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A physical approach of the short-term wind power prediction based on CFD pre-calculated flow fields*

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Abstract: A physical approach of the wind power prediction based on the CFD pre-calculated flow fields is proposed in this paper. The flow fields are obtained based on a steady CFD model with the discrete inflow wind conditions as the boundary conditions, and a database is established containing the important parameters including the inflow wind conditions, the flow fields and the corresponding wind power for each wind turbine. The power is predicted via the database by taking the Numerical Weather Prediction (NWP) wind as the input data. In order to evaluate the approach, the short-term wind power prediction for an actual wind farm is conducted as an example during the period of the year 2010. Compared with the measured power, the predicted results enjoy a high accuracy with the annual Root Mean Square Error (RMSE) of 15.2% and the annual MAE of 10.80%. A good performance is shown in predicting the wind power's changing trend. This approach is independent of the historical data and can be widely used for all kinds of wind farms including the newly-built wind farms. At the same time, it does not take much computation time while it captures the local air flows more precisely by the CFD model. So it is especially practical for engineering projects.

Key words: short-term wind power prediction, physical approach, CFD model, flow field, database

Introduction

The wind power prediction is a very important and effective way to increase the wind power penetration and improve the security and the economy of the power system[1-3]. The mandatory requirements for the wind power prediction have already been put forward in China that the wind power prediction system should be available after the construction of new wind farms and all the wind farms have to send the predicted wind power curve of the next day to the dispatch department of the Power Grid Corp every day.

Most researches of the wind power prediction focus on the statistical models[4-9]. Fan et al.[8] predicted the wind power using the method of the Artificial Neural Network (ANN), analyzed the influence of the input wind speed data at different heights based on the prediction results, and finally completed the forecasting of the error band. Liu et al.[9] studied the wind velocity and the wind turbine power prediction of 3 h in advance by the persistence and the neural network methods. However, the success of the statistical model depends on a great number of measured historical data of the wind velocity and the power in the wind farms, and what is more, the historical data are required to have the same changing trend. Therefore, it cannot be used in the brand new wind farms without sufficient historical data[10,11].

With the physical approach, the wind speed at the wind turbine hub height is predicted according to the Numerical Weather Prediction (NWP) data and then the wind power is calculated based on the wind turbines' power curve. It is independent of the measured

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historical data and can be used for both the newly-built and the operating wind farms. The physical approach and several prediction systems were proposed based on the physical principle[12-14]. Landberg[12] established the first physical wind power prediction system in the world. Giebel et al.[13] suggested that in a complex terrain, the physical model should be adopted instead of the statistical model. In China, the relevant researches were few[15]. Feng et al.[15] employed the analytic principle to analyze the local effect of the wind farm and the wake effects of the wind turbines, and studied the short-term wind power prediction based on the physical principle.

For the prediction of the wind power during the upcoming tens of hours, namely, the short-term wind power prediction, the input data in the physical approach should be the NWP time-serial parameters, in which the atmospheric movement is taken into account. However, the NWP data provided by meteorological departments usually have a horizontal resolution of several kilometers, too coarse to reflect the effects of the wind farm topography and roughness and they cannot be directly used in the power prediction. The data must be downscaled until the site-specific wind at the hub height of the wind turbines is obtained. This is the key procedure of the physical power prediction approach and directly determines the accuracy of the predicted power. By downscaling the NWP data by a CFD model, the local air flow field affected by the wind farm terrain and roughness can be simulated, thus a precise wind speed distribution can be obtained with improved accuracy of the wind power prediction. But for the prediction, the Navier-Stokes equations should be solved for the air flow field, which would take too much computation time to meet the requirements of the prediction deadline, so the CFD method has not been successfully applied to the wind power prediction system so far.

In order to solve this problem, a new physical approach is proposed, based on the CFD pre-simulated flow fields and the wind power database. This prediction approach is applied to an actual wind farm and a one-year wind power prediction is made. By the comparison of the predicted and the measured wind powers, the prediction method is validated, and the precision of the results is evaluated.

1. Prediction ideas

On the assumption that the inflow wind is steady, theoretically, the wind power is determined by the wind speed distribution above the wind farm, and the wind speed distribution is determined by the inflow wind condition as well as the local topography and roughness. Therefore, for a wind farm, a specific inflow wind condition determines a unique local wind and a unique wind power. For each inflow wind condition, the steady wind distribution could be obtained by the CFD model simulation and then the wind power could be obtained from the power curve. Based on these results, the idea of pre-calculations of the wind field and the wind power is put forward, in which the wind power is pre-calculated for all the discrete inflow conditions and while the prediction of the wind power is obtained by referring to the pre-calculated wind power instead of by the CFD simulation again.

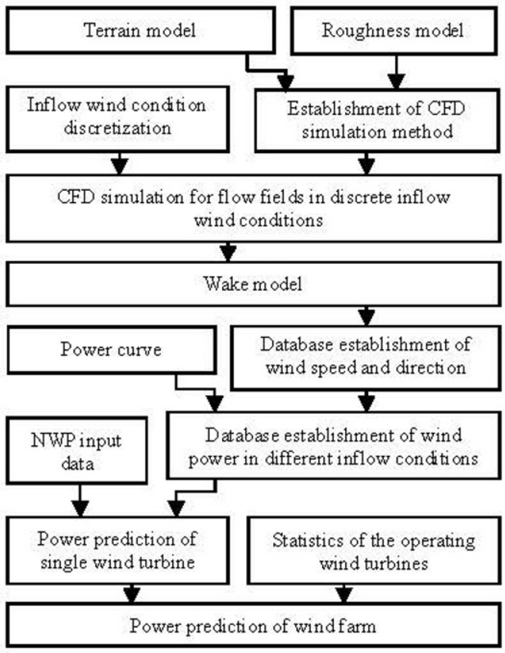

Fig.1 Structure diagram of wind power prediction

The whole prediction approach is divided into two parts. The first part is to simulate the air flow fields under all the discrete inflow conditions and to establish the pre-calculated flow field and wind power database. The second part is the power prediction according to the pre-calculated database by matching the NWP input data with the reference mast. The structure of this prediction approach is shown in Fig.1.

2. Establishment of pre-calculated flow field and wind power database

2.1 *Description of the wind farm*

The prediction approach will be verified by taking a wind farm located in the north China as an example. The altitude of the wind farm area is roughly 1 200 m to 1 900 m above the sea level. The wind farm covers an area of about 45 km^2, with some villages among the wind turbines. There are numerous farmlands planted with corn stalk crop. The installed capacity of the wind farm is 183 MW. It consists of 122 GE 1.5 serial 1.5 MW wind turbines of 67 m of hub height. The layout of the wind turbines is shown in Fig.2.

Fig.2 Layout of wind turbines

2.2 *Discretization of inflow wind conditions*

The generated wind power of the wind farms depends on the weather conditions. There are many parameters that are used to describe the weather conditions, such as the wind speed, the wind direction, the temperature, the pressure and the humidity. Among them, the wind speed and the wind direction have a much greater influence on the generated power than other parameters. Therefore, these two parameters are chosen to discretize the inflow wind conditions.

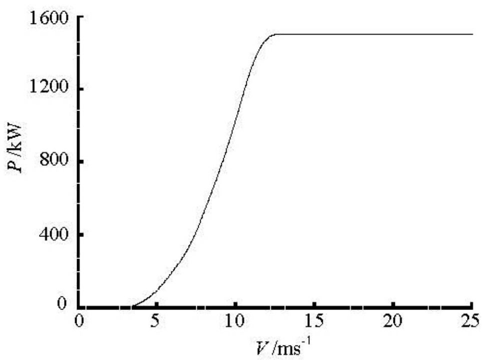

Fig.3 The wind turbines' power curve

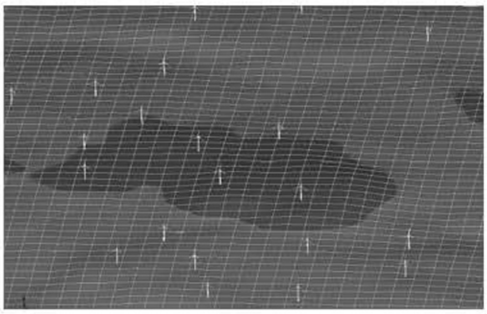

Fig.4 Part of the mesh in horizontal direction near the wind turbine

The discrete inflow speeds are selected according to the characteristics of the wind turbines and the wind resources of the wind farms. The wind turbines' power curve is shown in Fig.3. The effective wind speed of the wind turbines ranges from 4 m/s to 25 m/s, namely, the cut-in speed is 4m/s, the cut-out speed is 25 m/s and the rated speed is 13m/s. In order that the speed of the wind turbines' hub height from 4 m/s to 13 m/s could be covered at least, the discrete inflow speeds are set every 1 m/s from 3 m/s to 20 m/s. The discrete inflow wind directions are distributed in 16 sectors evenly, by setting a direction every 22.5^o from 0^o to 337.5^o. The combination of each wind speed and each wind direction makes up a discrete inflow wind condition, with 288 discrete inflow wind conditions in total.

2.3 *CFD pre-simulation*

The physical model of the wind farm is built according to the contour data of topography and roughness of the wind farm and the surrounding areas, and then the computational domain of the spatial air flow field is determined. To avoid some unreasonable air flow phenomena, the computational domain should extend 5 km out of the wind farm boundary in each horizontal direction, and have a height of no less than 20 times the total height of the wind turbine. The computational domain is meshed with mainly the structural mesh to reduce the number of grids. The mesh is denser close to the ground and the wind turbines. And the horizontal grid interval is about 70 m due to the limitation of the computational capability of computers. Part of the mesh in the horizontal direction near the wind turbine is shown in Fig.4.

The CFD numerical calculation is carried out by using the general-purpose commercial software. Because of the influence of the terrain and the ground roughness, the air flow near the ground is typically turbulent. Therefore, the standard $k-\varepsilon$ equation model is adopted to simulate the turbulence flow[16]. For each inflow wind condition, the position of the entrance in the computational domain is determined by the inflow wind direction. And the entrance boundary is set to be the wind speed profiles, as follows

$$u_n = u_1 \left(\frac{Z_n}{Z_1} \right)^{\alpha} \tag{1}$$

where α is the wind shear exponent, u_n is the wind velocity at the height Z_n, Z_1 is the height on the top of the atmospheric boundary layer, u_1 is the wind velocity at the height Z_1 and is set to be the speed of the inflow wind.

By taking the wind profiles as the boundary, the 288 local air flow fields can be pre-simulated for all the discrete inflow wind conditions.

2.4 *Wake effect*

Because a wind farm consists of many wind turbines, when the air flows through a wind turbine, a wake area will be formed downwind. In the wake area, the air velocity decreases, which may reduce the wind production. Due to the wake effects, the wind turbines' annual power generation would have a loss of 2%-20%[17]. So the wake loss is a considerable factor in the wind power prediction. Two methods can be used to simulate the wake effect, i.e., the CFD based method and the analytic method. At present, the CFD method cannot be adopted to simulate the wake loss directly because it involves too large amount of computation. The analytical method based on the Larsen wake model is adopted in this paper. At the position x downwind, the wind speed u_k can be calculated as follows:

$$u_k = u_{WT,k} + \Delta u_k \tag{2}$$

$$\Delta u_k = -\frac{u_{WT,k}}{9}(C_T A x^{-2})^{1/3} \cdot \left\{ R_w^{3/2}(3c_1^2 C_T A x)^{-1/2} - \left[\frac{35^{3/10}}{2\pi}(3c_1^2)^{-1/5}\right] \right\}^2 \tag{3}$$

$$R_w = \left(\frac{35}{2\pi}\right)^{1/5}(3c_1^2)^{1/5}(C_T A x)^{1/3} \tag{4}$$

where $u_{WT,k}$ is the CFD simulated wind speed on the hub height of the wind turbine k, Δu_k is the wind speed deficit of the wind turbine k, R_w is the radius of the wake effects area, A is the swept area, C_T is the thrust coefficient, and c_1 is dimensionless mixing length.

2.5 *Establishment of database*

The generated power of each wind turbine can be calculated according to the power curve and the corrected wind speed u_k. For all 288 inflow wind conditions, the important data are extracted to establish a pre-calculated database, including the parameters of the inflow wind condition, the air properties, the wind speed at each wind turbine's hub, the wind power of each wind turbine and so on.

3. Wind power prediction

3.1 *The NWP input data*

The input data used is the Weather Research and Forecasting (WRF) mesoscale NWP wind, provided by the State Key Laboratory of Alternate Electrical Power System with Renewable Energy Sources. The initial and the boundary field of the WRF model is the Global Forecasting System (GFS) $1^{o}\times1^{o}$ pattern forecasting field released by the National Centers for Environmental Prediction at 6 o'clock every day. The time step is 90 s, the forecast duration is 72 h. The WRF model is adopted to downscale the initial field to the horizontal resolution of 6 km×6 km, then the time-serial result from 24 o'clock a day to 24 o'clock the next day is extracted as the input data for the power prediction. According to the demand for the short-term wind power prediction, the time resolution is 15 min.

3.2 *The power prediction of single wind turbine*

Taking the time-series of the NWP wind speed and direction as the input data, and matching them with the position of the reference mast, the close inflow wind conditions are queried and the corresponding wind power of each wind turbine are read from the database. Then the wind power of every wind turbine could be predicted by a linear interpolation of the queried wind powers. The software Matlab is used to realize the prediction process.

3.3 *The wind turbines in operation*

In China, usually not all the wind turbines in a wind farm are in operation simultaneously because of the maintenance of wind turbines or the scheduling measures of restricting the wind farms' generating power capacity by the Grid Company. Especially in the heating season of the northeast China and Inner Mongolia, to ensure the heat providing, sometimes more than 50 percent of the wind turbines could not be permitted to generate power. So the number of the operating wind turbines in a wind farm often changes with time. The number of the wind turbines in operation has to be taken into consideration when predicting the power. Therefore, after judging which wind turbines are in operation, the wind power of the whole wind farm can be predicted as follows

$$Y_i' = \sum_{j=1}^{m} P_{i,j} \tag{5}$$

where $P_{i,j}$ is the wind power of the operative wind turbine j at the time point i, and Y_i' is the forecast wind power at the time point i.

4. The results and analyses

4.1 *The evaluation error indices*

Two parameters of the Root Mean Square Error (RMSE) and the Mean Absolute Error (MAE) are used to evaluate the wind power predicting approach, which are calculated as follows:

$$\text{RMSE} = \frac{1}{G}\sqrt{\frac{1}{N}\sum_{i=1}^{n}(Y_i - Y_i')^2} \tag{6}$$

$$\text{MAE} = \frac{1}{GN}\sum_{i=1}^{n}\left|Y_i - Y_i'\right| \tag{7}$$

where G is the total installed capacity of the wind farm, Y_i is the measured wind power at the time point i, and N is the total number of the forecasting points.

4.2 *The whole forecasting results*

In order to evaluate the whole effect of this approach in the long period, the 24 h ahead prediction of an actual wind farm is made during the whole year of 2010. Compared with the measured wind power, it is shown that the annual RMSE of the predicted power is 15.25% of the total installed capacity, and the annual MAE is 10.80%. It implies that as the short-term wind power prediction, the results are quite good. The monthly error of the forecast is shown in Table 1. It can be seen that in the summer, the forecasting error is small because the average wind speed and the generated power are both relatively small; while in the spring and winter, the error is a bit larger. But the RMSEs in all months are less than 20%, which are within the requirements of engineering applications.

Table 1 The statistics of monthly error

Month	RMSE (%)	MAE (%)
January	14.73	10.82
February	16.97	12.44
March	16.66	12.29
April	18.69	14.19
May	16.88	12.36
June	10.30	6.750
July	8.970	5.790
August	11.96	7.950
September	15.94	9.670
October	13.80	9.420
November	15.68	11.99
December	18.34	14.46

4.3 *The error frequency distribution*

After statistically analyzing the error for all predicting points in 2010, the frequency distribution histogram of error is obtained as shown in Fig.5. It can be seen that it is a normal distribution and the predicted power with the absolute error of almost zero has the highest probability. In addition, the larger the absolute error of the predicted power, the smaller its probability. The probability of the absolute error which is less than 20% reaches up to more than 84%, which indicates that the wind power prediction approach proposed in this paper has a high accuracy, not only in the overall prediction but also in the single point prediction.

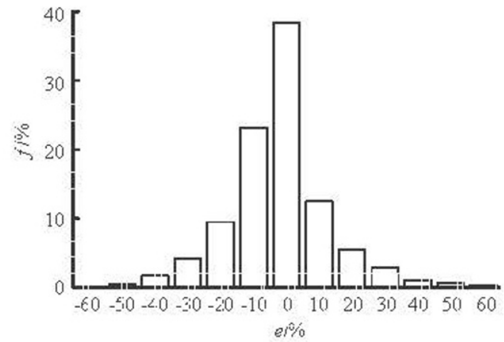

Fig.5 Frequency distribution histogram of forecasting wind power error

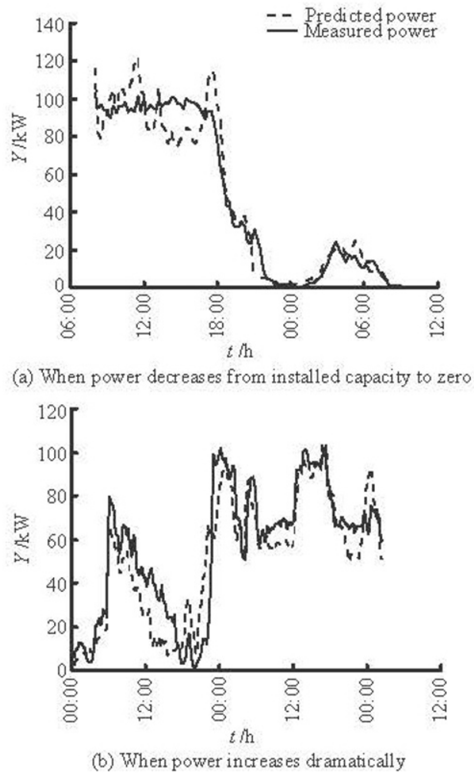

Fig.6 Comparison of predicted and measured power (2010)

4.4 *The prediction of wind power changing trend*

Figure 6 shows the comparison of the time series of the predicted and measured powers, in which Y is the power of the wind farm. Figure 6(a) shows the prediction results when the power output decreases from the installed capacity to zero, and Fig.6(b) shows the result when the power output changes drastically in a short time. The forecasting interval in both figures is two days. It can be seen from Fig.5 that the predicted power has almost the same changing trend as the measured power, which implies that this forecasting approach has a good performance for the prediction of the wind power's changing trend. But generally speaking, the forecasting power is slightly less than the measured power. Moreover, it is difficult to predict the slightly power fluctuating with time.

5. Conclusions

A physical approach of the wind power prediction based on the CFD pre-calculated flow field is proposed in this paper. It is applied to an actual wind farm and the conclusions are as follows:

(1) This approach has a high predicting accuracy, not only in the overall prediction of the wind power, but also in the single point prediction. It also enjoys a good performance in predicting the wind power's changing trend with time.

(2) This approach is independent of the historical data of the measured wind power, so it can be used for all kinds of wind farms, including the newly-built wind farms. By pre-calculating the flow fields and establishing the wind power database, the prediction process does not take much time, which effectively meets the timing requirements of the prediction in engineering applications. Furthermore, the problem of the number of the wind turbines in operation is easily solved by summing the powers of all the wind turbines in operation.

(3) The disadvantage of this approach is that the prediction result is strongly dependent on the accuracy of the NWP input wind. In order to reduce the error of the prediction results, more technical details should be further studied in the future.

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