Wind Power Forecasting Based on the BP Neural Network

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Abstract. Accurate short-term wind power forecasting has important significance to safety, stability and economy of power system dispatching and also it is a difficult problem in practical engineering application. In this paper, by use of the data of numerical weather forecast, such as wind speed, wind direction, temperature, relative humidity and pressure of atmosphere, a short-term wind power forecasting system based on BP neural network has been developed. For verifying the feasibility of the system, some experiments have been were carried out. The results show that the system is capable of predicting accurately the wind power of future 24 hours and the forecasting accuracy of 85.6% is obtained. The work of this paper has important engineering directive significance to the similar wind power forecasting system.

Introduction

With more and more serious of environment problem and energy crisis, as a renewable energy sources, people pay more and more attention to the wind power generation technology [1]. However, because of intermittence and wave properties of wind speed and wind direction, the wind power has serious impact on normal dispatching of power system and makes the dispatching more difficult. Therefore the research and development of an accurate short-term wind power forecasting system has an important significance for dispatching and stability of power system and wind farm operation [2].

In the past few years, in order to facilitate to establish reasonable power generation scheduling, some research groups have already reported the performance of system of wind power forecasting system and many method has been employed, such as time series method, Calman filtering method, Neural Network method, statistical method, gray prediction method and so on[3-7]. However, the forecasting accuracy of these methods need been improved further.

In this paper, based on the data of numerical weather prediction, such as wind speed, wind direction, temperature relative humidity and pressure of atmosphere, the BP neural network method is employed to predict accurately wind power of future 24 hours. In section 2 the forecasting principle based on BP neural network is present. In section 3 the experiment and result analysis is discussed. Finally, a conclusion is given in section 4.

Forecasting Principle Based On BP Neural Network

As a method applied extensively, BP neural network has a well self learning ability and a simple network structure. Theoretically for a three layer, the BP neural network can approximate to a nonlinear function with arbitrary precision. Therefore, in this paper a three-layer BP neural network is employed to satisfy our goal.

In fact these are some factors have the direct influence on output power of wind farm, for example, the wind speed, wind direction and the air density. And also the air density has relation to the relative humidity, temperature and pressure of atmosphere [8]. Therefore the data of numerical weather forecast, such the wind speed, wind direction, relative humidity, temperature and pressure can been employed to act as the input node of BP Neural Network. Undoubtedly, for output layer the wind power is selected as the only output node. However for hidden layer, it is difficult to determinate of node number. In our network, a empirical formula is used to calculate the node number of hidden layer, which can been written by[9].

$$nl = \begin{cases} n + 0.618(n-m) & n \ge m \\ m - 0.618(m-n) & n < m \end{cases} \tag{1}$$

where n and m are the node number of input layer output, respectively. According to this formula, the node number of hidden layer is set as 7 or 8. Figure 1 shows a three-layer neural network.

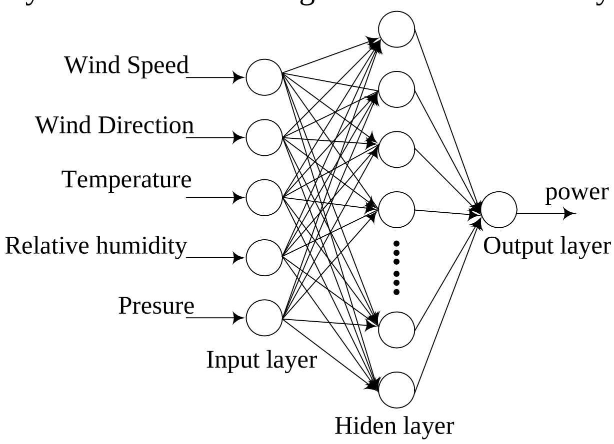

Fig 1. Three layers BP neural networks for wind power forecasting

Considering that these are some negative values in practical wind power signal, therefore the tansig type function ranged from -1 to 1 are selected as the activation functions of output layer and hidden layer, respectively. The tansig function can be written by following equation.

$$f(x) = \frac{1-e^{-x}}{1+e^{-x}}, \tag{2}$$

Generally, the objective function of network is defined as

$$J = \frac{1}{2}e^2(k) = \frac{1}{2}[y_c(k) - y_m(k)]^2 \tag{3}$$

where $y_c(k)$ is network forecasting power value of output layer and $y_m(k)$ is the practical power value, namely, teaching signal value.

The gradient descent method is used to correct the weight coefficients of each layer of neural network and also a momentum term, which can speed up the convergence of searching process and facilitate to obtain the global minimum value, is attached after weight coefficient correction equation. Therefore the weight coefficient correction equation of output layer can be given by

$$\Delta w_{li}^{(3)}(k+1) = -\eta \frac{\partial J}{\partial w_{li}^{(3)}} + \alpha \Delta w_{li}^{(3)}(k) \tag{4}$$

where η is learning rate and α is momentum factor.

The derivative term of correction equation can be written as

$$\frac{\partial J}{\partial w_{li}^{(3)}} = \frac{\partial J}{\partial y_c(k)} \cdot \frac{\partial y_c(k)}{\partial O_l^{(3)}(k)} \cdot \frac{\partial O_l^{(3)}(k)}{\partial net_l^{(3)}(k)} \cdot \frac{\partial net_l^{(3)}(k)}{\partial w_{li}^{(3)}} \tag{5}$$

where $\partial J / \partial y_c(k+1) = e(k)$, $\partial O_l^{(3)}(k) / \partial net_l^{(3)}(k) = f'[net_l^{(3)}(k)]$, $\partial net_l^{(3)}(k) / \partial w_{li}^{(3)} = O_i^{(2)}(k)$ .Because $\partial y_c(k) / \partial O_l^{(3)}(k)$ is unknown, $\partial y_c(k) / \partial O_l^{(3)}(k)$ can be substituted by the sign function of $sgn[\, \partial y_c(k) / \partial O_l^{(3)}(k) \,]$. The resulting influence of error can be compensated by adjusting the learning rate η. Therefore the weight coefficient correction equation of output layer can be described as

$$\begin{cases} \Delta w_{li}^{(3)}(k+1) = \eta \delta_l^{(3)} O_i^{(2)}(k) + \alpha \Delta w_{li}^{(3)}(k) \\ \delta_l^{(3)} = e(k+1) \cdot \dfrac{\partial y_c(k+1)}{\partial O_l^{(3)}(k)} \cdot f'[net_l^{(3)}(k)] \\ l = 0 \end{cases} \tag{6}$$

Similarly the weight coefficient correction equation of hidden layer also can be given by

$$\begin{cases} \Delta w_{ij}^{(2)}(k+1) = \eta \delta_i^{(2)} O_j^{(1)}(k) + \alpha \Delta w_{ij}^{(2)}(k) \\ \delta_i^{(2)} = f'[net_i^{(2)}(k)] \sum_{l=0}^{4} \delta_l^{(3)} w_{li}^{(3)}(k) \\ i = 0, 1, \cdots, \ m-1 \end{cases} \tag{7}$$

where $f`[\bullet] = [1 - f^2(x)]/2$

Figure 2 shows the flow diagram of BP neural network training and testing process.

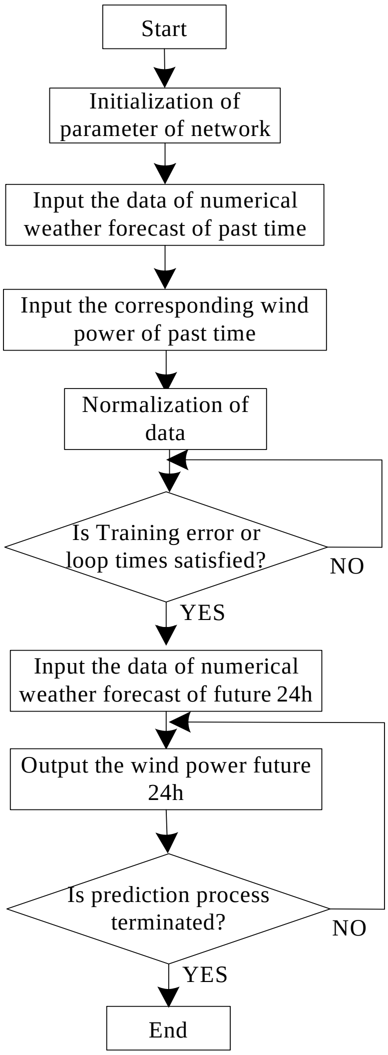

Fig.2 The flow diagram of BP neural network training and testing process.

Experiments and Results Analysis

According criterion of the State Grid Corporation of China, the wind power forecasting system should provide power forecasting value of 24 hours of next day, namely, which corresponding total 96 forecasting value when time resolution being less then 15 min. For evaluating the preference of system, the root-mean-square error (RMSE), system accuracy, mean absolute error (MAE) and correlation coefficient generally are employed to verify the feasibility of system, which are defined as, respectively [10].

$$RMSE = \frac{\sqrt{\sum_{i=1}^{n}\left(P_{Mi} - P_{Pi}\right)^2}}{Cap \bullet \sqrt{n}} \tag{8}$$

$$a = \left[1 - \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(\frac{P_{Mi} - P_{Pi}}{Cap}\right)^2}\right] \times 100\% \tag{9}$$

$$MAE = \frac{\sum_{i=1}^{n}\left|P_{Mi} - P_{Pi}\right|}{Cap \bullet n} \tag{10}$$

$$r = \frac{\sum_{i=1}^{n}\left[\left(P_{Mi} - \overline{P}_M\right) \bullet \left(P_{Pi} - \overline{P}_P\right)\right]}{\sqrt{\sum_{i=1}^{n}\left(P_{Mi} - \overline{P}_M\right)^2 \bullet \sum_{i=1}^{n}\left(P_{Pi} - \overline{P}_P\right)^2}} \tag{11}$$

where, P_{Mi} is practical power of i time, P_{Pi} is predict power of i time, Cap is average of working power capacity of the total power farm and n is number of samples.

The data of numerical weather prediction is obtained from local weather bureau and the practical wind power from 12 April to 9 May 2012 were obtained from local a wind farm located at western region of China which capacity is up to 45MW. Figure 3(a) shows the practical wind power data from 12 April to 9 May 2012 which time resolution is 15 min.

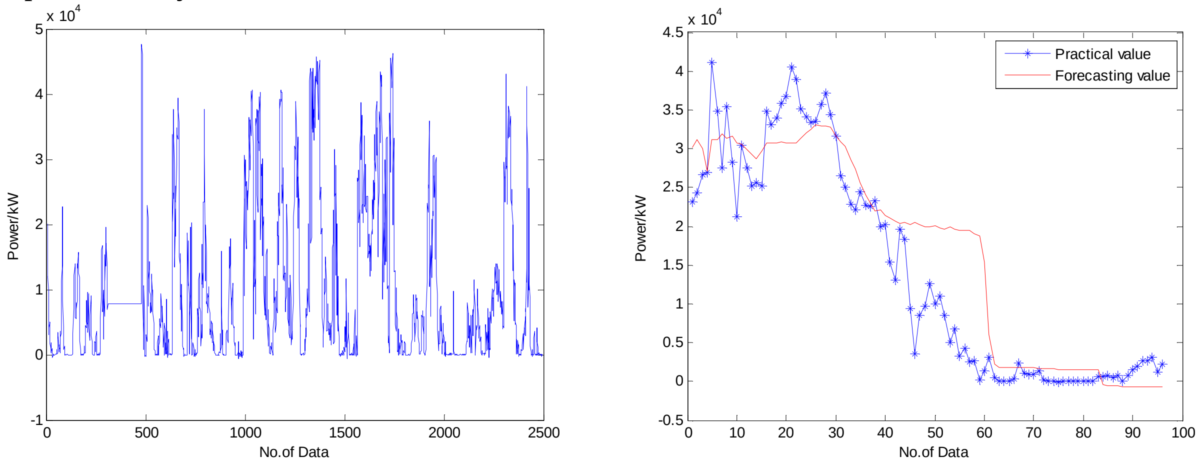

Fig.3(a) Practical wind power data from 12 April to 9 May 2012 which time resolution is 15 min
(b) The comparison between forecasting power in 7 May 2012 and the practical power

The data of numerical weather prediction and the corresponding practical wind power data from 12 April to 6 May 2012 are selected as the input and output, respectively, to train the BP network. The goal error is set as 0.001 and the loop times is number is 1000. The tansig function is selected as the activation functions of output layer and hidden layer, respectively. When train error is satisfied or loop times are reached, the network is trained well. Then the data of numerical weather prediction of next day, namely 7 May 2012, are input the network trained, the forecasting power of future 24 hours value can be obtained. Figure 3(b) shows the forecasting power value in 7 May 2012 which is marked by red line. The blue asterisk line is the practical power of the same day.

It is obvious that the forecasting value was in good agreement with the practical power. Through the calculation from Eq. (8) to Eq. (11), the RMSE was 0.144 and the system accuracy is up to 85.6%, the MAE is 0.0423 and correlation coefficient is 0.8345.

Conclusion

By using a large number of the data of numerical weather prediction, such as wind speed, wind direction, temperature relative humidity and pressure of atmosphere of past time as input data and using corresponding wind power as output data, the BP neural network is trained. After network is trained well, the data of numerical weather prediction of future 24 hors are input into trained system, the corresponding total 96 values wind power forecasting are obtained. Some experiments have been were performed for verifying the system preference. The results show that the system is capable of forecasting accurately the wind power value of future one day and the more than 85% of forecasting accuracy is obtained. The work of this paper has important engineering directive significance to the similar wind power forecasting system.

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