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A New Combination Prediction Model for Short-Term Wind Farm Output Power Based on Meteorological Data Collected by WSN

Li Ma[1, 2, 3], Bo Li[1, 2], Zhen Bin Yang[4], Jie Du[1, 2] and Jin Wang[1, 2]

[1] *Jiangsu Engineering Center of Network Monitoring, Nanjing University of Information Science & Technology, Nanjing 210044*
[2] *School of Computer & Software, Nanjing University of Information Science & Technology, Nanjing 210044*
[3] *Key Laboratory of Meteorological Disaster of Ministry of Education, Nanjing University of Information Science & Technology, Nanjing 210044*
[4] *CMA Public Meteorological Service Centre, Beijing 100081*

mali1775088@163.com; nmjnlxd@sina.com; wangjin@nuist.edu.cn

Abstract

The prediction of wind farm output power is considered as an effective way to increase the wind power capacity and improve the safety and economy of power system. It is one of the hot research topics on wind power. The wind farm output power is related to many factors such as wind speed, temperature, etc., which is difficult to be described by some mathematical expression. In this paper, Back Propagation (BP) neural network algorithm is respectively combined with genetic algorithm (GA) and particle swarm optimization (PSO) to establish the combination prediction model of the short-term wind farm output power based on meteorological data collected by Wireless Sensor Network (WSN). The meteorological data is used to determine the input variables of the BP neural network. Meanwhile, the GA and the PSO is respectively used to adjust the value of BP's connection weight and threshold dynamically. Then the trained GA-BP and PSO-BP neural network are used to predict the wind power by combination method. The experiment results show that our method has better prediction capability compared with that using BP neural network, GA-BP neural network and PSO-BP neural network alone.

Key words*: Wind Farm, Combination Prediction, GA, PSO, WSN*

1. Introduction

Wind energy is a kind of renewable and clean energy which has been concerned all over the world. Wind power is one of the fastest growing and most mature renewable power generation technologies. However, wind power also has its drawbacks. Due to the properties of volatility, intermittency, low energy density, and uncontrollability, wind power is fluctuant and intermittent. When the proportion of wind power in power grid is small, the above characteristics are not able to influence the performance of power grid. However, as the development of wind power, the power generated from wind plays a very important role in power generation. Hence, in order to make a reasonable power generation plan and ensure the steady performance of power system, the prediction model of wind farm output power is required [1-3]. According to different standards, the methods of power prediction can be divided into different class. For example, 1) in accordance with the prediction time, the methods of power prediction are classified into long-term prediction method, mid-term

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prediction method, short-term prediction method and super short-term prediction method. 2) In accordance with the prediction parameters, the methods of power prediction are classified into wind speed-based prediction method and output power-based prediction method. 3) In accordance with the prediction models, the methods of power prediction are classified into physical prediction method, statistic prediction method, and learning method. In this paper, we use the neural network method to research the prediction of wind farm output power [4-5].

Recently, the technical of wind power prediction is not mature in China. Previous researches by continuous method, time sequence method, and neural network method make some improvement in practical experiment, without prediction accuracy [6-7]. Most of them lack of wind farm output power based on meteorological information collected from WSN. Furthermore, the combination prediction method on the basis of BP neural network respectively using GA and PSO optimization is rarely mentioned. Therefore, in this paper, we design a new wind farm output power combination model, which is based on the meteorological data collected from WSN and BP neural network respectively using GA and PSO optimization to perform the short-term wind power prediction. It is worth noting that short-term prediction can satisfy the requirement of market trade, system maintenance scheme, and safe power supply.

2. Meteorological Data Collected by WSN

Meteorological data can be collected by WSN. However, the way of data collection and transmission is manual setup or wired operation. When the number of wind fans in wind farm is huge, it will result in high communication cost and complicated route. It is not easy to operate. ZigBee is a wireless transmission technology with short distance, low speed, lower-power consumption, low cost, and low complexity. It works on the public frequency of 2.4 GHz. Moreover, the number of node in ZigBee network can reach 255 [8-9]. Therefore, in this paper, we use ZigBee-based technology to collect the meteorological data of wind farm fans. The steps of meteorological data collected by WSN are as follows: First, the meteorological data is collected by meteorological sensors. Secondly, the collected data is sent to processor by analog circuit, and then transmitted to data transmission module after AD transforming. Thirdly, data receiving module receives data and transmit it to Single Chip Microcomputer (SCM). Finally, the meteorological data is stored in SD card by SCM processing.

3. Data and Methods

3.1 The Selection of Data

In this paper, we use the meteorological data collected by WSN to perform the short-term prediction, where the data is gather from Apr.1st to 15th in 2012 by a wind farm from Yunnan province. Note that the data is collected every 1 minute, and averaged every 10 minutes from 10 selected values. It means that we can get 6 average values per hour. Finally, we receive 15 days' average values in term of wind speed and power. We select the first 10 days' data as training samples of the neural network, while the last 5 days' data as the prediction samples. First of all, the data of wind speed in neural network training samples is used as input. Power is used as output. When the training neural network is finished, the data of wind speed in prediction samples is used as input again, while the data of power is still used as output to compare the error.

3.2 The Determination of BP Neural Network Structure

The common method for the training of network connection weights and thresholds is BP neural network algorithm, which is a kind of algorithm based on error back propagation algorithm. Actually, it is a multilayer forward artificial neural network with supervisor training method. Furthermore, the BP neural network can approach nonlinear function with arbitrary accuracy. It has the ability of learning, self-adaption, and fault tolerance. Therefore, the constructed model has good robustness. The neuron of the BP neural network is denoted by a node, and the link vector between nodes is called weights vector. The basic structure of BP neural network contains three parts: the input layer, the hidden layer, and the output layer. The hidden layer includes one layer or multi layers, and neurons of different layer are connected by the connection weights [10-12]. Through the analysis of the previous part, we know that the number of neurons in the output layer is 1, which is the wind power of wind farm, while the input data contains wind speed. However, the number of neurons in the input layer can not be determined easily, because different number of neurons in the input layer can make different prediction result, so does the hidden layer. Hence, according to the experiment requirement the number of neurons in the input layer is determined among 1 to 5, while according to the experiment requirement the number of neurons in the hidden layer is determined among 5 to 12. The following Table 1 shows the different prediction error through the different number of neurons in the input layer and the hidden layer.

Table 1. The prediction error of different number of neurons in the input layer and hidden layer

The number of input layer neuron	The best suitable number of hidden layer neuron	Mean relative error	Mean absolute error
1	7	0.6933	192.5580
2	5	0.5464	140.9012
3	7	0.4645	166.1487
4	8	0.2560	85.0576
5	11	0.4673	181.0491

From the Table 1, we choose the number of input layer neuron is 4, while the number of hidden layer neuron is 8. Consequently, the basic structure of BP neural network is 4-8-1.

In addition, the data of the input layer must be normalized before training. The normalization method is a common data processing method before prediction, where all the data are transformed into the area from 0 to 1. The purpose is to eliminate the order of magnitude differences among different dimension data, and to avoid the error of network prediction caused by the order of magnitude differences between the input and output data.

The data normalization method used in this paper is called maximum minimum method, which is as follow.

$$x_k = \frac{(x_k - x_{\min})}{(x_{\max} - x_{\min})} \qquad (1)$$

Where $x_{\min}$ is the minimum value among the data, and the $x_{\max}$ is the maximum value among the data [13].

By the way, the choice of the hidden layer function and output layer function has a great influence on the prediction accuracy of BP neural network. In normal case, the transition function of node in the hidden layer is Logsig function or Tansig function, and the transition function of node in the output layer is Tansig function or Purelin function [14].

3.3 The Connection Weights and Thresholds of BP Neural Network Adjusted by GA and PSO

The performance of BP neural network algorithm is very good, but the training speed is slow and the minimum value is sometime a local value. Note that GA and PSO is global searching algorithm compared with the BP algorithm, the searching speed for optimal area of GA and PSO is faster [15-16]. Therefore, in this paper, we respectively choose GA and PSO algorithm to optimize the BP neural network, which is GA-BP and PSO-BP, and then the two methods are combined together to perform prediction.

Because the number of nodes in the input layer, output layer, and hidden layer is set as 4, 1, and 8, where there are 40 weights and 9 thresholds. Consequently, the code length of the initial individual is 49, which is based on the real number coding method. In addition, the scale of the population also has affection on GA and PSO. Probably the scale of the population is chosen as 10 to 160. In this paper, the scale of the GA and PSO's initial population is set as 40, according to the experiment request. Moreover, the number of evolution for GA and PSO is very important to prediction result. So, we will discuss it at next section.

By the way, the fitness of GA and PSO is determined by the value of objective function. The objective function is presented as follow.

$$F = \frac{1}{n}\left(\sum_{i=1}^{n}(y_i - o_i)^2\right) \qquad (2)$$

Where n $n$is the number of output training samples. $y_i$$y_i$ is expected output of the ith node in BP neural network, ando_i o_i is prediction output of the ith node.

After determining the fitness function the GA perform the selection operation, crossover operation, and mutation operation sequentially, while the PSO perform the velocity updating, location updating, individual extremum updating, and global extremum updating. We repeat these operations of GA and PSO in different evolution sequences, and choose the best one from all the individuals. It will stop evolution when the number of evolution reaches the maximum or the objective function reaches the pre-defined value. At this time, the optimal values are set as the initial weights and thresholds of the BP neural network.

3.4 The Combination Prediction Model

Combination prediction is a method which its prediction result can be determined by the result of several prediction methods' weighted average. It aims for eliminating the bigger error of single prediction method in order to improve the prediction accuracy. Figure 1 shows the combination method by GA-BP and PSO-BP [17].

There are two functions of weighted average. One is equally-weighted average method, which is as follow.

$$P_{\Sigma} = \frac{P_{GA-BP} + P_{PSO-BP}}{2} \qquad (3)$$

Where P_{Σ} is the total prediction output power, P_{GA-BP} is the prediction output power of GA-BP method, and P_{PSO-BP} is the prediction output power of PSO-BP method.

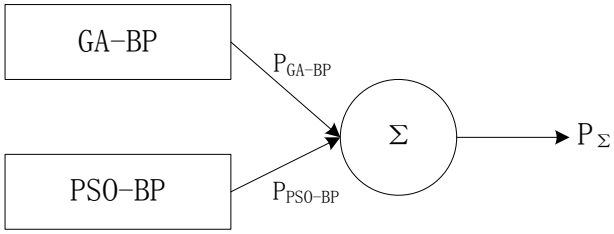

Figure 1. Combination Prediction Model

Another function of weighted average is as follow named differently-weighted.

$$P_{\Sigma} = \lambda_1 P_{GA-BP} + \lambda_2 P_{PSO-BP} \quad (4)$$

Where λ_1 is the weight of GA-BP method, while λ_2 is the weight of PSO-BP method. Note that $\lambda_1 + \lambda_2 = 1$.We should firstly select the objective function in order to determine the value of weight. There are two common functions to determine the value of weight such as root mean square error (RMSE) and mean relative error (MRE), which is as follow [18].

$$e_{RMSE} = \sqrt{\frac{\sum_1^N (O-P)^2}{N}} \quad (5)$$

$$e_{MRE} = \frac{1}{N}\sum_1^N \left|\frac{O-P}{O}\right| \quad (6)$$

Where e_{RMSE} is the RMSE, e_{MRE} is the MRE, O is the real output power, P is the prediction output power, and N is the number of samples. From the above two functions, we can conclude that the same error will lead to the larger MRE when the real output power is small, while the same error will lead to the smaller MRE when the real output power is large. Hence, in this paper, we choose the RMSE as the objective function. Note that, the best number of evolution about GA and PSO is from 20 to 100. It is selected by the experiment result, which is as Table 2.

Table 2. The different RMSE of different evolution number

The number of evolution	The RMSE of GA-BP	The RMSE of PSO-BP
20	114.1673	165.3093
30	119.8119	128.5964
40	138.6896	133.7570
50	185.6245	106.2455
60	115.4298	109.2114
70	109.8434	115.9150
80	113.0729	110.7877
90	105.4011	108.4911
100	131.7375	114.5889

From the Table 2, we can get the best number of GA's evolution is 90, while the best number of PSO's evolution is 50, which the RMSE of GA-BP and PSO-BP reach the smallest. In addition, we find the prediction result of GA-BP is better than the prediction result of PSO-BP in their evolution number. Consequently, the value of λ_1 is larger than the value of λ_2. The following Table 3 shows the different result of combination prediction through the different weights. From the Table 3, the smallest RMSE is 103.8429. Hence, the value of λ_1 is set as 0.9 and the value of λ_2 is set as 0.1.

Table 3. The different result through the different weights

λ_1	λ_2	RMSE
0.9	0.1	103.8429
0.8	0.2	118.2117
0.7	0.3	109.2251
0.6	0.4	104.2794

4 Experiment Analysis

In this section, we use the prediction samples and the trained combination prediction model to perform the analyzing of 12 hours in advance for wind power prediction. First, we analyze the prediction result of the three simple methods, which are simple BP method, GA-BP method, and PSO-BP method. Figure 2 presents the comparison between the real value of wind power and the predicated value of wind power from the above three methods.

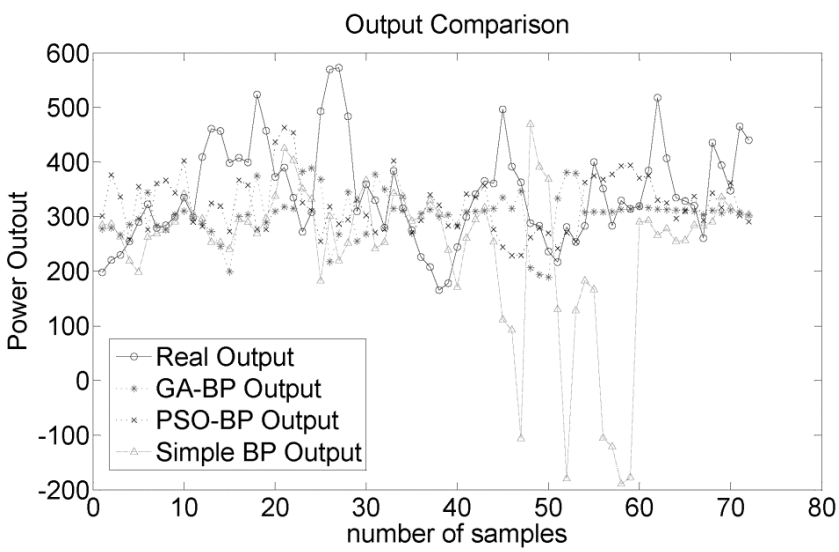

Figure 2. Output Comparison of Three Methods

From the Figure 2, it shows that the method of simple BP is the worst one, because the difference between the real value and the predicated value from simple BP is the largest, compared with the difference between the real value and the predicated value from GA-BP and PSO-BP. Figure 3 shows the absolute errors calculated by the three methods. Note that, the real prediction error can be also reflected by absolute error. From the observation of Figure 3, we can get the average absolute error is 135.7459, and the RMSE is 189.3201 by

simple BP, while the average absolute error is 95.0512, and the RMSE is 117.0837 by PSO-BP, while the average absolute error is 90.0510, and the RMSE is 100.8276 by GA-BP.

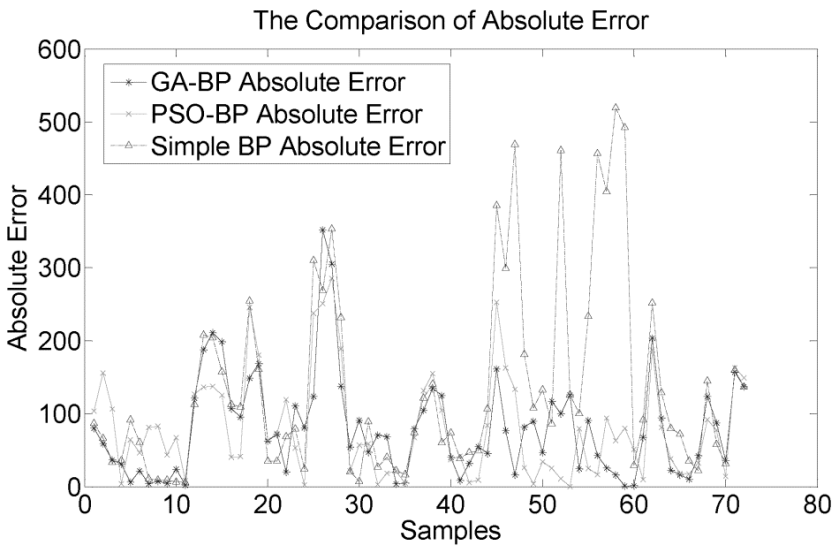

Figure 3. Absolute Error of Three Methods

Secondly, we analyze the prediction result of the two combination prediction methods, which are equally-weighted combination method, and differently-weighted combination method. Figure 4 presents the comparison between the real value of wind power and the predicated value of wind power from the above two methods.

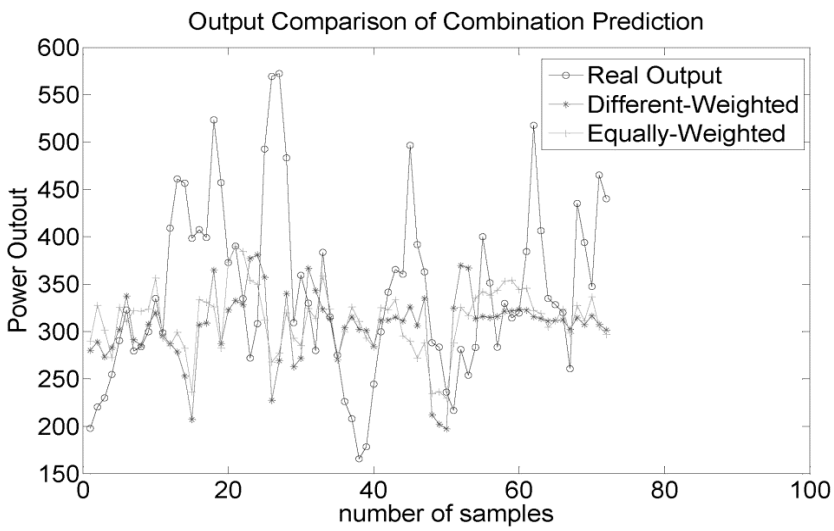

Figure 4. Output Comparison of Combination Prediction

Figure 5 shows the absolute errors calculated by the two combination methods. From the observation of Figure 5, we can get the average absolute error is 74.1053, and the RMSE is 90.9773 by differently-weighted combination method, while the average absolute error is 80.9015, and the RMSE is 95.1119 by equally-weighted combination method.

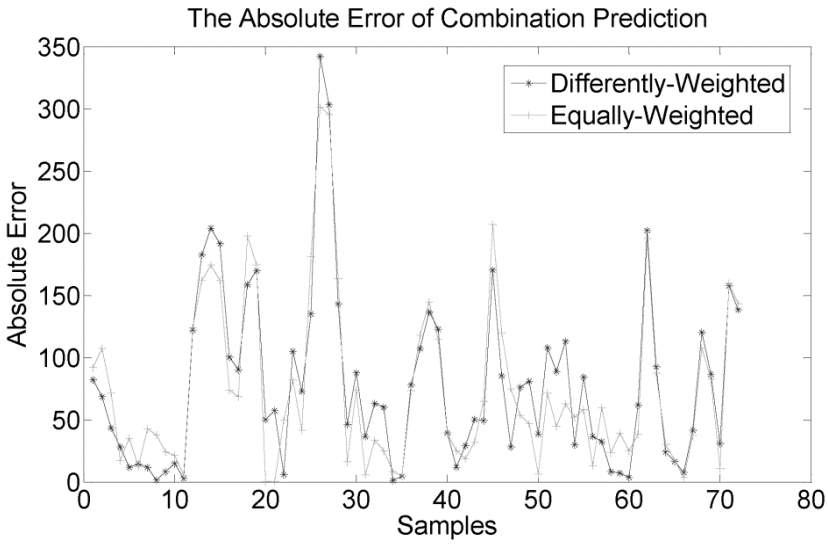

Figure 5. Absolute Error of Combination Prediction

Finally, we make Table 4 in order to clearly analyze these data by above prediction methods.

Table 4. The prediction result of above prediction methods

Methods	Absolute Error	RMSE
Simple BP	135.7459	189.3201
PSO-BP	95.0512	117.0837
GA-BP	90.0510	100.8276
Differently-weighted combination	74.1053	90.9773
Equally-weighted combination	80.9015	95.1119

5. Conclusions

In this paper, we study the wind farm short-term power prediction method based on combination prediction model. We used the meteorological data collected by WSN as the training samples and prediction samples.

(1) The experiment results show that the GA-BP and PSO-BP is better than the simple BP. By the way, they avoid the fact that simple BP neural network fall in down local minimum value. In addition, they also revolve the slow convergence speed in simple BP.

(2) According to the experiment, although the GA-BP method is better than the PSO-BP method, the PSO-BP method also has good prediction result. Hence, we use the two methods to perform combining, which is suitable for the wind power prediction.

(3) In this paper, the combination prediction method is better than any another methods. There are two kinds of combination prediction, which are differently-weighted method and equally-weighted method. In accordance with the experiment result, the differently-weighted

method is better than the equally-weighted method. Consequently, the differently-weighted combination method can be used to predict the real wind power. It plays an important role in management of power grid system.

(4) In the future, we usually lack of real data. In order to establish the prediction model, we need to research the model established by the forecast data. Furthermore, we need to research whether the model established by the real data is suitable for the wind power prediction calculated by the forecast data.

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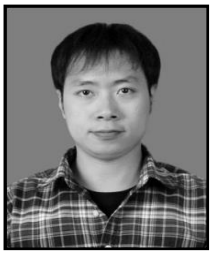
Authors

Li Ma

She received her B.S. degree in 1985 from the Chengdu Institute of Meteorology and her Ph. D degree in 2011 from Nanjing University of Information Science and Technology. She is a professor and tutor for graduates in Nanjing University of Information Science and Technology. Her main research interests include image processing, pattern recognition, and meteorological information processing and data assimilation.

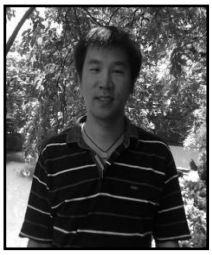


Bo Li

He was born on May 12, 1987. Currently He is a master candidate in Nanjing University of Information Science and Technology. He received his bachelor degree in Chongqing Normal University. His areas of interest are short-term wind power prediction, meteorological information processing and data assimilation.

Zhen Bin Yang

He hold a B.S. in Weather Dynamics from Lanzhou University and an M.S. in Atmospheric Physics and Atmospheric Environment from Peking University. He is a senior scientist and the director of the Office of Resources, Environment and Engineering Meteorology at CMA Public Meteorological Service Centre (PMSC). He leads and conducts research and analysis on wind and solar energy, including on the wind energy potential assessment, forecasting; on the solar energy potential assessment, forecasting; on climatic feasibility study of engineering.



Jie Du

He was born on July 20, 1978. He is an associate professor and master tutor in Nanjing University of Information Science and Technology. He received his B S, master, Ph. D degree from Nanjing University of Technology. He worked in the college of electrical engineering, Zhejiang University mobile post-doctoral stations. His main research interests include short-term wind power prediction, nonlinear time series intelligent prediction method, neural network, data mining and genetic algorithm.

Jin Wang

He received the B.S. and M.S. degree in the Electronical Engineering from Nanjing University of Posts and Telecommunications, China in 2002 and 2005, respectively. He received Ph.D. degree in the Ubiquitous Computing laboratory from the Computer Engineering Department of Kyung Hee University Korea in 2010. Now, he is a professor in the Computer and Software Institute, Nanjing University of Information Science and Technology. His research interests mainly include routing protocol and algorithm design, performance evaluation and optimization for wireless ad hoc and sensor networks. He is a member of the IEEE and ACM.

