Abstract

The utilization of wind energy has attracted extensive attentions in the last few decades around the world, providing a sustainable and clean source to generate electricity. It is a common phenomenon of wake interference among wind turbines and hence the optimization of wind farm layout is of great importance to improve the wind turbine yields. More specifically, the accuracy of the three-dimensional wake model is critical to the optimal design of a real wind farm layout considering the combinatorial effect of wind turbine interaction and topography. In this paper, a novel learning-based three-dimensional wake model is proposed and subsequently validated by comparison to the high-fidelity wake simulation results. Moreover, due to the fact that the inevitable deviation of actual wind scenario from the anticipated one can greatly jeopardize the wind farm optimization outcome, the inaccuracy of wind condition prediction using the existing meteorologic data with limited-time measurement is incorporated into the optimization study. Different scenarios including short-, medium-, and long-term wind data are studied specifically with the wind speed/direction prediction errors of $(\pm 0.25 \, \text{m/s}, \pm 5.62 ^\circ)$, $(\pm 0.08 \, \text{m/s}, \pm 1.75 ^\circ)$ and $(\pm 0.025 \, \text{m/s}, \pm 0.56 ^\circ)$, respectively. An advanced objective function which simultaneously maximizes the power output and minimizes the power variance is employed for the optimization study. Through comparison, it is found that the optimized wind farm layout yields over $210 \, \text{kW}$ more total power output on average than the existed wind farm layout, which verifies the effectiveness of the wind farm layout optimization tool. The results show that as the measurement time for predicting the wind condition gets longer, the total wind farm power output average increases while the error of power output prediction decreases. For the wind farm with 20 wind turbines installed, the individual power output is above $500 \, \text{kW}$ with an error of $90 \, \text{kW}$ under the short-term wind $(\pm 0.25 \, \text{m/s}, \pm 5.62 ^\circ)$, while it is above $530 \, \text{kW}$ with an error of $10 \, \text{kW}$ under the long-term wind $(\pm 0.025 \, \text{m/s}, \pm 0.56 ^\circ)$. 

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Keywords
layout optimization, wind farm, learning-based wake model, wind prediction, power confidence interval

Introduction
The Utilization of wind energy has attracted extensive attentions in the last few decades around the world, providing a sustainable and clean source to generate electricity (Latifi et al., 2017). In order to compete with the traditional fossil fuels or other potential renewable resources, reducing the cost of wind energy production is an imperative task which can be achieved either by cutting down the wind farm developing cost with the advancement of material, operational, and strategic technologies, or by enhancing the wind farm power production (Gonzalez-Rodriguez, 2017; Hao et al., 2017). Due to the clustered wind turbine placement inside a wind farm, the phenomena of wake interference among wind turbines is unavoidable which as a result curtails the total wind farm power output to a large extent (Fang et al., 2020; Feijóo and Villanueva, 2017; Li et al., 2018). In this regard, researchers have strived to come up with various approaches to mitigating the wake interference, among which wind farm layout optimization (i.e. optimal placement of wind turbines inside the wind farm) is one of the most prominent tools to reach the goal and it has been a hot topic of research in recent years (Amaral and Castro, 2017; Bossanyi, 2018).

The study of wind farm layout optimization consists of multiple aspects including: 1) complex wind farm modelling (Wang et al., 2017), 2) real wind condition inclusion (Wang et al., 2017), 3) accurate wake modelling (Kuo et al., 2016), and 4) efficient optimization algorithm and method (Beşkirli et al., 2018). Wang et al. (2015) considered the landowners’ decisions on the participation of different land plots of a wind farm, to investigate the importance of different land plots to the overall layout optimization results. Kusiak and Song (2010) proposed the discretization method for the calculation of wind turbine power output under Weibull wind distribution to find the optimum placements of wind turbines inside a circular-shape wind farm. Yang et al. (2018) modified the popularly genetic algorithm (GA) with the Boolean code to optimize the wind turbine positions inside the benchmark square-shape wind farm and the optimization results are compared to the previous publications. Bansal et al. (2018) improved the biogeography-based optimization method with the inclusion of fitness difference for a more efficient optimization process, and the effectiveness of the new optimization method is tested by comparing to the earlier published results. For the study of wind turbine wake modeling, Parada et al. (2017) developed a two-dimensional wake model which considers the variation of wind speed in the wake region with Gaussian wind distribution. The effectiveness of the proposed wake model is validated by comparison to the optimization results with other benchmark models. Kuo et al. (2015) proposed a mechanistic semi-empirical wake interaction model that differs from the widely employed sum-of-square model to accurately capture the wake effect of multiple wind turbines, and the new wake interaction model is based on the energy balance principle inside the far wake region. Ti et al. (2020) applied the novel machine learning method to develop a new model to describe the wake velocity and turbulence with high accuracy and good efficiency. Kuo et al. (2018) proposed a new wake model applied for the wind farm design on complex terrains which however is based on solving a simplified Navier-Stokes equation to save computational cost and hence may possibly lack accuracy. The similar means of proposing the three-dimensional wake model based on the simplified flow
theory such as conservation law (Sun and Yang, 2018), linear propagation law (Song et al., 2016) and simplified two-dimensional wake model (Gao et al., 2020; Sun and Yang, 2020) has been in aid of the research in published references. However, the model is simplified two-dimensional and only applicable to an ideal wind farm with flat-terrain. Though various topics of the wind farm layout optimization research have been investigated, a lack of the realistic wind farm optimization study which considers the real wind farm design factors (such as the more accurate wake model) has been observed in literature.

When optimizing a wind farm layout, wind conditions are most commonly approached by using the past meteorological statistics to predict the future ones, which might bring big prediction errors (Foley et al., 2012). Large deviations of actual real wind condition from the design-employed, will probably jeopardize the outcome of wind farm operation and may lead to the wind farm optimization failure, if not properly considered at the initial design stage (Gaumond et al., 2014; Wang et al., 2016). MirHassani and Yarahmadi (2017) published a research paper on wind farm layout optimization under the uncertainty of different hub height wind turbines and a generalized optimization model expression for various wind characteristics, while the wind uncertainty factor was not investigated. Messac et al. (2012) characterized wind uncertainty by establishing a model to propagate the uncertainty into the wind farm power output evaluation. González et al. (2012) considered the uncertainty of wind conditions by testing four different wind direction scenarios and different Weibull distribution scale parameters in the wind farm layout optimization. Yin et al. (2016; 2017) took into account wind uncertainty with several different risk management models, and subsequently analyze the wind farm power output, cost, and risk by the layout optimization of the benchmark square-shape wind farm.

Based on the research gap, a real coastal onshore wind farm located in Southeastern Australia is targeted in this paper for the layout optimization study. A realistic three-dimensional wake model based on machine learning algorithm is proposed to quantify the wake effect of wind turbine interaction and topographic influence of the non-flat terrain. An advanced objective function integrating both the power output and power variability is employed. Due to the limited-time wind data measurement, the inaccuracy of wind condition prediction is studied for the wind farm layout optimization for the first time. The remainder of this paper is organized as follows. Section 2 describes the modelling and the methodology applied for the wind farm layout optimization, including the wind farm and wind turbine models, the new three-dimensional analytical wake model, the wind condition prediction model, and the mathematical optimization formulations. Section 3 discusses the comparison of the wind farm results between the existing and optimized wind farm layouts, followed by the wind farm optimization results under different scenarios of wind data prediction. Section 4 concludes the research work.

**Modelling and methodology**

**Wind farm and wind turbine models**

The real wind farm model studied in this paper consists of two separate small wind farms (named Grasmere and Albany wind farm), which is situated along the coastline of Southeast Australia (Gu and Wang, 2013). In this particular wind farm, a total of 18 Enercon 2.3 MW wind turbines (accomplished in 2011) have been installed with the detailed properties of the wind turbine shown in Table 1.
Learning-based two-dimensional wake model

The widely applied Jensen’s wake model (Jensen, 1983) for the wind farm layout optimization study is one-dimensional considering the axial wind speed deficit alongside the incoming wind. However, it is non-realistic since the wind speed deficit takes place both in the axial and radial wind directions. It has been further reported in literature that the wake speed variation with Gaussian axisymmetric profile is more accurate in predicting the wind characteristic (Chamorro and Porté-Agel, 2009; Tian et al., 2015). Nevertheless, the arithmetic-based wake model with analytical equations still lacks satisfactory accuracy in comparison to the computational model which is characterized by the advantage of capability in accurately predicting the flow field in the wake (Wang et al., 2016). Therefore, a learning-based two-dimensional wake model based on the CFD simulation method is applied in this paper which is introduced in detail as follows.

Actuator disc method. When quantifying the wind turbine wake effect with CFD simulations (Li et al., 2018; Li et al., 2018; Wu et al., 2015), the actuator disc model has been widely employed in the wind farm optimization and the model regards the wind turbine as a thin disc. According to the actuator disc theory (see Figure 1 (a) which is replicated from reference (Wang and Alden, 2017)), when the incoming free-stream wind with a velocity of $U_\infty$ approaches the front of the disc, the wind speed reduces to $U_d$ while the pressure rises to $P_d^+$. Subsequently, the wind passes through the actuator disc with a loss of the kinetic energy. At the place right behind the disc, the wind pressure reduces to $P_d^-$, with a pressure drop between the front and back of the disc of $\Delta P$. When the wind further propagates after the actuator disc, the wind speed is gradually restored due to the action of viscosity (Qu et al., 2018; Zhao et al., 2018). The pressure drop is calculated based on the law of conservation of energy which gives:

$$\Delta P = P_d^+ - P_d^- = \frac{1}{2}\rho(U_\infty^2 - U_w^2)$$ (1)

in which, the velocity $U_w$ is the velocity at the infinite outlet, and the relationship between $U_\infty$ and $U_w$ can be expressed as:

$$U_w = (1 - 2a)U_\infty$$ (2)

where $a$ is the induction factor and by substitution $\Delta P$ is represented by:

$$\Delta P = 2\rho U_\infty^2 a(1 - a) = \frac{1}{2}\rho U_\infty^2 C_T$$ (3)

Table 1. Details of the installed wind turbine properties.

| Parameters                  | Values       |
|-----------------------------|--------------|
| Rated power                 | 2300 kW      |
| Rotor diameter              | 71 m         |
| Hub height                  | 64 m         |
| Cut-in wind speed           | 2.5 m/s      |
| Rated wind speed            | 15 m/s       |
| Cut-out wind speed          | 28-34 m/s    |
| Turbine power curve         | $P = 0.6815v^3$ kW |
where $\rho$ is the air density, $C_T$ is the thrust coefficient and $C_P$ is the power coefficient. whose relationship to $a$ are expressed by:

$$C_T = 4a(1 - a)$$  \hspace{1cm} (4)

$$C_P = 4a(1 - a)^2$$  \hspace{1cm} (5)

With all the parameters calculated based on the above formulas, the porous-jump scheme of the wind turbine actuator disc in Fluent software is set up to simulate the energy loss right in front of and after the disc which gives an expression of the pressure drop as:

$$\Delta P = \left( \frac{1}{2} C_2 \rho V + \frac{\mu}{\alpha} V \right) \Delta n$$  \hspace{1cm} (6)

the first term in the bracket is to simulate the internal energy loss where $C_2$ is Pressure-Jump Coefficient and the wind velocity $V$ is equal to $U_d$, the second term in the bracket is the resistance loss term which is ignored for the calculation of $\Delta P$, and $\Delta n$ is the disc thickness.

Given the disadvantage of the high computational resource cost, the machine learning method is introduced for attaining the computational wind turbine wake model by training and learning the wake flow patterns out of the dataset. Figure 1 (b) shows the wind turbine actuator disc model in the CFD simulation for generating the wind turbine wake dataset. The boundary conditions are set as the velocity inlet and pressure output. The wall boundary is set as free slip wall boundary and the residual criterion is set as $10^{-4}$. Four different scenarios of the mesh size including 0.86, 1.13, 1.52 and 2.35 million are tested for the wind turbine wake simulation. Since our target of the simulation is to obtain the wake velocity field, the simulation outcomes of the velocity distribution are compared. It is found that once the meshes exceed the 1.13 million, there are no big differences of the velocity distribution for the ADM simulation results. Hence, the mesh size is chosen to be 1.13 million.

**Wake model based on machine learning method**

**Dataset preparation.** Prior to introducing the artificial neural network for the training purposes, the dataset of wind turbine wake under various wind speed conditions must be prepared beforehand.
In our established wake model, the only input variable is the incoming wind velocity. The output variables are the resultant two-dimensional wind speed distribution behind the wind turbine rotor, which are reshaped into a wind profile matrix \( V (V_x \times V_y) \). Given the computational/training cost and accuracy, the resolution of the velocity field is chosen to be \( 64 \times 128 \) with 8192 data points in total. Subsequently, the velocity matrix \( V \) is converted into one dimensional to facilitate the training process.

Between the cut-in and cut-out wind speeds, the wind speed samples are divided into 316 bins with 0.1 m/s interval to generate the wind turbine flow fields by CFD simulations. By creating the Python scripts to set up the wind speed value and automate the CFD simulation to run and post-process the simulation results under different wind speeds, the automatic CFD simulation platform to generate the flow field database in the wind turbine wake is established. As a result, the matrix of the detailed wind speed variation at the chosen data points behind the wind turbine rotor is obtained under various incoming wind conditions.

**Architecture design of artificial neural network.** With the massive data of wind speed distribution in the wake as a function of incoming wind conditions prepared, the connection between the incoming wind velocity and the wake flow profile is established with the Artificial Neural Network (ANN) which is based on the machine learning theory. Specifically, the back propagation (BP) ANN which has been one of the most widely applied ANN branch types is employed for training the dataset. The BP ANN consists of input layer, hidden layer and output layer in sequence. The number of input and output layers is constantly one while the hidden layer can be multiple depending on the settings. The adjacent layers are mutually connected with corresponding weight matrix. During the training procedure, the BP algorithm will pass the residual between the network output value and the real value backwards and the weights of all layers are updated along with the back-propagation process towards reaching a minimal value of the residual.

Figure 2 shows the schematic of the wind turbine wake ANN architecture. In the architecture design of our paper study, the input layer neuron number is one which is the incoming wind velocity and the output layer neuron number is 8192 which is equal to the wake profile data points. There are three hidden layers with the neuron numbers of 650, 1300 and 4096, respectively. Apart from the output layer, all other layers require the activation function to guarantee the accuracy of the back-propagation process. In our study, the widely applied Rectified Linear Unit (Relu) function is employed as the activation function. The network is established and trained in the Pytorch platform with the Mean Square Error loss function (MSELoss) as the loss function for training process and Adam as the optimization module. The training procedure is carried out by GPU means and the configuration of the operational hardware platform is RTX 2060 with 6 GB memory. As a result of the built and trained ANN architecture, the two-dimensional wake profile of the wind turbine can be acquired in seconds under any given incoming wind velocity.

Figure 3 shows the resultant two-dimensional wind turbine wake model established from the ANN machine learning method. Figure 4(a) and Figure 4(b) presents the CFD simulated and the ANN predicted wind turbine wake profiles respectively, while Figure 4(c) presents the error between the simulation and prediction results in percentage. As can be seen, the prediction results are fairly satisfactory with the largest discrepancy below 10% which is sporadically distributed along the axis direction of the wake.

The two-dimensional wake model is introduced above based on the machine learning method with the aid of actuator disc theory and artificial neural network. The learning-based two-dimensional wake model is extended to be three-dimensional accounting for both the
wind turbine wake interaction and topographic effect inside a real wind farm with non-flat terrains.

**Three-dimensional wake model incorporating terrain effect**

On the basis of the aforementioned two-dimensional wake model, a novel three-dimensional wake model is proposed by incorporating the topographic effect of non-flat terrain into the wind turbine wake quantities. In this section, a 3-D wind multiplier method is introduced to account for the wind speed variation over non-flat terrain, followed by the verification of the novel wake model compared to the high-fidelity CFD simulation results.

*Wind multiplier method.* With the learning-based two-dimensional wake model, the wind turbine wake interactions inside a real wind farm cannot be accurately described due to the influence of the topography on wind behavior over non-flat wind farm terrain. Here, a 3-D wind multiplier method is employed to modify the wake-affected wind speed calculated by the two-dimensional wake model. The process of the wind multiplier calculation is presented below.

Firstly, a three-dimensional wind farm model free of wind turbines is generated by the combination of transforming the terrain altitudes into the contour data by a geographic information system (GIS) handling software package and the Rhino3D computer-aided design software is applied to establish the real wind farm terrain model. The real wind farm three-dimensional model is then subtracted from the encapsulated solid rectangle to obtain the air flow model for computational fluid dynamics (CFD) simulation of wind farm.

The wind farm CFD simulations are performed by importing the three-dimensional model into the ANSYS Fluent software with pre-processing steps taken. Specifically, the velocity inlet and pressure outlet are set as the inlet and outlet boundary conditions for the simulations,
Figure 3. Wind speed contour calculated from the ANN machine learning method: (a) CFD simulation result, (b) prediction result and (c) distribution of prediction error over CFD simulation.

Figure 4. CFD simulation detail for validating the wake model: (a) dimension and boundary condition of the simulation model without wind turbine and (b) simulation model with an actuator disc wind turbine to calculate the wake wind speed.
respectively. Furthermore, as the free-stream wind speed varies as a function of the altitude, a user defined function (UDF) for the velocity inlet boundary condition is programmed in the Fluent software and it obeys power law pattern by:

\[ u(h) = u_0 \left( \frac{h}{h_{ref}} \right)^{1/7} \]  

(8)

where \( u(h) \) is the wind speed at an altitude \( h \), and \( u_0 \) is the fixed speed at a reference altitude \( h_{ref} \). The criterion of residual convergence is \( 10^{-4} \). After the wind farm CFD simulations, the wind speed at the hub height altitude over the potential wind turbine positions are extracted by post-processing the simulation results. By normalizing the resultant wind speed to the free-stream wind speed at a given position \((x, y)\) of the wind turbine \( i \), wind multiplier \( M_i(x, y) \) is calculated by:

\[ M_i(x, y) = \frac{\text{Wind speed from CFD simulation}}{\text{Free - stream wind speed}} \]  

(9)

For the wind direction divided into 12 sectors in this case, the wind farm CFD simulations under each of the 12 wind direction sectors are performed to calculate the respected wind multiplier distribution. The wind multiplier results under different incoming wind directions can be referred in the authors’ previous publication (Wang et al., 2017).

Based on the two-dimensional PARK-Gaussian wake model and the wind multiplier value, the resultant wind speed \( v \) over non-flat terrain under an free-stream wind speed \( v_0 \), is given by:

\[ v = v_0 \left( 1 - \sum_{i=1}^{N} \sqrt{\frac{d_i^2}{\text{def}_i^2}} \right) \cdot M_i(x, y) \]  

(10)

Note that in the equation the combined wake effect by multiple wind turbines is considered with the sum of square (SOS) superposition model, which has been widely accepted and employed in literature for wake superposition effect.

**Wake model validation by high-fidelity CFD simulation.** Due to a lack of the real onshore wind farm (with terrain altitude variations) test data to validate the accuracy of the proposed wake model, the high-fidelity CFD simulation is carried out for a standalone wind turbine to compare the proposed wake model and the simulation results of the wind speed variation over a non-flat terrain.

For the validation with CFD simulation, the exactly same wind turbine model shown in Section 2.1 is employed while the wind farm terrain is simplified. As can be seen in Figure 4, the tested wind farm has a fixed slope of 20°. The boundary conditions of velocity inlet and pressure outlet are set. The velocity inlet abides by the pattern of the exponential variation with altitudes the same as Eq. (8). The free-stream wind speed at an altitude of the wind turbine hub height is set to be 12 m/s. The simulation convergence residual is \( 10^{-4} \). Note that in Figure 4 (a), the wind speed extraction area for the comparison of the proposed wake model and the CFD simulation is highlighted by the dark grey color plane. When calculating the wind multiplier coefficients, the wind turbine is absent in the wind farm. By importing the two-dimensional wake model and the wind multiplier results, the wind speed variation behind an upstream wind turbine rotor on the plane with a hub height altitude and parallel to the slope can be obtained as shown in Figure 4 (a). For the wind turbine wake effect predicted by CFD simulation, one actuator disc is placed right at the beginning of the slope as shown in Figure 4 (b). By comparing the wind speed distribution of the proposed
wake model and the high-fidelity CFD simulation (see Figure 5), it is found that the stratification of the wind speed distribution is extremely evident due to the altitude increase. For the far-wake region (more than 5 times diameter), the wind speeds of the two scenarios agrees very well and that is where the wake model works for the wind farm layout optimization study (since the proximity distance of any two wind turbines is set to be more than that).

In summary, a novel three-dimensional wake model based on complex Navier-Stokes equations (computational model), taking into account both the wind turbine interaction and the topographic effect on the wind speed variation (Gao et al., 2016), is proposed for a real wind farm optimization study. The novel wake model is achieved by means of: 1) machine learning algorithm to establish the implicit relationship between the wake velocity and incoming wind speed; and 2) distribution of the wind multiplier coefficient obtained by CFD simulation, which is incorporated into the original wake model to account for the wind speed variation over non-flat terrain. In order to validate the new proposed three-dimensional wake model, the comparison of the wind speeds calculated from the proposed wake model and the high-fidelity CFD simulation is made. Results show that though the discrepancy among the near-wake region (less than 4 times diameter) is non-negligible, the new wake model agrees very well with the CFD results among the far-wake region, which proves the validity of the new model applied for the real wind farm layout optimization (considering the proximity constraint of wind turbines is beyond 5 times diameter).

**Wind data prediction model**

*Continuous Weibull distribution model.* Most wind conditions in the reported wind farm optimization studies are ideal, which are characterized by the discrete wind description including the constant/variable wind speed(s)/direction(s). Realistically, both wind speed and wind direction are continuously changing which can be approximated by certain kinds of distribution form, e.g., the Rayleigh or normal distribution (Safari and Gasore, 2010). In this paper, the Weibull distribution which has been most widely applied in reference study (Soulouknga et al., 2018), will be applied for approximating the wind speed variation as an example. Note that it is used as an example of demonstration

![Figure 5. Comparison of (a) the proposed three-dimensional wake model and (b) the high-fidelity CFD simulation results.](image-url)
and can be replaced by other forms of distribution so long as it matches the characteristics of the local wind scenario. The mathematical expression of Weibull distribution is given by (Seguro J and Lambert, 2000):

$$f(x) = \frac{k}{c} \left(\frac{x}{c}\right)^{k-1} \exp\left(-\left(\frac{x}{c}\right)^k\right)$$

(11)

where \(f(x)\) is the probability density function, \(c\) and \(k\) are the scale and shape parameters, respectively. The cumulative distribution function \(F(x)\) of wind speed is represented by:

$$F(x) = 1 - \exp\left(-\left(\frac{x}{c}\right)^k\right)$$

(12)

For this real wind farm study, Table 2 shows the variation of the shape and scale parameters of Weibull distribution under different wind direction sectors. Evidently, it is divided into 12 sectors with the constant 30° interval.

**Discrete wind data generation over short-, medium- and long-terms.** Due to a lack of the meteorological observation wind condition data for the real wind farm, the wind data can only be obtained by the Monte Carlo simulation based on the continuous wind distribution model.

According to reference (Wang et al., 2015; Xue et al., 2020), the intention of forecasting wind power is to estimate the average power production of wind farm in the near future. The estimation can be categorized into short-term, medium-term and long-term. The short-term are considered for power system management or energy trading. The medium-term are considered for planning maintenance of wind farms, while the long-term are considered for the optimal design of wind farms. As the name suggests, the wind condition data extracted for different estimation purposes are correspondingly performed over short, medium and long time period, respectively. For an optimal wind farm design, long-term wind condition data are preferred to reduce the discrepancy between the measured wind data and the predicted future wind data. Even so, the error of the wind condition prediction can still be huge due to the unpredictability of the wind condition(Kang et al., 2014; Wang et al., 2018). The time period of the wind measurement is always restricted which bring about the problem of the selection of the wind sampling time. In this paper, Monte Carlo (MC) simulation is performed to acquire the random discrete data obeying the continuous Weibull distribution model(Chen et al., 2015; Hu et al., 2020). Sample numbers with three magnitudes, i.e., 1000, 10,000 and 100,000, are adopted for the MC simulation to mimic the wind data measured under various time periods. With the commonly used 5 min frequency of wind condition measurement, the simulated short-, medium- and long-term durations are approximately 3 days, 1 month, and 1 year.

**Table 2.** Parameters of wind speed Weibull distribution under different wind direction sectors.

| l-1 | \(\theta_{l-1}\) | \(\theta_l\) | k   | c   | l-1 | \(\theta_{l-1}\) | \(\theta_l\) | k   | c   |
|-----|----------------|-------------|-----|-----|-----|----------------|-------------|-----|-----|
| 0   | 0              | 30          | 1.79| 6.4 | 6   | 180           | 210         | 1.89| 8.0 |
| 1   | 30             | 60          | 1.75| 7.8 | 7   | 210           | 240         | 1.81| 7.5 |
| 2   | 60             | 90          | 1.93| 9.3 | 8   | 240           | 270         | 1.83| 7.3 |
| 3   | 90             | 120         | 1.92| 9.9 | 9   | 270           | 300         | 1.96| 7.0 |
| 4   | 120            | 150         | 1.96| 9.8 | 10  | 300           | 330         | 1.65| 8.8 |
| 5   | 150            | 180         | 1.85| 8.9 | 11  | 330           | 360         | 1.81| 7.4 |
The Root Mean Square Error (RMSE) is calculated to obtain the discrepancy of the probability of occurrence between the predicted and the actual values, which is given by:

$$\text{RMSE} = \sqrt{\frac{1}{S-1} \sum_{i=1}^{S} (\phi_i(MC) - \phi_i(\text{Weibull}))^2}$$  \hspace{1cm} (13)

where $S$ is the number that the whole region is divided into $\phi_i(MC)$ and $\phi_i(\text{Weibull})$ are the probabilities for the $i$-th simulation sample and distribution wind speed interval, respectively. Figure 6 shows the comparison of RMSE values of wind speed approximation using Monte Carlo method for different wind direction sectors.

After acquiring the discrete dataset, the average speed $\mu_v$ and its standard deviation $\sigma_v$ for each direction bin are calculated. The wind speed with 95% confidence is given by:

$$\mu_v \pm 1.96 \times \frac{\sigma_v}{\sqrt{S}}$$  \hspace{1cm} (14)

where the second term of the equation is called the margin of error (MoE). Figure 7 shows the average wind speed and its prediction error for the 12 wind direction sectors predicted by Monte Carlo simulation over different time span of wind data measurement. Obviously, the longer time span is, the smaller wind speed prediction error is under all different wind direction sectors. By averaging the MoE of the 12 wind direction sectors, the average wind speeds calculated from Monte Carlo simulation over different time span from short-term to long-term have an average MoE of $\pm0.25$ m/s, $\pm0.08$ m/s and $\pm0.025$ m/s, respectively.

The probability of different wind direction sectors has been extracted from reference (Wang et al., 2017) for the real wind farm optimization. Figure 8 shows the probability density of occurrence for different wind direction sectors. In the similar manner as wind speed, Monte Carlo simulation over different time span of wind data measurement has been performed for the wind direction prediction. Corresponding to the wind speed representation, the MoE of wind direction prediction are $\pm5.62^\circ$, $\pm1.75^\circ$, and $\pm0.56^\circ$ for the short-term, medium-term and long-term time span of wind data.

**Mathematical optimization formulation**

For the wind farm layout optimization, the objective function is the confidence interval (CI) of the mean total power output. In order to increase the likelihood of achieving the most power output...
under different scenarios of wind data time span, we aim to simultaneously maximize the total wind farm power average and minimize the width of its CI. Hence, the lower end of CI (with 95% confidence) is maximized. The two options of the objection function for wind farm layout optimization can be mathematically formulated as:

Objective: \( E(X) - 1.96 \times \frac{\sigma_X}{\sqrt{S}} \)  \hspace{1cm} (15)

\[ s.t.: \ Y_{lower}^i \leq y(X, i) \leq Y_{upper}^i \quad \forall \ i \in N \]  \hspace{1cm} (16)

\[ \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2} \geq d_{min} \quad \forall \ i, \forall \ j \in N \]  \hspace{1cm} (17)
where $E(X)$ and $\sigma_X$ are wind farm expected total power output and the power standard deviation, respectively. $S$ is the sample size. $X$ is the potential solution which consists of $x$ and $y$ Cartesian coordinates. $y(X, i)$ is the $y$ coordinate of $i$-th wind turbine in solution $X$. $Y_{\text{lower}}^x$ and $Y_{\text{upper}}^x$ are the lower and upper bounds of $y$ coordinate for the wind farm boundary at the $x$ coordinate of $x_i$, and $d_{\text{min}}$ is the minimum distance allowed for any two wind turbines apart. Equation (16) is the boundary constraint to ensure each optimized wind turbine location is feasible. Equation (17) is the distance constraint to impose the minimal required distance between adjacent wind turbines. When the optimization is performed, both the total power and power variance are considered. Specifically, the total power output average is maximized and its margin of error (MoE) is minimized.

In the objective function, the mean total power output $E(X)$ is the sum-up of all wind turbine power, which gives:

$$E(X) = \sum_{i=1}^{N} P_i$$

where the individual power ($P_i$) is calculated according to the wind turbine power curve and the wake-affected wind speed ($v_i$), which is given by:

$$P_i = \begin{cases} 
0 & \text{if } v_i(2.5 \text{ m/s or } v_i)28 \text{ m/s} \\
0.6815v_i^3 & \text{if } 2.5 \text{ m/s} \leq v_i < 15 \text{ m/s} \\
2300 & \text{if } 15 \text{ m/s} \leq v_i \leq 28 \text{ m/s}
\end{cases}$$

(20)

note that here in this paper, the energy production is expressed as the power output per unit time for simplifying the calculation. In the same manner of aggregating the individual wind turbine power deviation, the power output deviation can be obtained as well, which is given by:

$$\sigma_X = \sqrt{\frac{1}{S-1} \sum_{j=1}^{S} \left( \frac{1}{S} \sum_{i=1}^{S} P_i(j) - \frac{\sum_{i=1}^{S} P_i(j)}{S} \right)^2}$$

(21)

In this section, a three-dimensional wake model accounts for the wind speed variation by wind turbine interactions and by the topographic effect is proposed for a real wind farm optimization study based on the machine learning algorithm. A new optimization model integrating both the total power average and its power variance is introduced as well. It is expected that after the optimization, the wind farm can produce more power output and have a narrower power output confidence interval than the existing wind turbine locations.

**Results and discussion**

In this section, the comparison of the wind farm output performance with the existing and optimized wind turbine locations is made to verify the effectiveness of our wind farm layout optimization scheme in the first place. Subsequently, the optimization results under different scenarios of time span of wind data measurement are presented.

**Effectiveness of wind farm layout optimization**

The wind farm performance with the existing real wind turbine locations and the optimized wind turbine locations are compared in Figure 9 with a total of 18 wind turbines installed, and the results
are presented based on the long-term wind data ($\pm 0.025$ m/s, $\pm 0.56^\circ$). Note that the power output of the existing wind farm layout are the results from wake model calculation instead of from the measurements due to the lack of real power output data. As can be seen, the existing wind turbines are densely distributed at the inner places of the wind farm area. The individual power ranges from roughly 500 to 537 kW with a power loss between 4 and 40 kW. In comparison, the optimized wind turbine locations are more widely spread alongside the wind farm boundary. The wind turbine yields are between 534 and 540 kW with an individual loss up to 6 kW. Obviously, the optimized wind farm layout achieves a much more individual power and a less

Figure 9. Comparison of existed and optimized wind farm layouts: (a) existed wind turbine locations, (b) existing wind turbine power output average and losses including confidence interval, (c) optimized wind turbine locations and (d) optimized wind turbine power output average and losses including confidence interval.
individual loss than the existing wind farm layout. Lastly, the total wind farm power output and its confidence interval with existing and optimized wind turbine locations are compared in Table 3. The optimized wind farm layout not only yields over 210 kW more average power than the existing wind farm layout, also its power output confidence interval is entirely on the right hand side of that for the existing wind farm layout. The lowest power output of the optimized layout is 60 kW more than the highest power output of the existing layout, indicating the dominating superiority of the layout optimization.

**Comparison of optimized wind farm with wind data of different time-spans**

Figure 10 shows the power average and its margin of error (MoE) for overall wind farm power output based on different scenarios of wind data. As the wind turbine number increases, both the power and its MoE increase in general. It is observed that it yields a least wind farm power output average with a largest MoE under the scenario of short-term wind ($\pm 0.25$ m/s, $\pm 5.62^\circ$). When the time span of wind data measurement increases to medium-term, the wind farm produces a more power output with a less MoE. When the time span further increases to long-term, the mean power output is in between the short-term and medium-term scenarios while the MoE for power output is the smallest Figure 11 shows the optimized total wind farm power losses caused by the wake interactions between wind turbines under different scenarios. The power loss is calculated as the theoretical power output (neglecting the wake effect) subtracted from the real power output (considering the wake effect). As can be seen, both the wind farm power loss and its MoE monotonously increase with the number of wind turbines. For instance, under the medium-term wind scenario ($\pm 0.08$ m/s, $\pm 1.75^\circ$), the power loss increases from 26.7 kW to 89 kW and the MoE for power loss increases from 1.58 kW to 5.26 kW with the increasing number of wind turbines. It is understandable that more installed wind turbines indicate a more intense wake interaction and a larger error of power loss, which leads to a larger value of wake power loss and MoE. For the comparison of different time span of wind data measurement, both the power loss and the MoE decrease in general with more time efforts. When the time span increases from short-term ($\pm 0.25$ m/s, $\pm 5.62^\circ$) to long-term ($\pm 0.025$ m/s, $\pm 0.56^\circ$), the MoE decreases from 5.8 kW to 0.48 kW with minimum 15 installed wind turbines, and the MoE decreases from 13.2 kW to 1.27 kW with maximum 20 installed wind turbines. Unlike the change of total power output, the wake power loss monotonously decreases with the increase of time span of the wind data measurement which is more prominent when there are more turbines.

To compare the wind farm layout optimization results under different wind condition scenarios more comprehensively, the individual power and loss with their optimal placements inside the wind farm are presented. Figure 12 shows the results under the short-term wind scenario ($\pm 0.25$ m/s, $\pm 5.62^\circ$) with 15 and 20 wind turbines installed. Notice that their indices are labeled in the order of increasing power output. With 15 wind turbines, the discrepancy of power output is small and the MoE of power is close to each other for different wind turbines. For 20 wind turbine case, most

| Total power Layout scenarios | Output average | Output confidence interval |
|-----------------------------|---------------|--------------------------|
| Existing layout             | 9440.99       | [9366.46, 9515.5]        |
| Optimized layout            | 9651.02       | [9575.57, 9726.46]       |
wind turbines yield very close amount of power output (above 520 kW) while two of them produce much less power output with approximately 500 kW. In the contrary, the difference between individual wind turbine power loss is relatively large and for some most-yield wind turbines, the power loss is zero. As the individual power loss reduces, its error decreases and for those most-yield wind turbines, the error of power loss maintains zero. It is also found that as the number increases, the individual power output and MoE decrease while the individual power loss and MoE increase in general. The distribution of optimal wind turbine placement inside the Grasmere wind farm (top-left separate wind farm in the figure) is very much similar for the two cases which are spreading alongside the wind farm boundary.

Last, the individual wind turbine results under the long-term wind scenarios (± 0.025 m/s, ± 0.56 °) are shown in Figure 13 with 15 and 20 wind turbines installed. In comparison, the individual wind turbines yield less power output with more individual power loss for the 20 wind turbines case, while the MoE for both the power and loss are very much close to the results with a smaller number of wind turbines. By comparing the individual wind turbine results under the short-term and long-term wind scenarios, the differences of the individual power and MoE are evident. For instance, with 20 wind turbines installed the individual wind turbines yield an output of above 500 kW with a MoE around 90 kW under the short-term wind (± 0.25 m/s, ± 5.62 °), while it is above 530 kW with a MoE less than 10 kW under the long-term wind.

Figure 10. Optimized total wind farm power production and margin of error under different scenarios of time span: (a) total wind farm power production and (b) margin of error for the total power production.

Figure 11. Optimized wind farm power losses with margin of error under different scenarios of time span.
wind (±0.025 m/s, ±0.56 °). The differences of the individual power loss and MoE between the two wind scenarios are even more prominent. For 20 wind turbines installed, the maximum individual power loss and the MoE under the short-term wind (±0.25 m/s, ±5.62 °) are approximately 30 kW and 8 kW respectively, while the maximum individual power loss and the MoE under the long-term wind (±0.025 m/s, ±0.56 °) are 10 kW and 0.5 kW respectively. The distribution of wind turbine placement inside the wind farm are various for the situations of different number of wind turbines. However, the common feature is that the turbines are located close to the wind farm boundary lines as many as possible to increase their distances apart.

Figure 12. Optimal wind turbine placement and individual wind turbine results under wind data error of (±0.25 m/s, ±5.62 °) for different number of wind turbines: (a) 15 wind turbine layout, (b) corresponding individual power and losses, (c) 20 wind turbine layout and (d) corresponding individual power and losses.
Summary and conclusion

In this research, a novel three-dimensional wake model accounting for both wind turbine interaction and the topographic effect of non-flat terrain is proposed for a real wind farm layout optimization by means of machine learning algorithm. Moreover, the optimization study is carried out by considering the wind data prediction error over the short-term (days), medium-term (months) and long-term (years) time spans. By conducting the Monte Carlo simulation for the Weibull distribution wind

Figure 13. Optimal wind turbine placement and individual wind turbine results under wind data error of ($\pm 0.025 \text{ m/s}$, $\pm 0.56^\circ$): (a) 15 wind turbine layout, (b) corresponding individual power and losses, (c) 20 wind turbine layout and (d) corresponding individual power and losses.
speed and wind direction with a predefined number of samples, the margin of error for average wind speed/direction are calculated to quantify the wind prediction errors of the different scenarios of time span. Specifically, the errors for the short-, medium-, and long-term wind data are ($\pm$ 0.25 m/s, $\pm$ 5.62 $^\circ$), ($\pm$ 0.08 m/s, $\pm$ 1.75 $^\circ$) and ($\pm$ 0.025 m/s, $\pm$ 0.56 $^\circ$), respectively. An advanced optimization objective function, i.e., the wind farm power confidence interval (with 95% confidence), incorporating both the wind farm power average and the power variance is maximized, to increase the likelihood of yielding more wind farm power.

The optimization results show that the total wind farm power output average after optimizing the wind farm layout increases by 210 kW, and its confidence interval also entirely shifts towards the increasing power output direction compared to the existing wind farm layout which justifies the effectiveness of the layout optimization work. As the time span of wind data measurement increases, the total power output average increases while the margin of error (MoE) decreases. In contrast, both the total power loss and its error decrease with the increasing time span. In general, the individual power output and its loss have the same pattern of change as the total power output under different wind data scenarios. With 20 wind turbines installed, the individual wind turbines yield a power output above 500 kW with a MoE around 90 kW, and the maximum power loss and MoE are approximately 30 kW and 8 kW for the short-term wind ($\pm$ 0.25 m/s, $\pm$ 5.62 $^\circ$). In comparison, the individual power output is above 530 kW with a MoE less than 10 kW, and the power loss and MoE are 10 kW and 0.5 kW for the long-term wind ($\pm$ 0.025 m/s, $\pm$ 0.56 $^\circ$).

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References

Amaral L and Castro R (2017) Offshore wind farm layout optimization regarding wake effects and electrical losses. *Engineering Applications of Artificial Intelligence* 60(February 2016): 26–34. DOI: 10.1016/j.engappai.2017.01.010.

Bansal JC, Farswan P and Nagar AK (2018) Design of wind farm layout with non-uniform turbines using fitness difference based BBO. *Engineering Applications of Artificial Intelligence* 71(February): 45–59. DOI: 10.1016/j.engappai.2018.02.007.

Beşkirli M, Koç I, Hakli H, et al. (2018) A new optimization algorithm for solving wind turbine placement problem: Binary artificial algae algorithm. *Renewable Energy* 121: 301–308. DOI: 10.1016/j.renene.2017.12.087.

Bossanyi E (2018) Combining induction control and wake steering for wind farm energy and fatigue loads optimisation. *Journal of Physics: Conference Series* 1037(3). DOI: 10.1088/1742-6596/1037/3/032011.
Chamorro LP and Porté-Agel F (2009) A wind-tunnel investigation of wind-turbine wakes: Boundary-layer turbulence effects. Boundary-Layer Meteorology 132(1): 129–149. DOI: 10.1007/s10546-009-9380-8.

Chen X, Chen X, Xu H, et al. (2015) Monte Carlo simulation and experimental measurements of grain growth in the heat affected zone of 304 stainless steel during multipass welding. The International Journal of Advanced Manufacturing Technology 80(5): 1197–1211. DOI: 10.1007/s00170-015-7024-3.

Fang Y, Gao Z, Yan M, et al. (2020) Characteristics of wind turbine flow field after blade vibration. Journal of Drainage and Irrigation Machinery Engineering 38(4): 390–395. DOI: 10.3969/j.issn.1674-8530.17.0182.

Feijóo A and Villanueva D (2017) Contributions to wind farm power estimation considering wind direction-dependent wake effects. Wind Energy 20: 221–231. DOI: 10.1002/we.2002.

Foley AM, Leahy PG, Marvuglia A, et al. (2012) Current methods and advances in forecasting of wind power generation. Renewable Energy 37(1): 1–8. DOI: 10.1016/j.renene.2011.05.033.

Gao X, Li B, Wang T, et al. (2020) Investigation and validation of 3D wake model for horizontal-axis wind turbines based on filed measurements. Applied Energy 260(December 2019): 114272. DOI: 10.1016/j.apenergy.2019.114272.

Gao X, Yang H and Lu L (2016) Optimization of wind turbine layout position in a wind farm using a newly-developed two-dimensional wake model. Applied Energy 174: 192–200. DOI: 10.1016/j.apenergy.2016.04.098.

Gaumond M, Réthoré P-E, Ott S, et al. (2014) Evaluation of the wind direction uncertainty and its impact on wake modeling at the horns Rev offshore wind farm. Wind Energy 17(April 2013): 1169–1178. DOI: 10.1002/we.1625.

González JS, Payán MB and Riquelme-Santos JM (2012) Optimization of wind farm turbine layout including decision making under risk. IEEE Systems Journal 6(1): 94–102. DOI: 10.1109/JSYST.2011.2163007.

Gonzalez-Rodriguez AG (2017) Review of offshore wind farm cost components. Energy for Sustainable Development 37: 10–19. DOI: 10.1016/j.esd.2016.12.001.

Gu H and Wang J (2013) Irregular-shape wind farm micro-siting optimization. Energy 57: 535–544. DOI: 10.1016/j.energy.2013.05.066.

Hao MR, Ismail RMTR and Ahmad MA (2017) Using spiral dynamic algorithm for maximizing power production of wind farm. Proceedings of the 2017 IEEE International Conference on Applied System Innovation: Applied System Innovation for Modern Technology, ICASI 2017. DOI: 10.1109/ICASI.2017.7988266.

Hu D, Sun T, Yao L, et al. (2020) Monte Carlo: A flexible and accurate technique for modeling light transport in food and agricultural products. Trends in Food Science & Technology 102: 280–290. DOI: 10.1016/j.tifs.2020.05.006.

Jensen NOO (1983) A note on wind generator interaction. Riso National Laboratory Roskilde. DOI: Riso-M-2411.

Kang C, Liu H and Yang X (2014) Review of fluid dynamics aspects of Savonius-rotor-based vertical-axis wind rotors. Renewable and Sustainable Energy Reviews 33: 499–508. DOI: 10.1016/j.rser.2014.02.011.

Kuo J, Rehman D, Romero DA, et al. (2018) A novel wake model for wind farm design on complex terrains. Journal of Wind Engineering and Industrial Aerodynamics 174(December 2017): 94–102. DOI: 10.1016/j.jweia.2017.12.016.

Kuo JYJ, Romero DA and Amon CH (2015) A mechanistic semi-empirical wake interaction model for wind farm layout optimization. Energy 93: 2157–2165. DOI: 10.1016/j.energy.2015.10.009.

Kuo JYJ, Romero DA, Beck JC, et al. (2016) Wind farm layout optimization on complex terrains – integrating a CFD wake model with mixed-integer programming. Applied Energy 178: 404–414. DOI: 10.1016/j.apenergy.2016.06.085.

Kusiak A and Song Z (2010) Design of wind farm layout for maximum wind energy capture. Renewable Energy 35(3): 685–694. DOI: 10.1016/j.renene.2009.08.019.

Latif SE, Momhammad E and Khakzad N (2017) Process plant layout optimization with uncertainty and considering risk. Computers and Chemical Engineering 106: 224–242. DOI: 10.1016/j.compchemeng.2017.05.022.
Li S, Yang C and Shi G (2018) Effect of concave-out’s Asymmetric airfoil on flow field of H-type vertical axis wind turbine. *Journal of Drainage and Irrigation Machinery Engineering* 36(2): 141–145. DOI: 10.3969/j.issn.1674-8530.17.3001.

Li Y, Wu Z and Tagawa K (2018) Numerical simulation on aerodynamic characteristics of vertical axis wind turbine with eccentric rotor structure. *Journal of Drainage and Irrigation Machinery Engineering* 36(5): 413–419. DOI: 10.3969/j.issn.1674-8530.17.0023.

Li Y, Zhao S and Jiang Y (2018) Numerical simulation on effects of number of blades with plate added at blade trailing edge on torque coefficient of vertical axis wind turbine. *Journal of Drainage and Irrigation Machinery Engineering* 36(3): 215–222. DOI: 10.3969/j.issn.1674-8530.17.3011

Messac A, Chowdhury S and Zhang J (2012) Characterizing and mitigating the wind resource-based uncertainty in farm performance. *Journal of Turbulence* 13(13): 1–26. DOI: 10.1080/14685248.2012.661863.

MirHassani SA and Yarahmadi A (2017) Wind farm layout optimization under uncertainty. *Renewable Energy* 107: 288–297. DOI: 10.1016/j.renene.2017.01.063.

Parada L, Herrera C, Flores P, et al. (2017) Wind farm layout optimization using a Gaussian-based wake model. *Renewable Energy* 107: 531–541. DOI: 10.1016/j.renene.2017.02.017.

Qu J, Wang J and Xu M (2018) Drag-lift conversion characteristics of vertical axis wind turbine with adapting wind speed. *Journal of Drainage and Irrigation Machinery Engineering* 36(2): 154–158. DOI: 10.3969/j.issn.1674-8530.17.3004.

Safari B and Gasore J (2010) A statistical investigation of wind characteristics and wind energy potential based on the Weibull and Rayleigh models in Rwanda. *Renewable Energy* 35(12): 2874–2880. DOI: 10.1016/j.renene.2010.04.032.

Seguro J V and Lambert TW (2000) Modern estimation of the parameters of the Weibull wind speed distribution for wind energy analysis. *Journal of Wind Engineering and Industrial Aerodynamics* 85(1): 75–84. DOI: 10.1016/S0167-6105(99)00122-1.

Song Z, Zhang Z and Chen X (2016) The decision model of 3-dimensional wind farm layout design. *Renewable Energy* 85: 248–258. DOI: 10.1016/j.renene.2015.06.036.

Soulouknga MH, Doka SY, Revanna N, et al. (2018) Analysis of wind speed data and wind energy potential in Faya-Largeau, Chad, using Weibull distribution. *Renewable Energy* 121: 1–8. DOI: 10.1016/j.renene.2018.01.002.

Sun H and Yang H (2018) Study on an innovative three-dimensional wind turbine wake model. *Applied Energy* 226(March): 483–493. DOI: 10.1016/j.apenergy.2018.06.027.

Sun H and Yang H (2020) Numerical investigation of the average wind speed of a single wind turbine and development of a novel three-dimensional multiple wind turbine wake model. *Renewable Energy* 147: 192–203. DOI: 10.1016/j.renene.2019.08.122.

Ti Z, Deng XW and Yang H (2020) Wake modeling of wind turbines using machine learning. *Applied Energy* 257(July 2019): 114025. DOI: 10.1016/j.apenergy.2019.114025.

Tian L, Zhu W, Shen W, et al. (2015) Development and validation of a new two-dimensional wake model for wind turbine wakes. *Journal of Wind Engineering and Industrial Aerodynamics* 137: 90–99. DOI: 10.1016/j.jweia.2014.12.001.

Wang L, Cholette ME, Tan ACC, et al. (2017) A computationally-efficient layout optimization method for real wind farms considering altitude variations. *Energy* 132: 147–159. DOI: 10.1016/j.energy.2017.05.076.

Wang L, Tan ACC, Cholette M, et al. (2016) Comparison of the effectiveness of analytical wake models for wind farm with constant and variable hub heights. *Energy Conversion and Management* 124: 189–202.

Wang L, Tan ACC, Cholette ME, et al. (2017) Optimization of wind farm layout with complex land divisions. *Renewable Energy* 105: 30–40. DOI: 10.1016/j.renene.2016.12.025.

Wang L, Tan ACC, Gu Y, et al. (2015) A new constraint handling method for wind farm layout optimization with lands owned by different owners. *Renewable Energy* 83: 151–161. DOI: 10.1016/j.renene.2015.04.029.

Wang L, Yuan J, Cholette ME, et al. (2018) Comparative study of discretization method and Monte Carlo method for wind farm layout optimization under Weibull distribution. *Journal of Wind Engineering and Industrial Aerodynamics* 180: 148–155. DOI: 10.1016/j.jweia.2018.07.021.
Wang X and Alden MJ (2017) Resilient and robust control of time-delay wind energy conversion systems. *ASCE-ASME Journal of Risk and Uncertainty in Engineering Systems, Part B: Mechanical Engineering* 3(011005). DOI: 10.1115/1.4034661.

Wang X, Chiang H-D, Wang J, et al. (2015) Long-term stability analysis of power systems with wind power based on stochastic differential equations: Model development and foundations. *IEEE Transactions on Sustainable Energy* 6(4): 1534–1542. DOI: 10.1109/TSTE.2015.2454333.

Wu W, Hu Y, Yang S, et al. (2015) Optimal design of wind machine impeller for frost protection based on CFD and its field test on airflow disturbance. *International Journal of Agricultural and Biological Engineering* 8(5): 43–49. DOI: 10.3965/j.ijabe.20150805.1415.

Xue W, Wang C, Tian J, et al. (2020) Hybrid wind power forecasting based on extreme learning machine and improved TLBO algorithm. *Journal of Renewable and Sustainable Energy* 12(5): 53309. DOI: 10.1063/5.0020759.

Yang Q, Hu J and Law S (2018) Optimization of wind farm layout with modified genetic algorithm based on Boolean code. *Journal of Wind Engineering and Industrial Aerodynamics* 181(November 2017): 61–68. DOI: 10.1016/j.jweia.2018.07.019.

Yin PY, Wu TH and Hsu PY (2016) A power-deficiency and risk-management model for wind farm micro-siting using cyber swarm algorithm. *Applied Mathematical Modelling* 40(3): 2177–2189. DOI: 10.1016/j.apm.2015.09.039.

Yin P-Y, Wu T-H and Hsu P-Y (2017) Risk management of wind farm micro-siting using an enhanced genetic algorithm with simulation optimization. *Renewable Energy* 107: 508–521. DOI: 10.1016/j.renene.2017.02.036.

Zhao Z, Qian S and Zheng Y (2018) Enhancement approaches of aerodynamic performance of lift-type vertical axis wind turbine considering small angle of attack. *Journal of Drainage and Irrigation Machinery Engineering* 36(2): 146–153. DOI: 10.3969/j.issn.1674-8530.17.3002.