Short-term Power Forecast of Wind Power Generation Based on Genetic Algorithm Optimized Neural Network

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Abstract. With the rapid development of economy, human consumption of fossil energy has caused a global energy crisis. Nowadays, countries all over the world are making great efforts to develop clean energy. Wind energy as one of the pollution-free, renewable and high-quality clean energy, has attracted widespread attention. However, wind power generation is easily affected by natural factors and is instable. In order to improve the quality of wind power, this paper analyzes the influencing factors of wind power, studies the prediction method of wind power forecasting, and uses genetic algorithm optimization neural network to forecast the wind power of a wind farm in Northwest China, which may provide some reference for the power generation and grid connection of wind power plants.

1. Introduction
With the growth of population, the rapid development of urbanization and the increasing demand of society, people's demand for energy is also increasing. While the exploitation of traditional fossil energy accelerates the ecological destruction and environmental pollution. Under this situation, the utilization scale of clean energy such as natural gas, solar energy, wind energy, hydropower, geothermal and other clean energy begins to grow, and the world primary energy consumption structure is evolving into low carbon [1]. Wind power generation is greatly affected by environmental factors, and its intermittence and randomness will lead to the decline of power quality of the power grid, which may have a certain adverse impact on the safety and stability of the power system [2]. Therefore, accurate and stable prediction of wind speed is crucial to power grid security management and market economy.

2. Present Research Situation of Home and Abroad

2.1. Present Research Situation of Abroad
In order to better extract the data features of wind series, Azimi R and Ghofrani M et al. propose T.S.B K-means, a new K-means clustering method based on time series. Combining with the T.S.B K-means, discrete wavelet transform (DWT), harmonic analysis time series (HANTS) method and multilayer perceptron neural network (MLPNN), the wind power is forecasted. Finally, the results show that the proposed new prediction method has superior performance [3].
Lahouar A and Ben Hadj Slama J used the random forest method to establish a wind power forecasting model. The data used to test the model come from the Sidi Daoud wind farm in Tunisia. The test results show that, compared with the traditional neural network prediction, the proposed model can significantly improve the prediction accuracy and greatly reduce different error standards [4].

Sharifian A and Ghadi M J et al. propose a method based on hybrid T2FNN-PSO algorithm for medium-and long-term wind power forecasting under uncertain data. By using Type-2 fuzzy sets as Type-2 fuzzifiers, this method can effectively deal with the uncertainties related to the initial data obtained from SCADA systems, NWP and measurement tools. In addition, this method has a simple structure, so it can reduce the calculation time of the training phase in the system. Simulation results show that this method can be used for accurate wind energy prediction in power system control centers [5].

Nielson J and Bhaganagar K et al. successfully forecasted the power curve and energy of the specific location by using 4-layer feedforward propagation (FFBP) artificial neural network (ANN). The results prove that, compared with other methods that utilized the atmospheric stability or density correction power curve, this method improves the performance of the power curve [6].

2.2. Present Research Situation of Home

Liang Yaoguang of Guangxi University established a wind power forecasting model by using artificial fish swarm algorithm to optimize the parameters of support vector machine. And simulation experiments conducted by MATLAB software verified that the AFSA-SVM optimization model performs better in short-term wind power forecasting [7].

Lu Xin, Shen Yanxia et al. construct a simple interval prediction model of wind power based on artificial bee colony neural network (ABC-NN). According to the state transition probabilities of Markov chain, the numerical points of wind power in the prediction interval are analyzed, and the prediction accuracy is improved [8].

A prediction method of wind power integration of Boosting regression tree and random forest is used to predict the actual data, and the root mean square error is as low as 0.1488 [9].

Wu C and Wang J proposed a novel hybrid prediction system, which includes effective data decomposition techniques, multi-objective optimization algorithms, prediction algorithms and a set of comprehensive evaluation methods. Taking Shandong Peninsula of China as an example, the wind speed data are collected every 10 minutes for comprehensive evaluation. The results showed that the hybrid system proposed surpassed other single models and traditional models, and had high precision and strong stability at the same time [10].

2.3. Overview of current situation and research content

The wind power industry in China started relatively late, the supporting facilities of the wind power plant are not perfect, and there is a certain gap between the actual performance and the theoretical performance of the generator set. A single method has difficulties in solving the current complex problems, so it is necessary to integrate various methods [11]. Therefore, this paper will use neural network to predict the short-term power of wind power generation, and genetic algorithm will be used to optimize the weight and threshold of neural network to prevent the model from falling into local optimization and improve the accuracy of neural network prediction.

3. Mathematical principle

3.1. Neural Network

Artificial neural network (ANN) is a model established by imitating the interconnection of biological neurons with mathematical expressions, which can have the same simple perception and judgment ability as human beings. Different connections between neurons can construct different kinds of neural networks, BP (Back Propagation) neural network is one of the most commonly used. When the desired output is obtained, the error is propagated in the opposite direction of the neural network to modify the
weight between the layers, and the required accuracy is achieved in the continuous correction learning. The structure of the BP neural network is shown in figure 1, where the pk is the number of nodes in the k-layer hidden layer, k=1, ..., l.

The values before and after the node of the k-th hidden layer are respectively

\[ u_j^k = \sum_{i=1}^{l} \omega_{ij}^k + b_j^k, u_j = f_k(u_j^k), j=1, \ldots, pk \] (1)

The signals before and after the transfer function of the output layer are respectively

\[ y_j^l = \sum_{i=1}^{p_k} u_i y_{ij} + \omega_{ij}, y_j = f_{l}(y_j^l), j=1, \ldots, pl \] (2)

Figure 1. Basic structure of BP Neural Network [12].

3.2. Genetic algorithm

Genetic algorithm (GA) is a parallel random search optimization method proposed by Professor Holland to simulate the heredity and evolution of organisms in nature. According to the selected fitness function starting from a group of randomly generated initial populations, individuals are screened through random selection, crossover and mutation operations, and after continuous reproduction and evolution, it converges to the global optimal solution in continuous iteration [13].

The selection operation is to select a number of individuals from the previous generation to the next generation with a certain probability. The higher the individual fitness value is, the greater the probability of being selected is.

The crossover operation is to randomly select two individuals in the population and randomly select one or more points on the chromosome to exchange.

The mutation operation is to randomly select an individual in the population and randomly select a point on the chromosome to mutate, which is used to produce better individuals.

4. Model building

4.1. Data collection

Wind energy depends on many meteorological parameters, such as wind speed, wind direction, humidity and temperature. It can be regarded as a nonlinear mapping function of these variables and their previous values [14]. Five input variables are set, which are wind speed of wind tower 70m, wind direction of wind tower 70m, temperature, air pressure and humidity, and one output variable is the actual power generation. The data was obtained from the log of a northwest wind farm at an interval of 15 minutes. After preliminary screening and processing of the data, 96 groups of data from a random day were selected. After random disturbance, the first 80 groups were selected as the training group and the last 16 groups as the prediction group.
4.2. Algorithm Flow Diagram

- Determine the network structure
- Initialize the network
- Individual coding of initial population
- Input data
- Data normalization
- Train a neural network
- Use training error as fitness
- Select
- Cross
- Mutations
- Select
- Calculate fitness
- Whether the end condition of genetic algorithm is met

Figure 2. Algorithm Flow Diagram.

4.3. Algorithm Flow Diagram

The topology of the neural network is determined. The input layer has five input variables, two hidden layers, each hidden layer has 10 nodes and one output variable. The first 80 groups of data were used as the training group, and the last 16 groups of data were taken as the test group.

Assign the weights and thresholds of the optimal individual to the neural network, and some of the key codes are shown in figure 3.

The training of neural network can be completed by using the train() function of the deep learning toolbox of MATLAB.

4.4. Algorithm Flow Diagram

Several individuals are selected to form the initial population, and the population size is set to 15. The sum of the error absolute value between the predicted value and the expected value is taken as the fitness
function $F$, and the lower the $F$ value is, the better the individual is. Selection, crossover and mutation are calculated as follows [15].

The selection operation adopts roulette. The formula is as follows:

$$P_i = \frac{f_i}{\sum_{i=1}^{n} f_i}$$  \hspace{1cm} (3)

Where $P_i$ is the probability of individual $i$ is selected; $f_i$ is the fitness value of individual $i$; $n$ is the number of individuals in the population.

The real number crossing method is used in the crossover operation. The chromosome crossover manipulation between the $k$-th chromosome $a_k$ and the $l$-th chromosome $a_l$ at the $j$ position, as shown in formula 4:

$$a_{kj} = a_{kj}(1 - b) + a_{lj}b$$
$$a_{lj} = a_{lj}(1 - b) + a_{kj}b$$  \hspace{1cm} (4)

where $b$ is random number in $[0,1]$.

Select the $j$ gene of the $i$-th chromosome for mutation operation, as shown in formula 5 and formula 6:

$$a_{ij} = \begin{cases} a_{ij} + (a_{ij} - a_{\text{max}})f(g), & r \geq 0.5 \\ a_{ij} + (a_{\text{min}} - a_{ij})f(g), & r < 0.5 \end{cases}$$  \hspace{1cm} (5)

$$f(g) = r_2 \left( 1 - \frac{g}{G_{\text{max}}} \right)$$  \hspace{1cm} (6)

Where $a_{\text{min}}$ is the lower boundary of gene; $a_{\text{max}}$ is the upper boundary of gene; $r$ is the random number in $[0,1]$, $r_2$ is a random number, $g$ is the current number of iterations; $G_{\text{max}}$ is the iterative coefficient.

5. Result analysis

The training process of the optimized neural network is shown in figure 4, and the final training error is $3.93e-5$. The comparison between the prediction and the actual data is shown in figure 5, which indicates that the model can forecast the short-term wind power within the acceptable error range. The decline process of the predicted mean square error is shown in figure 6, which shows that the optimal result is obtained when the training is up to the 63rd time. In the process of genetic algorithm optimization, the decline of fitness is shown in figure 7. The regression analysis results are shown in figure 8, $R=0.93$ indicates that the model has a good fit level. The method used in this paper can describe the relations between the factors affecting wind power generation and the output electric power to some certain extent.

![Figure 4. Neural network training process](image-url)
6. Discussion
In this paper, the data of a power plant in northwest China is to train in the neural network, and genetic algorithm is used to optimize the weights and thresholds of the neural network. And then 16 groups of data are selected for prediction, the mean square error of the prediction result is 3.93e-5, which indicates that the model has the higher fit level, and it is can be conducted easily with the help of MATLAB 2020a software. As a whole, it has a certain reference and application value for wind power forecasting.

In the prediction process of this paper, five variables are selected as inputs. However, for such a complex model as wind power forecasting, there still be some situations that cannot be well considered. The wind power prediction model established in this paper only studied from the perspective of mathematics, and the actual physical information is not taken into account, such as topography, longitude and latitude. At the same time, there are some factors that interfere with the data, such as maintenance, unstable fan performance. Therefore, there is still much room for improvement of the model.

7. Conclusion
In the process of short-term prediction of wind power, genetic algorithm is creatively used to optimize the neural network in this paper, and a model with high degree of fitting is obtained. The model can predict the short-term wind power, which may be conducive to power grid planning and security and stability analysis, and has a certain value in practice. In the future, the screening mechanism of data can be added, and the model can be optimized with the knowledge of geography and meteorology to improve the forecasting accuracy of the model.

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