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Study of Short-term Wind Power Prediction Considering the Individual Sample Prediction Error Correction

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Abstract

Wind power prediction of wind farm plays a decisive role in stable electric power system operation.The BP neural network's basic principle was introduced, and the numerical weather prediction (NWP) data and power data of wind farm as the training data of BP neural network was selected and trained; a linear regression model about the sample prediction error was presented, which considers the coupling relationship between the individual sample prediction error, the individual sample prediction error of BP neural network was selected as the regression factor, the individual sample prediction result of BP neural network was modified. As the modified prediction results performing, the prediction algorithm of short-term wind power considering the sample prediction error correction, has good self-learning and adaptive ability of BP neural network. It has overcome the shortcoming that the BP neural network has only considered the overall the prediction error of training samples, but without considered the prediction error of individual samples. This has further improved the prediction accuracy of BP neural network.

Keywords: *Wind Power Prediction; Numerical Weather Prediction; BP Neural Network; Prediction Error*

1. Introduction

Energy is the material foundation to support the progress of human civilization and also an integral part of the basic conditions for the development of modern society. In China to achieve modernization and all the people in the process of common prosperity, the energy is always playing an important strategic issue. Vigorously developing new and renewable energy is a key strategic measure for promoting the multiple and clean development of energy, and fostering emerging industries of strategic importance. It is also an urgent need in the protection of the environment, response to climate change and achievement of sustainable development. Through unswerving efforts in developing new and renewable energy sources, China endeavors to increase the shares of non-fossil fuels in primary energy consumption and installed generating capacity to 11.4 percent and 30 percent, respectively, by the end of the 12th Five-Year Plan [1].

Wind power as the most development value of renewable energy in the world, has been widely developed and utilized. However, due to the randomness of the wind speed, the wind power has a lot of instability and uncertainty, and this has an impact to the stable operation of the power system, which limits the power system to absorb the wind power. According to the national energy bureau the latest statistic report pointed out, Inner Mongolia wind power installed capacity accounted for about 30% of the total energy in the region, the share of wind

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turbine capacity connected to the power grid, however, less than 2% of the total wind power installed capacity. In order to improve the development and utilization of wind power, there is a need to further improve the accuracy of the wind power prediction. the use of traditional BP neural network to forecast the short-time power of the wind farm was introduced in [2-3], which considered the seasonal changes of wind speed in the prediction process, the predicted results met the application requirements; the different of wind power prediction between the using historical power information and the using historical meteorological information as well as power information is presented in [4], which pointed out that the result is more accurate using historical meteorological information as well as power information; a wind farm power prediction algorithm which combined with a variety of prediction algorithms was introduced in [5-7], which pointed out that the prediction accuracy of the combination forecast algorithm is better than the single prediction algorithm, but the calculation time is longer than the single one; the calculation method based on the uncertainty analysis of wind power prediction was introduced in [8-12], this method was used to determine the compensation for power fluctuations of wind farm, and given a statistical model for the statistics of the wind power prediction error, a punishment has been done for prediction model which have larger prediction error using the statistical results of the statistical model, thus contributing to the improvement of power prediction accuracy.

The BP neural network was presented in this paper, the numerical weather prediction (NWP) data and power data of wind farm as the training data of BP neural network was selected and was trained. The BP neural network only considers the Statistical relationship of these data, in order to consider the coupling relationship of the individual sample prediction error and to improve the prediction accuracy, a linear regression model about the sample prediction error was presented, the individual sample prediction error of BP neural network was selected as the regression factor, the individual sample prediction result of BP neural network was modified. As the modified prediction results displaying, the prediction algorithm of short-term wind power considering the sample prediction error correction, not only makes overall error of the sample meet prediction requirements, but also reduces the prediction error values of individual samples, and further improves the prediction accuracy of BP neural network.

2. BP Neural Network and its Improvement

2.1. The Theory of BP Neural Network

The BP network is also called error back propagation algorithm. A typical BP network is composed of input layer, hidden layer and output layer, and a whole link between each layer. The learning process of BP network is composed of mode forward propagation, error back propagation, memory training and learning convergence.

(1) Mode Forward Propagation

Mode forward propagation begins with the input layer of the network, the input pattern was provided to the input layer, and each unit of input layer corresponding to the individual elements of the input pattern vector. Make input pattern vector $Xz = (x1, x2 \ldots xn)$ and $(z = 1, 2 \ldots m)$, where z is the number of learning mode, n is the number of input layer unit. Corresponding to the input pattern, a desired output vector is $Yz = (y1, y2 \ldots yq)$, where q is the number of output layer unit. According to the calculation principle of BP network, the input of hidden layer can be expressed as follow.

$$S_j = \sum_{i=1}^{n} w_{ij} a_i - \theta_j \tag{1}$$

In the formula (1), S_j is the input value of hidden layer; θ_j is the threshold of hidden layer,$j = 1, 2 \dots p$; p is the number of hidden layer unit; w_{ij} is the connection weight between input layer and hidden layer; a_i is the i -th neuron of the input layer, $i = 1, 2 \dots n$.

In order to simulate the nonlinear characteristics of biological neurons, S_j was selected as the independent variable of S function, the output of the hidden layer was calculated, the mathematical expressions of S function as follow.

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

In the formula (2), b_j is the output value of j-th neural unit in hidden layer.

The threshold value θ_j of unit output has been set for simulating the threshold potential of biological neural; it is constantly being modified in the training process. The input of each unit in output layer is shown as follow.

$$L_t = \sum_{j=1}^{p} v_{jt} - \gamma_t \tag{3}$$

$$C_t = f(L_t) \tag{4}$$

In formula (3) and (4) , v_{jt} is the connection weight between the neural j in hidden layer and the neural t in output layer; γ_t is the threshold value of the output layer neuron, t is number of output layer neurons,$t = 1,2 \dots q$; f is the S function; L_t is the input value of the output layer neuron.

(2) Error Back Propagation

The first step of the error back propagation is to calculate the error. The process of error back propagation is the process of passing the error d_j of output layer to the error e_j of hidden layer. The calibration error of output layer can be expressed as follow:

$$d_t^k = \left(y_t^k - C_t^k\right) f'(L_t) \tag{5}$$

In the formula (5), $\left(y_t^k - C_t^k\right)$ is the absolute error between the wanted output and actual output of the network, $k = 1, 2 \dots m$, $f'(L_t)$ is the amount of deviation adjustment based on the actual response of each unit.

In order to complete the process of error propagation to the hidden layer, the calibration error of each unit in hidden layer needs to be calculated. The calibration error of hidden layer can be expressed as follow.

$$e_j^k = \sum_{t=1}^{q} v_{jt} d_t^k f'(s_j) \tag{6}$$

The physical meaning of the formula (6) and (5) is similar. But the calibration error of each intermediate unit in the hidden layer comes from the transformation of q units' calibration error in output layer.

After got the calibration error d_t^k and e_j^k, the connection weights between output layer and hidden layer, hidden layer and input layer, and the output threshold value of each unit were adjusted in reverse direction. The adjustment formula can be expressed as follow.

$$\Delta v_{jt} = \partial d_t^k e_j^k \tag{7}$$

$$\Delta \gamma_{jt} = \partial d_t^k \tag{8}$$

$$\Delta w_{ij} = \beta e_j^k a_i^k \tag{9}$$

$$\Delta \theta_j = \beta e_j^k \tag{10}$$

In the formula (7) to (10), α, β are the learning rate, 0<α<1, 0<β<1.

2.2. The Improvement of BP Neural Network

Due to the slow convergence speed and easy to fall into local minimum point for traditional BP neural network algorithm, the effect of actual use is poorer. In this paper, the inertial correction algorithm has been used to improve the traditional BP neural network algorithm. The so-called inertial correction algorithm is that in every time to correct the connection weights or output threshold value, it should plus the previous study correction in a certain proportion, namely the inertia item. That it can accelerate the convergence of network learning.

$$\Delta W\ (N)\ = d + \eta \Delta W\ (N-1) \tag{11}$$

In the formula (11), $\Delta W(N)$ is the deserved correction value in this time; $\Delta W(N-1)$ is the previous correction value; d is the correction value of error calculated in this time; η is the inertia coefficient($0 < \eta < 1$).

The learning rateα, β mentioned above is the constant in standard BP algorithm. If the learning coefficient is incorrect, it will lead to the slower convergence speed and the longer operation time of network. So it is a difficult thing that how to choose the best learning coefficient in training. This paper has adopted a method called the adaptive learning rate adjustment [8]. In the process of training, the learning rate is constantly adjusted according to the local error surface. The adjustment of learning rate can be expressed as below:

$$\alpha(n+1) = \begin{cases} k_{inc}\alpha(n), & E(t+1) < E(t) \\ k_{dec}\alpha(n), & E(t+1) > E(t) \\ \alpha(n), & E(t+1) = E(t) \end{cases} \tag{12}$$

In the formula (12), the increment of learning rate is greater than 1; the reduction of learning rate is less than 1. When $E(t+1) < E(t)$, means that the *t*-th iterative operation is effective, so that the learning rate should be increased. When $E(t+1) > E(t)$, means that the *t*-th iterative operation is invalid, so that the learning rate should reduced.

3. Model Establishing and Data Processing

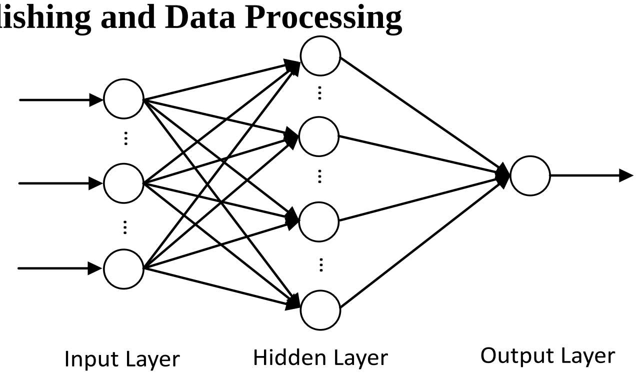

Figure 1. Neural network structure

According to the principle of BP neural network above, combined with the numerical weather forecast data and power data of the wind farm, a BP neural network model has been built. The neural network model of this paper is constituted by 3-layer, namely an input layer, a hidden layer and output layer .The input data of the input layer is mainly numerical weather prediction data, which include wind speed, wind direction, temperature, humidity and pressure. The wind direction can be expressed by the sine value and the cosine value of angle. So the number of neurons of input layer in neural network is 6.According to the construction experience of neural network, the number of hidden layer neurons is about 2 times the number of neurons in the input layer. In this paper, the number of hidden layer neuron is 13. The output of the output layer is mainly wind power, so that the number of output layer neurons is 1. Figure 1 is a neural network structure designed in accordance with the paper required.

The numerical weather prediction data and the output power data of the wind farm, from June 8 to August 8 were selected as data sample. The data samples were collected every 15 minutes. The type of fan in this farm is GE Company's 1.5MW, whose cut in speed is 3m/s, and its rated wind speed is 13m/s.

4. Network Training and Data Analysis

The 60 days' numerical weather data were selected as input data, and the 60 days' actual power as target output, to train the neural network. The training times are 2000, and the training error is 0.03. The final training results of error are shown in figure 2. As figure 2 shown, the network training will be end when the training time reaches 609 and the gradient decreases to 9.78e-6. At this time the optimal error value is 0.0457, and the percentage value is 4.57%.

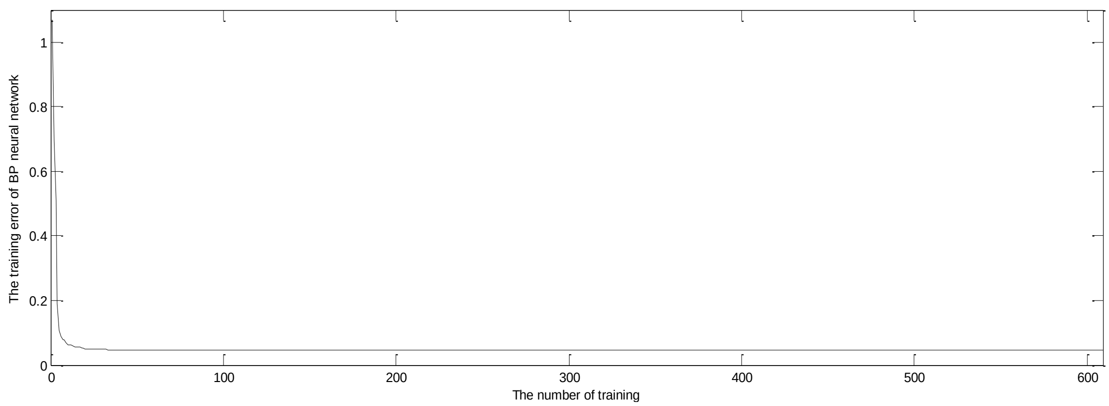

Figure 2. The processing of error changing

Figure 3 is a comparison between the actual output power of wind farm and the network computing power. In this figure, the black line is the actual output power of wind farm, and the blue line is the network computing power. It is can be known from the figure that the same trend between the actual output power of wind farm and the output power of neural network, the power prediction error of wind farm is 13%, which is less than 20% and meet the requirements of the power system [12].

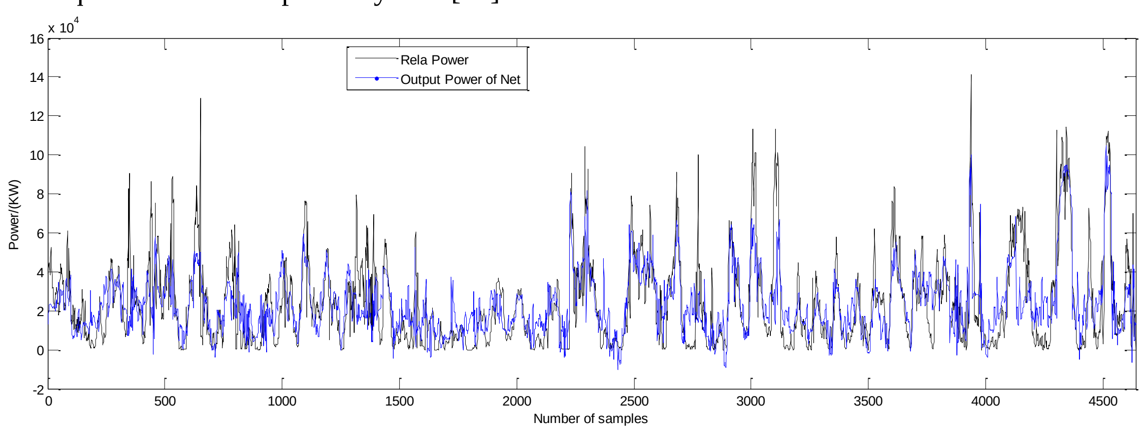

Figure 3. Real power and output of net

Figure 4 is the individual sample error percentages between the actual power value and the BP neural network predictive value. It can be seen from the figure that some sample error percentage has reached to 100%, which shows that a single sample error value is large and it cannot meet the requirements of the power system. The reason for this is because the BP neural network only considers the overall sample error value, but not considers the coupling relationship of individual sample error. During the power system operation, the error values of individual samples have played a truly decisive role to the stability of power system. Therefore, how to reduce individual sample error value needs further research.

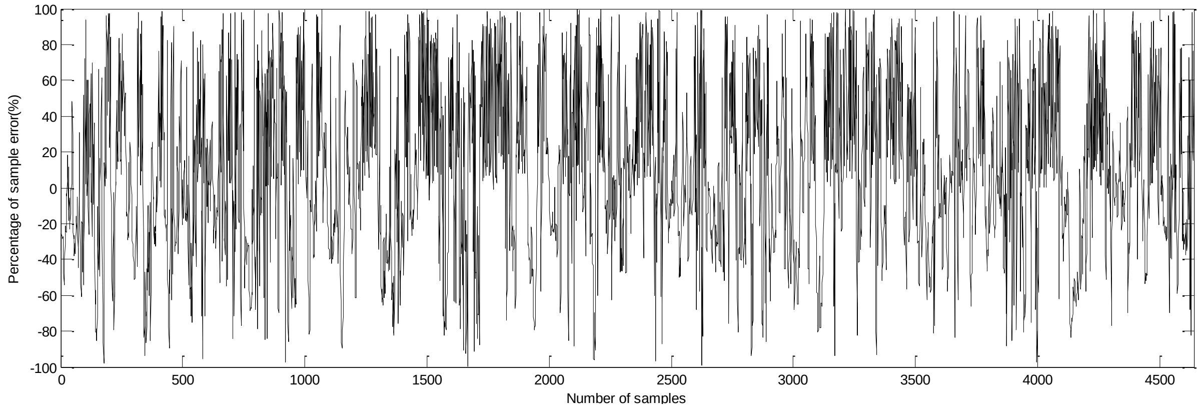

Figure 4. percentage of sample error

5. The Linear Regression Model of Individual Sample Prediction Error

The conclusion above shows that for the BP neural network prediction system, the overall sample error satisfies the requirement of the power system, but the individual sample error cannot. So this paper proposes a linear regression model to reduce the individual sample prediction error, the idea is as follows:

(1)Assuming that the sample of actual output power and the corresponding sample of predicted power are $y1, y2, y3, y4, y5, y6 \ldots ym$ and $x1, x2, x3, x4, x5, x6 \ldots xm$, getting n consecutive values of the actual output power and its corresponding predicted power value respectively, $y1, y2, y3, y4, y5, y6 \ldots yn$ and $x1, x2, x3, x4, x5, x6 \ldots xn$;

(2)The error of each point was calculated by $Ei = yi - xi$, where $i = 1,2, \ldots, n$;

(3) The error of $E\ (n+1)$ can be calculated by multiple linear regression, the formula is (13);

$$E\ (n+1) = \beta 1E1 + \beta 2E2 + \cdots \beta nEn \tag{13}$$

In formula (13), βi is the regression coefficient; βi can be calculated by the least square method.

(4) When the $E\ (n+1)$ was calculated by formula (13), the prediction power of individual sample by BP neural network can be revised as follow:

$$P(n+1) = \frac{P_p(n+1)}{1-E(n+1)} \tag{14}$$

In formula (14), $P_p(n+1)$ is the prediction power of individual sample by BP neural network, $P(n+1)$ is the prediction power of individual sample after revised.

Using the linear regression model of individual sample prediction error, the prediction power of BP neural network was corrected by (14). The correction result of individual sample error was shown in figure 5. As the figure shown, the individual sample error after corrected is reduced obviously .In this case, the prediction power of BP neural network improves the stability of power system.

Figure 6 is the comparison of the individual sample prediction error; the black dot line is the individual sample prediction error of BP neural network before corrected, the blue line is the individual sample prediction error of BP neural network after corrected by the linear regression model, the individual sample error after corrected is reduced obviously in figure 6.

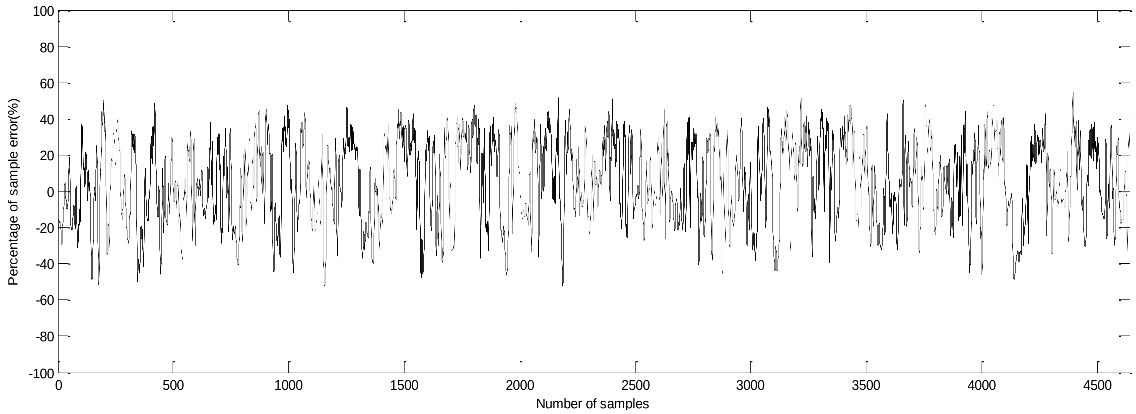

Figure 5. Percentage of the individual sample error after corrected

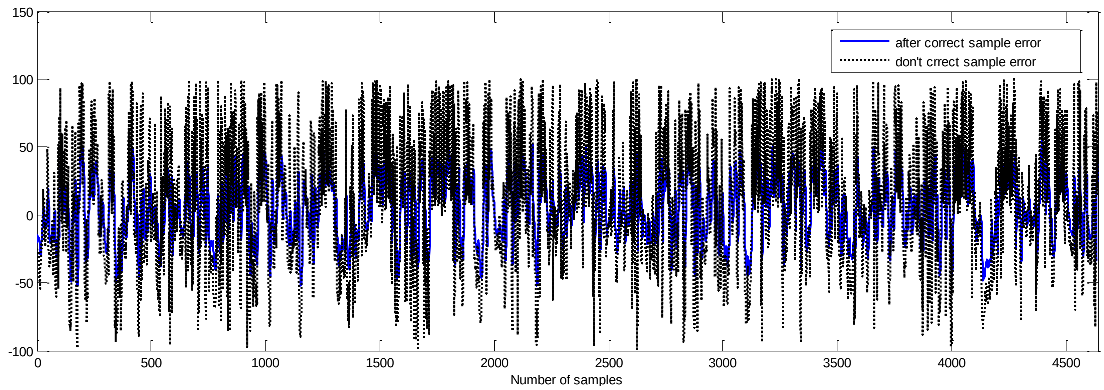

Figure 6. Comparison of the individual sample prediction error

6. Conclusion

Principle of BP neural network is introduced, and a BP neural network model has been built and improved according to the characters of data from wind farm. The numerical weather prediction (NWP) data and power data of wind farm are selected as the training data of BP neural network; the BP neural network was trained. The wind power has been predicted using the trained BP neural network.

A linear regression model about the sample prediction error was presented, which considers the coupling relationship between the individual sample prediction error, the individual sample prediction error of BP neural network was selected as the regression factor, the individual sample prediction results of BP neural network was modified. The comparison of the individual sample prediction error is introduced; the individual sample error after corrected is reduced obviously compare to before corrected.

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