Chapter 20
Study of Short-Term Wind Power Prediction Based on Advanced BP Neural Network Model

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Abstract Wind power prediction is important to wind power system operation with a large amount of wind power integration. Effective prediction for wind power can reduce the difficulty of grid dispatching. In this paper an advanced neural network model was proposed to predict the short-term output power of a single wind turbine in a wind farm. According to the relevant wind speed, wind direction, temperature, output power and other data obtained from the wind farm, the model was established to predict the output wind power ahead of 10 min and 1 h. The simulation results showed that the proposed advanced BP neural network model had a higher prediction accuracy comparing to the existing BP neural network model.

Keywords Wind power · Wind farm · BP neural network · Short-term prediction

20.1 Introduction

With the development of wind power technology, wind turbine unit capacity and the number and size of grid-connected wind farms is expanding, and the proportion of wind power in the power grid is also increasing. The impact of wind power on the grid is more and more obvious, especially when several planned wind farms of million kilowatts level connected to grid, which will have a significant impact

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on the stability, power quality, flow distribution and dispatch mode of the grid [1]. To meet the power demand, guarantee the stability of grid operation and reliability of power supply, effective planning and scheduling is essential to power system. However, the inherent volatility, intermittent, and anti-shaving characteristics of wind power, increases the difficulty of power system planning and scheduling. If wind power can be accurately predicted, it's beneficial to make scheduling plan, reduce its adverse effects on the entire grid, and reduce the power system operating costs and spinning reserve. It can also increase the wind power penetration limit, and is conducive to develop power exchange plan accurately under the open electricity market.

Artificial neural network has parallel processing, distributed storage and fault tolerance characteristics, along with self-learning, self-organizing and self-adaptive capacity, so it's very effective for solving complex problems. Because of these advantages, neural network technology gets the widest application in wind power prediction [2, 3]. However, there are some problems in using the neural network models for wind power prediction. The models select data of a long continuous time before forecast point when choosing training data set [4, 5]. By training the neural network to achieve the non-linear input–output mapping relation under all weather conditions, and then make predictions based on the mapping relation. This way needs a huge number of training data, resulting in a long training time and a slow convergence speed [6, 7], easily falling to over-fitting. Besides, the gained mapping relation is an average approximation under all weather conditions, which would limit further improving the prediction accuracy. The existing neural network models that use weather data to make wind power prediction all have this problem [8].

For the above shortcomings of the existing neural network prediction models, this paper designed an advanced BP neural network model choosing training data set based on weather data similarity.

20.2 Advanced BP Neural Network Model Based on Weather Data Similarity

This advanced BP neural network prediction model selected the appropriate training data set based on weather data of every forecast period, and then made specific training to get the mapping relation under weather condition of the period for wind power prediction.

20.2.1 Choose Input and Output Data

The data used in this paper is from a single wind turbine in a wind farm, which is all kinds of system and environmental data from 01/02/2008 to 24/02/2008,

recording every 10 min. From various types of historical data, selecting the average wind speed, wind direction and the average environmental temperature that affect the output active power mainly, and take the vector {average wind speed, wind direction sine, wind direction cosine, environmental temperature} as input data of the model. This paper adopted direct prediction method, therefore selected active power as the BP neural network model output data. This paper called input data and the corresponding output data as the source data.

20.2.2 Remove Bad Data Set

Wind power prediction modeling requires a large number of historical data as training samples. However, the historical data would be affected not only by measurement error of measuring device itself, but also by data transmission errors and scheduling plan as well as other factors. So, the historical data may contain data missing, unusual fluctuations and non-real data. This paper took prediction based on weather data, so when limiting the wind farm output power because of scheduling plan, weather data and wind farm output power would not accurately reflect the right mapping relation. Take the weather data and wind farm output power in this case as bad data.

The training sample set containing bad data; it will probably get the wrong mapping relation, leading to serious distortions in predictions. So that, identifying and removing bad data is a necessary safeguard for training neural network.

20.2.3 Data Normalization and Anti-Normalization

In order to prevent weight adjustment entering the flat area of the error surface because the absolute input value is too large, usually the input and output data needs proper process to improve the generalization ability and prediction accuracy. Data processing commonly uses normalization method, the network input and output data will be limited to [0, 1] or [−1, 1]. In this paper, the normalized formula is as follows, the input and output data is limited to [−1, 1].

$$Y_i = \frac{X_i - X_{min}}{X_{max} - X_{min}} \tag{20.1}$$

where, X_{max} and X_{min} are the defined maximum and minimum values of input and output data, X_i and Y_i are the input and output data values before and after normalization.

After getting prediction value, it needs to be anti-normalized to restore to the original data range. Anti-normalization formula is as follows:

$$X_j = Y_j \cdot (X_{max} - X_{min}) + X_{min} \tag{20.2}$$

where, X_{max} and X_{min} are respectively the maximum and minimum values of output data, Y_j and X_j are prediction values before and after anti-normalization.

20.2.4 Weather Data Similarity

The proposed BP neural network model used the input vector $X = \{$average wind speed, wind direction sine, wind direction cosine, environmental temperature$\}$. Using the weighted Euclidean distance to determine the weather data similarity, the formula is:

$$S_{i,j} = 1 - \sqrt{\sum_{k=1}^{4} w_k \cdot (X_{i,k} - X_{j,k})^2} \tag{20.3}$$

where, $S_{i,j}$ is the similarity between input vector Xi and Xj, w is the weight vector. The wind speed is the greatest impact factor which plays a decisive role. Constrained by the wind farm topography, different wind direction has different impact to wind farms, so wind direction is also an important factor. Environmental temperature affects air density, so it can affect the wind turbine active output power, too. This paper determines the weight vector w = $\{0.7, 0.1, 0.1, 0.1\}$.

20.2.5 Determine the Network Structure

The designed BP neural network model is of three-layer structure, including input layer, hidden layer and output layer. Input layer node number equals to the number of input variables, therefore, take the input layer node number as 4. As well, take the output layer node number as 1.

There is no perfect theoretical basis for selecting hidden layer node number at the present time, only some empirical formulas. For example, through research on three-layer BP network, Kolmogrov found that the number of hidden layer node should be $2N + 1$, where N is the number of input layer node. Based on his geometric interpretation of multi-network functions, Lippman figured that the number of second hidden layer node should be $2M$, where M is the number of output layer node. Refer to empirical formulas, this paper conducted manifold experiments on three typical wind speed sections namely low-speed (<5 m/s), medium-speed (5–9 m/s), high-speed (>9 m/s) in many areas. According to the result, determine a single hidden layer structure, and the number of nodes is 13.

20.3 The Modeling and Forecasting Process of the Advanced BP Neural Network

The flow chart of modeling and forecasting process is as follows.

1. Build up BP neural network model, determine the net structure.
2. Remove bad data set from source data.
3. Normalize source data.
4. Forecast period t = 1.
5. Normalize weather data of the current prediction period according to the source data normalization format.
6. Work out weather data similarity between the source data and weather data of the current prediction period, and choose train data set according to the similarity.
7. Train the BP neural network with the gained training set.
8. Do prediction simulation, and then anti-normalize the prediction results.
9. t = t + 1, if t > T, end; else, go to step 5.

20.4 Prediction Results Analysis

To evaluate the performance of the proposed advanced BP neural network prediction model scientifically and objectively, this paper made prediction results analysis taking existing BP neural network models as a basis for comparison. Percentage error PE1 is prediction error relative to the actual value and the percentage error PE2 is prediction error relative to the installed capacity of wind turbines. The maximum absolute percentage error MRPE1 and mean absolute percentage error MAPE1 are taken as sensitivity indicator, MRPE2 and MAPE2 are taken as accuracy indicator. The formulas are as follows:

$$PE1(i) = \frac{f_i - r_i}{r_i} * 100\,\% \tag{20.4}$$

$$PE2(i) = \frac{f_i - r_i}{P} * 100\,\% \tag{20.5}$$

$$MRPE1 = \max_{i=1}^{N}\{|PE1(i)|\} \tag{20.6}$$

$$MRPE2 = \max_{i=1}^{N}\{|PE2(i)|\} \tag{20.7}$$

$$MAPE1 = \frac{1}{N}\left[\sum_{i=1}^{N}|PE1(i)|\right] \tag{20.8}$$

$$MAPE2 = \frac{1}{N}\left[\sum_{i=1}^{N}|PE2(i)|\right] \tag{20.9}$$

where, f is the predictive value of wind turbine active power output, r is the actual value of wind turbine active power output, N is the number of prediction samples, P is the installed capacity of wind turbine.

Set the number of hidden layer node as 13, the maximum number of epochs to train as 400, the performance goal as 0.0005, the minimum gradient as 10–10. The transfer function uses "tansig". When equally using hourly data of the previous 23 days as source data to predict hourly power output of the 24th day, the prediction results comparisons are as in Figs. 20.1, 20.2 and 20.3.

Keep BP neural network parameter settings unchanged, use every 10 min data of the previous 23 days as source data, to predict the previous 4 h' 10 min power output of the 24th day, the prediction results comparisons are as in Figs. 20.4, 20.5 and 20.6.

By comparing the three curves of the prediction results, it can be figured that, the advanced BP prediction model has higher prediction precision than the existing BP prediction models. The error range of the advanced BP prediction model is smaller, and plus and minus error are well-distributed, and this trend is even more apparent with the source data increase, which is helpful for the development of scheduling plan. In addition, short-term changes of wind power is very significant, the hourly average power range of the first 4 h is about 500–700 kW, while the every 10 min power average reaches even 300–900 kW.

Table 20.1 is the sensitivity indicator and accuracy indicator contrast. It can be figured that, the advanced BP prediction model is superior to the existing BP prediction models, and along with the source data increases, the advantage of the advanced BP prediction model is more obvious. For example, for hourly
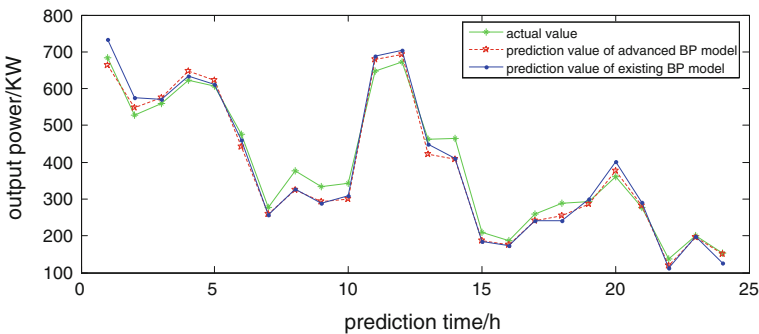

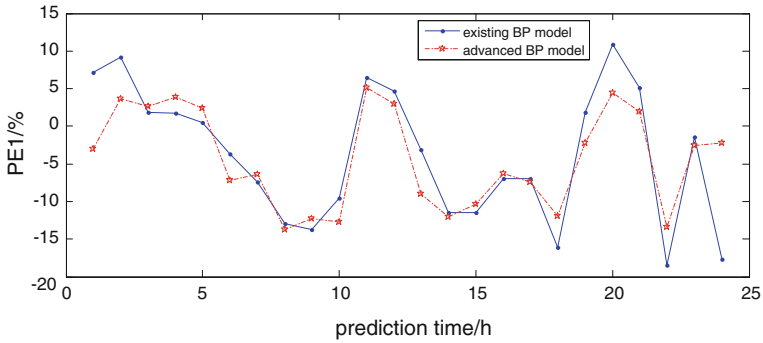**Fig. 20.1** Contrast of hourly prediction results

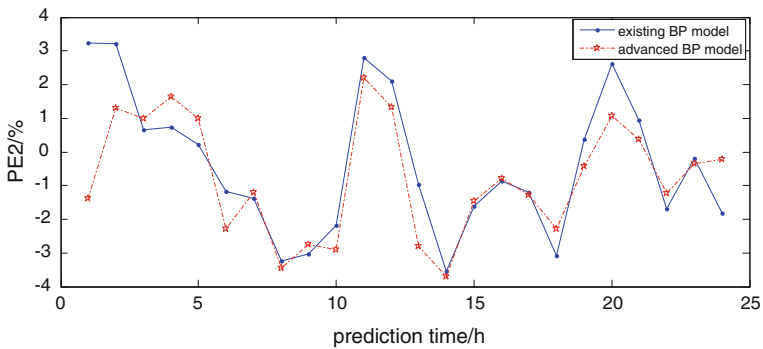Fig. 20.2 Contrast of hourly prediction results *PE*1 curve

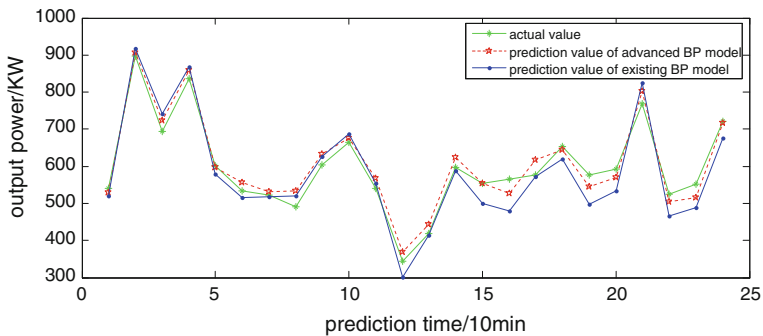Fig. 20.3 Contrast of hourly prediction results *PE*2 curve

Fig. 20.4 Contrast of every 10 min prediction results

prediction, the MRPE1 and the MAPE1 of the existing BP prediction model are respectively 18.5063 and 7.9397 %, while the MRPE1 and the MAPE1 of the advanced BP prediction model are respectively 13.7214 and 6.6606 %; and for every 10 min prediction, the MRPE1 and the MAPE1 of the existing BP prediction
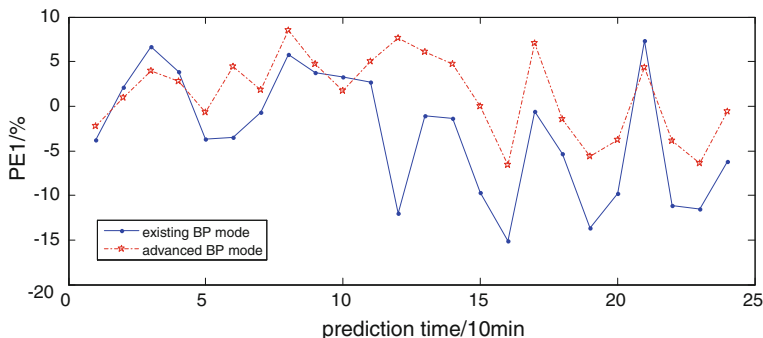
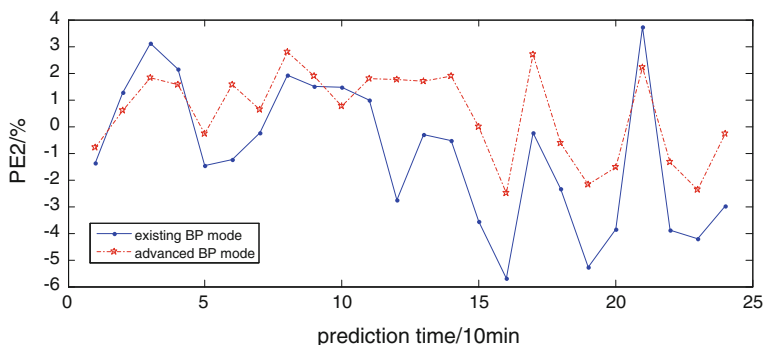**Fig. 20.5** Contrast of every 10 min prediction results $PE1$ curve

Fig. 20.6 Contrast of every 10 min prediction results $PE2$ curve

Table 20.1 Contrast of prediction results sensitivity indicator and accuracy indicator

Model	Hourly prediction		Every 10 min prediction	
	Advanced BP model (%)	Existing BP model (%)	Advanced BP model (%)	Existing BP model (%)
$MRPE1$	13.7214	18.5063	8.5072	15.1236
$MAPE1$	6.6606	7.9397	3.9605	6.0253
$MRPE2$	3.7067	3.5527	2.7858	5.6985
$MAPE2$	1.5955	1.7875	1.4816	2.3358

model are respectively 15.1236 and 6.0253 %, while the MRPE1 and the MAPE1 of the advanced BP prediction model are respectively 8.5072 and 3.9605 %. It shows that, the advanced BP prediction model chooses the appropriate training data set based on the weather data character of every prediction period, and then made specific training to get the mapping relation under weather condition of the period for wind power prediction. So that, the model is more sensitive and accurate, and with source data under all kinds of weather conditions increase the prediction accuracy can be further improved.

20.5 Conclusions

This paper briefly described the problems of the existing neural network models for wind power prediction at first. Then, for the shortcomings of the existing neural network model in selecting the training data sets, the advanced BP neural network model based on weather data similarity was proposed, and the improved modeling approach and prediction process was detailed. Finally, by prediction results analysis showed that the improved BP neural network model is advantage than the others of BP neural network model.

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