Available online www.jocpr.com

Journal of Chemical and Pharmaceutical Research, 2014, 6(4):858-863

Research Article

ISSN : 0975-7384
CODEN(USA) : JCPRC5

Wind power interval prediction utilizing SOM-BP artificial neural network

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ABSTRACT

Because of randomness and uncertainty of the wind, it is difficult to predict wind power output accurately.In order to objectify the wind power output, we proposed a new interval prediction method. Firstly, we utilize the SOM neural network to cluster the measured data to smooth the fluctuations and reduce the noise. Secondly, we establish the classic BPNN prediction model .and record the upper and lower of each cluster.Then we regard them as several intervals to enhance the performance. Experiments are constructed on a set of measured data. The results demonstrate that our method has an excellent performance and can be reasonable applied to predict wind power output.

Keywords*:* Wind Power Prediction; SOM Clustering; BP Neural Network; Interval Prediction.

INTRODUCTION

Due to the increasingly serious energy and environmental problems, renewable energy has become an important research topic, and extensive research has been conducted to advance the technologies of power generation systems based on various renewable sources, such as solar energy, geothermal, biomass, fuel cell and industrial waste heat [1, 2, 3, 4]. Wherein, wind power technology is one of the fastest growing and the most mature technologies in renewable energy. However, wind power has intermittent and volatility and other shortcomings.

Wind power prediction based on short-term forecasts of the different physical quantities can be divided into two categories: one is to predict the wind speed firstly. Then, calculate the output power according to the wind speed. Another is to predict the wind power through the relevant factors directly.

The main mathematical models to predict the wind power are time series method [7, 8, 9], Kalman filtering [10, 11], neural networks [12] and auto-regression machine vector model [13, 29]. Depending on the input prediction system, it can be divided into two categories. One use numerical weather prediction system data. Another does not use numerical weather prediction system data.

In common methods, the model doesn't take into account the interval of the data and the accurate interval estimate is necessary for wind power prediction [23, 24]. In fact, the wind power data has strong volatility and contain much noise. So, we consider that it is necessary to cluster them previously.

In some other similar researches, original data are clustered by k-means or some other clustering algorithms [14, 15]. These need to enter the number of clusters and randomly initial the cluster centers previously. So, we utilize the SOM neural network to cluster each set of data respectively.

The paper is organized as follows: In Section 2, we utilize the SOM algorithm to cluster the parameters data to clusters respectively, then, we record the upper and lower of each cluster. In Section 3, we establish the BPNN prediction model and train it by utilizing the clustering data. Then, we predict the further data and estimate the intervals through the uppers and lowers. The experimental results are presented in Section 4 contain the BP prediction and the interval prediction result. Conclusions on this paper and further studies are discussed in Section 5.

EXPERIMENTAL SECTION

SOM Clustering

Self-organizing map neural network (SOM) is a classical neural network widely used in clustering, it is an unsupervised learning neural network model and proposed by Kohonen [26, 27]. The main function of it is to map the *N*-dimensional input data into a low-dimensional space (typically one-dimensional or two-dimensional) and maintaining the topological relationship between the original data. Distinguish to other types of logic neural network is that: It is not in the state vector of a neuron or a network to reflect the classification results, but rather to reflect the number of neurons in parallel classification results. With this manner, SOM neural network can reflect the spatial distribution of the statistical properties of the input mode through the study of input pattern repeatedly [28].

The procedures of SOM utilized to cluster the data are briefly as follows.
(1) Initially, construct the network and set the weights of each node in the output layer.
(2) Randomly select the input samples as input vector and calculate the weights by reducing the distances.
(3) Define the winning unit and adjust the weights to make it closer to the input vector in neighborhood.
(4) Add the new samples into the network for training.
(5) Contract the neighborhood radius, reducing the learning rate, repeat the iterations until less than the threshold.

Finally, output the clustering results.

SOM neural network is organized by input layer and output layer as illustrated in Fig.1. Each neural in input layer was linked to the output layer through the weights.

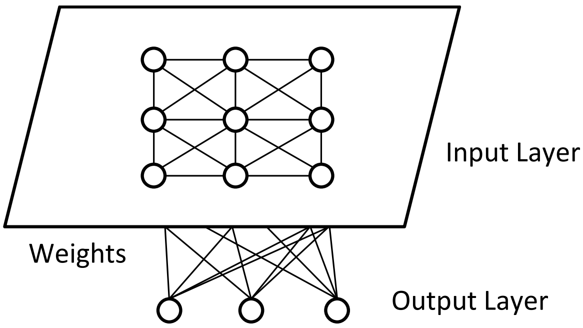

Figure 1. Illustration of the classically structure of SOM neural network

To illustrate the effectiveness of the algorithm, we select one wind farm's data as example. Selecting 31 days data from October 1 to October 31 and sampling interval is 10 min. These 4032 sets of data are regarded as the training sample, the last 1032 sets of data is regarded as a test sample. Some sets of measured data are shown in Tab.1.

Table 1. Some sets of measured data

Wind Power	Para1	Para2	Turbulence Wind speed	Para4	Para5
52.2	5.2	0.5	0.55	218.9	1.5
50.4	5.1	0.5	0.24	215.7	1.3
51.7	5.2	0.5	0.27	216.1	1.3
75	5.4	0.6	0	213.4	1.1
73.4	5.4	0.5	0	213.4	1
72.9	5.4	0.4	0.25	210.9	1
91	5.5	0.4	0.39	209.5	1
89.7	5.6	0.5	0.19	214.3	1
88.9	5.6	0.6	0.21	219.5	0.9
47.3	5.6	0.7	0.33	216.7	0.8
44.7	5.5	0.6	0.39	208.4	0.8
42.8	5.4	0.5	0.45	208.8	0.8

From Tab.1 we can find that the changes most variables are regularly except the turbulence wind speed and many of them have the same data. Base on this phenomenon, we consider to cluster them to several clusters. Traditional clustering method such as k-means is very unstable and very dependent on the initial clustering centers [16, 17, 18, 19]. So, we utilize SOM neural network to cluster them and record the upper and lower .Biologist's study illustrates that the brain cells located in different spatial positions effect different organ behaviors of human. Similarly, the cells are showing different sensitive to the same stimulation signal from a particular aspect. Self-Organizing Feature Map (SOM) artificial neural network is desired by this performance and developed by Kohonen, [5, 6, 22] this method is an important branch of artificial neural networks.

The microcontroller is sampling the input voltage and manages the width of the driving transistor pulses in order to achieve a stable output voltage.

BPNN Interval Prediction

Because it has a good nonlinear mapping ability, BP neural network is a common pattern recognition model is often used to identify, predict and so on [20, 21]. The procedure of the prediction method in this paper is detailed as follows:

Step1. Given the number of clusters, obtain the scale of SOM neural network and initial the structure of the network.
Step2. Cluster each variable to several clusters and record the upper and lower of each cluster.
Step3. Construct the prediction model and initial the parameters of BPNN. Train the BP neural network utilizing the clustering results without the turbulence intensity. Then, train another network contains the turbulence intensity.
Step4. Predict the wind power utilizing the trained network respectively.
Step5. According to the upper and lower to calculate the interval prediction values.
Step6. Calculate the precision of BPNN and compare the two networks.

Fig.2 shows the training results of BPNN without turbulence wind speed. Obviously, the fitting results are fairly accurate.

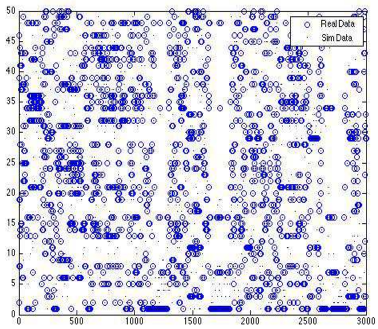

Figure2.Training Results of BPNN without Turbulence wind speed

Fig.3 shows the training results of BPNN contain the turbulence wind speed. Cause it contains more information

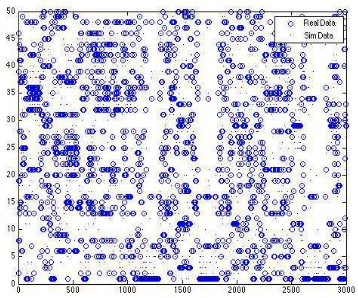

Figure 3. Training Results of BPNN

RESULTS AND DISCUSSION

Our experiments are constructed on a set of measured data contains most wind power parameters such as average wind speed, wind direction and so on.

Firstly, we record the upper and lower of each cluster by calculating the maximum and minimum of them. As illustrated in Fig. 4 and Fig. 5, the intervals almost covering all of the wind power data.

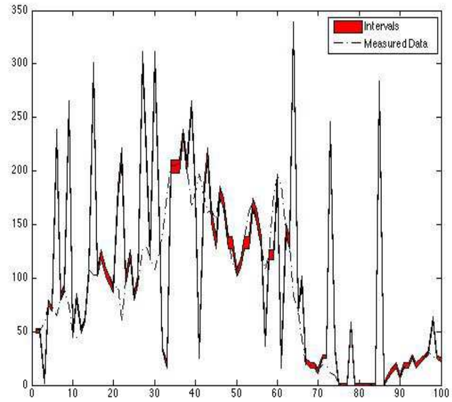

Figure 4. Fitting Results of Interval Prediction without turbulence intensity

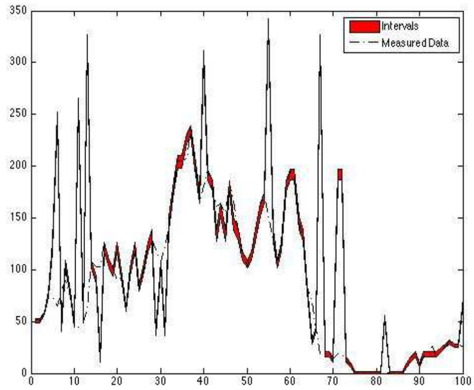

Figure 5. Fitting Results of Interval Prediction

After training the BP neural network, we predict the future data utilizing the clustering results. When we get the prediction results, we can get the interval according to the upper and lower of the clusters.

In order to better exhibition our results, we plot the interval prediction results and the real measured data together as shown in Fig.6 and Fig.7.Finally, we calculate the precision of our model as shown in Fig. 8. The left is fitting precision and right is prediction precision.

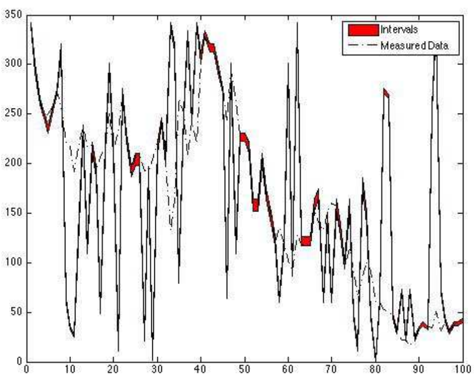

Figure 6. Interval Prediction Results without turbulence intensity

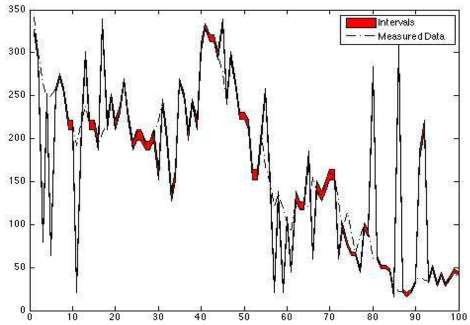

Figure 7. Interval Prediction Results

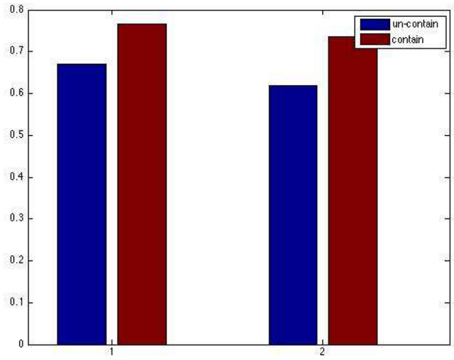

Figure 8. Precision of BP Prediction Model

From figure 8 we can find the prediction model contains turbulence intensity has a higher precision than un-contain model. The fitting precision and prediction precision are both quite high. This also proves the validity of our model.

CONCLUSION

In this paper, we have presented a novel wind power output interval prediction approach that multiply SOM neural network and BP neural network. Firstly, the relevant parameters data are clustering by SOM neural network. Through this method we can solve the disadvantages of traditional clustering method. Then, we establish the prediction model based on the BP neural network. In order to enhance the reliability, we consider the interval of each data. The core idea of our method is consider the upper and lower as the interval of each cluster. The experiment was constructed on one set of measured data and the results demonstrated the reliability and accuracy of our model.

Future work focuses on two aspect: (i) Because the upper and lower of each cluster are still large, so, how to define the interval of each cluster more accuracy is an important problem; (ii) there still exist relevant parameters of wind power output, further work should select more reasonable variables to establish the prediction model.

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