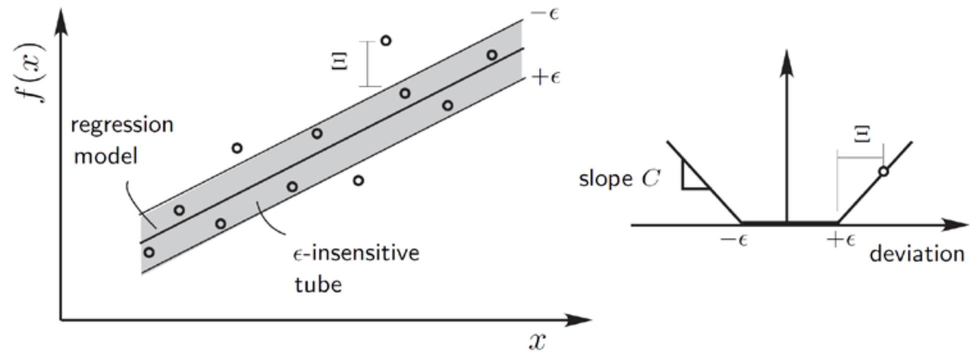


Figure 5. The ε-insensitive loss function[18]

C. Wind Distribution

Wind speed distribution is necessary to quantify the available energy (power density) at a site and to design optimal wind plant configurations. The Multivariate and Multimodal Wind Distribution (MMWD) model[19] can capture the joint variation of wind speed, wind direction, and air density and also represents multimodally-distributed data. The MMWD model was developed based on kernel density estimation. For a *d-variate* random sample $U_1, U_2, \cdots, U_n$ drawn from a density f, the multivariate kernel density estimation is defined as

$$\hat{f}(x;H) = \frac{1}{n}\sum_{i=1}^{n} K_H(u - U_i) \tag{7}$$

where $u = (u_1, u_2, \cdots, u_d)^T$, $U_i = (U_{i1}, U_{i2}, \cdots, U_{id})^T$, and $i = 1,2,\cdots,n$. Here, $K(U)$ is the kernel that is a symmetric probability density function; H is the bandwidth matrix, which is symmetric and positive-definite; and $K_H(u) = |H|^{-1/2} K(H^{-1/2}u)$. The choice of K is not crucial to the accuracy of kernel density estimators. In this paper, $K(u) = (2\pi)^{-d/2}\exp\left(-1/2u^T u\right)$ was considered the standard normal throughout. By contrast, the choice of H is crucial in determining the performance of $\hat{f}$.[20] In the MMWD model, an optimality criterion, the asymptotic mean integrated squared error, is used to select the bandwidth matrix. The details of the MMWD model can be found in the paper by Zhang et al.[19]

D. Uncertainty in the Power Response of Turbines (Under In-Wake and Out-of-Wake Scenarios)

Turbine manufacturers generally provide a smooth (monotonic) power curve to represent the power generation as a function of the incoming wind speed. However, in practice, the power generated by the turbines could be significantly different from that given by the power curve with respect to the incoming wind speed recorded at the hub height. This discrepancy can be attributed to the following major factors:

i. Wind shear—the variation of wind with vertical distance from the ground, resulting in nonuniformity of the wind faced by the entire turbine rotor

ii. Turbulence effects—the power generation depends on both mean wind speed and turbulence

iii. Turbine reliability—the uncertainty in the turbine performance (aerodynamic and control performance)

It is, however, challenging to uniquely attribute uncertainties to these different sources simply based on the recorded incoming conditions and power generation (in on-field turbine operation). In this paper, we particularly focused on illustrating how the degree of uncertainty in the turbine power generation varies between the in-wake and out-of-wake scenarios. In general, in an in-wake scenario a turbine is exposed to a greater amount of turbulence—a combination of atmospheric boundary layer turbulence and wake-induced turbulence—which was expected to impact the variance in the power response of the turbine. In addition, we also explored whether the estimated variance in the power generation was lower when it was represented as a function of both mean speed and turbulence intensity of the incoming wind (compared to only the mean wind speed).

The uncertainty in power generation with respect to a *published/reported power curve* (Fig. 3(c)) can be represented as a distribution of the following error (E_{pc}):

$$E_{pc}=P_c(U)-P_g(U) \tag{8}$$

where $P_g(U)$ and $P_c(U)$ represent the recorded power generation and the expected power generation, respectively, given by the power curve for the same incoming mean wind speed.

The uncertainty in power generation with respect to the *estimated power response* that accounts for only mean wind speed (Eq. 1) can be represented as a distribution of the following error (E_{pf}):

$$E_{pf}=P_g(U)-P_f(U) \tag{9}$$

where $P_f(U)$ represents the power generation of a turbine (as a function of mean wind speed) given by the regression model (Eq. 1) fitted from the recorded data.

The uncertainty in power generation with respect to the *estimated power response* that accounts for both mean wind speed and TI (Eq. 2) can be represented as a distribution of the following error (E_{pfI}):

$$E_{pfI}=P_{gI}(U,TI)-P_{fI}(U,TI) \tag{10}$$

where $P_{fI}(U,TI)$ represents the power generation of a turbine (as a function of mean wind speed and TI) given by the regression model (Eq. 2) and $P_{gI}(U,TI)$ represents the actual power generation recorded for the same incoming mean wind speed and TI.

The above-defined power generation error values were separately determined for the in-wake and out-of-wake scenarios. The error values were normalized by the turbine rated power value (1,500 kW). The distribution of the normalized errors was then determined using the kernel density estimation method.

IV. Results and Discussion

A. Distribution of Wind Speeds

Figure 6 shows the distribution of wind speeds estimated by the MMWD model. The wind speeds measured from both A10 (the anemometer is located on top of the nacelle) and MET01 during 2011 were analyzed. It was observed that the wind speed distributions from the all-data in-wake scenarios presented two modes. The wind speed distributions from the two out-of-wake scenarios were practically unimodal. For all three types of wind distributions (using all-data, out-of-wake, and in-wake), the wind distribution measured from MET01 was slightly on the right side of the wind distribution measured from the turbine nacelle. This is because the anemometer is located behind the turbine rotor.

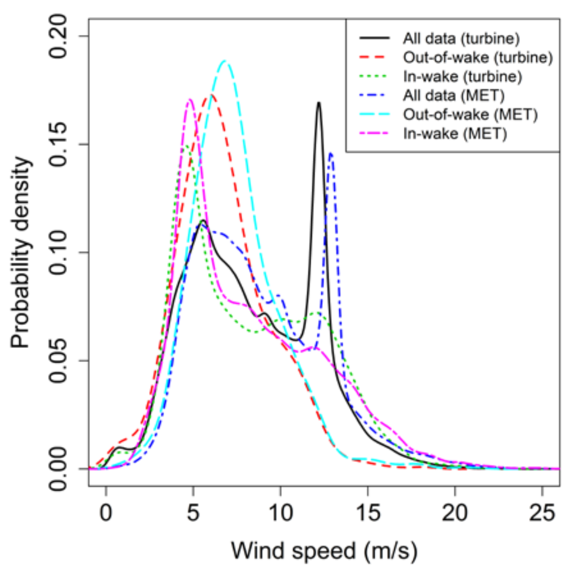


Figure 6. Distribution of wind speeds

B. Uncertainty in Power Generation with Respect to Reported Power Curve

The discrepancy between the recorded power generation (from the turbine A10) and the expected power generation given by the power curve for the same incoming mean wind speed was calculated by Eq. 8; the recorded wind speed from the MET01 at 80 m was used. The uncertainty in the turbine power generation with respect to the power curve in Fig. 3(c) was quantified by the distribution of the power discrepancy, which is shown in Fig. 7. The power generation error was normalized by the turbine rated power (1,500 kW). The mean, standard deviation, skewness, and kurtosis of power generation errors are listed in Table 1. Skewness is a measure of the asymmetry of the probability distribution, and it was the third standardized moment. The discrepancy is equal to the expected power generation minus the recorded power generation; a positive skewness of the forecast errors leads to an over-expected tail, and a negative skewness leads to an under-expected tail. Kurtosis is a measure of the magnitude of the peak of the distribution—or, conversely, the width of the distribution—and it was the fourth standardized moment. The difference between the kurtosis of a sample distribution and that of the normal distribution is known as the excess kurtosis. In the subsequent analysis, the term *kurtosis* was treated synonymously with *excess kurtosis*. A distribution with a positive kurtosis value is known as leptokurtic, which indicates a peaked (narrow) distribution; whereas a negative kurtosis indicates a flat (wide) data distribution, known as platykurtic. The pronounced peak of the leptokurtic distribution indicates a large number of very small turbine power generation errors.[21] According to standard deviation, there was relatively more uncertainty in the power generation in the in-wake scenario. The negative mean and skewness values for the in-wake scenario indicated that the power curve overall tended to underestimate the wind turbine power generation.

Table 1. Statistical moments of power generation errors with respect to the reported power curve

Scenario	Mean	Standard deviation	Skewness	Kurtosis
Out-of-wake	0.026	0.114	-1.625	5.679
In-wake	-0.069	0.164	-2.017	5.453

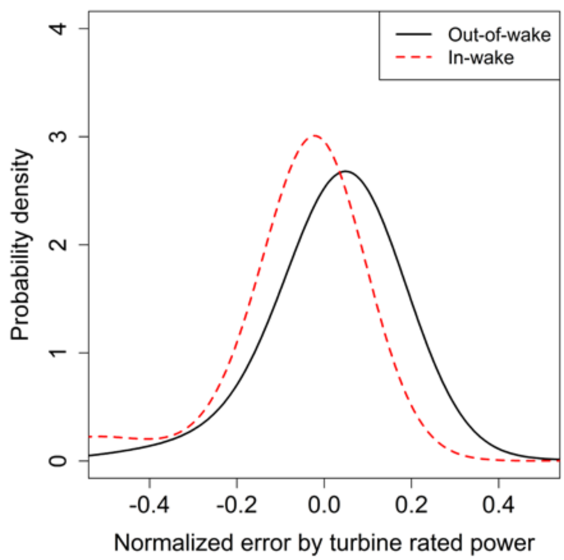


Figure 7. Uncertainty in power generation with respect to the reported power curve

C. Surrogate Modeling and Uncertainty Quantification: Power=f(U)

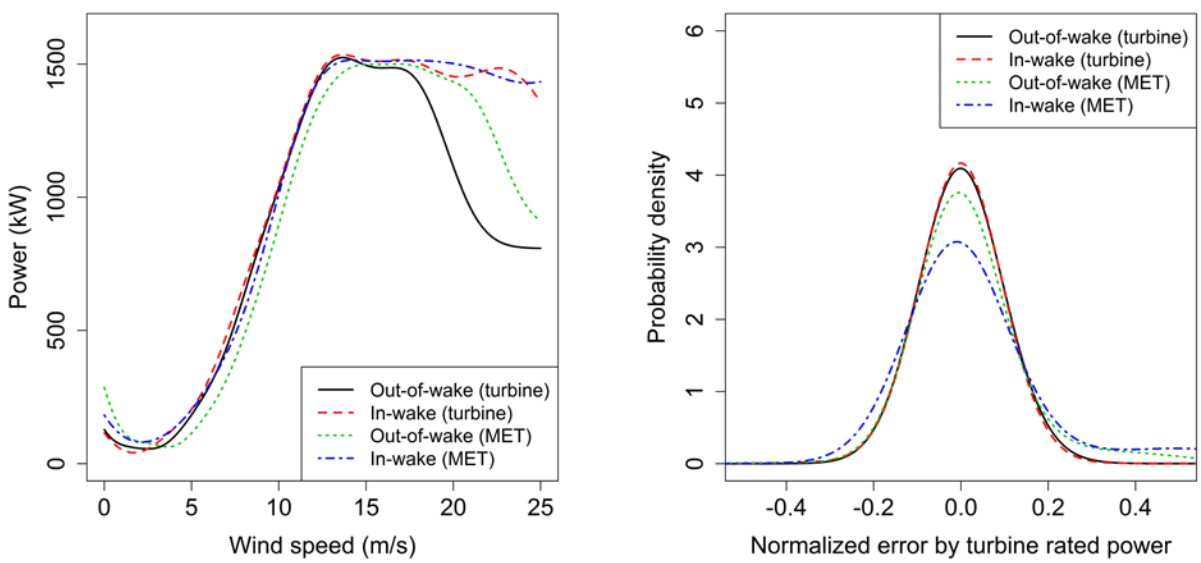
Two surrogate models were developed to represent the wind turbine power generation as a function of the wind speed for the in-wake and out-of-wake scenarios, as shown in Fig. 8(a). The 10-minute data from the whole year 2011 was used for this case. In the figure, the solid and dashed lines represent the surrogates developed using the wind speeds measured from A10; the dotted and dot-dashed lines represent the surrogates developed using the wind speeds measured from MET01. It was observed that the turbine generated different power under the same wind conditions between in-wake and out-of-wake scenarios. By comparing the surrogate models developed using the turbine downstream speeds, we observed that (i) the turbine generated more power in the in-wake scenario than in the out-of-wake scenario, when the wind speed was between approximately 3 m/s and 9 m/s and greater than 12 m/s;

and (ii) the turbine almost produced the same power in the in-wake and out-of-wake scenarios when the wind speed was between approximately 9 m/s and 12 m/s. In the surrogate models developed using wind speeds measured from MET01, it was observed that the turbine A10 generated more power in the in-wake scenario than in the out-of-wake scenario during the entire wind speed period. Overall, the results indicated that wake turbulence could be helpful in increasing wind power generation for the analyzed wind turbine A10.

The uncertainty in power generation with respect to the *estimated power response* that accounts for only mean wind speed is quantified in Fig. 8(b). The figure shows the distribution of fitted power errors between the recorded wind power generation and the surrogate estimations. Both wind speeds measured from the anemometers installed on the turbine and the meteorological power were analyzed. The fitted power errors were normalized by the rated power of A10, which is 1,500 kW. The mean, standard deviation, skewness, and kurtosis values of the error distributions are listed in Table 2. According to the mean and standard deviation values, there was relatively more uncertainty in the surrogate of the in-wake scenario than that of the out-of-wake scenario, thus there was more uncertainty in turbine power generation in the in-wake scenario. It was also observed from statistical moments that the surrogate developed using wind speeds measured from A10 was more accurate than the surrogate developed using wind speeds measured from MET01.

Table 2. Statistical moments of fitted power generation errors in the case of Power=f(U)

Anemometer location	Scenario	Mean	Standard deviation	Skewness	Kurtosis
Wind speed measured from turbine	Out-of-wake	0.002	0.047	2.526	29.191
	In-wake	0.001	0.067	4.687	82.847
Wind speed measured from MET01	Out-of-wake	0.020	0.108	2.362	9.505
	In-wake	0.038	0.162	2.339	6.460



(a) Surrogate models

(b) Distributions of fitted power errors

Figure 8. Surrogate modeling and uncertainty quantification in the case of Power=f(U)

D. Surrogate Modeling and Uncertainty Quantification: Power=f(U, TI)

In the previous section, the surrogate model was developed to represent the turbine power generation as a function of wind speed only. Part of the uncertainty in the developed surrogate can be attributed to the lack of incoming condition characterization—e.g., not considering incoming turbulence intensity. Therefore, another surrogate model was further developed to represent the turbine power generation as a function of wind speed and turbulence intensity. The data from the 2011 summer period (July, August, and September) was used for this case. The 10-minute average turbulence intensity was calculated based on the 1-minute wind speed measured from MET01. First, a surrogate was built to investigate the relationship between the wind speed and the turbulence intensity at MET01, which is shown in Fig. 9. At the studied wind plant, the turbulence intensity was relatively high when the wind speed was fairly low (less than 5 m/s) or high (greater than 20 m/s).

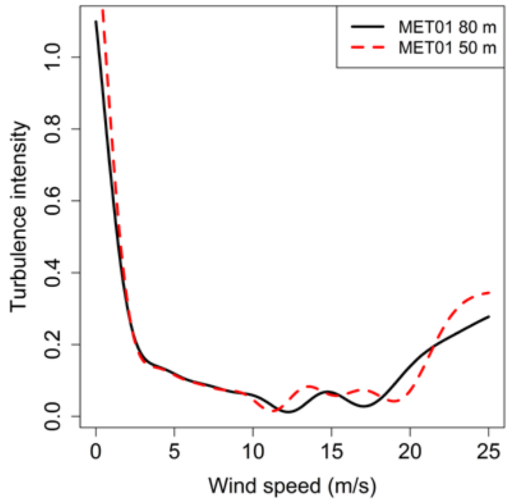


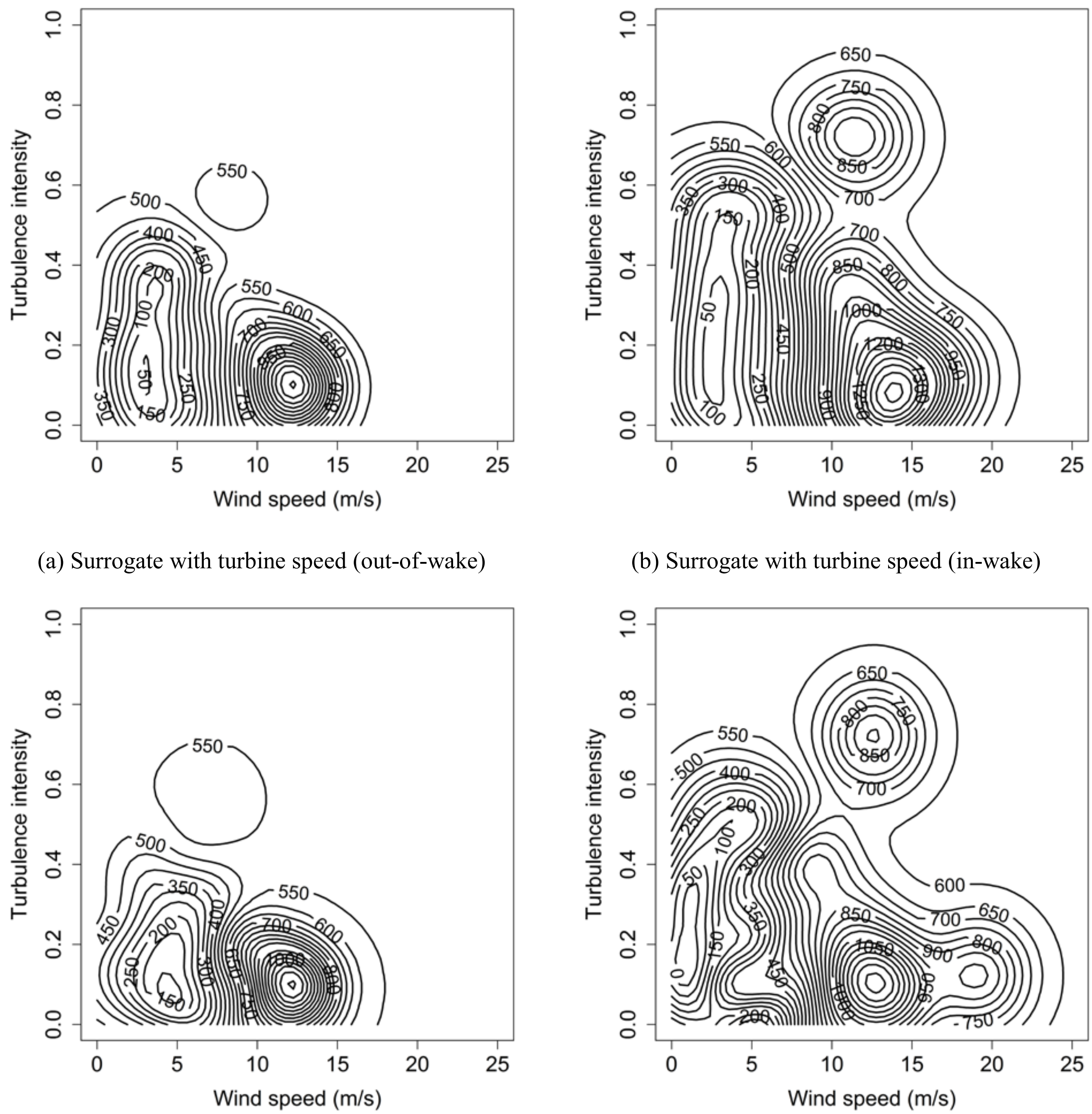
Figure 9. Turbulence intensity measured at the meteorological towers

Two surrogate models were developed to represent the turbine power generation as a function of the wind speed and the turbulence intensity for the in-wake and out-of-wake scenarios. The wind speed data measured from both A10 and MET01 was used. The contour plots of the developed surrogates are shown in Fig. 10. The surrogates for the out-of-wake and in-wake scenarios that were developed based on measured wind speeds from A10 are shown in Fig. 10(a) and 10(b), respectively; the surrogates for the out-of-wake and in-wake scenarios that were developed based on measured wind speeds from MET01 are shown in Fig. 10(c) and 10(d), respectively. Figure 10 shows that the turbine power generation is sensitive to both wind speed and turbulence intensity. It was observed that: (i) for the out-of-wake scenario, the power generation was more sensitive to the turbulence intensity with lower wind speeds than with higher wind speeds, and (ii) for the in-wake scenario, the power generation was more sensitive to the turbulence intensity when the wind speed was close to the turbine rated speed. In addition, the power generation changed with the turbulence intensity even when the wind speed was greater than the turbine rated speed. By comparing the out-of-wake (Figs. 10(a) and 10(c)) and in-wake (Figs. 10(b) and 10(d)) scenarios, we observed that the turbine power generation was more sensitive to turbulence when the turbine was in the wake of other turbines.

The uncertainty in the power generation with respect to the estimated power response that accounts for both mean wind speed and TI is quantified in Fig. 11. Both wind speeds measured from the anemometers installed on the turbine and the meteorological tower were analyzed. The fitted power errors were normalized by the rated power of A10, which is 1,500 kW. To compare the uncertainties in the power generation between the cases, $\tilde{P} = f(U)$ and $\tilde{P} = f(U, TI)$, surrogates of the power generation as a function of the wind speed only was again developed using the A10 and MET01 data during the 2011 summer. Table 3 lists the mean, standard deviation, skewness, and kurtosis values of the error distributions. According to the standard deviation values, the uncertainty in the surrogate model was reduced by considering the turbulence intensity. For surrogates developed using wind speed measured from the turbine, the uncertainty levels in Fig. 11(a) were not significantly different; for surrogates developed using wind speed measured from the meteorological tower, the uncertainty in the out-of-wake scenario was significantly lower than that in the in-wake scenario. It was again observed from the statistical moments that the surrogate developed using wind speeds measured from A10 was more accurate than the surrogate developed using wind speeds measured from MET01.

Table 3. Statistical moments of fitted power generation errors in the case of Power=f(U, TI)

Anemometer location	Scenario	Mean	Standard deviation	Skewness	Kurtosis
Wind speed measured from turbine	Out-of-wake (speed only)	0.007	0.045	1.307	1.609
	In-wake (speed only)	0.007	0.050	2.590	18.388
	Out-of-wake (speed and TI)	0.007	0.044	1.390	1.833
	In-wake (speed and TI)	0.004	0.048	2.892	22.774
Wind speed measured from MET01	Out-of-wake (speed only)	0.031	0.095	1.747	2.855
	In-wake (speed only)	0.069	0.196	1.201	0.473
	Out-of-wake (speed and TI)	0.020	0.086	1.676	3.832
	In-wake (speed and TI)	0.042	0.186	1.167	1.075



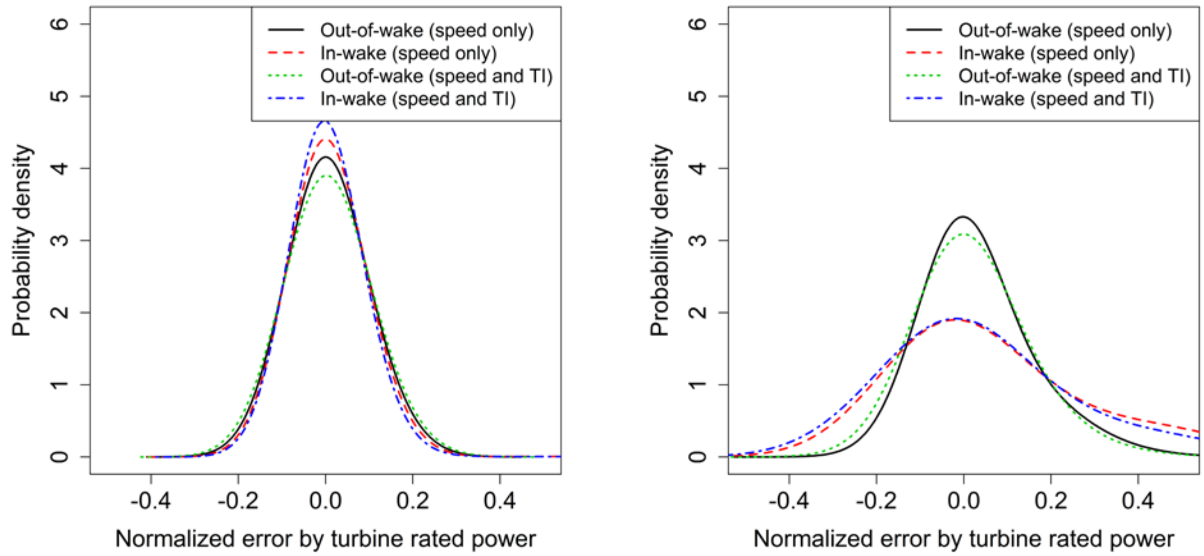
(a) Surrogate with turbine speed (out-of-wake)

(b) Surrogate with turbine speed (in-wake)

(c) Surrogate with MET01 speed (out-of-wake)

(d) Surrogate with MET01 speed (in-wake)

Figure 10. Surrogate modeling in the case of Power=f(U, TI)



(a) Surrogate with speeds measured from turbine

(b) Surrogate with speeds measured from MET01

Figure 11. Uncertainty quantification in the case of Power=f(U, TI)

V. Conclusions

This paper developed a methodology to analyze how the ambient and wake turbulence affect the power generation of a wind turbine. The monitoring wind speed, wind direction, and power generation data from the Cedar Creek wind plant was used for the analysis. For the analyzed in-wake and out-of-wake scenarios, surrogate models were developed to represent the turbine power generation (i) as a function of the wind speed and (ii) as a function of the wind speed and turbulence intensity. Uncertainties in the surrogate models and thereby in the turbine power generation were quantified.

For the analyzed wind turbine A10, we found that in the same wind conditions the turbine generated different power between the in-wake and the out-of-wake scenarios, and the turbine generally produced more power in the in-wake scenario. In the surrogate model that represented the power generation as a function of wind speed and turbulence intensity, we found that (i) in the out-of-wake scenario, the power generation was more sensitive to the turbulence intensity with lower wind speeds than with higher wind speeds; and (ii) in the in-wake scenario, the power generation was more sensitive to the turbulence intensity when the wind speed was close to the turbine rated speed. The uncertainty quantification results generally showed that more uncertainty in the power generation was present in the in-wake scenario than in the out-of-wake scenario.

Future work will analyze turbulence effects on the power generation of an entire wind plant and quantify the uncertainty in the power generation.

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