Research on Ultra-short term Forecasting Technology of Wind Power Output Based on Wake Model

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Abstract. The concept of sustainable development promotes the development of new energy power generation industry. At the same time, in the field of wind power, wind curtailment and power limit gradually appear, and the output prediction of power plants has become one of research hotspots. Because of the wake effect between wind farms, the wind speed of the wind tower can not represent the real numerical value. Therefore, in this paper, we established various wake models of wind farm group under different wind direction to modify the wind speed of wind tower and get more accurate results. We also used the Long Short-Term Memory network (LSTM) to forecast the wind farm output, and finally obtained excellent forecast results. Compared with traditional prediction algorithm, it had improved the prediction accuracy.

Keywords: wind power prediction, wake model, LSTM, wind speed

1. Introduction
Wind is an important indicator of wind power, including size and direction, also known as wind speed and wind direction. The wake effect means that after the natural wind passes through the wind turbine, the wind turbine captures the wind energy and converts it into mechanical energy for blade rotation, and finally converts it into electrical energy. At this time, the wind energy carried by the natural wind decreases. The wind turbines in the downstream can only acquire less wind energy. The degree of wake effect is affected by a variety of factors, such as the distance between wind turbines, the change of the wind direction, the size of the wind speed, the geographical location and the shielding area formed by upwind wind turbines to downwind wind turbines.

Several types of wind information are commonly used in the prediction of the wind power output: the wind speed of wind towers and turbines, numerical weather forecast information, etc. Wind towers are generally set up around wind farms or other locations less affected by wake flow. We can think of it is a kind of description of windward wind speed, which can play an important role in forecasting the wind speed of the whole wind farm. However, it can't reflect the impact of wake effect of wind turbines. The measurement position is on each wind power generator unit, which can accurately represent the change of wind speed. It is of great significance to judge the working condition these units. Numerical weather prediction is the calculated information based on the atmospheric conditions,
and its prediction of the wind speed are more macroscopic in both time and space. In actual wind farms, the inflow wind speed at the fan is not necessarily the same, and the detected wind speed can not be directly used to analyze the output. Through analysis, we can find that the wind speed of downwind turbine is less than that of upwind turbine in the wind farm, which is mainly caused by wake effect.

2. Wind Speed Model Considering Dynamic Spatial Characteristics of Wind Speed in Wind Farms

2.1. The Wind Speed-power Curve of the Wind Turbine

The wind turbine's wind speed-power curve describes the functional relationship between the output power and the wind inlet velocity of the wind turbine, which is often used in the physical prediction model of output. The theoretical wind turbine’s wind speed-power curve is generally provided by manufacturers. The standard theoretical curve is shown in figure 1 below. The measured curve of Ganbei Second Wind Farm in Gansu province is shown in figure 2.

![Figure 1. Theoretical power curve of the wind turbine.](image1)

![Figure 2. Actual power curve of the wind turbine.](image2)
As can be seen from the comparison above, the distribution of data points in the actual wind speed-power curve is relatively scattered, and one wind speed value may correspond to multiple output power values. The reason may be that the wind speed at the nose is the wind speed remaining on the windward side after it passes through the turbine. Wind speed at the nose is not only affected by the generator itself, it will also be affected by upstream wake effect, wind turbulence, the sensors’ precision, the operation condition and the precision of data transmission. Therefore, the measured wind speed is not accurate. It needs to be corrected to make better use of it.

2.2. Technical Route and Implementation Plan

So far, for the power prediction of domestic large wind farms, there are three methods which are most commonly used. They are accumulative method, benchmarking turbine method and the overall calculation method [1].

The first is a simple accumulation method, that is, we can use the wind speed, historical output as well as temperature, pressure, wind direction and other meteorological data of each turbine's nose, and abandon the data acquired by the wind tower and other sensors, then independently do the prediction for each wind turbine [2]. Finally all output results are superimposed to become the overall output of the wind farm. The advantage of the accumulation method is obvious and simple. We don’t need to add additional processing on the basis of the original output prediction of each single wind field. At the same time, the accumulation method has carried out the careful calculation for each wind field, and the final prediction result will obviously be more accurate. However, the limitations in the practical application are also very obvious. For all related wind fields, we need to analyze the wind speed and the wind power separately, which will lead to a longer single computation cycle, and cause greatly consumption of human resources. Especially in the short term and ultra-short term forecast, it is not desirable [3]. Similarly, the prediction of the wind power output for all wind farms in the same wind power base will greatly consume storage space and computing resources.

The benchmarking method is formulating the actual output network diagram according to the actual output of the single machine. The next step is to select the benchmarking turbine. Generally, the benchmarking turbine is the benchmarking unit currently in use in the selected wind farm, which is directly given by the wind farm [4]. The final theoretical output of the wind farm is calculated as follows: total output of all available benchmark turbines * (the number of total turbines minus number of faulty and restricted fans)/total number of available benchmark turbines). The accuracy of this method depends on the selection of the benchmark and the operation of the whole wind farm. The adaptability of this method is poor and the accuracy varies greatly under different operating conditions.

The third is to take the wind farm output as a whole, and refer to the single turbine’s wake effect model [5-7]. This method uses the historical wind tower data and the correlation between each wind farm, and puts forward the wake effect model between wind farms, and calculate the distribution network. Then it takes the historical output data of the whole wind farm, wind speed data, temperature, pressure, wind direction and other meteorological data as inputs into the forecaster to get the power output of the whole wind farm [8].

Figure 3 shows the process of establishing the wind speed model between wind power farms considering the wake effect. (1) Firstly, we need to obtain the wind tower data of each single wind field. (2) Secondly, we should establish the wake effect model between wind farms within the same field group; (3) Thirdly, the wake effect model in (2) is used to modify the wind speed distribution of each wind farm, so as to obtain the wind speed distribution network within the whole wind farm group.

![Figure 3. Establishment of the wind speed network considering the wake effect between wind farm groups.](image-url)
2.3. Spatial Distribution Characteristics of Wind Speed in Wind Farms
At present, wake effect models which are widely used include Jensen model, Lissaman model, etc., which describe how wind speed decays in the track formed while passing through turbines [9]. In order to simplify the calculation and improve the time efficiency, this paper intends to use Jensen model to calculate the wake effect.

2.3.1. Wake Effect between Wind Turbines. Jensen Wake Model, also known as the linear wake model, believes that the wake flow formed by natural wind while passing through the turbine presents an axisymmetrical state, and the radius of the influence range of the wake effect increases linearly with the distance between two wind turbine impellers [10].

For the wake effect between two wind turbines, a simplified schematic diagram of Jensen's model is shown in figure 4 below:

![Figure 4. Schematic diagram of wake effect.](image)

Where, $V_0$ is the wind speed of the inflow, and $V_{s0}$ is the wind speed after passing through the impeller. $r(d)$ is the wake radius of the upstream turbine at distance d. $v_w(d)$ is the wind speed at distance d. $r_{wt}$ is the radius of wind turbine impeller. $\tan \alpha = k$ is the attenuation factor in the wake effect, which is used to represent the expansion speed of wake radius $r(d)$ in the propagation process of natural wind passing through the impeller. The calculation formula of $r(d)$ is as follows:

$$
\begin{align*}
    r(d) &= r_{wt} + d \tan \alpha \\
    \tan \alpha &= k = \frac{1}{2 \ln \left( \frac{H}{r_c} \right)}
\end{align*}
$$

Where, H is the hub’s height; Re is the degree of the ground roughness where the wind farm is located.

According to the aerodynamic theory, the wind speed after passing through the impeller is:

$$
V_{s0} = (1-a)V_0
$$

In the formula, $a = 1 - \sqrt{1-C_t}$ represents the ratio of the loss of the inlet wind speed caused by the blade rotation to the inlet wind speed. $C_t$ is the thrust coefficient of wind turbine and its value can be obtained from the fitting curve based on the thrust coefficient given by the manufacturer.
According to the conservation of momentum, we can get:

$$\pi r_w^2 v_{\text{sw}} + \pi (r(d)^2 - r_w^2) v_0 = \pi r(d)^2 v_w(d)$$

(3)

According to formulas (1) - (3), we can conclude that under the influence of wind wake at O, the calculation formula of the inflow wind speed at d is as follows:

$$v_w(d) = v_0[1 - (1 - \sqrt{1 - C_f})(\frac{r_{out}}{r_{out} + k d})^2]$$

(4)

2.3.2. Wake Effect between Wind Farms. In this paper, Jensen’s wake model of the wind turbine is extended to wind farms by reference, and we describe the wake effect between wind farms as follows: For the natural wind speed U as an inflow, the wake is formed after passing through the wind farm j and the velocity attenuates to $u_i$ when it reaches the wind farm i. The specific formula is:

$$u_i = (1 - \delta u(L^d, L', \alpha_j))U$$

(5)

where $L^d$ and $L'$ are respectively the distance in the wind direction and the deviation direction of the wind farm, as shown in figure 5. $\delta u(L^d, L', \alpha_j)$ is the reduction factor of the wind speed, which is a measure of the decrease in wind speed. $\alpha_j$ is the induction factor, which measures the change of wind speed after wind passing through the wind farm, and is defined as:

$$\alpha = \frac{U_{\text{in}} - U_{\text{out}}}{U_{\text{in}}}$$

(6)

$U_{\text{in}}$ and $U_{\text{out}}$ respectively represent the input and output wind speed of the wind farm. They can be expressed by the theoretical wind speed on the windward side of the first layer turbine under the wind direction and the wind speed on the nose of the last layer turbine of the wind farm j.

$\tan \beta = k$

$L_{\text{max}}$ is the wake attenuation factor, $L_{\text{max}}$ is the influence distance of wake flow. Through the statistical analysis of real wind farm data, we use the method of

$$\delta u(L^d, L', \alpha_j) = \begin{cases} \alpha_j \left( \frac{D_j}{D_j + k L'} \right)^2, & \text{if } L' \leq L_{\text{max}} \\ 0, & \text{otherwise} \end{cases}$$

(7)

Where $D_j$ represents the initial influence diameter of the wake effect, which in this paper represents the footprint size of wind farm j. $\tan \beta = k$ is the wake attenuation factor, $L_{\text{max}}$ is the influence distance of wake flow. Through the statistical analysis of real wind farm data, we use the method of
looking for the correlation of wind speed between different wind farms under this wind direction to get it. Figure 6 shows the relationship between the distance between wind fields and the correlation coefficient of wind speed. The fitting equation of data is:

$$y = -4.396 \times 10^{-6} x + 0.9904$$  \hspace{1cm} (8)

We may assume that if the correlation coefficient is greater than 0.8, there is wake influence, and then we can obtain $L_{\text{max}} = 43.31 \text{km}$.

![Figure 6. Correlation coefficient between distance between wind fields and wind speed.](image)

The wake stream which is formed behind the upstream wind farm affects the downstream wind farms. This is similar to a chain action [11]. If we use the wind speed formed behind the upstream wind farms as the input speed of the downstream wind farms, with the influence of the wake effect accumulating continuously, when we calculate the wind speed of the $j$th wind farm, we need to consider the influence of all wakes from the upstream wind farms, which can be expressed as the product of wind speed ratio of upstream wind farms:

$$u_j(U) = \left[ \prod_{j} (1 - \delta u(L', L', \alpha_j)) \right] U$$  \hspace{1cm} (9)

2.4. Dynamic Distribution Characteristics of Wind Speed in Wind Farms

In the actual operation of wind farms, when the wind direction changes, due to the role of a yaw system, the windward side is always perpendicular to the direction of the inflow wind, so the relative position of wind farms in the same group will also change. As a result, the upstream and downstream relationship between wind farms, the wake direction, the scope of influence will also have different performance [12]. In this paper, the variation of wind speed under the influence of wind direction is called the dynamic distribution characteristic of wind speed in wind farm group.
2.4.1. Modeling of Wake Effect when Wind Direction Changes.

![Figure 7. Change of wake effect when wind direction changes.](image)

Two wind farms are shown in figure 7. They are \(WF_i\), \(WF_j\) and their coordinates are \((x_i, y_i), (x_j, y_j)\). Then the distance between the two wind farms is \(d_{ij}\):

\[
d_{ij} = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2}
\]

When the inflow wind direction is \(\beta_1\), the influence radius of the electric field \(WF_i\) at the wind farm \(WF_j\) is \(r_{\beta_1}\):

\[
r_{\beta_1}(x) = r_w + k \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2}
\]

When the inflow wind direction is \(\beta_2\), the angle of the change is \(\gamma\). Wind turbines in a wind farm are always perpendicular to the inflow wind direction. At this time, the influence radius of the electric field \(WF_i\) at the wind farm \(WF_j\) is \(r_{\beta_2}\):

\[
r_{\beta_2}(x) = r_w + k \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2} \cos \gamma
\]

According to the comparison of equations (11) and (12), it can be seen that the influence radius of wake decreases after the wind direction changes. Therefore, the characteristics must be considered to quantify the influence of wind direction change on wake effect [12].

2.4.2. Wind Direction and the Coordinate Transformation of Wind Farms. In order to solve the problem of wind direction change, it is necessary to change the coordinate of the wind farm where wake effect is to be calculated, including the change of coordinate axis (the default positive direction of X-axis is the wind direction of upstream wind farm when wake effect is calculated).

In the process of transformation, we can specify that the positive x direction is from west to east, and the positive y direction is from south to north. When the wind direction is not strictly west, in order to adapt to the change of wind direction, the coordinate system needs to be rotated to meet the condition that the positive direction of X-axis is the same as the wind direction. The coordinate transformation is shown in figure 8 below:
Figure 8. Coordinate transformation diagram.

The coordinate transformation process is as follows:

1. The original rectangular coordinate system (XOY) is established with any point in the wind farm group as the origin. The coordinate of each wind farm in the original rectangular coordinate system is determined according to the arrangement position in the field group. For example, the coordinate of the $i$th wind farm is $(x_i, y_i)$.

2. When the Angle between the inflow wind direction and the original rectangular coordinate system $x$ axis is $\theta$, we need to find the first wind farm perpendicular to the inflow wind direction. We need to take a random point outside the field group and in the upstream of the inflow wind direction as the reference point, and calculate the distance between each wind farm in the field group and the reference point. In this way, we can find that the wind farm $WF^{1}_{y}$ closest to the reference point, which is the first wind farm in the direction of incoming wind. We could set its original coordinates to be $(x_{\beta11}, y_{\beta11})$.

3. Next, we need to translate and rotate the original coordinate axis so that the coordinate origin is shifted to the point $(x_{\beta11}, y_{\beta11})$. We rotate the coordinate system $\theta$ degrees counterclockwise with the point $O$ as the center of the circle. At this time, the coordinates of the $i$th wind farm $(x_{\beta11}, y_{\beta11})$ are transformed into $(x'_{\beta11}, y'_{\beta11})$. The same applies to other wind farms:

$$
\begin{align*}
    x'_{\beta11} &= (x_i - x_{\beta11}) \cos \theta + (y_i - y_{\beta11}) \sin \theta \\
    y'_{\beta11} &= -(x_i - x_{\beta11}) \sin \theta + (y_i - y_{\beta11}) \cos \theta
\end{align*}
$$

When the incoming wind direction changes again, we can repeat the above steps to obtain the coordinates of all wind farms in the new coordinate system, and then calculate the wake effect. Thus, the solution process of wake effect considering the dynamic distribution characteristics is shown as follows:
Figure 9. Flow chart of calculation of wake effect between wind farms.

2.5. Actual Simulation Analysis
We analyzed the data of Guazhou Wind Power Base in Gansu province at 08:55 on September 28, 2020. The relative positions and wind direction of 22 wind farms in this field group are shown in FIG. 2.10. The blue box is the Ganbei second wind farm, which will be used as the reference wind farm in this experiment to calculate the influence of other wind farms.

Figure 10. Distribution of wind farms and wind direction.

Based on the analysis of the wind tower data measured at this time, it can be seen that the general
wind direction at the hub height (70m) of the wind farm group is between 60 and 95, and almost northeast. As can be seen from the above, when the distance between downwind and upwind turbine in the wind direction of the upwind turbin is greater than 43.31km, wake effect has little influence. Therefore, we only simulated and calculated the wake effect between 15 wind farms in the black box in the figures 9 and 10 above.

By analyzing the wind speed attenuation caused by wake effect on this wind farm, the results are shown in figure 11 below. It can be calculated that the attenuation degree caused by wake effect is about 8.3%.

![Figure 11. Comparison of wind speed before and after modification of wake effect.](image)

3. Ultra-short Term Prediction Model and Result Analysis of Wind Power Station Based on Wake Model

3.1. Information source
All data and information used in this article are from 22 wind farm clusters composed of several small wind farms in Gansu province. The latitude and longitude of the field group is about 95°27'E, 40°40'N, and the altitude is about 1260 meters. The hub height of wind turbines in the field group is 70 meters. We mainly used the wind tower data (including wind speed, wind direction, temperature, humidity, pressure, etc.) and the output data collected every 15 minutes from July 2020 to October 2020.

3.2. Data Normalization
Before we input the raw data into the neural network, we have to perform data normalization. It transforms data sets originally in different or larger range by specific normalization function with the purpose of canceling the difference of order of magnitude between data of different dimensions and avoiding the phenomenon of large network prediction error. Mapmaxmin function is one of the data normalization methods. Its functional form is as follows:

$$x_k = (x_k - x_{\text{min}})/(x_{\text{max}} - x_{\text{min}})$$

(14)

Where, $x_{\text{min}}$ is the minimum value in the data sequence and $x_{\text{max}}$ is the maximum value in a data sequence.

3.3. Long Short-Term Memory(LSTM) Network
Long Short-Term Memory network is known as LSTM. It can be seen as a special type of RNN recurrent neural network. The wavelet neural network mentioned above is a kind of feedforward
neural network according to the topological structure. RNN adds the backward function on the basis of feedforward network. The result of hidden layer calculates the data of input layer and also the value of the hidden layer at the last moment, so it has the "memory" function, which is especially suitable for the prediction of time series data. Figure 12 shows the comparison of the structure of RNN network and feedforward neural network.

![Figure 12. Comparison of RNN network and feedforward neural network.](image)

The original RNN will have gradient explosion and other problems, that is, the perception of nodes in the later time will decline compared with nodes in the earlier time. This means that the training effect will decline with the depth of network increasing. In order to solve this problem, Hochreiter and Schmidhuber created LSTM. LSTM designs memory units in neural network nodes on the basis of RNN model, which are used to determine the validity of information. It uses a gate structure to control the flow of information. There are three gates which are called input gate, forget gate, and output gate. The information that meets the algorithm authentication will be retained, while other information will be forgotten and deleted. This design solves the problem of information disappearance or explosion, and it can learn long-distance dependence. The cell diagram of LSTM is shown in figure 13.

![Figure 13. CELL structure diagram.](image)

3.4. Results Analysis
In order to test whether the model proposed in this paper has satisfactory performance, we trained the LSTM prediction model on the training data set to predict the power output of the wind power station, and compared and analyzed the prediction results of each model. The prediction evaluation indexes include RMSE, MAPE and MAE.
Figure 14. Comparison of results of different prediction models.

Table 1. Comparison table of wind power output prediction and evaluation index results.

| Model                              | RMSE   | MAE    | MAPE  |
|------------------------------------|--------|--------|-------|
| The wake effect is not considered  | 6.5380 | 4.0582 | 0.1342|
| The wake effect is considered      | 3.2851 | 2.7338 | 0.0927|

As shown in figure 14 and table 1, we obtained different prediction results when the wake effect is considered or not. It can be seen that the accuracy of the model with the wake effect is better than that without it. This is because the size of wind speed is the key factor to determine the wind energy, and the accuracy of wind speed directly affects the accuracy of output power. The wind speed corrected by wake effect can better represent the actual wind speed obtained by wind turbine. Using the corrected wind speed as the input of the model is beneficial to improve the prediction accuracy.

4. Conclusion
This paper introduces three kinds of information commonly used in wind farms: wind speed of the wind tower and the nose, as well as the numerical weather forecast information. We analyzed and established the overall calculation scheme of wind farm output. By extending the wake model between wind turbines to the dimension of farms, we analyzed the spatial distribution within wind farms. At the same time, considering that the change of wind direction can have great influence on the wake effect between wind farms, we analyzed the dynamic distribution characteristics of wind speed by means of coordinate transformation. Considering the above two characteristics, we established model which is specially designed for wind speed considering the dynamic spatial characteristics in the field group, so as to correct the wind speed. Finally, we combined the LSTM network with the wake model, and verified the excellent performance of the ultra-short-term prediction of the wake model through the comparative test.

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References
[1] Gao Sh, Zhang N Y 2009 A review of different methodologies for solving the problem of wind
power's fluctuation Sustainable Power Generation and Supply SUPERGEN’09. International Conference 1(5): 1-7.

[2] Yang J P 2012 Short-term Wind Speed and Power Forecasting in Wind Farm Based on ANN Combination Forecasting Chongqing:Chongqing University.

[3] Hu J, Wang J, Zeng G 2013 A hybrid forecasting approach applied to wind speed time series Renewable Energy 60: 185-194.

[4] K. Dragomiretskiy, D. Zosso 2014 Variational mode decomposition IEEE Trans. Signal Process 62(3): 531-544.

[5] Tao Q, Chang H Y, Yang Y, Gu Ch Q, Li W J 2010 A rotary chaotic PSO algorithm for trustworthy scheduling of a grid workflow Computers and Operations Research 38(5).

[6] Fan G F, Peng L L, Zhao X J, Hong W Ch 2017 Applications of Hybrid EMD with PSO and GA for an SVR-Based Load Forecasting Model Energies 10(11).

[7] Vapnik V 1995 The nature of statistical learning theory NewYork:Spring-Verlag.

[8] Yang D Y, Cai G W 2015 The short-term wind speed forecasting for wind farm based on EEMD and LS_SVM Journal of Northeast Dianli University 35(3): 44-49

[9] Wang Y M 2018 Research on Multi-fidelity Simulation Methods for Wind Farm Wake and Output Power North China Electric Power University(Beijing).

[10] Guo Z , Zhao W , Lu H , et al 2012 Multi-step forecasting for wind speed using a modified EMD-based artificial neural network model RENEWABLE ENERGY 37(1): 241-249.

[11] Sun H, Xu J, Sun Y Z, Lei R B 2015 A Method for Wind Power Calculation Considering Wind Speed Spatial and Temporal Distribution and Wind Turbine Operation Status Automation of Electric Power Systems 39(02): 30-38+60.

[12] Yang P H, Hu Q L, Fu P, Hu Zh L 2016 The Modeling of Wind Farm Considering the Changes of Wind Speed, Wind Direction and Wake Effect Renewable Energy Resources 34(05): 692-698.