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STUDY OF WIND POWER SHORT-TERM PREDICTION OF WIND FARM BASED ON NWP AND FUZZY NEURAL NETWORK

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ABSTRACT

Wind power prediction of wind farm plays a decisive role in stable electric power system operation. Firstly to introduce fuzzy neural network's basic principle; secondly to use 60 days numerical weather prediction (NWP) data and power data, from Jun.08 to Aug.08, as the training data of fuzzy neural network to train the fuzzy neural network; finally to use the next 2 days NWP data, from Aug.09 to Aug.10 as input data of fuzzy neural network, to predict the next 2 days output power of wind farm. The training process and prediction result show that fuzzy neural network has fuzzy decision and judgment, and has good self-learning and adaptive ability, which improves the stability of prediction system and prediction accuracy.

Keywords: *Wind Power Prediction Of Wind Farm; Numerical Weather Prediction (NWP); Fuzzy Neural Network; Prediction Error*

1. INTRODUCTION

Energy is the material foundation to support the progress of human civilization, also is an integral part of the basic conditions for the development of modern society. In China to realize modernization and common prosperity of all the people, the energy is always 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. At the end of "Twelfth Five-Year Plan ", non fossil energy consumption accounts for the proportion of primary energy consumption will reach 11.4%; non-fossil energy power installed a proportion to achieve 30% [1].

Wind power is the most potential energy 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 great volatility and uncertainty; this Influences the stable operation of the power system, which limits the power system to absorb the wind power. 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 this region, the share of wind 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, it is necessary to improve the accuracy of the wind power prediction. In [2-3], traditional BP neural network is used to forecast the short-time power of the wind farm, the seasonal changes of wind speed is considered in the prediction process, the predicted results met the application requirements; YUAN Tie-jiang [4] pointed out the difference between only using historical power information to predict future wind power and using historical meteorological information and historical power information in the same time to predict future wind power, he pointed out that using historical meteorological information and power information in the same time is more accurate forecasts; in [5-7], a kind of wind farm power prediction algorithm is introduced which is combined by multiple prediction algorithm , this kind of wind farm power prediction algorithm shows that the prediction accuracy of the combination forecast algorithm is better than the

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single prediction algorithm, but the calculation time is longer than the single prediction algorithm.

This paper first introduces the fuzzy neural network's basic principle; Secondly, using 60 days numerical weather prediction (NWP) data and power data, from Jun.08 to Aug.08, as the training data of fuzzy neural network to train it; finally to use 2 days NWP data, from Aug.09 to Aug.10 as input data of fuzzy neural network, to predict the next 2 days output power of wind farm. The training process and the prediction results show that, the fuzzy neural network has fuzzy decision and judgment, and has good self-learning and adaptive ability, it overcomes the disadvantages of fuzzy logic about strong subjective factors, it also overcomes the disadvantages of neural network which is easy to fall into local minimum and slow convergence speed, improves the stability and the prediction accuracy of the prediction system.

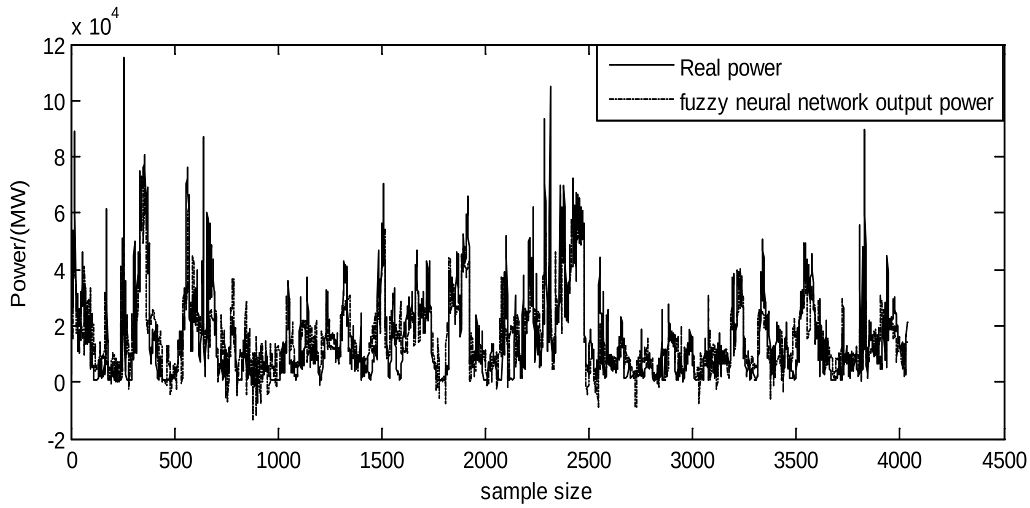

Figure 5: Real Power And Prediction Power

2. DATA ANALYSIS AND FUZZY SUBSET

NWP data for the wind farm, which mainly includes wind speed, wind direction, temperature, humidity and pressure of the 5 data. Wind turbine during operation, have the function to aim at the wind direction automatically, so the wind direction on the influence of wind power output cannot be considered in. For temperature, humidity and pressure the 3 NWP data, humidity on the influence of wind power output is more significant, and the changes in temperature and pressure can be reflected through the humidity. So this paper only considers the humidity information, then the wind speed fuzzy subset and humidity fuzzy subset can be got.

(1) Wind speed fuzzy subset

Wind speed and wind power have 3 power relations, the change of wind speed in wind power change plays a decisive role. Therefore, in the wind power fuzzy subset division, you should as far as possible divide the scope of the fuzzy subset into smaller. Commonly the wind speed range of wind turbine operation is between 3-20m /s, the wind speed change for every 2m /s is divided into a subset; 9 wind fuzzy subsets can be obtained.

(2) Humidity fuzzy subset

In china, all the year round the humidity change range is 10%-100%, every 10% humidity change is divided into a fuzzy subset, and 9 humidity fuzzy subsets can be got.

3. THE ESTABLISHMENT OF FUZZY NEURAL NETWORK MODEL

3.1 The Structure of Fuzzy Neural Network

Fuzzy neural network has five layers, namely input layer, fuzzy layer, fuzzy reasoning layer, de-fuzzy layer and output layer.

(1) Input Layer

This layer plays the role to transmit the training data of network to the next layer, the number of its input node is decided by the dimension of the input vector. For the prediction system in this paper, the input data are wind speed and humidity, which can identify the number of the fuzzy neural network's input layer neuron, the number is 2.

(2) Fuzzy Layer

In this layer, each node represents a language variable value; its role is to calculate the input component belongs to the language variable fuzzy

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set membership function value. The following equation is used to express as:

$$\mu_i^j = \mu_i^j(x_i) \qquad i=1,2 \quad j=1,2\cdots,m_i \tag{1}$$

In equation (1), x_i is the first i component of the input variables, and m_i is the number of the fuzzy grade division of x_i. According to the principle of fuzzy subset classification presented in the last section, two input variables of the fuzzy grade respectively are $m_1 = 9$ and $m_2 = 9$, so the total number of this layer is $N_2 = \sum_{i=1}^{2} m_i = 18$·

Due to the Gaussian function has the characteristics of smooth transition; therefore, the membership function uses Gaussian function in this paper. The equation as:

$$\mu_{A_{ij}}(x_i) = exp[-(\frac{x_i - c_{ij}}{\sigma_{ij}})^2] \tag{2}$$

In equation (2), c_{ij} is the first j fuzzy grade center of the input components x_i, and σ_{ij} is the first j fuzzy grade width of the input components x_i.

(3) Fuzzy reasoning layer

Each node in this layer represents a fuzzy rule and it used to match the former parts, and then calculate the fitness of each rule, its computation equation as show:

$$a_j = \mu_1^{j1}\mu_2^{j2} \tag{3}$$

In equation (3), $j_1 \in \{1,2,\cdots 9\}$ $\quad j_2 \in \{1,2,\cdots 9\}$, $j = 9\times 9 = 81$.So the number of node in this layer is 81($N_3 = j = 81$).

(4) de-fuzzy layer

This layer realizes the normalized calculation, and the calculation equation as:

$$\bar{a}_j = a_j \Big/ \sum_{j=1}^{81} a_j \,, j = 1,2,\cdots 81 \tag{4}$$

In this layer the number of node is the same as the third layer.

(5) Output layer

The output layer realizes the clear calculation, as:

$$y = \sum_{j=1}^{181} \omega_j \bar{a}_j \qquad j = 1,2,\cdots 81 \tag{5}$$

In equation (5), ω_j is the connection weight between the fourth layer and the fifth layer, the number of node in this layer is $N_5 = 1$, the node is the output value of the prediction result. So the fuzzy neural network model structure is 2-18-81-81-1. The fuzzy neural network structure is shown in figure 1.

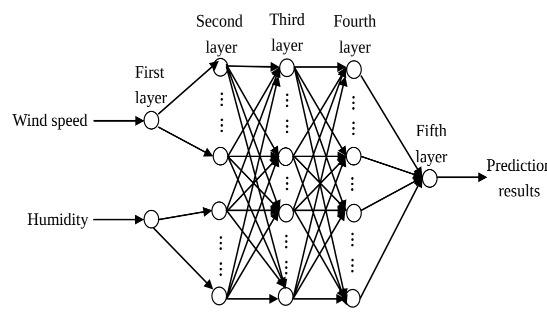

Figure 1: Fuzzy Neural Network Structure

3.2. Parameter Adjustment

The parameters of fuzzy neural network are adjusted in the training process, and finally satisfied requirements of the model parameter values. These parameters which are adjusted include the membership function center value c_{ij} and width value σ_{ij} of the fuzzy layer and the connection weights ω_j between the de-fuzzy layer and output layer. The training algorithm of fuzzy neural network commonly include gradient descent, least square, error back propagation and hybrid learning algorithm, etc. In this paper, the error back propagation algorithm is used to train of c_{ij}, σ_{ij} and ω_j. The training process is as follows:

(1) The training process of connection weights

$$\omega_j(t+1) = \omega_j(t) + \beta(y_d - y)\bar{a}_j \cdot x_i \tag{6}$$

In equation (6), t represents the number of training time, β is learning rate, $(y_d - y)$ is the difference of the target output and actual output.

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(2) The training process of central value c_{ij} and width value σ_{ij}

$$c_{ij}(t+1) = c_{ij}(t) + \beta \frac{\partial E}{c_{ij}} \tag{7}$$

$$\sigma_{ij}(t+1) = \sigma_{ij}(t) + \beta \frac{\partial E}{\sigma_{ij}} \tag{8}$$

Where

$$E = \frac{1}{2}(y_d - y)^2 \tag{9}$$

4. NETWORK TRAINING AND DATA ANALYSIS

NWP data during 60 days were collected as input data, to train fuzzy network. The training times were 120, and the training error is 0.03, error training process as shown in figure 2. From the figure 2, it is known that when training time is 105, the mean square error has reached the training requirements.

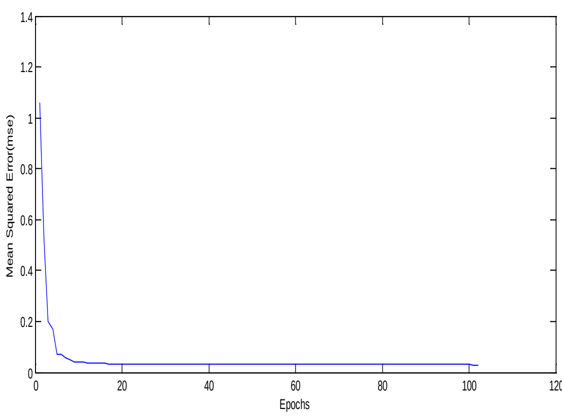

Figure 2: Error Training Process

The initial membership function distribution about the fuzzy subset of wind speed was shown in figure 3 figure 4 is the trained membership function distribution about the subset of wind speed. From figure 3 and figure 4, it is known that the parameters change is not obvious between the initial membership function and the trained membership function about fuzzy subset of wind speed; this indicate that it is reasonable to divide wind speed range into 9 fuzzy subsets.

Figure 5 is a comparison result between the fuzzy neural network prediction power and the real power from wind farm. In this figure the solid line represents the actual output power of the wind farm, the dotted line represents fuzzy neural network prediction power. From the changes of the two curves, it can be seen that fuzzy neural network accurately reflects the variation rule of the wind farm output power with the NWP data.

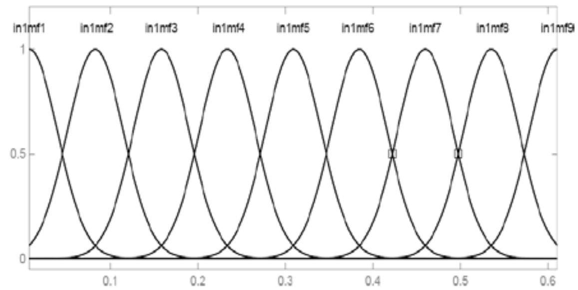

Figure 3: Initial Membership Function

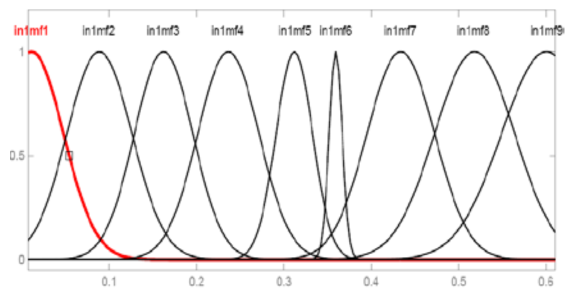

Figure 4: Trained Membership Function

5. CONCLUSION

This paper analyzes the fuzzy neural network's basic principle, and proposes the wind power prediction model based on NWP data and fuzzy neural network algorithm. Firstly, to analyze and process the NWP data, then selects the wind speed data and humidity data as the fuzzy neural network's input data, the input data is fuzzified; Secondly, fuzzy neural network construction process and training process are presented. Finally, a complete fuzzy neural network model is established.

To use 60 days numerical weather prediction (NWP) data and power data, from Jun.08 to Aug.08, as the training data of fuzzy neural network to train the fuzzy neural network; then to use the next 2 days NWP data, from Aug.09 to Aug.10, as the fuzzy neural network's input data, to predict output power of the wind farm in the next 2 days. The training process and prediction result shows that fuzzy network has the intelligent judgment and decision making, and also has the good self-learning and adaptive ability. This model has overcomes the disadvantages such as strong

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subjective factors of the fuzzy logic, easy to fall into local minimum of the nerve network and slow convergence speed. The fuzzy neural network prediction system improves the stability of prediction system and prediction accuracy.

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