Short Term Wind Power Prediction Based on Wavelet Transform and BP Neural Network

Shuang Zheng, Zhaoju Jia, Ziwei Zhang, Fugang Liu(✉), and Long Han

Heilongjiang University of Science and Technology, Harbin 150022, China
zs1980225@126.com, liufugang@mail.usth.edu.cn

Abstract. Wind power generation has great randomness because of its randomness and uncontrollability. Due to the instability of wind energy, the power system access to large-scale wind power will pose a serious threat to the system. The accuracy of wind power prediction is very important to the security and stability. In this paper, a prediction model of electric power based on wavelet and BP neural network is proposed. The wavelet can further refine the periodic and nonlinear characteristics of electric power, and it solves many uncontrollable features when testing with BP neural network alone. The simulation shows that the prediction results of this method is better than that of BP neural network.

Keywords: BP neural network · Wavelet transform · Wind power prediction

1 Introduction

Wind energy is a conversion of solar energy, which is an important strategic choice for many countries to develop new energy and achieve sustainable development. According to the 2018 Global Wind Report by Global Wind Energy Council, the share of wind power is steadily increasing. In 2018, the new installed capacity of the global wind energy industry was 51.3 GW, and the global offshore market grew by 0.5%. During the utilization of wind energy, the randomness and fluctuation of wind speed will result in the unstable output of turbine. The power quality cannot be guaranteed [1]. In addition, due to the instability of wind energy, the power system access to large-scale wind power will pose a serious threat to its safe and stable operation. Accurate wind power prediction can solve the grid connection problem well, which is conducive to reducing the operating cost of wind energy plants.

The influence factors of wind power forecast include wind turbine arrangement, terrain, roughness, air pressure, temperature, speed, direction and other environmental conditions. It is also affected by the actual conditions such as unit operation status, wake effect, turbulence and other factors. Currently, the common statistical model methods for wind power forecast are Kalman filter method [2], time series method [3, 4], artificial neural network method [5–8], wavelet analysis method [9, 10], SVM regression method [11] and combined model method [12, 13]. They are based on the statistics of historical wind patterns, the physical data from the site and the physical properties of wind

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turbines. Kalman filter method needs to be closely combined with the estimated target in application. Accurate mathematical modeling of the estimated target is helpful to the design and implementation of Kalman filter algorithm. In [2], the authors explored a new Kalman filter method, which can get the curves of wind speed and predict it. The prediction models of random time series include several models. In [4], the authors proposed an improved Markov chain model. They utilized a three-dimensional state transition probability matrix to generate wind power time series. However, the forecast error of high wind speed is still large, especially when the wind speed changes violently in a short time, the power will climb rapidly. To further improve the forecast accuracy of high wind speed period, some scholars choose the deep convolution neural network with more layers of network structure. In [11], the authors presented a Support Vector Machine method using Dutch Hill Wind Farm data and got a better result than linear Support Vector Machine model. In this paper, we study the recent researches and establish a wind power forecast model based on wavelet transform and neural network. In Sect. 2, we introduce the basic theory of BP neural network and the specific process of wind power forecast by BP neural network. In Sect. 3, we explore wind power forecast method based on wavelet neural network. In Sect. 4, we took a wind power plant in North China as an example and compared the application effect of wavelet neural network and BP neural network model in wind power forecast based on one month's local weather data. Finally, we present the conclusion and discuss the issues involved in wind power forecast.

2 Wind Power Forecast by BP Neural Network Algorithm

BP (Back Propagation) neural network algorithm is a reverse transmission algorithm simulating human brain neurons. The structure of BP neural network is shown in Fig. 1. In this algorithm, the two processes of "signal forward transmission" and "error back propagation" are carried out in a reciprocating manner, to meet the conditions of the error between the output and the expected value.

The forward transmission of signal is to calculate the output of network with given signals. Set the input vector of input layer as $U_k(u_1, u_2, \cdots, u_n)$, $k = 1, 2, \cdots, n$. The corresponding input information actual vector is $d_k = (d_1, d_2, \cdots, d_n)$, so the hidden layer input s is:

$$s_j = \sum_{i=1}^{n} w_{ij} u_i - \theta_j \; j = 1, 2, \cdots, p \tag{1}$$

Where w_{ij} is the connection weight, θ_j is the threshold value, p is the number of neurons in the hidden layer.

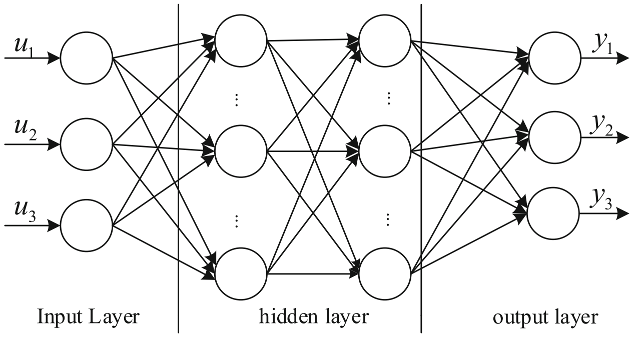


Fig. 1. Topological structure of BP neural network

2.1 Back Propagation of Error

Calculate the error and change the weight accordingly. The error E of the output layer is:

$$E = \frac{1}{2}(\mathrm{d} - O)^2 = \frac{1}{2}\sum_{k=1}^{q}(d_k - O_K)^2 \tag{2}$$

By expanding the above error definitions, we can see that the error is a function of the weight of each layer, and then we can change the error by adjusting the weight. The change of the weight of each neuron is directly proportional to the decrease of the error gradient. The weight adjustment amount is:

$$\Delta v_{jk} = -\eta\frac{\partial E}{\partial v_{\mathrm{jk}}}, \quad j = 0, 1, 2, \cdots, p, \;\; k = 1, 2, \cdots q \tag{3}$$

$$\Delta w_{jk} = -\eta\frac{\partial E}{\partial v_{\mathrm{ij}}}, \quad i = 0, 1, 2\cdots, m, \;\; k = 1, 2, \cdots p \tag{4}$$

Where η is the proportional coefficient.

2.2 Wind Power Forecast Based on BP Neural Network

The historical weather forecast data (including wind speed and numerical weather forecast, such as humidity, wind direction, atmospheric pressure and temperature) are used as input data for training, and the weight coefficients of different layers of neural network are obtained. The power forecast is realized according to the future weather forecast data by applying this model.

The specific learning process of BP neural network is as follows:

1. Initializing the weights w_{ij} and v_{jt}, the thresholds θ_j and γ_t;
2. Input initial learning sample $U_k = (u_1, u_2, \cdots, u_n)^{\mathrm{T}}$ and the final target sample $Y_k = (y_1, y_2, \cdots, y_m)^{\mathrm{T}}$;

3. Calculate hidden layer net input s_j and output b_j:

$$s_j = \sum_{i=1}^{n} w_{ij}u_i - \theta_j,\ j = 1, 2, \cdots, p \tag{5}$$

$$b_j = f\left(s_j\right),\ j = 1, 2, \cdots, p \tag{6}$$

4. Calculate output layer net input l_t and net output c_t:

$$l_t = \sum_{j=1}^{p} v_{jt}b_j - \gamma_t,\ t = 1, 2, \cdots, m \tag{7}$$

$$c_t = f\left(l_t\right) \quad t = 1, 2, \cdots, m \tag{8}$$

5. According to $Y_k = (y_1, y_2, \cdots, y_m)^{\mathrm{T}}$ and the output, the correction error d_t is calculated as:

$$d_t = (y_t - c_t)f\left(l_t\right)\ t = 1, 2, \cdots, m \tag{9}$$

6. According to the known v_{jt},d_t,b_j and e_j, the correction error of hidden layer is calculated as

$$e_j = \left[\sum_{t=1}^{m} v_{jt}d_t\right] f\left(s_j\right),\ j = 1, 2, \cdots, p \tag{10}$$

7. Modify the implicit connection weight v_{jt} and threshold γ_t of the output layer according to the known d_t and b_j

$$\Delta v_{jt} = \eta d_1 b_j,\ j = 1, 2, \cdots, p;\ t = 1, 2, \cdots, m \tag{11}$$

$$\Delta\gamma_t = \eta d_1,\ t = 1, 2, \cdots, m \tag{12}$$

8. According to the known e_j $U_k = (u_1, u_2, \cdots, u_n)^{\mathrm{T}}$, correct the connection weight input of the hidden layer

$$\Delta w_{ij} = \beta e_j u_i,\ i = 1, 2, \cdots, n;\ j = 1, 2, \cdots, p \tag{13}$$

$$\Delta \theta_j = \beta e_j,\ j = 1, 2, \cdots, p \tag{14}$$

In the above process, steps 3. and 4. are the forward propagation, and steps 5. to 8. are the error back propagation, to correct the weight and threshold error. The global error satisfying the condition is obtained by using all the samples to repeat the cycle.

In the process of solving BP algorithm, the local optimal solution is easily got by gradient descent operation along the error value. According to the experimental simulation in Sect. 4 of this paper, the forecast accuracy cannot meet the corresponding accuracy requirements only by applying BP neural network algorithm.

3 Wavelet Neural Network Algorithm for Forecast Wind Power

3.1 Wavelet Neural Network Algorithm

Wavelet analysis method is developed for the deficiency of Fourier transform. It can obtain local time interval information. A basic function $\varphi(t)$ is given:

$$\varphi_{\mathrm{a},b}(t) = \frac{1}{\sqrt{a}}\varphi(\frac{t-b}{a}) \tag{15}$$

where $\varphi_{\mathrm{a},b}(t)$ is the base wavelet, a, b are the scale and displacement parameter respectively. Given that the square integrable signal $x(t)$, then the continuous wavelet transforms of $x(t)$ is defined as:

$$WT_x(a, b) = \frac{1}{\sqrt{\mathrm{a}}}\int x(t)\varphi^*(\frac{t-b}{a})dt = \int x(t)\varphi^*_{a,b}(t)dt = \langle x(t)|\varphi_{a,b}(t)\rangle \tag{16}$$

If a and b are discretized, $a = a_0^j$, $b = a_0^j b_0$,

$$WT_x(j, k) = \int_{-\infty}^{+\infty} x(t)\varphi_{j,k}dt, j, k \in Z \tag{17}$$

Combining the multi-resolution feature of wavelet with the tower method, the pyramid decomposition and reconstruction algorithm of discrete signal based on wavelet is expressed as:

$$C_n^k = \frac{1}{\sqrt{2}}\sum_{j\in Z} C_j^{k-1}\bar{h}_{j-2a} \tag{18}$$

$$b_n^k = \frac{1}{\sqrt{2}}\sum_{j\in Z} C_j^{k-1}\bar{g}_{j-2a} \tag{19}$$

After the decomposition operation, the formula is reorganized as:

$$\left(\overline{F}_n\right)_n = \frac{1}{\sqrt{2}} \sum_{j \in Z} f_{n-2ja_j} \tag{20}$$

Where c_n^k, b_n^k denote the decomposition coefficient of wavelet; h_j, g_j denote the discrete filter of wavelet. The decomposition and reconstruction of wavelet is to divide the wind power time series into n layers at different frequencies, and then get n high frequency signal components and one approaching signal component.

The BP neural network algorithm mentioned above is easy to get local optimal solution. In addition, the output power of turbine unit fluctuates greatly, and forecast accuracy of the traditional neural network model is not satisfactory. In this paper, we studied the method of using wavelet neural network to forecast wind power. The actual power of a single unit in each wind farm has a quasi-periodic characteristic within 24 h. Wavelet decomposition can bring forward some periodic and nonlinear characteristics of electric power, and further refine them.

According to the rules of each sub sequence, the method of matching prediction is used. BP neural network can play the advantages of dealing with the problems of nonlinearity and no clear rules. Combining the models of the two algorithms can effectively improve the accuracy of wind power forecast. Wavelet neural network is based on wavelet basis function. The input parameters are weighted by the weight of wavelet neural network in hidden layer. The topological mechanism is shown in Fig. 2.

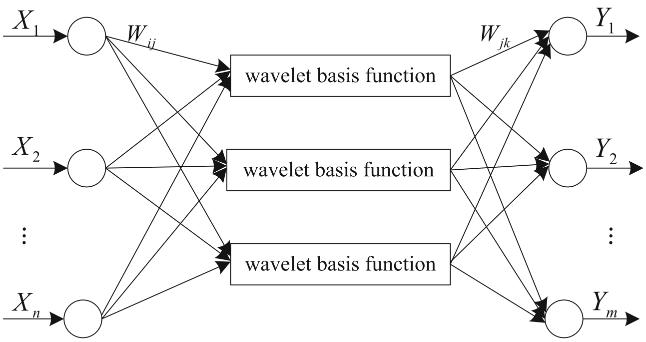


Fig. 2. The topological mechanism of wavelet neural network

When the signal sequence is $X_i(i = 1, 2, \cdots, k)$, the hidden layer calculation formula is

$$h(j) = \left(\sum_{1}^{k} w_{ij} x_i - b_j \Big/ a_j \right) \tag{21}$$

The output layer calculation formula of wavelet neural network is as follows:

$$y(k) = \sum_{k=1}^{m} w_{ik} h(i) \quad k = 1, 2, \cdots m \tag{22}$$

Where W_{ik} is the weight from hidden layer to output layer;

In the process of autonomous learning, wavelet neural network needs to modify the parameters of neural network. The forecast error can be got from the formula (23):

$$e = \sum_{k=1}^{m} yn(k) - y(k) \tag{23}$$

The weights and coefficients of wavelet neural network are modified according to the above formula. They are shown in formula (24)–(26).

$$W_{n,k}^{(i,j)} = W_{n,k}^{j} + +\Delta W_{n,k}^{(i,j)} \tag{24}$$

$$a_k^{(i,j)} = a_k^j + +\Delta a_{(n,k)}^{(i,j)} \tag{25}$$

$$b_k^{(i,j)} = b_k^j + +\Delta b_{(n,k)}^{(i,j)} \tag{26}$$

According to the calculation of network prediction error, the results of the above formula are as follows (γ is the learning rate):

$$\Delta W_{(n,k)}^{(i,j)} = -\gamma \frac{\partial e}{\partial W_{n,k}^{(i)}} \tag{27}$$

$$\Delta a_k^{(i,j)} = -\gamma \frac{\partial e}{\partial a_k^{(i)}} \tag{28}$$

$$\Delta b_k^{(i,j)} = -\gamma \frac{\partial e}{\partial b_k^{(i)}} \tag{29}$$

3.2 Wind Power Forecast Based on Wavelet Neural Network

Because the single sequence of wavelet decomposition on different scales has different characteristics, the prediction method matching with itself is determined according to the change of wind power. The large scale of the subsequence corresponds to the low frequency part of the wavelet space, which reflects the curve characteristics of the wind power time series. The small scale of the sequence reflects the relationship between the nonlinear characteristics of the system. Therefore, in order to accurately depict the power subsequence on different scales, the matching BP neural network should be determined respectively for modeling and forecast. In this paper, the wavelet transform divides the wind power time series into n layers at different frequencies, and obtains n high frequency signal components and an approaching signal component. Then, the decomposed single sequence is respectively forecasted by BP neural network matching with this. Finally, combined with the forecast results of each sequence, the forecast value of wind power series is reconstructed. The specific training process is as follows:

(1) Network initialization such as expansion factor a_k, translate factor b_k, network connection weight W_{jk}, and network learning rate γ;

(2) Classifying the samples into training samples and test samples.
(3) Prediction output. Input the training samples, calculate the network output and calculate the error between network output and actual output.
(4) Correct the network weight based on wavelet function parameters and the error. Make network prediction approach real value.

4 Experimental Simulation Analysis

Taking a wind power plant in North China as an example, the weather data of a month are used, including wind speed and numerical weather forecast. The numerical weather forecast includes humidity, wind direction, atmospheric pressure and temperature. These data were measured every 15 min from 10:00 a.m. to 11:45 p.m. every day, and a total of 1753 samples are collected. In this experiment, 1533 data groups were used for training and 120 data groups for prediction. Figure 3 shows the forecast results of the two algorithms.

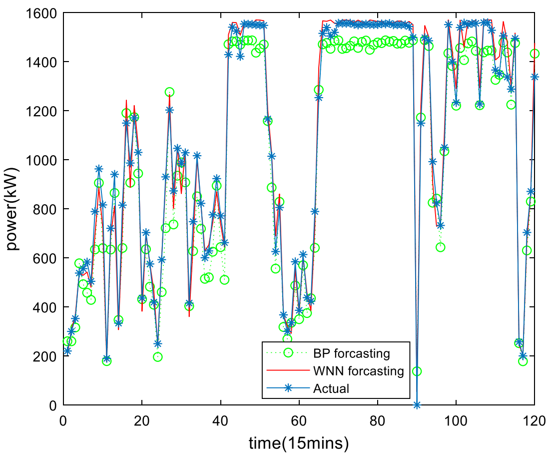
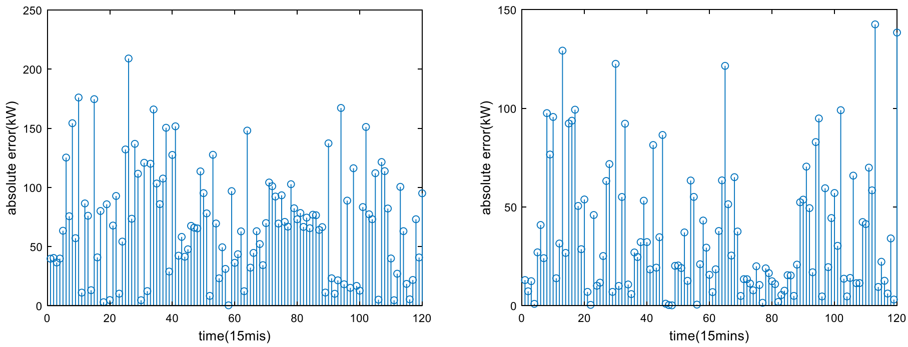


Fig. 3. Wind power forecast result

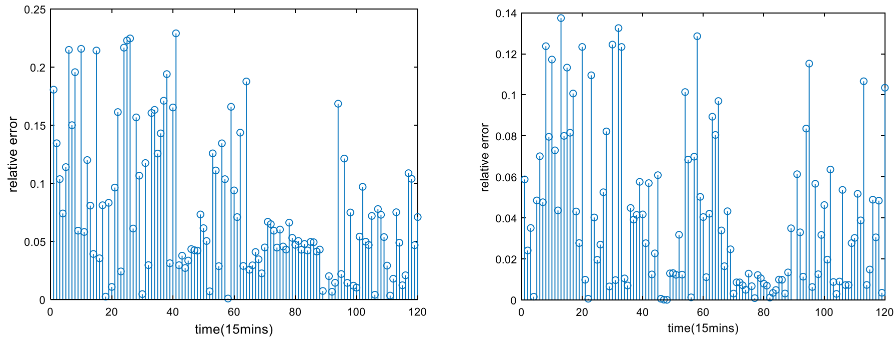
In Fig. 3, there is a big difference between the actual power result and the wind power prediction by only using BP neural network. When the actual power is high, even if the actual power data fluctuates little, the prediction error of the model cannot reach the ideal effect. The reason is that the model does not grasp the overall law in depth and fails to consider the data variation interval of each time period. The prediction effect of wavelet neural network model is better than the former, but the prediction effect of the algorithm is not good when the actual power is small, and the fluctuation is large.

Figure 4 and Fig. 5 show the forecast errors of the two algorithms. Figure 4 (a) and Fig. 5 (a) are directly forecasted by using BP neural network, and Fig. 4 (b) and Fig. 5 (b) are the forecast results by using wavelet neural network. The maximum error by using BP neural network forecast method is 23%, and the overall error change is relatively large. Generally, it cannot meet the prediction standard. The prediction error of wavelet



(a) BP neural network (b) Wavelet neural network

Fig. 4. The absolute error of two algorithms



(a) BP neural network (b) Wavelet neural network

Fig. 5. The relative error of two algorithms

neural network is about 10%, the mean square deviation is 84.16 kW, and the overall error is relatively small.

5 Conclusion

In this paper, the application effect of wavelet neural network and BP neural network model in wind power prediction is compared. It can be concluded from the theoretical analysis that the feature information of wind power can be extracted quickly by decomposing the wind power sequence in different frequencies through wavelet transform, which can be used as the input data of neural network prediction model. The simulation results show that the accuracy of forecast model can be improved by using the good time-frequency analysis ability of wavelet to non-stationary signals and the nonlinear mapping ability of BP neural network. In addition, for some limitations of the Morlet function, we can change the prediction effect of the model by changing the wavelet basis function in future.

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