Short-term forecasting of wind power generation Based on the Similar Day and Elman Neural Network

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***Abstract*—This Wind power forecasting is significant to reduce the impact of wind power generation integration on the power grid. According to the characteristics of power generation of wind power system and the factors impacting wind power output, a method for selecting similar days is proposed. By the historical data similar to the features of the forecasting day are selected and are considered as training data sets. Elman Neural Network is used to calculate the wind power output. The method is validated by wind power system data, and the forecast error is calculated and analyzed. Experimental results show that our proposed method has high accuracy, which provides reference to short- term forecasting of wind power generation.**

I. INTRODUCTION

Wind power generation has the advantages of safety, reliability, noiseless and low pollution, in recent years which has been rapid developed. Easily affected by the wind speed, weather, temperature and some random factors, the power of wind power generation has the characteristics of intermittence and volatility, uncontrolled, and so on [1]. The large-scale distributed wind power generation integrated on grid has brought great challenges to security and stability of power grid operation, effective scheduling and other work. Therefore, accurately forecast the output of wind power generation system has become particularly important, and it is also a prerequisite for electric power dispatching, power grid planning, which has practical significance [2].

At present, the research of wind power generation forecast technology is not much, such as neural networks [3], support vector machines [4], time series analysis [5], and so on. Forecasting method can be divided into two classes, one based on the relationship of wind speed and power, the other one based on power. The method based on the relationship of wind speed and power, firstly, established the wind speed forecasting model and the wind power relationship model, and derived forecast power according to the relationship between wind speed and power. The method based on historical power data regarded the power output as the input to achieve power prediction model, and the modeling method can be time series analysis, kalman filter and neural network method. This method is applied to the wind farm which is always full [6]. However, in the generator active power output controllability and the power control of the wind farm is bound to change the output power of the unit. At this time unit is not in accordance with the maximum power output, this method is no longer practical. So, in this paper, we use one based on the relationship of wind speed and power to realize power prediction.

In this paper, the selection method of the similar day is proposed. The similar day of output power curve of wind power generation system has a good similarity. According to the similarity of meteorological information and history output power data, the output power of the solar short-term direct prediction model is established using Elman neural network method, and the prediction model can reflect the change trend of wind power.

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II. SIMILAR DAY CLUSTERING

A. Similar days

Due to the random changing of wind as well as the inconsistencies of training data, prediction of the dates often difficult to achieve the desired results on this training set to establish model which the variation of the wind characteristics is inconsistent. Proper selection and classification of modeling data can improve the similarity and consistency of the data, which is beneficial to improve the accuracy of the model. On the basis of the above, a new method of power generation based on similar day clustering is proposed [7-9].

At present, the main short-term wind power forecast demands a day for the unit, so the sample data clustered by day can match the training data and forecast results. In order to reflect the diurnal variation of light and temperature, the relevant physical quantities are selected, and a sample of similar days is constructed as follows:

$$x = \left[S_{\max}, S_{aver}, S_{\min}\right]$$

Where $S_{\max}$, S_{aver}, $S_{\min}$ represents the maximum, mean and minimum values of the wind speed, respectively [10].

B. K-means algorithm

The clustering method used in this paper is the traditional K-means algorithm. The basic idea is to use K points in the space as the center of clustering then classifying the objects closest to them. By iteration, the value of each clustering center is updated until the best clustering results are got. Prior input of N data objects are partitioned into K clusters so that the obtained clustering is consistent with that. The objects in same

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cluster have high similarity, and objects in different clusters have smaller similarity. Similarity clustering is calculated by a center of each cluster obtained by the mean value of the objects. Suppose the sample set is divided into C classes, the clustering steps are described as follows:

- C cluster center is initialized by properly selecting from the N sample.
- in the K iteration, for any sample, the distance from the sample to the C center is calculated, then this sample is classified to the nearest center.
- update the central values of the class using the mean value.
- for all C clustering centers, if use the iterative method of second and three, the value remains unchanged, then end the iteration, otherwise continue.

III. ELMAN NEURAL NETWORK

After the sample is clustered by similar day, the Elman neural network can be used to establish the forecasting model based on the clustering results.

A. Elman neural network model

Elman neural network is a typical local recurrent neural network, which is based on the BP neural network and store the internal state is to make its mapping dynamic function through the introduction of feedback signal. In addition to the input layer, the hidden layer and the output layer unit, there is a special connection layer. The connection layer is used to memory the output value of the previous time, at the next time which can be treated as the input of the hidden layer with the input of the network. It can be considered as a step delay. This property makes it sensitive to historical data, so that the network has a dynamic memory function, and can achieve the purpose of dynamic modeling.

The basic Elman network, as shown in Figure 1, consists of an input layer, a hidden layer, a connection layer and an output layer. The input of each layer is weighted and the transfer function of the hidden layer is a kind of nonlinear function, general Sigmoid function. That of the output layer is linear function, and that of the connecting layer is linear function [11].

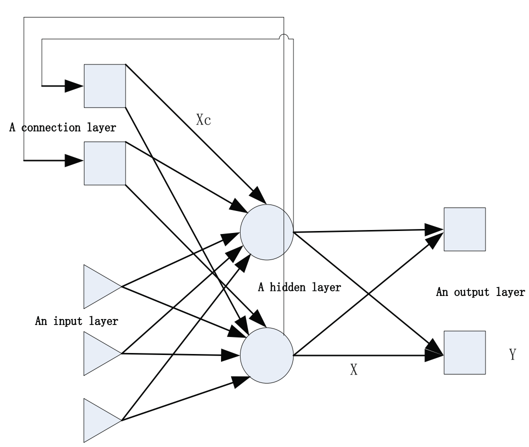

Fig. 1. Elman network structure

B. Elman neural network learning process

Elman neural network algorithm is shown in Figure 2.

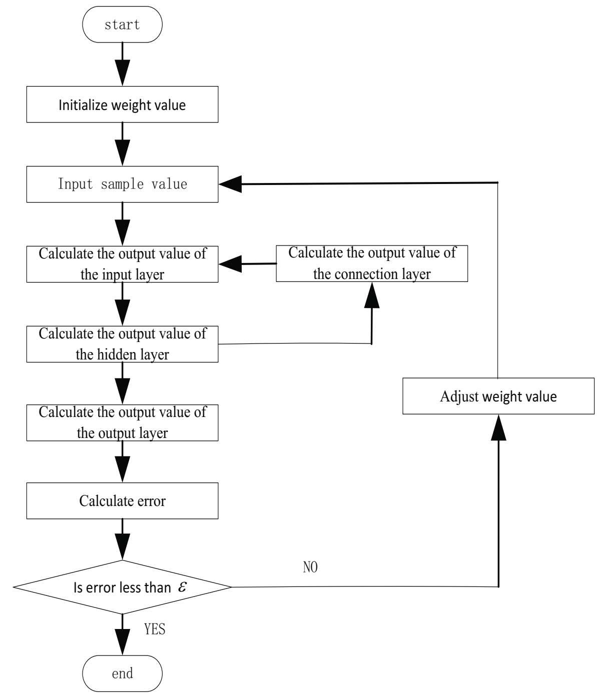

Fig. 2. Elman network structure

The nonlinear state space expression of Elman network is as follows:

$$y(k) = g\left[w3 * x(k)\right]$$

$$x(k) = f\left\{w1 * xc(k) + w2 * \left[u(k-1)\right]\right\}$$

$$xc(k) = x(k-1)$$

Where y is n-dimensional output vector; x is n-dimensional intermediate layer node unit vector; u is r-dimension input vector; xc is n-dimensional feedback state vector; $w3, w2, w1$ is the weight of the intermediate layer to the output layer, the input layer to the middle layer, the connection layer to the middle layer, respectively; $g(\cdot)$ is the transfer function of the output neurons which is a linear combination of the intermediate layer output; $f(\cdot)$ is the transfer function of intermediate layer neurons which is often used in S function.

Elman network is also BP algorithm to carry out the weights, learning index function uses the function of error sum of squares:

$$E(w)=\sum_{k=1}^{n}\left[y_k(w)-\overline{y_k(w)}\right]^2$$

Where $\overline{y_k}$ is target expectation output vector [12].

IV. SIMULATION AND RESULTS

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A. Test description

In this paper, the data of a wind farm is adopted to verify comparison. Select the wind speed data from September 1th 2011 to September 22th 2011 as the training set to predict the wind power output in September 23th / 24th / 25th 2013. According to the similar day selection method, select the date from September which is most similar with the data in September 23th / 24th / 25th. Regard similar day data and forecast meteorological as input data to predict the wind output in 23th / 24th / 25th, and finally compare the predicted data with the actual value.

For the selected wind farm data is analyzed, we select $k=5$ will get better results when wind speed data is clustered by similar day. It can be got the same day categories as shown in Table I.

TABLE I. SIMILAR DAY CLASS

Similar day class	Table Column Head
1	1,4,5,9,23
2	6,11,17,19,20,21,25
3	2,8,10,14,18
4	3,13,24
5	7,12,15,16,22

Constructing Elman neural network forecast model based on the results of similar day, we can predict following similar days of the target date.

B. Results

Place According to the target date belonging to the similar day categories, we use the corresponding model to predict, respectively. Than power output of the target date is obtained, and the results of each prediction method are shown in Table II.

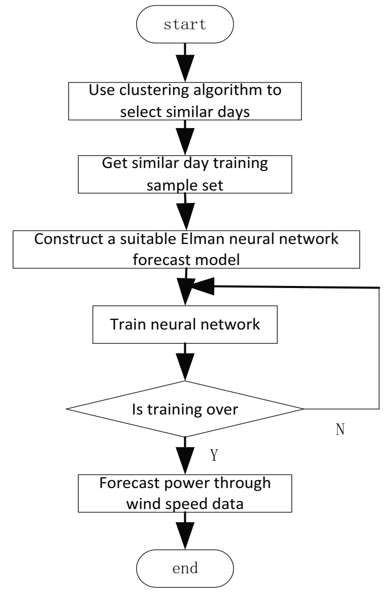

Fig. 3. Forecast algorithm

TABLE II. TABLE TYPE STYLES

data	Elman neural network based on similar days		BP neural network based on similar days		Elman neural network	
	error	*absolute error*	*error*	*absolute error*	*Error*	*absolute error*
23	-28.37	15.93%	-41.35	23.22%	61.1	34.31%
24	74.85	16.13%	65.62	14.14%	92.54	19.94%
25	12.18	2.93%	-48.7	11.71%	60.87	14.64%

Table II is the comparison result of the three days. The proposed method is compared with Elman neural network method and BP neural network method based on similar days. Among them, the mean absolute error of wind power generation prediction with Elman neural network method based on similar days is 11.66%, and the mean absolute error with Elman neural network is 22.96%. Also the mean absolute error of prediction with the BP neural network method based on similar days clustering is 16.35%. From the mean absolute error, we can see that the Elman neural network method based on the similar day clustering has higher prediction accuracy.

V. CONCLUSION

In this paper, the principle of similar days clustering and Elman neural network are utilized to predict wind output power. Experiments using the running data of a wind power station are conducted to demonstrate the efficiency of the prediction method. Experimental results show that wind power prediction method can effectively predict the wind output power with a high prediction accuracy. Also, the computation time is acceptable. However, due to the limited training data, the meteorological factors are not fine-tuned to some extent. In future, we would like to focus on combining evolutionary algorithms [13-15] with Elman neural network so as to optimize parameters of the predication model, and to further enhance the predication accuracy.

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