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Research Article

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Forecasting of short-term wind farm generation output based on a new plant growth neural network

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ABSTRACT

Due to the real-time characteristics and nonlinear feature of short-term wind power prediction, a wind power prediction model based on Plant Growth algorithm and neural network (PGNN) is proposed. PGANN model combines the ability of BP neural network for solving nonlinear problem and the ability of Plant Growth algorithm (PG) for global optimization. And in this model, the PG algorithm is utilized to optimize the weights of BPNN. In order to enhance the effective of PG, we add the Metropolis criterion in it to avoid the local minima value problem. The simulation results show that based on the actual data of a wind farm, the forecasting results predicted by the improved PGNN is more precise than those by BP neural network model. Finally, we added the turbulence intensity in our prediction model and it really enhanced the predict precision. Thus, we provide an effective way to forecast short-term wind farm generation output.

Keywords: short-term wind power; Plant Growth; BP neural network; Metropolis; turbulence intensity

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INTRODUCTION

Wind power prediction is important to the operation of power system with comparatively large amount of wind power. If the prediction of wind power is accurate, the dispatching department of power system can change the production planning timely. The results not only effectively diminish the influence of large-scale wind power on power systems, but also reduce the cost of power system operation and spinning reserve capacity. At the same time, wind power penetration limit is improved and the way for the implementation of wind power bidding is paved [1].

Short-term wind power not only related to wind speed, but also related to other factors such as the direction of the wind, temperature, pressure, humidity, roughness, wake turbulence. Those causes the change of short-term wind power has highly nonlinear and uncertainty. At present, the wind farm output power prediction can be divided into three classes in terms of time[2]:(1) super short-term forecasting (a few minutes), (2) short-term forecasting (a few hours or a few days), (3) medium-term forecasting (a few weeks or a few months). The wind farm output power prediction can be divided into four classed in terms of the mathematical model [3]: Physical prediction method[4], statistics forecasting method[5], intelligent forecast method[6,7] and combination forecast method[8]. Physical prediction method based on numerical weather prediction has a complex model and large amount of calculation. Time series method as a representative of statistics forecasting method has a simple model. But the results of prediction is unstable and the prediction error is more. Neural network method as a representative of intelligent forecast method generally does not need the accurate mathematical model of the research object. The result of prediction is more accurate.

BP neural network has caused wide public concern in the wind power prediction research because of its good non-linear approximation ability, simple structure and easy operation [9-12]. Because the common methods that usually used to train BP algorithm have poor global search capability and easy to fall into the local minima, so the accuracy of BP network is need to be improved. Plant Growth algorithm [13] is a global parallel random search method. The searching process does not rely on gradient information and has a strong robustness. So, it is an effective way to solve this problem.

Specific to the shortage of the BP neural network algorithm, this paper established the short-term wind farm output power forecasting model which based on PG-BPNN. PG-BPNN model combines the ability of BP neural network for solving nonlinear problem and the ability of Plant Growth algorithm (PG) for global optimization. In this model, PG is used to search the global optimal weights the neural network. The simulation results show that PG algorithm effectively solve the problems of slow convergence speed, and easy to fall into local minimum of BP neural network. Based on the actual data of a wind farm, the forecasting results by the proposed method is more precise than those by BP neural network model, providing an effective way to forecast short-term wind farm generation output.

I. BP NEURAL NETWORK FORECASTING MODEL

BP neural network is presently mostly researched and the most widely applied neural network models in neural network field. This neural network is a multilayer feed-forward type network which is formed by the interconnection of input layer , output layer and several nodes among the hidden layer.

The generation of BP network owes to obtain BP algorithm. BP algorithm is a supervised training method in fact. This algorithm is consisted of two parts [14]: positive transfer of information and counter-propagation of error. In the course of forward-propagating, input information is calculated by the hidden layer step by step from input layer to output layer. The state of neurons in every layer only affect the state of neurons in next layer .If the output in output layer is not desired, change value of output layer error is calculated. Then counter-propagation is used .Following the original connected pathways by network error signal reverse back to modify weight of neuron in every layer until the output is desired.

According to Kolmogorov theorem, feed-forward neural networks which have three layers can carry on the free precision to any continual nonlinear function approaching. So the BP neural network of prediction mode select structure of three layers neurons that is an input layer, a hidden layer and an output layer. Then we select four main influence factors of wind farm output power: wind speed, the direction of the wind, temperature and air pressure as the neural network's input. So the number of neurons of input layer is four. We select wind power values as output. So the number of neurons of output layer is one. The number of neurons of hidden layer select is 1 add 2 times of neurons of input layer [15]. So the number of neurons of hidden layer is 9.Activation function of hidden layer is tansig function. Activation function of output layer is purelin function. Network training function is traingd function. Learning rate is 0.01. The largest number of training is 1000. Training target is 0.01.

Although BP network has good non-linear approximation ability, its train methods unavoidably exist many problems such as poor global searching ability and easily fall into local minimum.

In order to overcome the deficiency of the BP algorithm, people put forward improved method such as increasing momentum, self-adaptive gradient, introducing the adopted factor, using other gradient optimization algorithm, etc. These methods improved the convergence rate of neural network in varying degrees, but all exist problem of local minimum .So we can use global optimization function algorithm such as Plant Growth algorithm to optimize neural network's weights.

II. PLANT GROWTH ALGORITHM AND NEURAL NETWORK

Plant Growth algorithm is a modern optimizing algorithm, there is a protein called PIN1 in the process of plant growth, it can extract the auxin from cells and pull the auxin to leaves to promote leaf growth. PR (protain) PIN1 auxin also be attracted to a place, to a certain part of the plant, then PIN1 attract more auxin accumulation over, so the growth hormone in somewhere will be much higher than other places, so this place is the future leaves appear [16-18].

Plant Growth Simulation Algorithm is a new optimization algorithm has obvious advantages on fast optimization of complex nonlinear problems [13]. This method does not require complex extraction and setting parameters. In particular, it is simple to design, don’t like some other optimization algorithms must be continuous and without too many parameters to be set.

The greatest feature of the algorithm is to plant a wide search range, each with an initial starting point to compare the performance of poor who removed the plant to make up the perfect algorithm optimization process broadness, plant growth simulation algorithm and BP neural network can not only get the perfect combination exact solution, but also improves the computing speed, fully embodies the simplicity of the method, accurate and fast. In this paper, plant growth algorithm is mainly used for training BP neural network weights in order to improve the prediction accuracy of the network.

Plant growth algorithm is divided into three main steps:

Step 1. Initial the set of growing points, calculate the fitness function values.
Step 2. Probability selected the growing point, the larger fitness, the greater the probability.
Step 3. To the growing point, based on the optimal growth of the search and replace the original growing point position.

As seen above, plant growth algorithm is a heuristic search algorithm. Based on a random search, it adds the concepts of population and fitness. So, it has global search capability. However, during the search, simply replace use the better growing point is easy to fall into local optimum value. So, we added idea of the simulated annealing algorithm [19], if satisfy the probability criterion we replace it also. The flowchart of our algorithm is as follows:

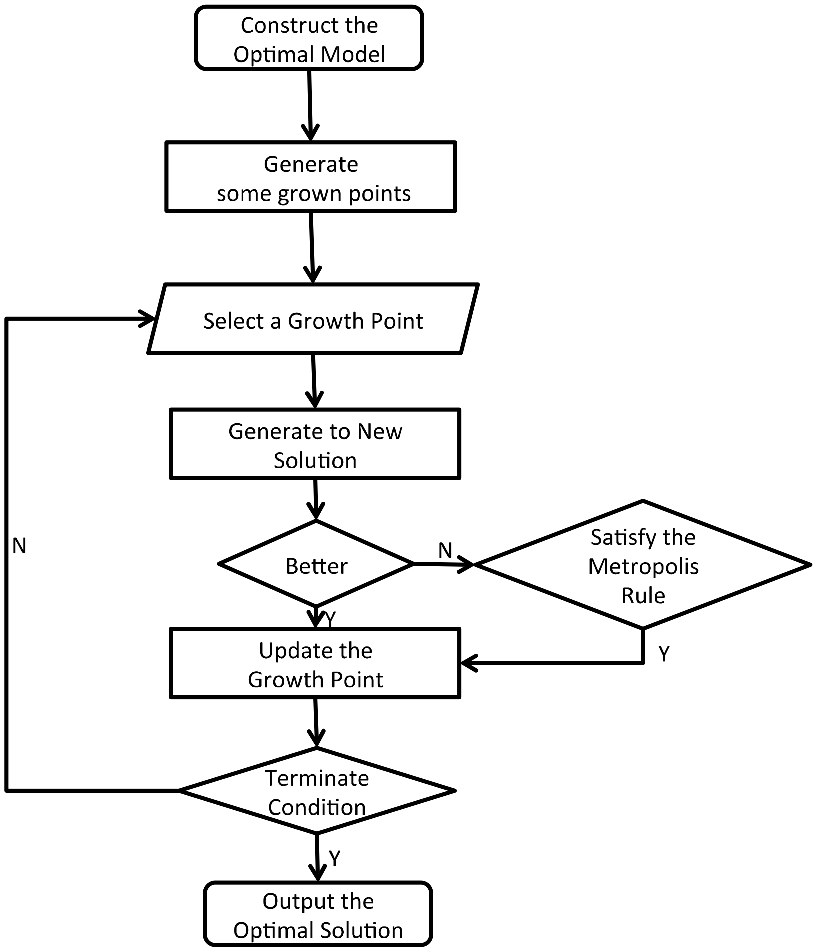

Fig. 1 Flow chart of optimizing weights with PG algorithm

III. EXAMPLE ANALYSES

A. Sample selection and pretreatment

The sample data of this research select field data of a wind farm in Inner Mongolia. Selecting 31 days data from October 1 2009 to October 31 2009 , sampling interval is 10 min, the 4032 sets of data in headmost 28 days is regarded as the training sample, the 1000 sets of data in the last three days is regarded as a test sample, we establish a wind farm output power short-term forecast model .

In order to eliminate the influence of the difference of variables unit and magnitude which in the input-data matrix $X_{4032\times 4}$, input-data matrix is normalized by using premnmx function, and then the normalized data is regarded as output of neural network.

B.The results of simulation and forecast analysis

First, we use Plant Growth algorithm to optimize the weight and the threshold value of the neural network. Till the terminate condition, Plant Growth algorithm is exited. Then we obtain optimal weights of BPNN. Optimizing process is show in Fig. 2.

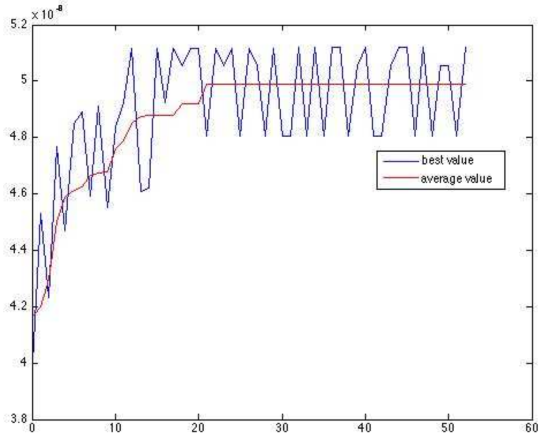

Fig. 2 Evolution curve of fitness function

From Fig. 2, we can see the best fitness function has no longer changes when iteration breed to the last several iterations. Namely Plant Growth algorithm had searched the stable weights of the neural network. The searching results are regarded as the optimal value of neural network's weight.

In order to validate the validity of the proposed PG neural model, An Inner Mongolia wind farm field data has carried on the short-term wind power prediction simulation. And the simulation result is compared with the practical wind power value, the BP neural network predictive value, Fig. 3 is rendering of PG neural network forecasting model, the solid line is actual wind power value, and dotted line is PG neural network predictive value.

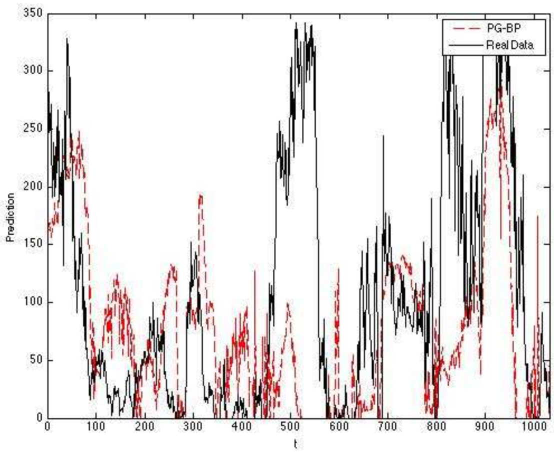

Fig. 3 The prediction result of PGNN

The prediction error is shown in Tab. 1.In the table e_{MAE} and e_{RMSE} were common international two error evaluation index: mean absolute error and root mean square error.

Table 1:Prediction error of PGNN

e_{MAE}/%	e_{RMSE}/%
3.09	4.96

e_{MAE} and e_{RMSE} separately calculate in the following formula:

$$e_{MAE} = \frac{\sum \left| y_i^{'} - y_i \right|}{nP} \tag{1}$$

$$e_{RMSE} = \frac{1}{P}\sqrt{\frac{\sum (y_i^{'} - y_i)^2}{n}} \tag{2}$$

y_i is actual power value of wind farms. $y_i^{'}$ is wind power prediction value. P is wind power rating capacity. n is Sample number.Fig.4 is a comparison diagram of PG neural network and the BP neural network prediction results. The solid line is wind power the actual value, dotted line is PG neural network predictive value, chain line is the BP neural network predictive value.

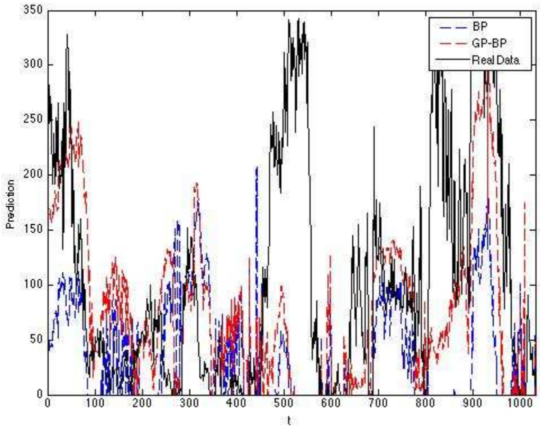

Fig. 4 Comparison of prediction results of PGNN and BPNN

Comparison of prediction error of PGNN and BPNN is shown in Tab.2

Table 2. Comparison of prediction of error of PGNN and BPNN

Index	PGNN	BPNN
e_{MAE}/%	3.09	3.81
e_{RMSE}/%	4.96	7.54

From the Fig. 4 and Tab. 2, compared with BP neural network mode, mean absolute error of PG neural network model was reduce by 4.53%, RMS error was reduced by 5.04%. This illustrate that using the Plant Growth algorithm to optimize the weights of the neural network can effectively solve the shortage of the BP neural network, and improve the precision of the model prediction.

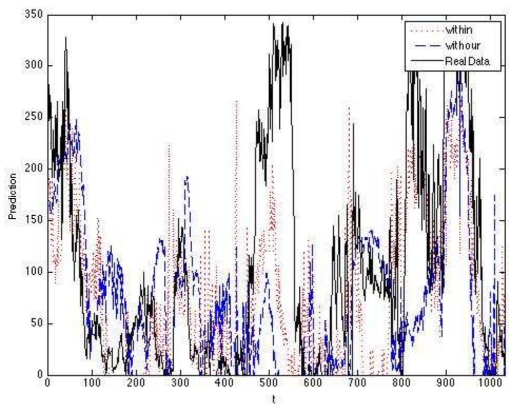

Fig. 5 Comparison of prediction results of PGNN within and without turbulence intensity

In order to further enhance our predictive model, we add another parameter turbulence intensity into our model. Contrast curve is shown in Fig.5, the solid line is wind power the actual value, dotted line is PG neural network predictive value, and chain line is the PG neural network predictive value with turbulence intensity.

Comparison of prediction error is shown in Tab.3.

Table 3.Comparison of prediction error of PGNN within and without turbulence intensity

PGNN	within	without
e_{MAE}/%	2.51	3.09
e_{RMSE}/%	4.96	7.54

Through the Fig.5 and Tab.3, it can be concluded that all of PG neural network contain the turbulence intensity is better than the previous model. Mean absolute error was reduced by 0.58%, the root mean square error was reduced by 2.58%.

CONCLUSION

Plant Growth algorithm effectively solve the problems of slow convergence speed, and easy to fall into local minimum of BP neural network. Based on the actual data of a wind farm, the forecasting results by the proposed method are more precise than those by BP neural network model. The predicting model based on Plant Growth algorithm and neural network (PGNN) is an effective way to forecast short-term wind farm generation output. In addition, our model takes into account the turbulence intensity. And the experiment results proved that it performance better than common wind power prediction models.

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