https://doi.org/10.1016/j.apenergy.2020.115880

Wind Turbine Power Modelling and Optimization Using Artificial Neural Network with Wind Field Experimental Data

Haiying Sun[a*], Changyu Qiu[a], Lin Lu[a], Xiaoxia Gao[b], Jian Chen[c], Hongxing Yang[a*]

[a]Renewable Energy Research Group, Department of Building Services Engineering, The Hong Kong Polytechnic University, Hong Kong
[b]Department of Power Engineering, North China Electric Power University (Baoding), Baoding, PR China
[c]School of Energy and Power Engineering, University of Shanghai for Science and Technology, PR China

Abstract

The wake effect is a major and complex problem in the wind power industry. Wake steering, such as controlling yaw angles of wind turbines, is a proven approach to mitigate the wake influence and increase the power generation of a wind farm. This paper proposes a power prediction model and optimizes yaw angles to minimize the entire wake impact on wind turbines. The power model adopts the artificial neural network (ANN) with the consideration of the wake effect, so it is called ANN-wake-power model. The model can estimate the total power generation of wind turbines for given wind speeds, wind directions, and yaw angles. A case study has been conducted to introduce the modelling process. The experimental data of five wind turbines from an operating wind farm have been used to train and evaluate the model. The ANN-wake-power model has proven to be effective in estimating the power generation. It performs a good balance between computational cost and accuracy. Subsequently, the model is applied to optimize the yaw angles by using Genetic Algorithm. With the optimized yaw angle strategy, the total power ratio of wind turbines can reach 0.96 in all directions involved. For a row of wind turbines, the optimal yaw control strategy for each wind turbine is different. Finally,it is worth noting that, to achieve a good performance of the ANN-wake-power model, sufficient input data should be adopted in the training process.

Keywords: Wind turbine power modelling; Artificial Neural Network; Wake effect; Wind field experiment; Yaw Angle Optimization.

1. Introduction

Wind energy is widely accepted as a clean and renewable energy source [1]. The wind energy industry is playing an important role in reducing greenhouse gas emissions and leading the transition to a sustainable energy system. 2019 was a remarkable year for the wind power industry, with a new installed capacity of 60.4 GW, bringing the global cumulative wind power capacity to 651 GW [2]. With the rapid development, one problem that should be noticed is the serious wake effect in wind farms. All operating wind turbines generate wakes behind themselves [3]. Specific phenomena include the defect momentum and the increase of turbulence intensity. When wind turbines are installed close to each other, land and civil works are reduced. However, the effect of wake interference also becomes serious, leading to the power reduction of wind farm and unstable loads on other machines [4]. These high fluctuating characteristics are significant challenges to integrate the generated power into the main electric grid [5]. Therefore, how to estimate the power output and mitigate the wake influence on a wind farm are two inevitable problems in the wind power industry.

Physical models and data-driven techniques are two frameworks for the research of wind power prediction [6]. Physical models are based on equations to model wind turbines. They are useful for studying individual turbines but are not practical for designing and optimizing the layout of wind farm [7]. In particular, modern wind farms are developing towards large capacity with hundreds of wind turbines. Correspondingly, the computational cost to obtain the optimal layout of an entire wind farm is increasing significantly, challenging the application of traditional models [8]. In contrast, data-driven techniques usually build the power generation model by analyzing the phenomenon in data, rather than integrating knowledge about the physical behaviour of wind turbines. Recently,

* Corresponding author
E-mail address: haiying.sun@connect.polyu.hk (Haiying Sun)
* Corresponding author
E-mail address: hong-xing.yang@polyu.edu.hk (Hongxing Yang)

machine learning techniques have been used to model wind farms. Li [9] used a recurrent neural network (RNN) combined with a back-propagation algorithm based on Kalman filter to predict wind power, and good results were obtained in the long-term prediction. Barbounis, et al. [10] applied an RNN to predict the long-term wind speed and power generation of a wind farm on the basis of meteorological information of Crete Island. Kusiak, et al. [11] established a model to forecast the power of wind farm by applying a data-mining approach based on the *k*-nearest neighbour method. Both a long-term case (3 - 84 hours ahead) and a short-term case (1 - 12 hours ahead) were investigated. Wu, et al. [12] conducted the research on time series-based models to forecast wind power. Fischer, et al. [13] pointed out that for a specific wind farm, the method of using actual local wind information input is the best, and the method of using the average data to stimulate meteorological wind forecasting may not be effective. Yan, et al. [5] trained a geometric model-artificial neural network (GM-ANN) using an offshore wind farm observation dataset. A two-dimensional (2-D) power curve was presented to estimate the power generation of a wind farm by using wind speeds and wind directions. It was found that the GM-ANN method was more precious than the traditional one-dimensional power curve.

The studies mentioned above contribute to predicting the power of wind turbines in a wind farm. Based on the wind turbine power modelling, wind farm control has recently become an active research area. Maximum power point tracking (MPPT) is a commonly used strategy, in which each wind turbine continuously adjusts the rotor speed and pitch angle to reach its maximum power coefficient at any wind speed and in any wind direction [14]. However, recent studies have shown that the strategy of the MPPT may not be the best control method for the entire wind field [8]. Fleming, et al. [15] pointed out that the coordinated control of individual wind turbines can improve the overall performance of wind farm. Suggestions have been given on controlling parameters of wind turbine by calculating wake interactions of nearby wind turbines. Active wake control based on yaw angle is an effective way that can divert the wake on downwind turbines by misaligning the yaw angle of the upwind turbine [16]. When a wind turbine is working in the yaw state, the wake intensity and the power generation will slightly decrease, and a wake deflection can be induced. Jiménez, et al. [4] studied the possibility of minimizing the wake interference in a wind farm through yaw control of wind turbines. The wake trajectory and deflection were investigated and compared with the results of a simple analytical model and experiments. Fleming, et al. [17] applied a high-fidelity wind farm modelling tool, Simulator for Off/Onshore Wind Farm Applications (SOWFA), to simulate the wake redirection and study several methods. Then, Fleming, et al. [18] organized a field campaign to test the wake steering on an operating wind turbine and compared the results with the predictions of a wake model based on wind farm control. The simulations indicated that the wake steering can have a positive influence on the annual power generations of wind farms. Gebraad, et al. [19] applied a yaw-based wake steering strategy and layout optimization method to improve the power generation of a wind power plant. It has been found that the wake steering and the layout optimization can complement each other to improve energy production, where wake steering can reduce more energy losses.

To date, studies on wake control are very limited due to the lack of relatively accurate and effective models to predict the power generations of wind farms. In this paper, firstly, the ANN method and the data measured from a wind field are applied to build an ANN-wake-power model for multiple wind turbines. The established model considers the wake effect, so it can accurately and quickly simulate the total power of wind turbines for given wind speeds and yaw angles. The model is then used in the yaw angle optimization process to maximize the total power generation. The rest of this paper is structured as follows. In Section 2, the methodology of the ANN-wake-power model is introduced. In Section 3, an ANN-wake-power model for a row of five working wind turbines is developed. In Section 4, the model is further applied to optimize yaw angles of wind turbines. Finally, the main conclusions from this study are drawn in Section 5.

2. Methodology of the ANN-wake-power model

ANN technology can map input vectors to the corresponding output vector without assuming any fixed relationship between them [20]. For a specific task, a well-trained ANN model can compete with a comprehensive physical model [21]. In this study, ANN is adopted to estimate the power generation of wind turbine and wind farm. The main expected objective of the proposed ANN-wake-power model is to predict the power generation of a cluster of wind turbines at the given conditions, including incoming wind speeds, wind directions, and yaw angles of selected wind turbines. The model can be deployed by six steps. Figure 1 demonstrates the process of the model development.

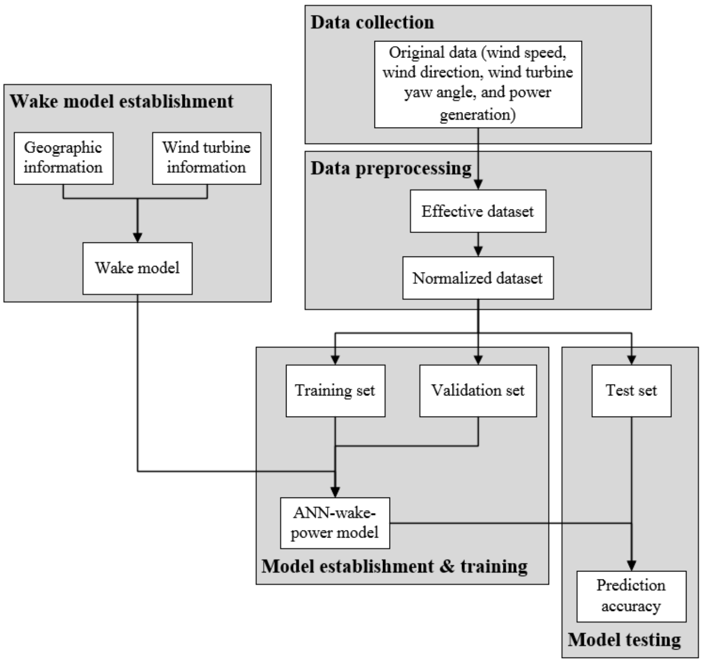


Figure 1 Flow chart of the ANN model development process.

Step 1: Data collection. An ANN model is established for a specific wind farm. The original data should be obtained from the wind farm measurements and analyzed for the development of the ANN model. Geographic and wind turbine information will be collected to build the specific wake model in the next step. The data of instantaneous wind speed, wind direction, wind turbine yaw angle, and power generation are selected for the training and validation of the proposed model.

Step 2: Wake model establishment. Based on the geographic and wind turbine information from Step 1, a comprehensive wake model of a specific wind farm can be established. Compared with traditional models, the new wake model is built for wind farms rather than individual wind turbines. For a wind turbine, the wake effect from all other wind turbines will be considered. The heights of all wind turbines are involved in calculating the wake-induced wind speed deficit, which makes the wake model more accurately, especially for wind farms with complex terrain.

Step 3: Data preprocessing. The original data of wind speed, wind direction, and yaw angle of wind turbine should be selected and filtered to obtain an effective dataset. The basic principle is that all wind turbines are operating normally. If some wind turbines are not working, the corresponding data should be eliminated. After selecting the effective data, the dataset is normalized for the ANN model development.

Step 4: Model establishment. The basic structure of the ANN model consists of the input layer, the hidden layer(s), and the output layer. The input layer contains wind speeds, wind directions and yaw angles of wind turbines. The output layer contains total power generations. The numbers of layers and neurons in each hidden layer should be determined according to the specific dataset.

Step 5: Model training. The effective dataset will be divided into a training set, a validation set, and a test set. The ANN model will be trained using the data of the training set. The data of the validation set are used to evaluate the effectiveness of the model in each training epoch. The numbers of layers and neurons can be adjusted. Finally, all parameters of the ANN model can be obtained.

Step 6: Model testing. The test set is completely independent from the model training process. After the training process, the performance of the ANN model should be tested by the test dataset. Statistical index, such as the mean square error (MSE) value, can be used to evaluate the prediction results.

After the above six steps, if the performance of the ANN model is good and accepted, the trained model is obtained; if not, the process should return to Step 4 and the structure of the model should be adjusted until the model achieves the required performance. The trained ANN model can estimate the total power of a specific wind farm using the given wind speeds and yaw angles of wind turbines.

3. A case study of the ANN-wake-power model

In this section, the complete process of training the ANN-based multiple wind turbine power prediction model will be demonstrated. The model is based on the experimental data from an operating wind farm.

3.1 Wind farm

The experimental data are obtained from Shiren Wind Farm in northern China [22]. Five wind turbines (WT10-1, WT10-2, WT10-3, WT10-4, and WT10-5) are selected, of which the location information is shown in Table 1 [23].

Table 1 Location information of wind turbines.

	WT10-1	WT10-2	WT10-3	WT10-4	WT10-5
Longitude	114.355° E	114.358° E	114.362° E	114.365° E	114.372° E
Latitude	40.999° N	40.998° N	40.998° N	40.998° N	40.997° N
Altitude	1857.4 m	1884.5 m	1880.7 m	1877.3 m	1894.1 m

The wind farm is installed on the hilly terrain. The average altitude of five wind turbines is 1878.8 m. The maximum height difference is 36.7 m. Figure 2 shows the location of the tested wind turbines.

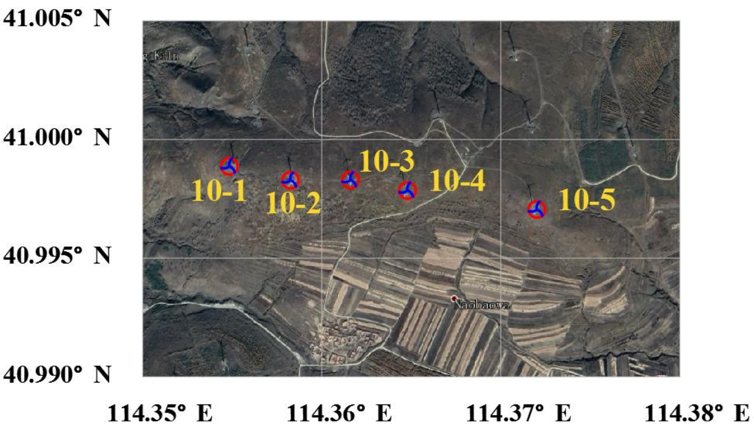


Figure 2 The location of the tested wind turbines.

The wind turbines in this experiment are the UP77-1500 type, with a rotor diameter of 77 m and a hub height of 65 m [24]. The specifications of the experimental wind turbine type are listed in Table 2.

Table 2 Specifications of UP77-1500 wind turbine.

Parameter	Value
Rated power (kW)	1550
Number of blades	3
Hub height (m)	65
Diameter (m)	77.36
Swept area (m^2)	4700.3
Cut-in wind speed (m/s)	3.0
Rated wind speed (m/s)	11.0
Cut-out wind speed (m/s)	25.0
Rotate speed (rpm)	9.7 - 19.5
Rated frequency (Hz)	50

Figure 3 and Figure 4 show the power curve and the thrust coefficient curve of the experimental wind turbines, respectively [25]. The maximum thrust coefficient is 0.9 when wind speed is 8 m/s.

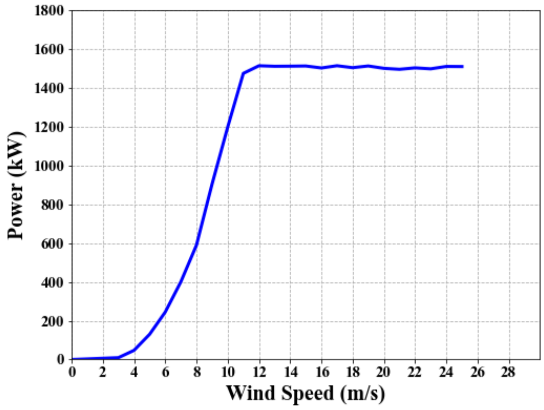


Figure 3 Power curve of UP77-1500 wind turbine.

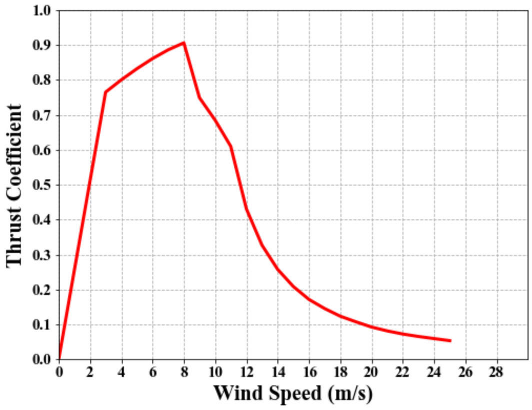


Figure 4 Thrust coefficient curve of UP77-1500 wind turbine.

3.2 Wake network

In an operating wind farm, upstream wind turbines both generate electricity and cause wakes, resulting in the diminishment of the performance of downstream wind turbines. Because of the wake interaction between turbines, the total power output is not simply the power generated by the wind turbine at the upstream wind speed multiplied by the number of turbines. In fact, downstream wind turbines will generate less power than their upstream counterparts. In the large-scale wind farm, the wake effect may cause power losses accounting for about 10-20% of total energy generation [26, 27]. When planning the layout of the wind farm, the wake effect should be considered to avoid power losses [28]. Wake effect is complex, and its characteristics are still yet to be revealed. In order to estimate the wake effect, plenty of wake models have been proposed for wake calculations [29]. Many studies have been carried out on wake models, either to reduce computational cost or improve accuracy [30]. Jensen wake model is the most widely used one for designing wind farm layouts. Compared with other models, the Jensen wake model has relatively high accuracy and requires the minimal computational cost [31]. It can well estimate the energy content in the wake. Figure 5 demonstrates the schematic diagram of the Jensen wake model.

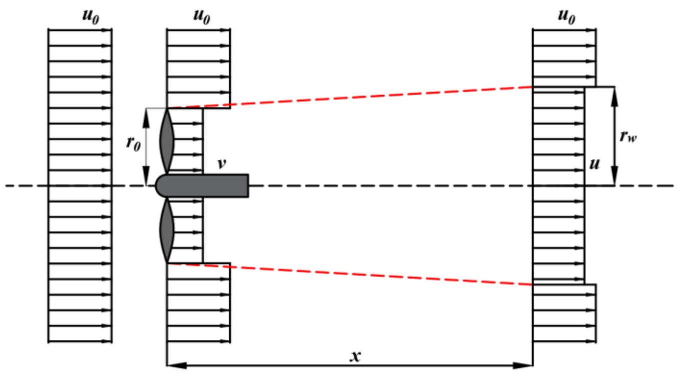


Figure 5 Schematic diagram of Jensen wake model [32].

The principle of the Jensen wake model is the theory of conservation of momentum. The assumption is that the wake linearly expands downwind of a wind turbine. The basic expressions of Jensen wake model are shown in Equation (1) and (2). When a wind turbine is affected by the wake of another wind turbine, Equation (1) should be used. If a wind turbine affected by the wake effect of several other wind turbines, the additional Equation (2) should be adopted to take into account the wake superposition effect.

$$u = u_0\left[1 - \frac{2ar_0^2}{(r_0 + \alpha x)^2}\right] \tag{1}$$

$$u = u_0\left[1 - \sqrt{\sum_{i=1}^{N}\left(1 - \frac{u_i}{u_0}\right)^2}\right] \tag{2}$$

u is the wind speed of the downstream wind turbine to be calculated, which is related to the incoming wind speed, the characteristics of upstream wind turbine, and the downstream distance. u_0 is the incoming wind speed before the wind farm, which is not affected by any structure in the wind farm. r_0 is the rotor radius of the upstream wind turbine. x is the downstream distance from the upstream wind turbine. a is the axial induction factor. u_i is the assumed incoming wind speed and is only influenced by the wake effect of the *i-th* wind turbine. The actual wind speed u is regarded as the incoming wind speed u_0 minus the total wake-induced wind losses.

Jensen wake model is not perfect. One obvious disadvantage is that the assumption of one-dimensional distribution of wind speed behind the blades is far from realistic. To deal with this situation, a conceptual 2-D wake model has been used in some studies, which is promoted from the Jensen wake model. In this study, with the consideration of the partial wake effect caused by wind direction and complex terrain, the 2-D wake model can calculate wind speed losses more accurately. Figure 6 illustrates the wake effect of the 2-D wake model applied in this study.

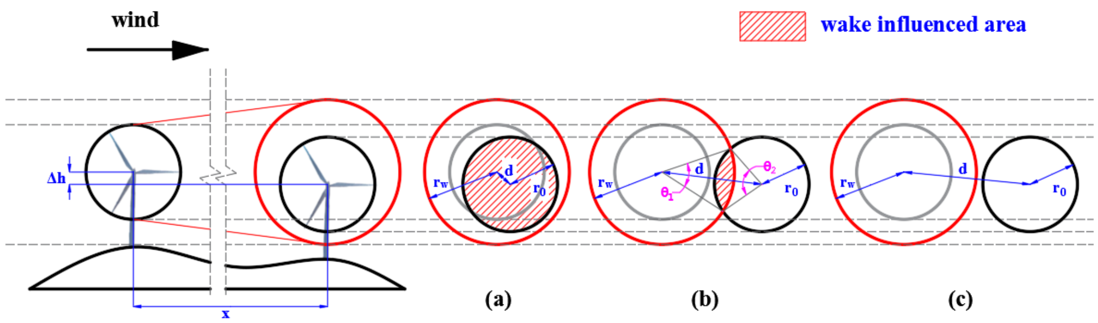


Figure 6 Two-dimensional wake model.

In a complex-terrain wind farm, wind turbines are likely to be fixed at different heights. Therefore, the wake effect should take height into consideration. As shown in Figure 6, d is the distance between two wind turbines in the direction perpendicular to the inflow direction, which is determined by the hub height difference Δh and the relative horizontal distance. For any two wind turbines, d changes with the wind direction. r_0 is the rotor radius of the wind turbine. r_w is the radius of the wake-influenced circular area at the downstream distance of x. The area influenced by wake should be discussed in three situations. In Figure 6 (a), when $d < r_w - r$, the downstream wind turbine is completely under the wake effect of the upstream one. In Figure 6 (b), when $r_w - r_0 \le d \le r_w + r_0$, the downstream wind turbine is partly under the wake effect of the upstream one. In Figure 6 (c), when $r_w + r_0 < d$, the upstream wind turbine is completely not under the wake effect of the upstream one. Thus, the equation of wake-affected wind speed for a wind turbine is modified as Equation (3).

$$\begin{cases} u = u_0\left[1 - \dfrac{2ar_0^2}{(r_0+\alpha x)^2}\right], & d < r_w - r_0 \\ u = u_0\left[1 - \dfrac{2ar_0^2}{(r_0+\alpha x)^2}\cdot\dfrac{S_w}{S}\right], & r_w - r_0 \le d \le r_w + r_0 \\ u = u_0, & r_w + r_0 < d \end{cases} \tag{3}$$

In the above equations, S is the swept area of the downstream wind turbine, which is calculated by Equation (4). S_w is the area on the downstream wind turbine influenced by wakes, which is considered according to the area-ratio principle. S_w is calculated by Equation (5).

$$S = \pi r_w^{\ 2} \tag{4}$$

$$S_w = \frac{\theta_1 r_w^{\ 2}}{2} + \frac{\theta_2 r_0^{\ 2}}{2} - r_w d \sin\frac{\theta_1}{2} \tag{5}$$

θ_1 and θ_2 are two angles related to wake-influenced area and the hub positions of upstream and downstream wind turbines, as demonstrated in Figure 6 (b). The two angles are calculated by Equation (6) and (7), respectively.

$$\theta_1 = 2\arccos\frac{r_w^{\ 2} + d^2 - r_0^{\ 2}}{2r_w d} \tag{6}$$

$$\theta_2 = 2\arccos\frac{r_0^{\ 2} + d^2 - r_w^{\ 2}}{2r_0 d} \tag{7}$$

Based on the specifications of the wind turbines and the 2-D wake model, the wind deficit caused by the wake in any direction can be calculated. A comprehensive wake network for the wind farm is obtained. Figure 7 demonstrates the rose diagram of wind speed efficiency for five individual wind turbines and the entire group of wind turbines.

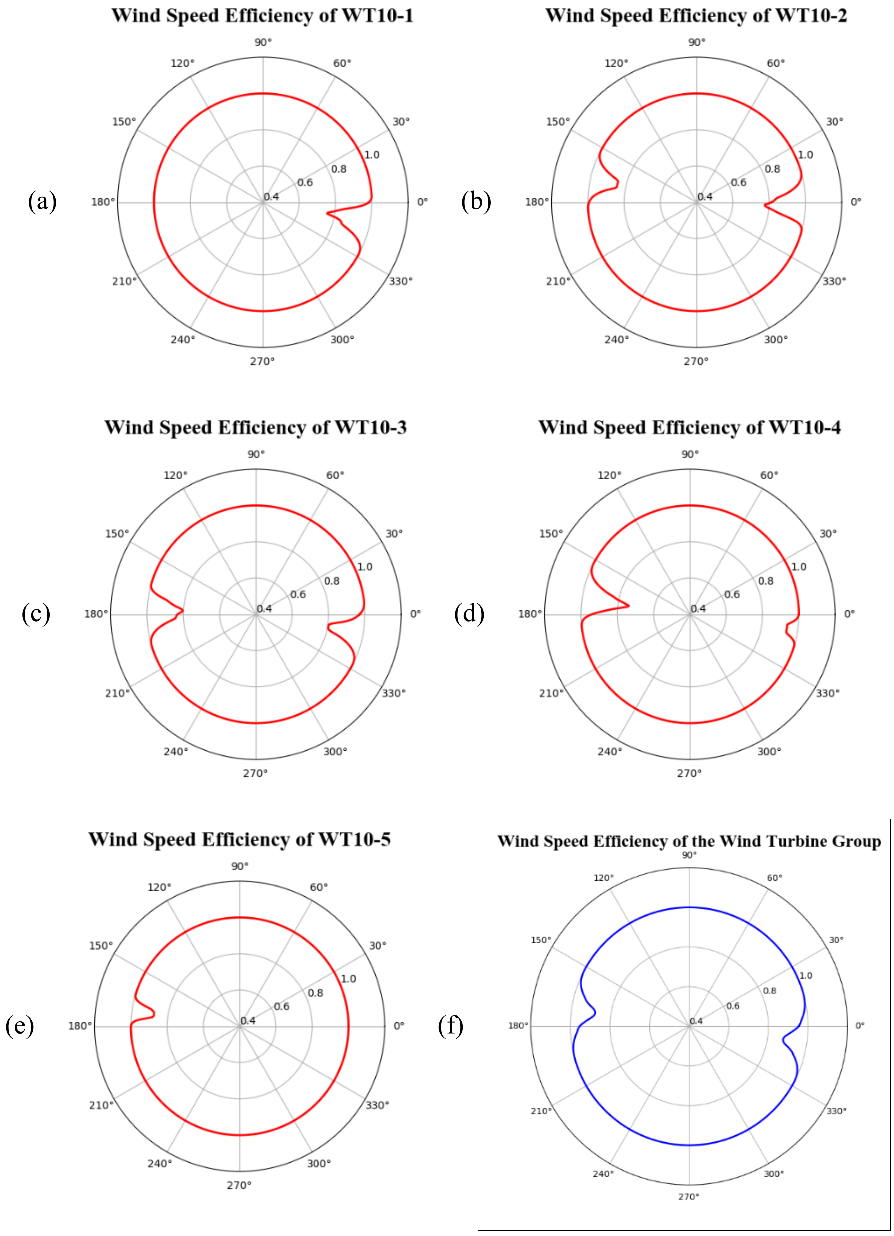


Figure 7 Rose diagram of wind speed efficiency for: (a) WT10-1; (b) WT10-2; (c) WT10-3; (d) WT10-4; (e) WT10-5; and (f) the wind turbine group.

Figure 7 (a) to (e) show the wind speed efficiencies of single wind turbines. For a particular wind turbine, since the relative position from upstream wind turbines changes with wind direction, the wake effect varies with the wind direction, which is reflected in figures by the change of the wind deficit ratio with the wind direction. For WT10-1, all other wind turbines are in the eastern direction of it. When the wind blows from directions of 330-0°, it is affected by wakes of other wind turbines. When the wind direction is 350°, the minimum wind speed efficiency is less than 0.8, which means that the maximum deficit ratio is greater than 0.2. For directions without wake effect, the wind speed efficiency is 1. For different wind turbines, the wake conditions can also be different. Taking WT10-2 and WT10-3 as examples, when the wind blows from the west, WT10-2 is affected by WT10-1, and WT10-3 is affected by WT10-1 and WT10-2. When the wind comes from the east, WT10-2 is under the wake effect of other three upstream wind turbines, while WT10-3 is only affected by two upstream wind turbines. Therefore, in a wind farm or a cluster of wind turbines, the wake condition for each wind turbine should be analyzed individually. Figure 7 (f) shows the average wind speed efficiency of all wind turbines. From Figure 7 (f), it is easy to perform a preliminary wake analysis of the entire group of wind turbines. When the wind blows from the east or the west, the efficiency of the entire cluster of wind turbines will decrease. There are two ranges of wind direction affected by wakes, namely 330-10° and 160-190°. By contrast, if the wind blows from the north or south, the wind turbines will not be affected by wakes from each other.

The wind speed efficiency of each wind turbine constitutes a wake network for the entire wind turbine cluster. Then, this wake network will be integrated with the ANN-wake-power model. The consideration of wind deficit caused by wake makes the ANN-wake-power model more accurate in predicting the power generation of wind turbines.

3.3 Selection of wind speeds

The prevailing winds of the selected wind farm are north winds to northwest winds. However, according to the previous analysis, when the prevailing wind is blowing, there is no wake interaction between wind turbines. In order to study the effectiveness of the ANN-wake-power model, the wind directions leading to the wake effect should be selected. With the consideration of local weather conditions, this study selects a number of westerly winds and the corresponding data of the wind turbine. Figure 8 demonstrates the wind rose diagram for the selected period.

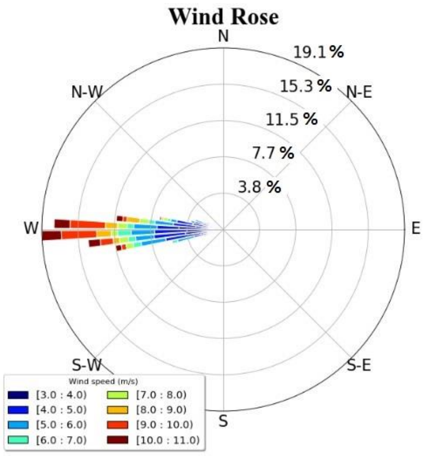
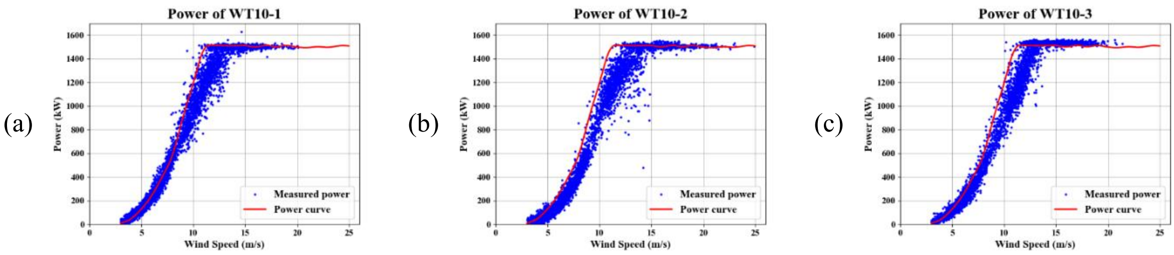


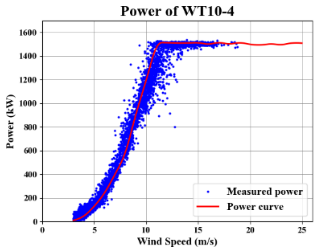
Figure 8 Wind rose diagram for the selected period.

The above wind information is obtained from the meteorological tower records. A total of 1956 time points of wind velocity have been selected. The range of wind direction is 150 - 198° and the range of wind speed is 3-11 m/s. The ANN-wake-power model will be developed based on these filtered data.

3.4 Development and validation of the ANN-wake-power model

The information of all wind turbines is collected from the Supervisory Control and Data Acquisition (SCADA) system, including the instantaneous power and yaw angles of wind turbines.1956 sets of data are selected from SCADA corresponding to the previous wind velocity data. The power of wind turbines are shown in Figure 9.



(d) 

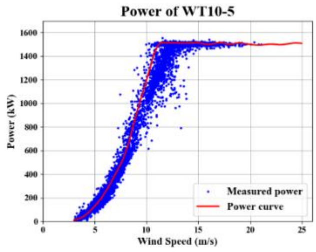
(e) 

Figure 9 Measured power of five wind turbines: (a) WT10-1; (b) WT10-2; (c) WT10-3; (d) WT10-4; (e) WT10-5.

The actual measured power data do not agree well with the power curve, especially when the wind speed is less than the rated wind speed. Therefore, estimating the power of a wind turbine based on wind speed alone is not accurate. It is necessary to build a more accurate model to estimate the power performance of each wind turbine. In the developed ANN model, more information is involved, including wake estimations, wind speeds, and yaw angles. The summary of the datasets is listed in Table 3.

Table 3 Summary of the datasets.

	Mean	Min	Median	Max
Wake1	0.051833	0	0.004482	0.261788
Wake2	0.050797	0	0.004693	0.261779
Wake3	0.050801	0	0.005085	0.261751
Wake4	0.052227	0	0.004856	0.259905
Wake5	0.052145	0	0.005704	0.259900
Wind Speed1 (m/s)	9.41	3.24	9.75	14.88
Wind Speed2 (m/s)	10.20	3.06	10.77	15.00
Wind Speed3 (m/s)	9.97	3.00	10.70	14.99
Wind Speed4 (m/s)	8.89	3.07	9.26	14.77
Wind Speed5 (m/s)	10.20	3.04	10.74	15.00
Yaw Angle1 (°)	0.23	-29.89	0.61	17.82
Yaw Angle2 (°)	-0.56	-28.93	-1.12	25.60
Yaw Angle3 (°)	0.59	-28.06	1.34	23.15
Yaw Angle4 (°)	-0.12	-28.91	-0.07	36.36
Yaw Angle5 (°)	-0.74	-27.17	-1.02	33.00
Power (kW)	4622.21	125.00	5307.00	7639.00

The data should be normalized before the ANN model training. The Min-Max Feature scaling is used, as shown in Equation (8).

$$X' = \frac{X - X_{\min}}{X_{\max} - X_{\min}} \tag{8}$$

X' is the normalized value of each sample item; X is the observation value; $X_{\min}$ is the minimum value of the observations; and $X_{\max}$ is the maximum value of the observations.

After the data preprocessing, the ANN-wake-power model is established. The structure of the model is demonstrated in Figure 10. The wake network related to wind direction is integrated into the model. The wind speeds and yaw angles of five wind turbines are also considered as the input variables. Therefore, there are a total of 15 neurons in the input layer. The first hidden layer contains 32 neurons and the second hidden layer contains 64 neurons. The total power is in the output layer.

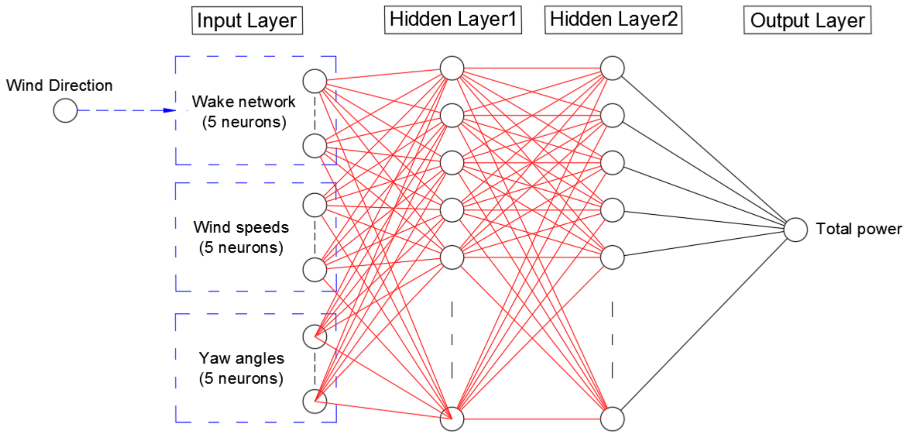


Figure 10 Structure of the ANN-wake-power model.

Two activation functions are used in the ANN-wake-power model. The Sigmoid activation function is applied in the first layer, as shown in Equation (9).

$$S(z) = \frac{1}{1+e^{-z}} \tag{9}$$

The Rectified Linear Unit activation function is applied in the second layer, as shown in Equation (10).

$$R(z) = \max(0, z) \tag{10}$$

The total data are divided into 70% of training data, 15% of validation data, and 15% of test data. Figure 11 shows the evolution of the validation performance of the ANN-wake-power model.

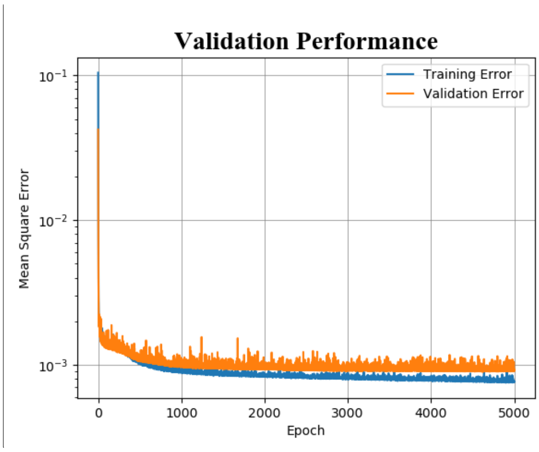


Figure 11 Evolution of the mean square errors of the ANN model.

5000 training epochs have been set to track the best validation MSE after each iteration. Both training and validation MSEs decrease dramatically at first, then decrease slowly throughout the entire training process, and eventually stabilize at less than 10^{-3}. Figure 12 demonstrates the performance of the ANN-wake-power model for different datasets.

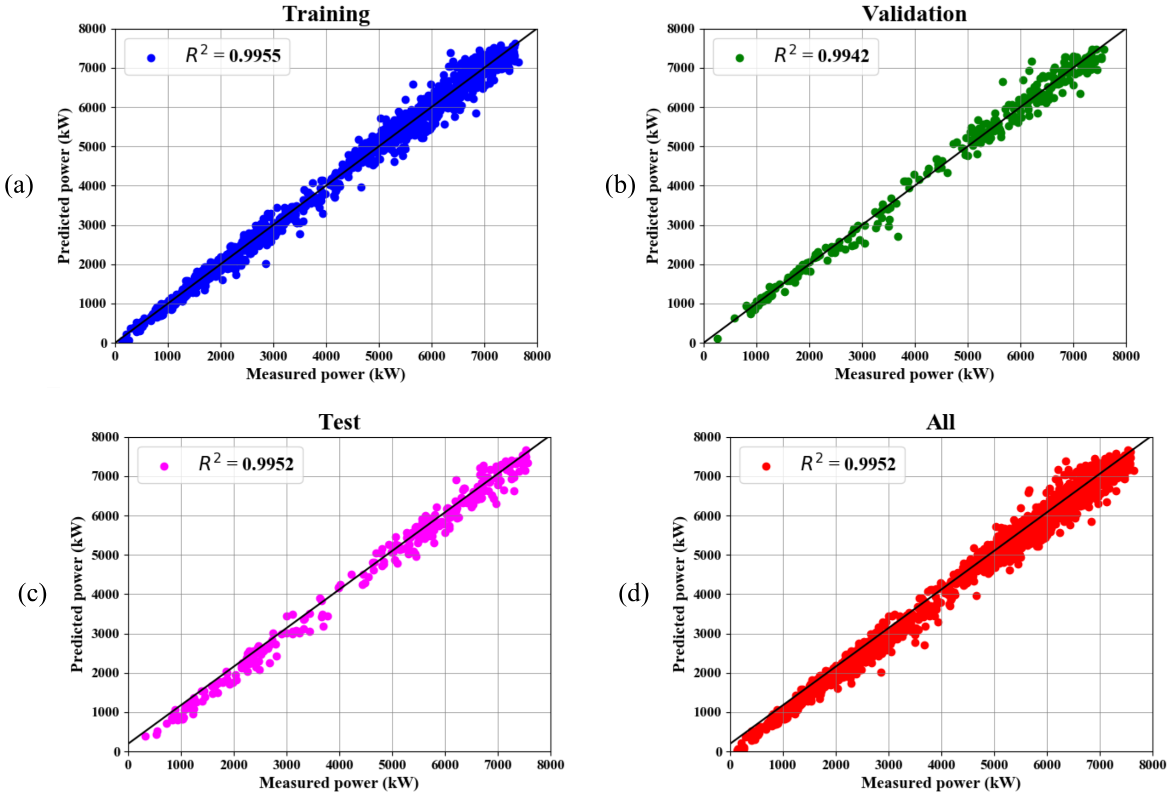


Figure 12 ANN performance for: (a) Training data; (b) Validation data; (c) Test data; and (d) All data.

The coefficient of determination (denoted by R^2) is applied to evaluate the ANN performance. It explains the strength of the relationship between an independent and dependent variable. The expression of the coefficient of determination is shown in Equation (11).

$$R^2(y, \hat{y}) = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \tag{11}$$

In the equation, n is the number of variables; y_i is the i-th observation of the response variable; $\hat{y}_i$ is the value estimated by the regression function; $\bar{y}$ is the mean value of the observations.

In this study, the R^2 of all datasets are larger than 0.99, indicating the good performance of the trained ANN-wake-power model. The ANN-wake-power model takes into account the influence of wake and yaw angle of wind turbine. Therefore, the power of wind turbines can be accurately estimated. The ANN-wake-power model is then applied to study the effect of yaw angle on power generation.

4. Optimization of yaw angles based on ANN-wake-power model

For a standalone wind turbine, the rotor area should be completely perpendicular to the incoming wind to achieve the best efficiency. However, for multiple wind turbines, yaw misalignment may have a beneficial effect because it can control the aerodynamic wake and reduce energy losses of downstream wind turbines [33]. Through the effective wake steering methods, the annual average power generation for wind turbines can increase by 7% to 13% [34]. The key process in wake steering is to accurately estimate the power generation of wind turbine under different yaw angle conditions. The well-trained ANN-wake-power model in this study can quickly and accurately predict the total power generation of wind turbines, which provides a considerable possibility to accomplish the optimal wake-steering strategy by combining with the yaw angle optimization.

4.1 Optimization process

Genetic Algorithm (GA) is applied in this study as the optimization tool. GA is a search heuristic method inspired by the theory of natural evolution. It imitates the process of natural selection, in which the most suitable individuals are selected to produce the next generation offspring [35]. The optimization process in this study is demonstrated in Figure 13.

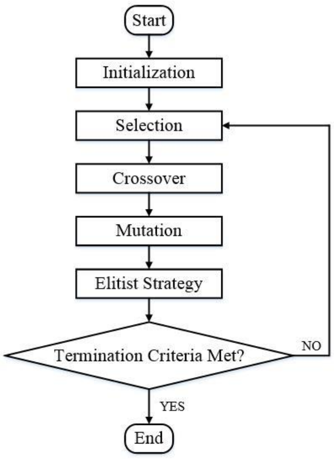


Figure 13 Flow chart of Genetic Algorithm.

In the GA process, the objective function and the corresponding termination criterion are first defined. Then, the initial population is randomly generated. It goes through the process of selection, crossover, and mutation in turn. Next, the population is selected by the elitist strategy. The final step is to determine whether the termination criterion is met. If yes, the best individual is obtained and the optimization can be terminated; if no, the new population will be generated and the process will return to the selection step. The optimization will continue until the termination criterion has been achieved.

In this study, to be specific, the wind turbine yaw angle is the population. The total power ratio is the key parameter of the objective function. Power ratio is defined as the actual power generation divided by the theoretical power generation, as shown in Equation (12). Some other studies have also adopted similar concepts [36, 37].

$$Ratio_{Power} = \frac{P_{actual}}{P_{theoretical}} \tag{12}$$

In this equation, $Ratio_{Power}$ is power ratio; P_{actual} is the actual power generation; and $P_{theoretical}$ is the theoretical power generation. If a wind turbine is not under wake effect, the actual power should be equal to the theoretical power and the power ratio should be 1. Whereas if a wind turbine is under the wake effect of other upstream wind turbines, the actual power would be less than the theoretical power and the power ratio should be less than 1. Power ratio reflects the power deficit caused by wake effect, which is more accurate than power generation in describing the influence of wakes on power generation.

The purpose of this optimization process is to find a set of yaw angles of wind turbines that can maximize the power ratio. In this process, the well-trained ANN-wake-power model is applied to predict the power ratio under different yaw angle conditions. This study sets 500 generations as the stopping criterion. In other words, if the maximum total power ratio keeps for 500 generations, the optimization process will stop and the result will be the optimized output.

4.2 Optimization results

The optimized total power ratios are compared with the original data, as shown in Figure 14. The incoming wind speed is assumed to be 9 m/s. The results include the power ratio optimized in wind directions of 150-200°, which cover the range of the original data. The yaw angles are set in the range of ±20°.

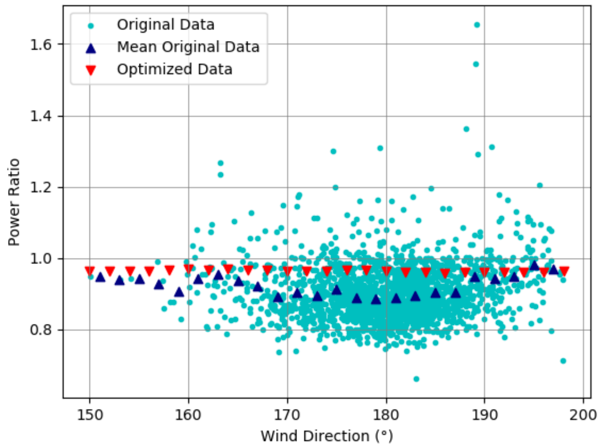


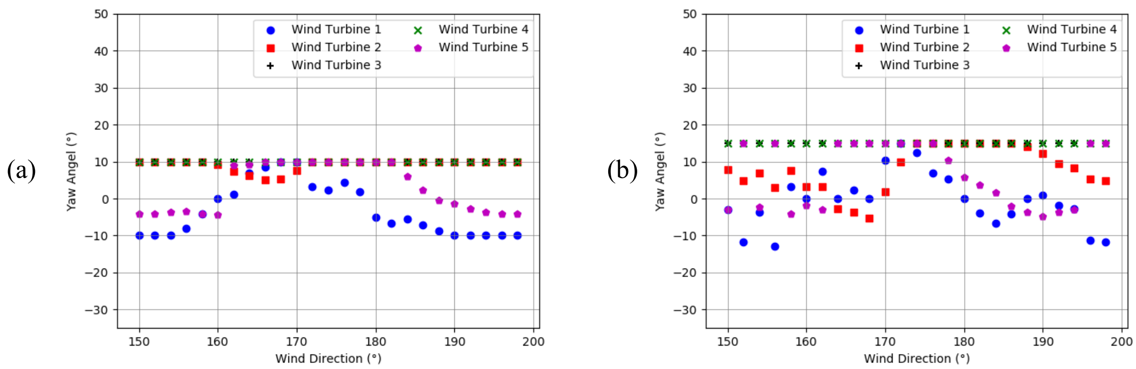
Figure 14 Comparison of original data and optimized results.

From the measured data, a specific wind direction may correspond to several power ratios. This is because yaw angles are always changing during the operating period to track the incoming wind direction. In other words, the yaw angle combinations may be different for the identical wind direction. While for the optimized result, each wind direction corresponds to only one power ratio, as only one set of yaw angles can maximize the power generation.

According to Figure 7 (f), 160-190° is within the range of wind direction affected by the wake. Due to the wake effect, most measured power output ratios are less than 1. Some power ratios greater than 1 may be due to the SCADA measurement errors, including incorrect measurements of incoming wind speed and inaccurate estimations of theoretical power. Therefore, a more accurate method to estimate the power of wind turbines is essential.

As expected, in the wind directions under the wake effect, the power ratios with optimized yaw angels are generally greater than the actual ratios of the same wind direction. All optimized power ratios are larger than 0.96. For wind directions larger than 195°, the optimized power ratios are smaller than the measured data. The main reason is that there are quite a few measured ratios greater than 1. As analyzed previously, it is reasonable to ignore the ratios greater than 1 when compared with the optimized results. This study demonstrates all measured data. Therefore, the inaccurate data may affect the evaluation of the optimization process.

When optimizing yaw angles, the angle range has a critical impact on the result. The optimized yaw angles in different angle ranges are demonstrated in Figure 15.



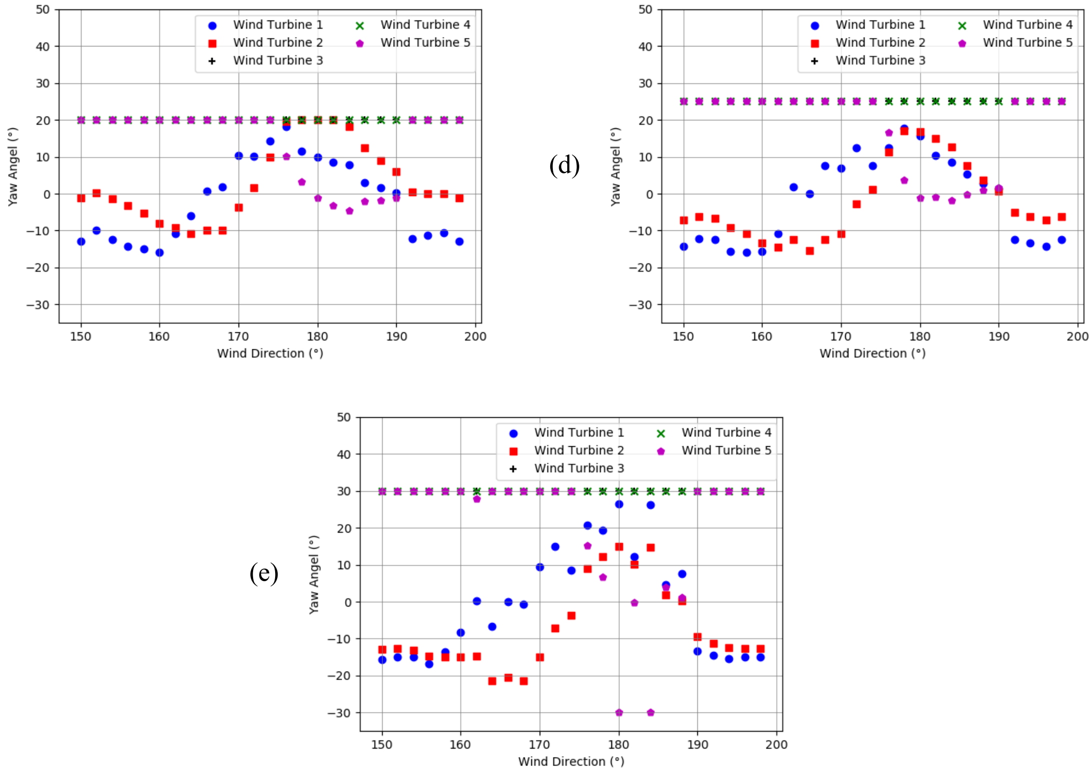


Figure 15 Optimized yaw angles in the angle range of: (a) -10° to 10°; (b) -15° to 15°; (c) -20° to 20°; (d) -25° to 25°; and (e) -30° to 30°.

To obtain the optimal results, wind turbines in different wind directions should be controlled by individual strategies. In this layout pattern of five wind turbines, the controls of WT10-1, WT10-2, and WT10-5 are relatively complicated. The first and last turbines (WT10-1 and WT10-5) should be carefully controlled to avoid either affecting other turbines or being affected by wakes of other turbines. Whereas for WT10-3 and WT10-4, the yaw angles can be set to the maximum positive value. This conclusion could also be applied to other wind turbines installed in a line.

As shown in Figure 15, the number of samples will also affect the trained model and further affect the optimized yaw angel results. In this case study, numerous samples are in the wind directions of 170-190°, so the corresponding results are relatively credible. For the samples exceeding this range, it is not recommended to use the corresponding results.

For a wind turbine co-located with other wind turbines, the wake-steering strategy can not only avoid the wake effect from upwind turbines but also minimize the influence on downwind turbines. The control of WT10-1 is to minimize the wake impact on downstream wind turbines, while that of WT10-5 is to avoid the wake impact from upstream wind turbines. The optimal yaw angle strategies of these two turbines are markedly different from other turbines. Therefore, for future work, the ANN-wake-power model can be used to investigate the effect of different wake-steering strategies.

5. Conclusions

This paper proposes a model using artificial neural network (ANN) to predict the power generation of wind turbines. Based on the ANN-wake-power model, the yaw angles of wind turbines are optimized to minimize the impact of wake on the entire wind farm. The main conclusions drawn from this paper are as follows.

A novel model using ANN is proposed to estimate the power generation of a cluster of wind turbines. The ANN-wake-power model is developed through six steps. Considering wake interactions between wind turbines, a two-dimensional wake model is adopted to estimate the wake effect. With the wake model and the terrain information, a wake network is established for the ANN-wake-power model. The wake network takes into account the partial wake effect, which is more applicable for complex-terrain wind farms.

The establishment process of the ANN-wake-power model is demonstrated through a case study of a row of five wind turbines. The experimental data have been selected for the ANN training from an operating complex-terrain wind farm in northern China. The dataset contains the simultaneous wind speeds, wind directions, yaw angles of wind turbines, and power generation. Data are filtered according to the effective time and wind directions. In other words, only the data when wind turbines are under the wake effect are selected. The processed data are divided into a training dataset, a validation dataset, and a test dataset. A wake network is established and integrated into the ANN-wake-power model. Therefore, the input layer contains the wind direction-related wake network, wind speeds, and yaw angles of wind turbines. The model is trained by the training dataset, validated by the validation dataset, and evaluated by the test dataset. As a result, the ANN-wake-power model achieved a good performance within the training process of 5000 epochs.

The ANN-wake-power model performs fast simulation for the total power generation of wind turbines with high accuracy, which makes it possible to optimize the yaw angles of wind turbines. An optimization process based on the ANN-wake-power model and the Genetic Algorithm is established. The concept of power ratio has been used to evaluate the power losses caused by wakes. The yaw angles of wind turbines are the variables to be optimized, and the maximum total power ratio is the objective. The optimization process is effective and can significantly improve the power ratio to 0.96 in all directions involved. From the optimized results of this study, it is suggested that wind turbines in different positions should adopt different yaw angle control strategies. Especially for the first and last turbines, the optimal yaw angle strategies are markedly different from other turbines, which should be paid more attention.

This study presents the possibility to apply the advanced machine learning methods to the wind energy industry. The established ANN-based model has good accuracy and requires little computation cost. The model is suitable for complex engineering problems, such as the wake-steering problem. It can also be applied to investigate the wake effect under wake-steering conditions. In addition, it is worth noting that the quality of the model largely depends on the amount of the input data. How to improve the accuracy and efficiency of a wind power prediction model under certain conditions is a challenging problem that needs further investigation.

Acknowledgement

The work presented in this paper is financially supported by the Research Institute for Sustainable Urban Development (No. BBW8) and the University Supporting Fund project (No. BBAV) of The Hong Kong Polytechnic University.

References

[1] H. Sun, X. Gao, and H. Yang, "A review of full-scale wind-field measurements of the wind-turbine wake effect and a measurement of the wake-interaction effect," *Renewable and Sustainable Energy Reviews,* vol. 132, p. 110042, 2020/10/01/ 2020.

[2] Global Wind Energy Council, "Global wind 2019 report Annual Market Update," *Global Wind Energy Council (GWEC), Brussels, Belgium,* 2020.

[3] C. L. Archer *et al.*, "Review and evaluation of wake loss models for wind energy applications," *Applied Energy,* vol. 226, pp. 1187-1207, 2018/09/15/ 2018.

[4] Á. Jiménez, A. Crespo, and E. Migoya, "Application of a LES technique to characterize the wake deflection of a wind turbine in yaw," *Wind energy,* vol. 13, no. 6, pp. 559-572, 2010.

[5] C. Yan, Y. Pan, and C. L. Archer, "A general method to estimate wind farm power using artificial neural networks," *Wind Energy,* vol. 22, no. 11, pp. 1421-1432, Nov 2019.

[6] A. Costa, A. Crespo, J. Navarro, G. Lizcano, H. Madsen, and E. Feitosa, "A review on the young history of the wind power short-term prediction," *Renewable and Sustainable Energy Reviews,* vol. 12, no. 6, pp. 1725-1744, 2008.

[7] H. Sun and H. Yang, "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,* vol. 147, pp. 192-203, 2020/03/01/ 2020.

[8] P. Hou, J. Zhu, K. Ma, G. Yang, W. Hu, and Z. Chen, "A review of offshore wind farm layout optimization and electrical system design methods," *Journal of Modern Power Systems and Clean Energy,* vol. 7, no. 5, pp. 975-986, 2019/09/01 2019.

[9] S. Li, "Wind power prediction using recurrent multilayer perceptron neural networks," in *2003 IEEE Power Engineering Society General Meeting (IEEE Cat. No. 03CH37491)*, 2003, vol. 4, pp. 2325-2330:

IEEE.
[10] T. G. Barbounis, J. B. Theocharis, M. C. Alexiadis, and P. S. Dokopoulos, "Long-term wind speed and power forecasting using local recurrent neural network models," *IEEE Transactions on Energy Conversion,* vol. 21, no. 1, pp. 273-284, 2006.
[11] A. Kusiak, H. Zheng, and Z. Song, "Wind farm power prediction: a data‐mining approach," *Wind Energy: An International Journal for Progress and Applications in Wind Power Conversion Technology,* vol. 12, no. 3, pp. 275-293, 2009.
[12] B. Wu, M. Song, K. Chen, Z. He, and X. Zhang, "Wind power prediction system for wind farm based on auto regressive statistical model and physical model," *Journal of Renewable and Sustainable Energy,* vol. 6, no. 1, p. 013101, 2014.
[13] A. Fischer, L. Montuelle, M. Mougeot, and D. Picard, "Statistical learning for wind power: A modeling and stability study towards forecasting," *Wind Energy,* vol. 20, no. 12, pp. 2037-2047, Dec 2017.
[14] S. M. Tripathi, A. N. Tiwari, and D. Singh, "Grid-integrated permanent magnet synchronous generator based wind energy conversion systems: A technology review," *Renewable and Sustainable Energy Reviews,* vol. 51, pp. 1288-1305, 2015/11/01/ 2015.
[15] P. Fleming *et al.*, "Field test of wake steering at an offshore wind farm," *Wind Energ. Sci.,* vol. 2, no. 1, pp. 229-239, 2017.
[16] J. Lee, E. Son, B. Hwang, and S. Lee, "Blade pitch angle control for aerodynamic performance optimization of a wind farm," *Renewable energy,* vol. 54, pp. 124-130, 2013.
[17] P. A. Fleming *et al.*, "Evaluating techniques for redirecting turbine wakes using SOWFA," *Renewable Energy,* vol. 70, pp. 211-218, 2014.
[18] P. Fleming *et al.*, "Full-Scale Field Test of Wake Steering," in *Journal of Physics: Conference Series*, 2017, vol. 854.
[19] P. Gebraad, J. J. Thomas, A. Ning, P. Fleming, and K. Dykes, "Maximization of the annual energy production of wind power plants by optimization of layout and yaw-based wake control," *Wind Energy,* vol. 20, no. 1, pp. 97-107, Jan 2017.
[20] G. Li and J. Shi, "On comparing three artificial neural networks for wind speed forecasting," *Applied Energy,* vol. 87, no. 7, pp. 2313-2320, Jul 2010.
[21] C. Qiu, Y. K. Yi, M. Wang, and H. Yang, "Coupling an artificial neuron network daylighting model and building energy simulation for vacuum photovoltaic glazing," *Applied Energy,* vol. 263, p. 114624, 2020/04/01/ 2020.
[22] H. Sun, X. Gao, and H. Yang, "Validations of three-dimensional wake models with the wind field measurements in complex terrain," *Energy,* vol. 189, p. 116213, 2019/12/15/ 2019.
[23] H. Sun, X. Gao, and H. Yang, "Experimental study on wind speeds in a complex-terrain wind farm and analysis of wake effects," *Applied Energy,* vol. 272, p. 115215, 2020/08/15/ 2020.
[24] X. Gao *et al.*, "Investigation of wind turbine performance coupling wake and topography effects based on LiDAR measurements and SCADA data," *Applied Energy,* vol. 255, p. 113816, 2019/12/01/ 2019.
[25] X. Gao *et al.*, "Investigation and validation of 3D wake model for horizontal-axis wind turbines based on filed measurements," *Applied Energy,* vol. 260, p. 114272, 2020/02/15/ 2020.
[26] R. J. Barthelmie *et al.*, "Modelling and measuring flow and wind turbine wakes in large wind farms offshore," *Wind Energy,* vol. 12, no. 5, pp. 431-444, 2009.
[27] B. Sanderse, "Aerodynamics of wind turbine wakes," *Energy Research Center of the Netherlands (ECN), ECN-E–09-016, Petten, The Netherlands, Tech. Rep,* 2009.
[28] H. Sun, X. Gao, and H. Yang, "Investigation into offshore wind farm repowering optimization in Hong Kong," *International Journal of Low-Carbon Technologies,* vol. 14, no. 2, pp. 302-311, 2019.
[29] N. O. Jensen, *A note on wind generator interaction*. 1983.
[30] H. Sun and H. Yang, "Study on an innovative three-dimensional wind turbine wake model," *Applied Energy,* vol. 226, pp. 483-493, 2018/09/15/ 2018.
[31] R. Shakoor, M. Y. Hassan, A. Raheem, and Y.-K. Wu, "Wake effect modeling: A review of wind farm layout optimization using Jensen′s model," *Renewable and Sustainable Energy Reviews,* vol. 58, pp. 1048-1059, 5// 2016.
[32] H. Sun and H. Yang, "Comparative study on a newly-developed three-dimensional wind turbine wake model," *Energy Procedia,* vol. 158, pp. 148-153, 2019.
[33] C. L. Archer and A. Vasel-Be-Hagh, "Wake steering via yaw control in multi-turbine wind farms: Recommendations based on large-eddy simulation," *Sustainable Energy Technologies and Assessments,* vol. 33, pp. 34-43, 2019/06/01/ 2019.
[34] M. F. Howland, S. K. Lele, and J. O. Dabiri, "Wind farm power optimization through wake steering," *Proceedings of the National Academy of Sciences,* vol. 116, no. 29, pp. 14495-14500, 2019.
[35] X. Ju and F. Liu, "Wind farm layout optimization using self-informed genetic algorithm with information

guided exploitation," *Applied Energy,* vol. 248, pp. 429-445, 2019/08/15/ 2019.
[36] H. Sun, H. Yang, and X. Gao, "Investigation into spacing restriction and layout optimization of wind farm with multiple types of wind turbines," *Energy,* vol. 168, pp. 637-650, 2019/02/01/ 2019.
[37] F. Liu, X. Ju, N. Wang, L. Wang, and W.-J. Lee, "Wind farm macro-siting optimization with insightful bi-criteria identification and relocation mechanism in genetic algorithm," *Energy Conversion and Management,* vol. 217, p. 112964, 2020/08/01/ 2020.