Short-term Wind Power Prediction Considering the Influence of Terrain

Le ZHANG [1], Yan ZHAO [*,2] and Guohua CHEN [1]

[1] Nantong Electrical Power Bureau, Nantong, Jiangsu, 226006, China
[2] *School of Power Engineering*, Nanjing Institute of Technology, Nanjing, 211167, China.

***Abstract* — Wind as a resource is strong, random and intermittent. With its connection to the grid, it is bound to endanger the security and stability of the power system. Besides, it will cause worse power quality. First, this paper predicts the wind speed with the method of BP neural network according to historical data, and uses CFD software to simulate the numerical operation of farm Merry when further taking the impact of terrain into consideration. The acceleration factor and the level bias and other data of each fan hub height are obtained. Second, the wind speed of each fan hub height are calculated by MATLAB software programming. Finally, the predicted power is estimated according to the power curve of the wind turbine to propose short-term wind power prediction methods considering the influence of terrain. The rationality and accuracy of this method are verified by a case study of actual wind data.**

Keywords - Wind power; forecasting; BP neural network; CFD software; MATLAB

I. INTRODUCTION

China's wind power industry is in rapid development. By the end of 2014, the total installed capacity has reached 114763.39 MW, increased by 25.5%.At the same time, the proportion of wind power in the grid is also rising. When wind power is connected to grid, its penetration power, the ratio of wind power to the total power, must be limited. Studies have pointed out that when the ratio is less than 8%, the power system will operate very well under normal circumstance. However, if the ratio goes up, wind power will bring convenience to people together with much inconvenience. Especially when the ratio exceeds a certain limit, it can greatly reduce the power quality, influence the safe and stable operation of power system, and may endanger the conventional generation mode, mainly for substantial fluctuations of the frequency and voltage [1-2]. In addition, wind resources have strong intermittent, greatly affected by geographical and meteorological factors. The reactive and active power in the wind farm change along with the changes of wind speed, in turn the wind power fluctuation may cause a significant impact to the voltage stability, power angle stability, frequency stability, the system loss, harmonics, voltage fluctuation and flicker, standby cost, generation plan, system reliability, etc. The distribution characteristics of China's wind resources make wind farm construction concentrated, while the intermittent and randomness of wind make the influence of wind power grid to the system more remarkable. Therefore, the wind power prediction research is very important for the development of wind power industry in China [3-4].

Short-term wind power prediction can guarantee the power dispatch departments understand the trend of wind power changes in advance, so as to adjust the scheduling plan, reduce system reserve capacity and operating costs [5].For the wind power developers, when the wind power farm built and participating in the market competition, compared with other control able generating way, its intermittent and randomness will greatly reduce its competitiveness, and even get financial penalties due to a lack of reliability of power supply. Wind power short-term prediction is an effective way to solve the above problem, and greatly improve the market competitiveness of wind power. It can also help arrange maintenance and repair, improve the coefficient of wind farm capacity, which means small wind farm can determine the appropriate time according to the results of wind speed prediction to test and maintain equipment, so as to improve the capacity and capacity of wind power coefficient [6-7].

II. PREDICTION PRINCIPLE

A. *Prediction Methods*

We first use the neural network model to predict wind speed and direction in the wind tower, with CFD software obtain the data of the wind speed factor and horizontal deflection of the hub height by numerical simulation of the wind flow in the wind farm, to calculate the wind speed, then with reference to the fan power curve, get the prediction power of the fan. Finally, we add up the prediction value of each fan power to get the prediction power of the wind farm[8-10]. The prediction flow chart is shown in Fig. (**1**).

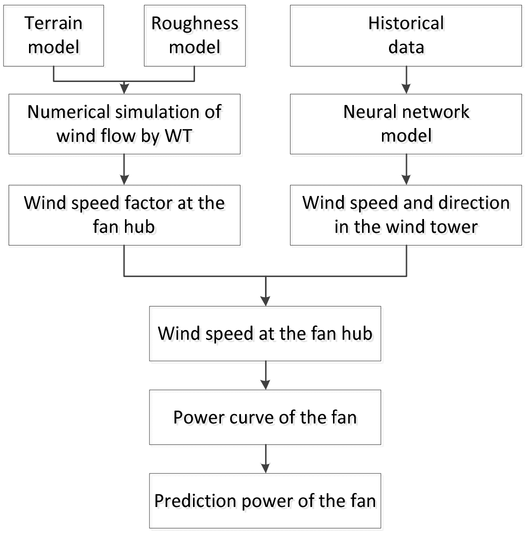

Fig. (1).flow chart of the wind power prediction

B. *Neural Network Model*

The BP neural network is an error back propagation network, which in addition to the input and output nodes, includes a layer or multilayer hidden nodes, and no connection between nodes of the same layer.

Input signals flow in from input layer nodes, through the hidden layer nodes, and flow out through output layer nodes. The output of each layer nodes only affects the next nodes output [11]. Theoretical research points out that the three-layer BP neural network with s-shaped function can approximate any continuous function with arbitrary precision[12].

BP neural network learning is also called training, the trained neural network, can also output nearly accurate results for input not belonging to the training samples. BP neural network has strong nonlinear fitting capability, and the training process is simple, and easy for the computer to calculate. So BP learning algorithm is often adopted in the neural network training [13,14].

To optimize the weight of each layer with the learning algorithm is to find the minimum error of the weight W. Training process can be summarized as selecting sample data, repeating the forward calculation and reverse feedback, fixing the weight. The weight learning process of each layer is reverse, meaning concluding the middle error by error of output layer, getting the input weight, repeating the process until getting suitable results. That is why it is called the error back propagation [15,16]. BP algorithm is described as follows:

1. Initialize the weight and threshold: assign a smaller initial value to the neuron threshold and the weight

2. Give the input matrix$x_k$and output targety_k;

3. Calculate the actual output$\hat{y}$(the feed-forward process);

4. Modify the weight (the reverse process): start from the input signal, the error signal propagate back, modify the weight of each layer to minimize the error:

$$w_{ij}^{(l)} = w_{ij}^{(l)} - \eta \frac{\partial E_k}{\partial w_{ij}^{l}} = w_{ij}^{(l)} - \eta \delta_{lk}^{l} O_{jk}^{(j-i)} \tag{1}$$

Where$w_{ij}^{(l)}$ is the weight of layer l number j neuron to layer l+1 number i neuron,η is the gain，δ_{lk}^{l} is the k model error of the layer l number I node，if number I node is an output layer node，then：

$$\delta_{lk}^{(l)} = \left(t_{ik} - O_{ik}^{(l)}\right) \cdot O_{ik}^{(l)} \cdot (1 - O_{ik}^{(l)}) \tag{2}$$

If number I node is an hidden layer node，then:

$$\delta_{ik}^{(l)} = O_{ik}^{(l)}(1 - O_{ik}^{(l)}) \sum_m \delta_{im}^{(l+1)} W_{mk}^{(l+1)} \tag{3}$$

C. *Numerical Simulation by CFD*

CFD is the abbreviation of Computational Fluid Dynamics, an analysis for systems involving such related physical phenomena as fluid flow and heat transfer. Its basic principle can be concluded as follows: substitute the original physics fields continuous in time domain and space domain, such as the velocity field and pressure field, for the variable value sets of series of finite discrete points; according to some certain principles and methods, build on algebraic equations of these relations between the field variables on the discrete points, solve the algebraic equations for approximate value of variables.

CFD can be thought of as the numerical simulation for the flow state under the control of the basic flow equation。Through this numerical simulation, we can get the basic physical quantities, such as velocity, pressure, temperature, concentration, etc. in each position in very complicated flow field, and their changes with time, to determine the vortex distribution characteristics, cavitation characteristics and taking off flow area, etc.

At present, many CFD software have been developed and widely used. In this paper, we choose Meteodyn WT software designed specifically for wind resource assessment. It is a wind resource assessment software suitable for complex terrain, which can automatically generate the mesh and boundary conditions based on the input files of terrain and roughness, use MIGAL solver to simulate the whole wind farm wind flow, and can show the simulation results in the form of 2D and3D with high degree of visualization.

III. STUDY CASES

A. *Wind Speed and Direction Prediction by BP Neural Network*

We take actual data of wind speed and direction at the height of 80 meters in a wind farm as sample data, containing sampling points of every ten minutes in a year. We select the representative data for network training. The number of input nodes is 6, the output nodes 1,which means we use six sample point data to predict wind speed and direction in the following ten minutes, and then the results as an input to predict data in the following twenty minutes. Similarly, we finally get six prediction data, namely using the last one hour data of wind speed and direction to predict the future one hour of that.

For the number of the hidden layer and hidden layer nodes, while the single hidden layer network with many nodes is enough precise, its generalization ability is weak and the prediction error is big. Double hidden layer network has the advantages of strong generalization ability and large error drop speed. Wind power has a strong randomness and intermittent and wind speed and wind direction are strongly nonlinear variables. Obviously the double hidden layer network is superior to the single hidden layer network for prediction. After repeated experiments, we finally choose double hidden layer structure, number of nodes in each layer of 6,15,10,1 respectively, the number of two hidden layer nodes 15 and 10 respectively.

We select 60 groups of data in 10 hours for the neural network training, and predict the wind speed and direction every 10 minutes in an hour in the future. After repeated experimental comparison, we finally choose the double hidden layer structure, the number of nodes in each layer is 6,15,10,1 respectively, the transfer function tansig, tansig and purelin, the training error is 0.002, and the training maximum is set to 2000. The comparison between the actual values and prediction results of wind speed and direction is shown in Fig. (2) and Fig. (3) respectively.

Usually root mean square error (RMSE) and mean absolute percentage error (MAPE) are used to measure the prediction effect, calculated with formula4 and 5:

$$E_{RMSE} = \sqrt{\frac{\sum(X_F - X_R)^2}{N}} \tag{4}$$

$$E_{MAPE} = \frac{1}{N}\sum\frac{|X_F - X_R|}{X_R} \times 100\% \tag{5}$$

Where E_{RMSE} is RMSE, E_{MAPE} is MAPE, X_F is the predictive value, X_R is the actual value, N is the number of prediction points。

After calculation, we get the predictive RMSE of wind speed and direction is 1.22m/s and 6.24°, MAPE 12.9% and 1.64%。It is obvious that the model is a good way to predict the wind speed and direction and their tendency for its small prediction error and high precision.

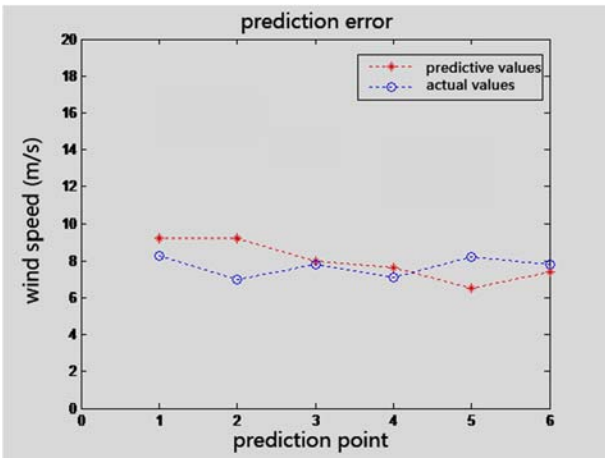

Fig. (2).Comparison between actual and predictive value of wind speed

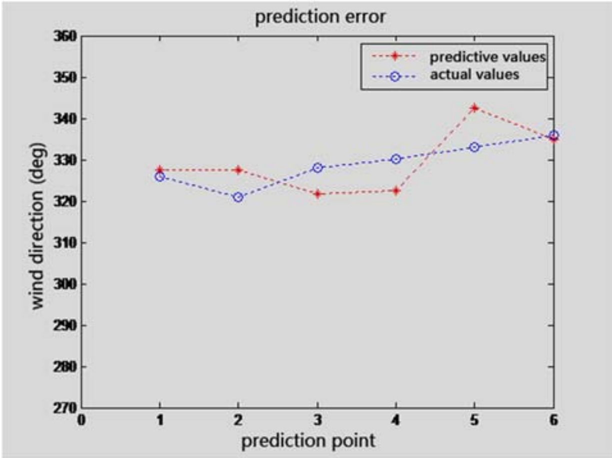

Fig. (3).Comparison between actual and predictive value of wind direction.

B. Numerical Simulation by CFD

Terrain files are generated by Global Mapper. Global Mapper is a mapping software, which not only can show data (e.g. SRTM data) as raster maps, elevation, vector map, can also realize map edit, printing, recording GPS, transformation, and using GIS data. Here we mainly use the software to transform wind farms SRTM data into terrain data recognized by WT software.

Roughness files are generated by Global Mapper and Google Earth. To make the surface roughness file is mainly according to the actual wind farms terrain surface to assign roughness value for CFD software to carry on the numerical simulation. Roughness of the assignment can be performed according to table 1 or formula" Tree height = 30 * roughness".

TABLE 1. DIFFERENT SURFACE ROUGHNESS

ground surface	roughness
Calm water	0.0001~0.001
Open land	0.03
Grassland, desert	0.1
forest	0.3~1.6
suburbs with many buildings	1.5
urban center	2

The WT software loads the files as well as wind power machine location files for simulation to get the wind speed factor of each fan in different sectors. The results are shown in table 2.

TABLE 2. THE WIND SPEED FACTOR IN OF WIND TURBINE WHEEL HUB HEIGHT IN EACH SECTOR (C)

fan	30	60	90	120	150	180
E1	1.33	1.29	1.28	1.32	1.34	1.46
E2	1.24	1.38	1.26	1.35	1.36	1.45
E3	1.25	1.48	1.27	1.32	1.34	1.35
E4	1.12	1.29	1.30	1.20	1.30	1.27
E5	1.34	1.38	1.38	1.24	1.36	1.44
E6	1.28	1.33	1.41	1.27	1.37	1.41
E7	1.35	1.23	1.29	1.34	1.34	1.38
E8	1.31	1.18	1.21	1.22	1.32	1.49
E9	1.50	1.28	1.35	1.41	1.51	1.54
E10	1.51	1.28	1.32	1.42	1.53	1.59
E11	1.44	1.27	1.31	1.39	1.44	1.46
E12	1.49	1.29	1.38	1.44	1.49	1.47
fan	210	240	270	300	330	360
E1	1.37	1.26	1.44	1.54	1.26	1.33
E2	1.31	1.24	1.42	1.53	1.24	1.44
E3	1.30	1.29	1.40	1.53	1.20	1.39
E4	1.22	1.17	1.35	1.45	1.24	1.33
E5	1.37	1.31	1.37	1.53	1.19	1.46
E6	1.33	1.29	1.40	1.54	1.25	1.48
E7	1.49	1.30	1.23	1.31	1.25	1.31
E8	1.52	1.32	1.11	1.15	1.42	1.43
E9	1.63	1.45	1.26	1.32	1.53	1.51
E10	1.57	1.43	1.25	1.33	1.44	1.45
E11	1.43	1.44	1.24	1.30	1.24	1.29
E12	1.48	1.45	1.27	1.40	1.29	1.33

C. Power Prediction

The formula 6 is for the power prediction:

$$P = \sum_{i=1}^{n} \varphi_i (v_0 \cdot \lambda_{ij})(j = 1,2, \dots ,12) \qquad (6)$$

Where P is the predictive power of the wind farm,φ_i represents the influence of wind speed of wind turbine wheel hub height for wind power, which can refer to the power curve of each fan,v_0 is the wind speed in the wind tower,λ_{ij} is the wind speed factor of faniin direction j sector, n is the number of fans in the wind farm [20-22].

The forecasting power of each fan in the future one hour in six directions is shown in table 3,and to sum up power for each fan, the predictive power of the wind farm is as shown in table 4.

TABLE 3. THE PREDICTIVE POWER OF EACH FAN(KW)

fan	E1	E2	E3	E4
1	581	511	515	369
2	580	509	513	366
3	414	325	329	232
4	347	274	277	203
5	214	179	181	133
6	319	254	257	191
fan	E5	E6	E7	E8
1	587	546	592	572
2	586	544	591	571
3	426	360	437	397
4	358	302	368	332
5	219	193	224	207
6	329	279	339	306
fan	E9	E10	E11	E12
1	605	605	608	606
2	605	605	608	607
3	564	567	520	556
4	508	513	453	496
5	307	311	268	298
6	477	482	419	464

TABLE 4 THE PREDICTIVE POWER OF THE WIND FARM(KW)

point	1	2	3
power	6698	6685	5127
point	4	5	6
power	4431	2735	4116

D. *The Result Analysis*

The actual power of each fan in the wind farm is as shown in table 5.Similar with neural network prediction, according to formula (4) and (5) we compute each fan root mean square error (RMSE) and mean absolute percentage error (MAPE), the calculation results, respectively, are shown in table 6 and table 7.

From the results we can see a maximum root mean square error of 12 turbines is 121 kw, the maximum average absolute percentage error is 25.7%, both in the reasonable scope, verifying the rationality and accuracy of the prediction method combined neural network with CFD numerical simulation.

TABLE 5. THE ACTUAL POWER OF EACH FAN（KW）

fan	E1	E2	E3	E4
1	715	429	659	458
2	481	417	580	300
3	493	387	276	276
4	274	211	349	168
5	265	218	136	158
6	376	323	319	235
fan	E5	E6	E7	E8
1	452	677	704	704
2	686	642	727	668
3	541	292	363	326
4	294	371	464	412
5	272	237	170	170
6	388	232	400	379
fan	E9	E10	E11	E12
1	466	496	724	467
2	708	708	499	710
3	417	675	645	439
4	635	395	371	610
5	381	236	330	226
6	353	569	348	548

TABLE 6 ROOT-MEAN-SQUARE ERROR（KW）

fan	E1	E2	E3	E4
E_{RMSE}	87	70	81	55
fan	E5	E6	E7	E8
E_{RMSE}	93	82	93	87
fan	E9	E10	E11	E12
E_{RMSE}	121	101	97	107

TABLE 7 MEAN ABSOLUTE PERCENTAGE ERROR

fan	E1	E2	E3	E4
E_{MAPE}	19.4%	21.0%	21.0%	18.7%
fan	E5	E6	E7	E8
E_{MAPE}	20.4%	19.3%	20.4%	19.3%
fan	E9	E10	E11	E12
E_{MAPE}	25.7%	21.5%	19.7%	22.8%

IV. CONCLUSION

To conclude, we propose Statistical method and physical method was proposed with the combination of wind power prediction method, concrete steps as follows: First, this paper predicts the wind speed with the method of BP neural network according to historical data, and uses CFD software to simulate the numerical operation of farm Merry when further taking the impact of terrain into consideration. The acceleration factor and the level bias and other data of each fan hub height are got .Second, the wind speed of each fan hub height are calculated by MATLAB software programming. Finally, the predicted power are estimated according to the power curve of the wind turbine. And the rationality and accuracy of this method are verified by a case study of actual wind data.

Wind farm terrain and roughness don't change obviously, and there is no need for CFD software to consider the meteorological data when it is used for numerical simulation. Therefore, after obtaining the wind speed factor and the horizontal deflection data, the computer can calculate directly the predictive power according to the wind speed and direction. It is of high efficiency.

The prediction method is integrated by the statistical method and physical method. If It changes NWP data for the predictive wind speed, it is an absolutely physical method, only affected by terrain and roughness of the wind farm without the historical data. It can also be applied to solve influence of changes of terrain and roughness for the wind for the power prediction for a new wind farm.

ACKNOWLEDGEMENTS

This work was financially supported by the Natural Science Foundation of Jiangsu Province (BK20130742), the Nanjing Institute of Technology Fund(YKJ201107).

REFERENCE

[1] Ferreira, L.A.F.M., "Evaluation of short-term wind predictability," *IEEE Trans. Energy Conversion*, vol. 7, no. 3, pp. 409 – 417, Sept. 1992.

[2] B. Ernst, B. Oakleaf, M. L. Ahlstrom, M. Lange, C. Moehrlen, B. Lange, U. Focken, and K. Rohrig, "Predicting the Wind," *IEEE power & energy magazine*, vol. 5, no. 6, pp. 79-89, Nov. 2007.

[3] X. Yang, X. Yang, S. Chen, "Wind speed and generated power forecasting in wind farm," *Proceedings of the CSEE*, vol. 25, no. 11, pp. 1-5, Nov.2005.

[4] E.A. Bossanyi, "Short-term wind prediction using Kalman filters," *Wind Engineering*, vol.9, pp. 1-8, 1985.

[5] D. Pan, H. Liu, Y. Li, "Optimization algorithm of short-term multi-step wind speed forecast," *Proceedings of the CSEE*, vol. 28, no. 26, pp. 87-91, Sept. 2008.

[6] L. Shuhui, D. C. Wunsch, E. A. O'Hair, M. G. Giesselmann, "Using neural networks to estimate wind turbine power generation," *IEEE Trans. Energy Conversion*, vol. 16, no.3, pp. 276-282, Sept. 2001.

[7] P. Flores, A. Tapia, G. Tapia, "Application of a control algorithm for wind speed prediction and active power generation," *Renewable Energy*, vol.30, no. 4, pp. 523-536, Apr. 2005.

[8] D. Ying, J. Lu, Q. Li, "Short-term wind speed forecasting of wind farm based on least square-support vector machine," *Power System Technology*, vol.32, no. 15, pp. 62-66, Aug. 2008.

[9] X. Gao, X. Fen, J. Zhang, C. Cao, "Short-term prediction of chaotic time series by wavelet networks," in *Proc. Fifth World Congress on Intelligent Control and Automation*, 2004, vol. 3, pp. 1931 -1935.

[10] M.C. Alexiadis, P.S. Dokopoulos, H. S. Sahsamanoglou, "Wind speed and power forecasting based on spatial correlation models," *IEEE Trans. Energy Conversion,* vol. 14, no. 3, pp. 836 – 842, Sept. 1999.

[11] Y. Wei, S. Han and S. Shi, "Modeling and simulation in combination of wind speed in power system". *Renewable energy*, 2010, 28 (2): 18-20.

[12] L. Li, J. Li, P. He, and C. Wang. "The use of wavelet theory and ARMA model in wind speed prediction". in*Proc.2011 Electric Power Equipment-Switching Technology* Conf., pp.23-27.

[13] M. Asari, T. Nanahara, T. Maejima, K. Yamaguchi and T. Sato, "A study on smoothing effect on output fluctuation of distributed wind power generation". in*Proc.2002 IEEE/PES Transmission and Distribution Conf.*, pp.6-10.

[14] Y. Ma, H. Yang, X. Zhou, L. Ji and H. Wen, "The dynamic modeling of wind farms considering wake effects and its optimal distribution", in *Proc.2009 World Non-Grid-Connected Wind Power and Energy Conf.*, pp. 24-26.

[15] K. Hagkwen, C. Singh and A. Sprintson, "Simulation and Estimation of Reliability in a Wind Farm Considering the Wake Effect". *IEEE Transactions on Sustainable Energy,* vol 3, no. 2, pp. 274-82, 2012.

[16] L. Wei and S.Z. Zhu, "The Impact of Wake Effect on the Aggregated Modeling of Wind Farm", in *Proc. 2012 Power and Energy Engineering Conf.*, pp. 27-29.

[17] W. Liu, Y. Zhao, J. Zhou, C. Wang, B. Hu, L. Zhang and et al. "Reliability evaluation taking wind farm power transmission and distribution into account". *Grid technologies.* 2008, vol 32, no. 7, pp. 0-73.

[18] N. Amjady, F. Keynia, and H. Zareipour, "Wind Power Prediction by a New Forecast Engine Composed of Modified Hybrid Neural Network and Enhanced Particle Swarm Optimization," *IEEE Transactions on Sustainable Energy,* vol. 2, pp. 265-276, 2011.

[19] H. Peng, F. Liu, and X. Yang, "A hybrid strategy of short term wind power prediction," *Renewable Energy,* vol. 50, pp. 590–595, 2013.

[20] A. Kusiak, H. Zheng, and Z. Song, "Short-Term Prediction of Wind Farm Power: A Data Mining Approach," *IEEE Transactions on EnergyConversion,* vol. 24, pp. 125-136, 2009.

[21] G. Grassi and P. Vecchio, "Wind energy prediction using a twohidden layer neural network," *Communications in Nonlinear Science and Numerical Simulation,* vol. 15, pp. 2262-2266, 2010.

[22] N. Amjady and F. Keynia, "Day-Ahead Price Forecasting of Electricity Markets by Mutual Information Technique and Cascaded Neuro-Evolutionary Algorithm," *IEEE transactions on power systems,* vol. 24, pp. 306-318, 2009.