Short-term Power Prediction of Wind Farm Power Based on BP Neural Network

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Abstract. With the proportion of wind power in the power systems increasing, consideration must be given to the fact that the randomness and volatility of wind power output will inevitably affect the stable operation of power grid. One of the effective ways to solve this problem is to forecast the output of wind power. In this paper, we employ the method of BP neural network to predict the wind power output in a period of time. To discuss the predictive performance of BP neural networks, we set different number of input variables to observe the prediction effect of BP neural network. We find that it's not that the more input information, the better the prediction effect. The data with strong correlation can be used as input to achieve better results.

1. Introduction
With the rapid development of economy in the world, the rate of energy consumption is increasing rapidly. As a result, people have paid more attention to how to use energy efficiently. Traditional fossil fuels gradually decrease in the proportion of energy consumption because of the pollution to the environment. At the same time, clean energy, such as wind and solar power, has received more and more attention, and accounts for a growing proportion in energy consumption for the sake of its cleanness and reproducibility. However, compared with conventional energy, wind is volatility, intermittent, randomness and low density. Because of the characteristics of wind, it is predicted that the output of wind power generation is fluctuation and random. When wind power accounts for a large proportion in the grid, the fluctuation and random of wind output will inevitably affect the stable operation of the power grid. Therefore, if we can have a better forecast for the output of wind power, wind power can be utilized while effectively avoiding the impact of its volatility on the power grid[1, 2].

Depending on the predicted time scale, wind power prediction can be divided into the following categories: ultra-short term wind power prediction, short term wind power prediction and mid-and-long term wind power prediction. The time period of ultra-short term wind power prediction is no more than 30 minutes, and is applied in wind turbine system. The time period of short term wind power prediction is measured in hours, and is applied in power systems dispatch. Mid-and-long term wind power prediction is measured in weeks or months, and is applied in power systems planning.

In this paper, the purpose of wind power output forecast is for power system dispatching. Therefore, the time scale of wind power prediction is short term. For this problem, many scholars have achieved lots of valuable results.
2. The Basic Theory of Bp Neural Networks

2.1 The Introduction to Neural Networks
Neural network is an abstract, simplification and imitation of human brain. It is a mathematical model to simulate the structure of brain synaptic connection for data processing. Neural network algorithm uses a simple mathematical model to represent the structure of biological neural network, and simulates the intelligent behavior of biological neural networks to some extent. Its purpose is to solve the problem of complex system which cannot be solved by traditional algorithm. In mathematics, the neural network model realizes the parallel processing of data. Neural network is not only a highly nonlinear dynamic system, but also a self-organizing and adaptive system. Therefore, it can be said that neural networks have strong ability to deal with complex nonlinear problems, such as associative memory, nonlinear mapping, classification and identification, and optimization computation[3].

2.2 Basic Principles of Neural Networks
In practice, neural network model is a special mathematical model which can carry out distributed parallel information processing. In order to achieving the ability of distributed parallel information processing, the interconnections between each neuron must be adjusted. Fortunately, neural network algorithm has the ability of self-learning and adaptation. The neural network analyzes the provided input and output data to obtain the rule between them, and then calculates the corresponding output according to the rule, this process is also known as training[4]. Similar to biological nervous system, artificial neural network is also composed of a large number of neurons as the basic unit, which is the basic unit of neural network. Figure 1 shows an artificial neuron model with multiple inputs and single outputs. The corresponding mathematical formula can be expressed as follows:

\[ net_i = \sum_j w_{ij}x_j - \theta_i \]  \hspace{1cm} (1)

\[ y_i = f(\text{net}_i) \]  \hspace{1cm} (2)

\( x_i \) is the ith input signal of the neuron, \( w_{ij} \) represents the connection weight from neuron \( j \) to neuron \( i \). \( \theta_i \) represents threshold values and \( f(\bullet) \) is the excitation function. \( y_i \) is the actual output of neural network model.

![Artificial neuron model](image)

**Figure 1.** Artificial neuron model

2.3 The Connective Structure of Bp Neural Network
Neural network is a very complex interconnection system, and the connection mode between each neuron can have an important impact on function of the network. There are various types of interconnection modes. In this paper, BP neural network as the research object, the connective structure of BP neural network is feed forward neural network.

For feed forward neural network, it is composed of several layers, each layer is arranged in sequence according to the propagation order of the input signal and neurons in each layer can only receive signals from neurons in the previous layer. Moreover, there is no signal transmission between neurons in the same layer, and there is no feedback. The feed forward neural network can be
represented by a group of directed acyclic graphs as shown in Figure 2.

It can be seen from the Figure 2 that the input nodes have no computing function, simply represents the value of each element of the input vector. By comparison, hidden layer nodes have data processing capabilities. It should be noted that hidden layer nodes and output layer nodes can have any input, but only one output, and the output of a neuron can be sent to any node as the input of that node[5].

![Figure 2. The connective structure of feed forward neural network](image)

2.4 Bp Neural Network Training

At present, there are many kinds of learning algorithms for neural networks. The most common learning algorithms are supervised learning and unsupervised learning. In the supervised learning algorithm, the network output is compared with the expectation, then the weight of the network is adjusted according to the difference between the network output and the expectation in order to minimize the difference. In the unsupervised learning algorithm, after the input mode enters the network, the network adjusts the weights according to certain rule, making the network has the function such as pattern classification. For BP neural network, the problem to be solved has a clear expectation, supervised learning algorithm is employed to train or adjust the weights of BP neural network. Specifically, training algorithm of BP neural network is Delta learning rule. For Delta learning rule, we need to assume the error criterion function which is shown as follow.

\[
E = \frac{1}{2} \sum_{p=1}^{P} (d_p - y_p)^2 = \sum_{p=1}^{P} E_p
\]  
(3)

\[
y_p = f(W^T X_p)
\]  
(4)

\[
X_p = (x_{p0}, x_{p1}, \cdots, x_{pm})^T
\]  
(5)

d_p represents the desired output of BP neural network, y_p represents the actual output of BP neural network. W is the vector composed of all weights of the neural network. X_p is input mode, and The number of training samples is \( p = 1, 2, \cdots, P \).

The purpose of Delta learning rule is to minimize the error function by adjusting the weights. Gradient descent method can be used to adjust the weights. In detail, the basic idea is to modify the weight along the negative gradient of the error criterion function until the function reaches its minimum. The corresponding mathematical expression can be expressed as follow.

\[
\nabla W = \eta \left( -\frac{\partial E}{\partial W_i} \right)
\]  
(6)

\[
\frac{\partial E}{\partial W_i} = \sum_{p=1}^{P} \frac{\partial E_p}{\partial W_i}
\]  
(7)
Let $\theta_p = W^T X$, $y_p = f(\theta_p)$, we can obtain,

$$
\frac{\partial E_p}{\partial W_i} = \frac{\partial E_p}{\partial \theta_p} \frac{\partial \theta_p}{\partial W_i} = \frac{\partial E_p}{\partial y_p} \frac{\partial y_p}{\partial \theta_p} X_p = -(d_p - y_p) f'(\theta_p) X_p
$$

(8)

Then, the weight correction rule is

$$
\Delta \omega = \eta \sum_{p=1}^{P} (d_p - y_p) f'(\theta_p) X_p
$$

(9)

So far, we have obtained the weight correction method as shown in (9).

3. Short-Term Output Forecast of Wind Farm Based on Bp Neural Network

3.1 Data Preprocessing

The input parameters of the neural network have different benchmarks, if the input data is used directly, the algorithm may not converge. In order to avoid the above situation, the input data needs to be preprocessed, that is to say the data needs to be normalized. In this paper, we use matlab mapminmax function to normalize the input data.

3.2 Selection of Hidden Layer Nodes

For the multi-layer feedforward neural network, the number of hidden nodes is the key to the success of the network structure. If the number of hidden layer nodes is too small, the network cannot get enough information to solve the problem. By contrast, if the number of nodes in the hidden layer is too large, it will not only increase the training time of the network, but also decrease the generalization ability of BP neural network. Therefore, it is very important to select the number of hidden nodes reasonably. In this paper, According to the theorem of kolmogorov, we give the following hidden layer node selection strategy: if the number of input variables is $n$, the number of nodes in the hidden layer is generally $2n+1$.

3.3 Simulation and Analysis

For the short-term prediction of wind power in power system, the commonly used data sampling cycle is 15 minutes. In this paper, we use the historical output information of the wind power output to predict the wind power output in a period of time. We can define that the wind power output after 2 hours is predicted. Now we need to face the problem is how to choose the neural network input variables, achieving the most effective prediction. In this paper, we take an experimental approach to determine the best input variables. We set the number of input variables as four, eight, ten and twelve respectively, where each input variable represents a historical sampling point data. The specific experimental settings are shown below.

Cas1: For the input variables, there are four collection points, and the number of hidden layer neurons is nine. The output of wind output for the next half hour is predicted.

Cas2: For the input variables, there are eight collection points, and the number of hidden layer neurons is seventeen. The output of wind output for the next half hour is predicted.

Cas3: For the input variables, there are twelve collection points, and the number of hidden layer neurons is twenty-five. The output of wind output for the next half hour is predicted.

Cas4: For the input variables, there are sixteen collection points, and the number of hidden layer neurons is thirty-five. The output of wind output for the next half hour is predicted.

Based on the information in figures 3, figures 4, figures 5 and figures 6, it is clear that BP neural network achieves the best prediction effect when there are four collection points and the number of hidden layer neurons is nine. This is to say it’s not that the more input information, the better the prediction effect. The data with strong correlation can be used as input to achieve better results.
4. Conclusion

In this paper, we first introduce the basic concept, structure and algorithm of BP neural network. After that, we employ the method of BP neural network to predict the wind power output in a period of time. To discuss the predictive performance of BP neural networks, we set different number of input variables to observe the prediction effect of BP neural network. We find that it's not that the more input information, the better the prediction effect. The data with strong correlation can be used as input to achieve better results.

**Figure 3.** Simulation result of Case 1

**Figure 4.** Simulation result of Case 2

**Figure 5.** Simulation result of Case 3
5. **Acknowledgments**
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