The Day-Ahead Neural Network Wind Power Prediction Method in Wind Farms

Wen-hui Zhao, Jin Ma, and Zheng-zhong Zhang

Abstract When the proportion of the wind energy is more and more in the word energy, the large scale of wind power grid has great influence on the power system scheduling and the safe operation. Because the day-ahead wind power prediction can help the scheduling department make electricity generation plan, it is very necessary for the wind farms. Now the wind power prediction method is mainly based on the short-term prediction. The prediction method expounded by this paper, is the application of the BP network to forecast the wind power in the wind farms, and improves the forecast model and day-ahead the prediction results.

Keywords Wind power • Prediction method • Day-ahead forecast • Neural network

1 Introduction

Since the global oil, coal and other fossil resources become increasingly scarce, wind and other renewable energy development and application has been paid great attention all over the world. After the large scale wind power connection with power grid, lots of experts devote to studying the wind power forecast method all over the world.

At present most mature wind power forecast system is mainly developed by Europe, the United States and other developed countries. For example, the Prediction system which is developed by Danish national laboratory uses the physical model [1];The Prediction system which is developed by German Walden university uses the combination forecast method, and can give 2 days of wind power prediction on large area [2];The ANMOS project, which is jointly developed by France,

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Ireland, Spain, German, Greece, Denmark and England, uses the combination forecast model and can be applied to both land and sea wind farms; In addition, there are also the EWind system which is developed by the United States TrueWind company and the GH-FORECASTER system which is developed by Garrad Hassan company. The forecast system which is designed by china electrical science institute has been put into application; its RMS error is about 15 % [3].

2 Wind Power Prediction Principle

According to different time scale [4], the wind power prediction can be divided into three kinds: one is the short-term prediction (a few minutes), mainly applied in the wind generator control; Another is medium-term prediction (hours to days), mainly used in wind power grid-connected and grid dispatching; The last one is long-term prediction (weeks and months), mainly used in wind farms and grid maintenance plan. According to the different needs for operation mode of the power system scheduling department arrangement, the wind power prediction can be divided into day-ahead prediction and real-time prediction, day-ahead prediction is the forecast ahead 24 h. Real-time prediction is the rolling forecast to each point. According to the different prediction model, the wind power prediction method can generally be divided into physical method and statistics method.

2.1 Physical Method

The physical methods essence is that using the wind speed, wind direction, temperature, humidity and other weather information to forecast. According to the wind farms geographic information and physical information to calculate the wind speed, wind direction, temperature, pressure and so on. The physical method does not require a lot of long measure data and applies to the complex terrain, but the researchers must have abundant weather knowledge to build an accurate model. When the model is rough, the prediction accuracy is poor. Figure 1 shows the physical prediction method.

2.2 Statistical Method

The statistical methods essence is that, building a mapping relationship between the system input (NWP, historical data, and the measured data) and wind power. The commonly used methods have duration method, stochastic time series method [5], support vector machine (SVM) method [6], artificial neural network method [7] and so on. In the wind power prediction, the input of the model is usually several

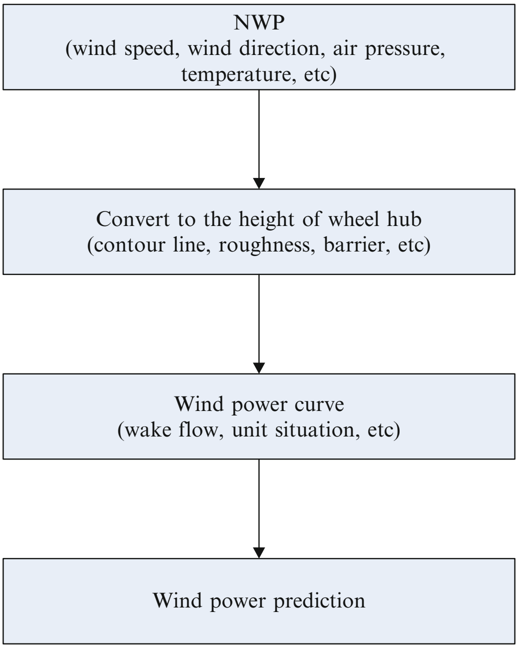


Fig. 1 Prediction flowchart of the physical method

historical data, the real-time data SCADA (supervisory control and data acquisition) system and digital meteorological forecast (NWP) data.

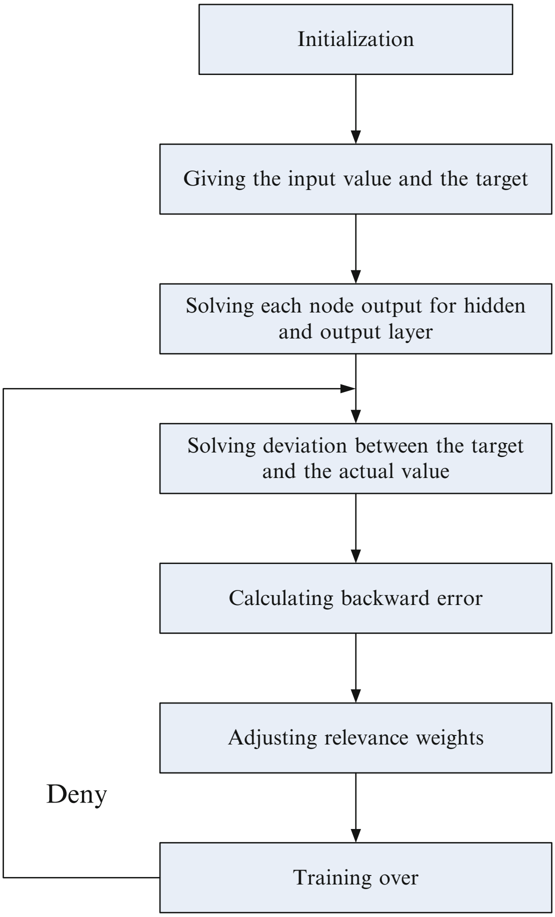
3 Neural Network Methods

Using the traditional statistics methods to predict the wind power has the characteristics of the model simple and speed fast, but in the face of complex nonlinear wind speed and wind power the prediction accuracy certainly will be affected. The advantage of Neural network is not needed to ensure the accurate mathematical model.

3.1 BP Neural Network

The BP neural network is a kind of the most commonly used neural network method, based on the error back propagation algorithm of artificial neural network includes the input layer, interface layer (hidden) and output layer. The BP neural network learning process is divided into positive spread and back propagation, namely the information positive dissemination and the error back propagation two processes are made up. In the process of positive transmission, the neurons of the

Fig. 2 Flow chart of BP network learning



input layer is responsible for receiving the information from outside, and pass the information to the neurons of the interface layer; Interface layer is the internal information processing layer, which is responsible for information transformation, according to the demand for information change capacity, interface layer can also be designed to single hidden layer or more hidden layer structure; Finally the hidden layer transfer the each neuron information to output layer, after the further processing completing a learning process is spread. Then the output layer output information processing results to the outside world. When output does not agree with output, it is time to turn into the error back propagation process. Through the network will return the error signal through the original connecting path, meanwhile modifying every layer neurons weights until it reaches the desired objective. In constant positive spread and error back propagation process, the model adjusts the weights of each layer, until the network error output reduced to the desired value, or the pre-set number of learning. Figure 2 shows the learning process.

3.2 Used for the Wind Power Prediction and the BP Neural Network Model

This paper uses the BP neural network model with the wind speed, wind direction sine, wind direction cosine, temperature as input parameters, and the wind power as the output.

In order to improve the prediction precision, firstly needing to input data optimized.

1. To calibrate the data of the numerical weather prediction system
   Using linear regression method. The correction model is that:

$$v^r_{NMP.t} = v_{NMP.t} - e_{NMP.t} \tag{1}$$

   Where $v_{NMP.t}$ is the wind speed of numerical weather prediction system at time t before the correction $v^r_{NMP.t}$ is the wind speed at time t after the correction.

$$e_{NMP.t} = a + b \cdot v_{NMP.t} \tag{2}$$

$$a = \overline{e}_{NMP} - \overline{b}_{NMP} \tag{3}$$

$$b = \frac{N_c \sum_{i=1}^{N_c} e_{NMP,i}\ v_{NMP,t} - \sum_{i=1}^{N_c} e_{NMP,i} \sum_{i=1}^{N_c} e_{NMP,i} \sum_{i=1}^{N_c} v_{NMP,i}}{N_c \sum_{i=1}^{N_C} v^2_{NMP,i} - (\sum_{i=1}^{N_c} v_{NMP,i})^2} \tag{4}$$

$$e_{NMP,i} = v_{NMP,i} - v_{means,i} \tag{5}$$

   Where the number of samples is N_c, $v_{means,i}$ is wind electric field measured wind speed.
2. Data normalization
   In order to be beneficial to the neural network training for the local minimum and as far as possible to train converge, the data initial selection cannot be ignored. In this paper, each input individually normalized in the interval [−1, 1], the normalization formula is that:

$$y_i = \frac{x_i - \min\{x_i\}}{\max\{x_i\} - \min\{x_i\}} \tag{6}$$

   Where $\{x_i\}$ is the sequence normalized before, $\{y_i\}$ is the sequence after normalized. The other input parameters are the same normalization method.

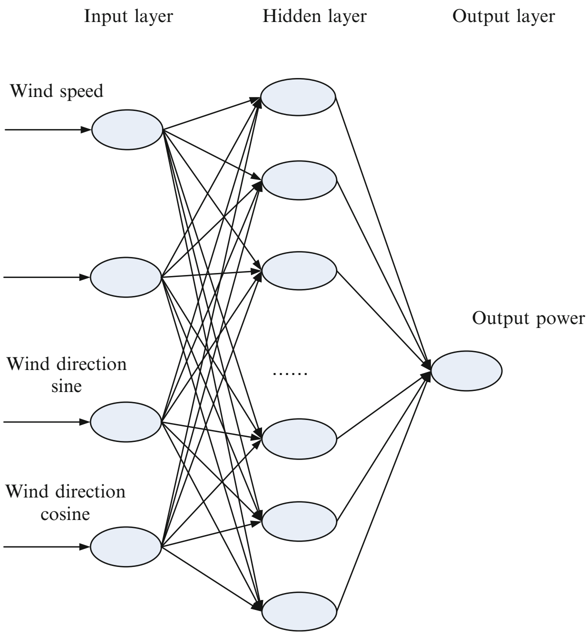


Fig. 3 Structure chart of BP neural network

3. BP neural network parameters
   According to the literature [8], the hidden layer node is selected as 9, transfer function uses the sigmoid function and linear function, hidden layer transfer function uses the tansig function, the output layer uses the purelin transfer function, training algorithm uses L-M algorithm. Figure 3 shows the BP neural network model.

4 Forecast Instance and Analysis

Figure 4 is the results of wind power prediction 24 h before, the abscissa has 96 time points and each point represents the interval of 15 min. Figure 5 is the results of wind power prediction 48 h before, the abscissa has 192 time points. Figure 6 is the results of wind power prediction 72 h before; the abscissa has 288 time points. In all figures the blue solid line is the real value which is collected by the wind farm SCADA system, the red dotted line is the forecast value of the BP neural network.

In the common, using two prediction errors of the common international indicators to analysis the predict results: one is the mean absolute error (MAE); the other is the normalized root mean square error (NRMSE). The mean absolute error is defined as:

$$MAE = \frac{1}{N}\sum_{n=1}^{N}\left|P_{measure} - P_{forecast}\right| \tag{7}$$

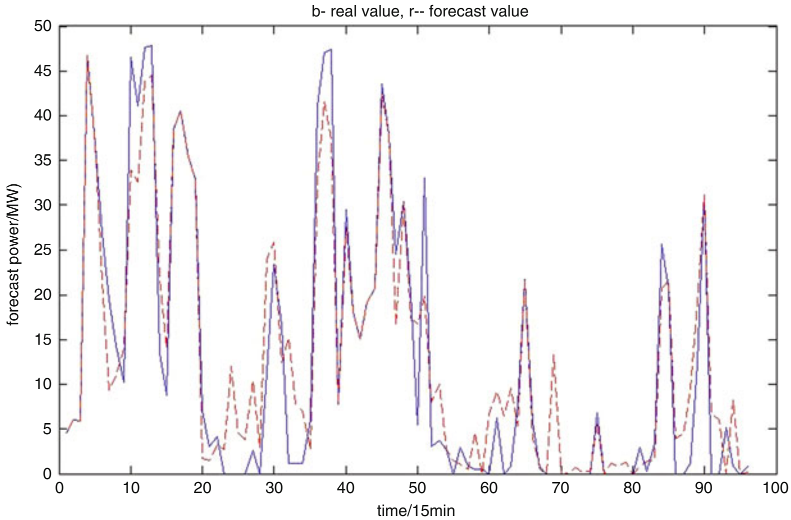


Fig. 4 Wind power prediction results of 24 h before

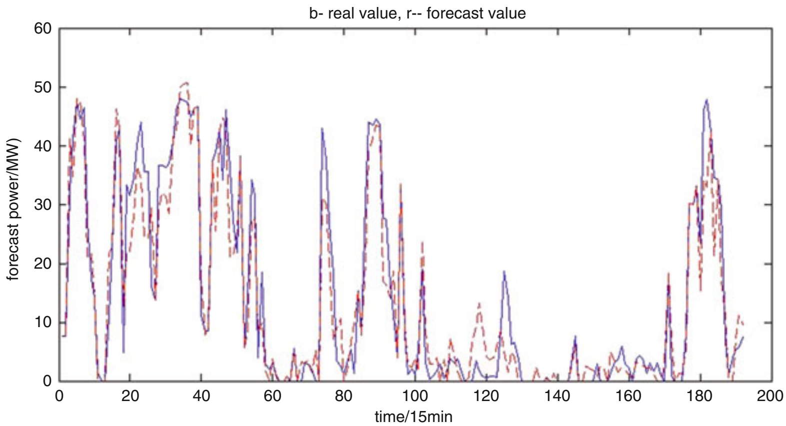


Fig. 5 Wind power prediction results of 48 h before

The normalized root mean square error is defined as:

$$NRMSE = \frac{1}{N}\sum_{n=1}^{N}\left(\frac{P_{measure} - P_{forecast}}{P_{rated}}\right)^{2} \tag{8}$$

Where $P_{measure}$, $P_{forecast}$, P_{rated} represent the real wind power value, BP neural network forecast value and the rated power of prediction wind generator, N is the number of forecast data.

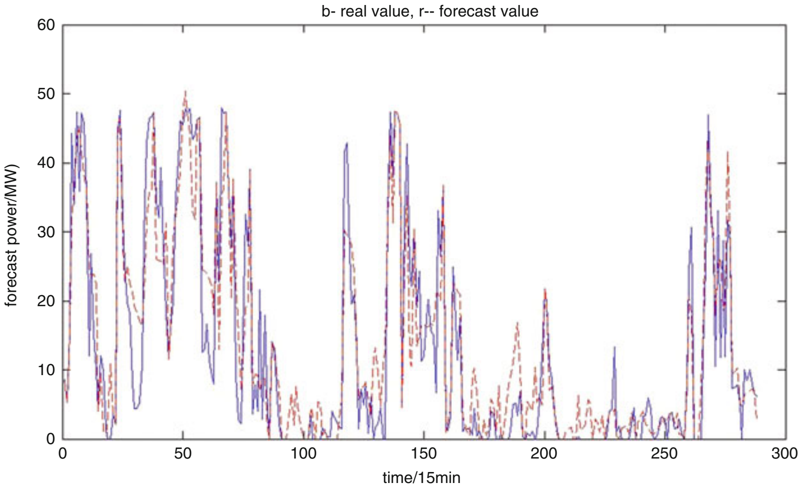


Fig. 6 Wind power prediction results of 72 h before

Table 1 The contrast of different time neural network prediction results

Predict ahead of time	MAE/MW	NRMSE/%
24 h	4.1690	12.26
48 h	5.4414	16.75
72 h	5.7333	18.15

Shown in Figs. 4, 5, 6 and Table 1, BP neural network is more accurate prediction of wind power results in 24 h before. More than 24 h after 48 h in advance and 72 h in advance of regularization of the root mean square error (NRMSE), but the average absolute error (MAE) changes in the rate of change of more than 30 % 48 h in advance and 72 h in advance, the average absolute error (MAE) rate of change of 5.36 %. This study shows that the BP neural network more accurate results in 24 h in advance of the wind power forecast from the formal rms error of about 12 %, more than 24 h after the prediction error will increase significantly, and the average absolute error changes, indicating that neural network on the recently predicted that the results were quite good, more than 24 h in advance accuracy will be significantly decreased. MAE and NRMSE of 48 h in advance and 72 h in advance or less, explain or less 48 h in advance and 72 h in advance of forecast accuracy.

5 Conclusion

By analyzing the result from the wind farm which is 49.5 MW rate power in 6 months, it is shown that the BP neural network can be very good at predicting the day-ahead forecast wind farm output power. Using wind speeds, wind direction sine, wind direction cosine and temperature as input variables and the network structure 4-9-1, the mean absolute error of 24 h in advance day-ahead prediction is 4.169 MW; its numerical root mean square error is 12.26 %. In this paper using the linear regression calibration to calibrate the numerical weather prediction system data and optimize the input parameters, thus improving the day-ahead wind power prediction accuracy of the BP neural network. It provides the scheduling department to design a power generation plan, improving the impact of wind power grid-connected.

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