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Wind Speed Prediction Modeling Based on the Wavelet Neural Network

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ABSTRACT

Wind speed prediction is an important part of the wind farm management and wind power grid connection. Having accurate prediction of short-term wind speed is the basis for predicting wind power. This paper proposes a short-term wind speed prediction strategy based on the wavelet analysis and the multi-layer perceptual neural network for the Dabancheng area, in China. Four wavelet neural network models using the Morlet function as the wavelet basis function were developed to forecast short-term wind speed in January, April, July, and October. Predicted wind speed was compared across the four models using the mean square error and regression. Prediction accuracy of model 4 was high, satisfying the forecasting wind power industry requirements. Therefore, the proposed algorithm could be applied for practical short-term wind speed predictions.

KEY WORDS: Artificial neural network, forecasting, wavelet transform, wind speed.

1 INTRODUCTION

RAPID development of the wind power industry and wind power grid technology means the proportion of wind power in the power grid continues to expand. However, the wind power operation is very challenging due to intermittent and random wind speed. Wind speed determines the power output. Therefore, accurate wind speed prediction is critical for the wind power operation, adjusting fan capacity and maintaining grid stability.

Many short-term wind speed prediction methods have been developed and are divided into two categories; statistical and artificial intelligence (AI) models (Kavasseri R G et al., 2009). Statistical models are suitable for predicting normally distributed data, but wind speed is random and intermittent. Hence, the statistical models of wind speed prediction are somewhat inaccurate (Pourmousavi KSA et al, 2011).Models, usually artificial neural networks (ANN) can capture subtle functional relationships in empirical data even though the underlying relationships are unknown or difficult to describe., They have attracted a lot of attention for forecasting wind speed(Zhang W et al, 2013).

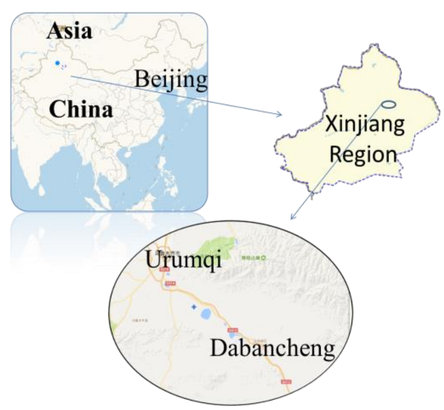

Figure 1. **The Study Area: Dabancheng, China.**

Figure 1 shows the Dabancheng area, which has one of the most abundant wind energy resources in China. Dabancheng is located in the northwest part of China (Xinjiang Autonomous Region) and has unique natural conditions(Wang C et al,2016) such as high altitude, low air humidity, frequent sandstorms, and large temperature differences between day and night, which makes the wind speed prediction more difficult(Liu D et al,2016). This paper proposes a new strategy for predicting short-term wind speed in the

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Dabancheng area using the wavelet analysis combined with a multi-layer perceptual neural network(Wang Jet al,2015). We developed four wavelet neural network models and used these to forecast short-term wind speed in January, April, July, and October. We compared the prediction results from each model, and analyzed the advantages and disadvantages of each model to identify the model with superior accuracy and performance (Wei Het al, 2016).

Special contributions of this paper include:

(1) The algorithm and model construction of the wavelet neural network are introduced.

(2) The construction process of the wind speed prediction model is introduced.

(3) The wavelet neural network model is applied to the wind speed prediction (Ramesh B Net al, 2014).

The rest of this paper is organized as follows: In Section 2, the algorithm process of the wavelet neural network model is introduced. In Section 3, the construction process of the wavelet neural network model is introduced. In Section 4, the wind speed prediction model is introduced. In Section 5, the wavelet neural network model is applied to the wind speed prediction and in Section 6, the full paper is summarized (Wang J-Z et al, 2015).

2 THE WAVELET NEURAL NETWORK ALGORITHM

THE difference between the wavelet neural network (WNN) models and other ANN models is that the hidden layer adopts different function types. The WNN hidden layer uses a wavelet basis function that not only preserves the original advantages of the ANNs, but also allows the threshold weight optimization and it overcomes the ANN local minimum problem through the signal amplification from the wavelet basis function (Louka Pet al, 2008). The WNN input and output layer vectors may be expressed as:

$$X = [x_1\, x_2\, \cdots x_k]^T \tag{1}$$

and

$$Y = [y_1\, y_2\, \cdots y_m]^T \tag{2}$$

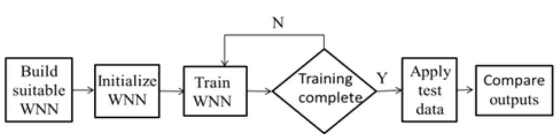

Figure 2. The Wavelet Neural Network Topology.

The transfer of the input layer to the hidden layer nodes, out1, and the hidden layer to the output layer nodes, out2, can be expressed as:

$$\text{out1} = f_1(\textstyle\sum_{i=1}^{I} w_{1ih} x_i + b_{1h}) \tag{3}$$

$$\text{out2} = f_2(\textstyle\sum_{j=1}^{J} w_{2jh}\, \text{out1} + b_{2j}) \tag{4}$$

$$\text{out2} = \bar{y}(t) \tag{5}$$

$$E = \frac{1}{2}\textstyle\sum_{j=1}^{J}[y(t) - \bar{y}(t)]^2 \tag{6}$$

where f_1 is a wavelet basis function; f_2 is a linear function; $\bar{y}(t)$ is the output of the wavelet neural network; $y(t)$is the actual value; i = 1, 2,…k; h = 1, 2,…n; and j = 1, 2,…m. Thus, the excitation function of the neurons in the hidden layer and the output function of the neurons in the output layer are:

$$f_1(t) = h(t) = \cos 1.75 \exp(\frac{t-b}{a}) \tag{7}$$

$$y(k) = \textstyle\sum_{j=1}^{n} w_{hj} h(j) \tag{8}$$

where k = 1, 2,…m, h(j) is the Morlet function or excitation function of the hidden layer of the neural network; k is the number of input neurons; n is the number of neurons in the hidden layer; m is the number of neurons in the output layer, and a and b are the scale and translation factors, respectively, of the wavelet function.w_{ih} is the weight between the input and hidden layer; and w_{hj} is the weight between the hidden and output layer.

3 THE WAVELET NEURAL NETWORK MODEL

THE WNN training steps are as follows and are shown in Figure 3.

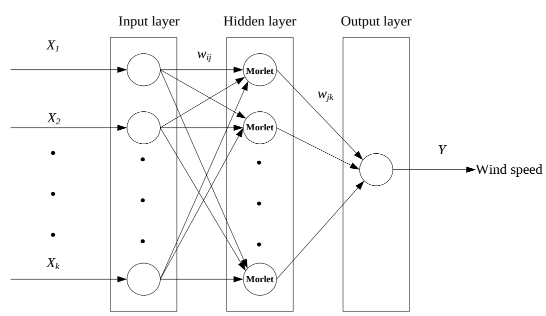

Figure 3. The Wavelet Neural Network (WNN) Algorithm.

Step 1: Initialize the network. Initialize the wavelet function stretching factor, a; translation factor, b; network connection weights, w_{ij} andw_{jk}; and network learning rate, η.

Step 2: Sample classification. Samples were divided into training and test sets. The training samples were used to train the network and test samples to test the resultant network's prediction accuracy.

Step 3: Output prediction results. Using the training samples, develop the WNN, then predict the outputs and calculate the expected output error.

Step 4: Weight Correction. Adjust the WNN weights and parameters to minimize the error compared to known wind speeds,

$$\begin{cases} \omega_{n,k}^{i+1} = \omega_{n,k}^{i} + \Delta\omega_{n,k}^{i+1} \\ a_k^{i+1} = a_k^{i} + \Delta\omega_k^{i+1} \\ b_k^{i+1} = b_k^{i} + \Delta b_k^{i+1} \end{cases}, \tag{9}$$

where $\Delta\omega_{n,k}^{i+1}$, Δa_k^{i+1}, and Δb_k^{i+1} are obtained from the prediction error,

$$\begin{cases} \Delta\omega_{n,k}^{i+1} = -\eta\frac{\sigma e}{\sigma\omega_{n,k}^{i}} \\ \Delta a_k^{i+1} = -\eta\frac{\sigma e}{\sigma a_k^{i}} \\ \Delta b_k^{i+1} = -\eta\frac{\sigma e}{\sigma b_k^{i}} \end{cases}, \tag{10}$$

where η is the learning rate.

Step 5: Terminate the algorithm. When the network error is less than the set value of the predicted values and the expected value, terminate the program. If termination conditions are met, stop processing. Otherwise return to step 3. The termination condition is

$$e = \sum_{k=1}^{m} yn(k) - y(k) \tag{11}$$

where $yn(k)$ is the desired output, and $y(k)$ is the forecast output.

4 WIND SPEED PREDICTION MODELING

THE key problem is to determine an appropriate network structure. According to the Kolmogorov Theorem (Louka Pet al., 2008), a three-layer back propagation (BP) ANN can approximate any nonlinear signal with any desired system accuracy. For a feed-forward network with three or more layers, increasing the number of hidden layers can improve the model accuracy. However, the increase in the number of hidden layers will greatly increase the time cost. To balance the model accuracy and time cost during the calculation, a three-layer wavelet neural network with a single hidden layer was selected to forecast the real-time wind speed.

There is currently no clear theory to determine the number of neurons per layer in an ANN. The design focus for the ANNs is to determine the number of hidden layers, which directly affects the complexity and convergence speed of the whole network. Although a larger number of hidden layers can enhance the ANN mapping capability, this impacts on over training, fault tolerance, and generalization ability. If the number of hidden neurons is small, the network structure is simple and the training time is short, but the prediction accuracy is low. Therefore, the neural network should meet the desired prediction accuracy while minimizing the number of hidden layer neurons.

The number of input and output layer neurons is usually related to the problem to be solved and the training dataset. The number of neurons in the hidden layer depends on the number of input and output layer neurons and network requirements. Currently, the number of hidden layer neurons is determined by testing and empirical formulas and is usually equal to the number of variables to be outputted.

This paper established four wavelet neural network models, shown in Table 1. Table 2 summarizes the dataset properties from the study area.

Table 1. The Wavelet Neural Network Models Considered.

	Model 1	Model 2	Model 3	Model 4
Input layer neurons	11	11	11	11
Hidden layer neurons	15	30	45	60
Output layer neurons	1	1	1	1

Table 2. The Dataset Summary

	Parameters	Min.	Max.
Input	Relative humidity (07:00)	8	53
	Relative humidity (14:00)	5	57
	Relative humidity (21:00)	7	64
	Soil temperature (5 cm)	-13.7	14.6
	Soil temperature (10 cm)	-11.2	12.3
	Soil temperature (50 cm)	4.2	7.2
	Air pressure (Pa)	88280	90790
	Sunshine duration (h/month)	179	320
	Air temperature (°C)	-26.6	27.8
	Days	1	31
Output	Wind speed (m/s)	0	24

5 PREDICTED WIND SPEEDS

THE data used for the experiment came from the Dabancheng Tianyi Wind Farm for January, April, July, and October of 2016, representing the four seasons, see Figure 4. This allows testing the developed models for the wind speed prediction over the different seasons. The wind speed data point interval was at 10 min.

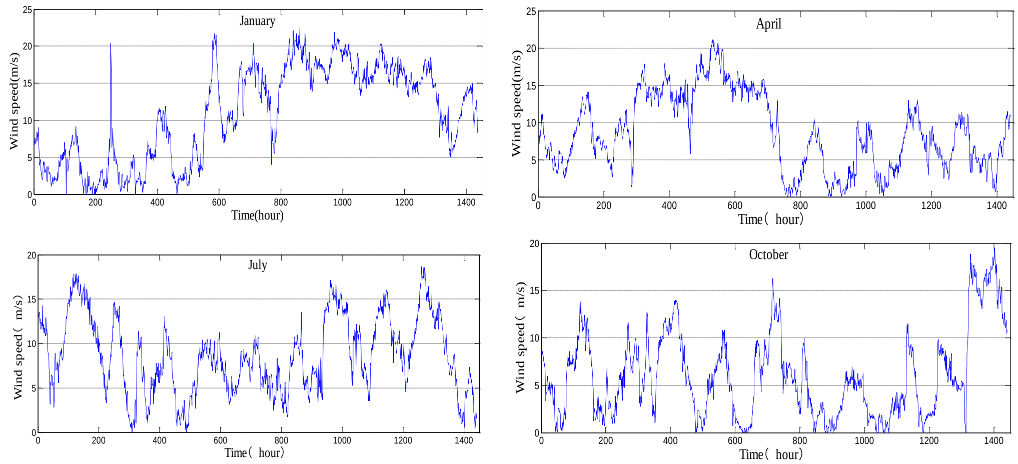

Figure 4. **The Dabancheng Mean Daily Wind Speed.**

The available wind speed datasets for each season were divided into training (1296 data points) and test (144 data points) sets. The wind speed was predicted for the day in advance of the included data.

The proposed algorithm was used to train the Dabancheng wind farm data set and applied to the test sets, as shown in Figures 5–6. A single month of wind speed during (January, April, July, and October) was selected as the test data for each season. The prediction results were compared using the mean absolute error,

$$MSE = \frac{1}{n}\sum_{t=1}^{n} e_t^2 \qquad (12)$$

Table 3 shows the error and regression values for each set of the forecasted results. The prediction accuracy of the WNN models differs with the number of neurons in the hidden layer. The errors between the predicted and actual wind speeds are large for Models 1 and 2, whereas the prediction accuracy of Models 3 and 4 is high. Model 4 provides the best predictions (R^2 = 0.9279, 0.9030, 0.99319, and 0.9378; and *MSE* =0.6337, 0.4981, 0.6256, and 0.7682 for January, April, July, and October, respectively).

These prediction results are of great significance to the wind speed prediction of the Dabancheng Electric Power Control Center.

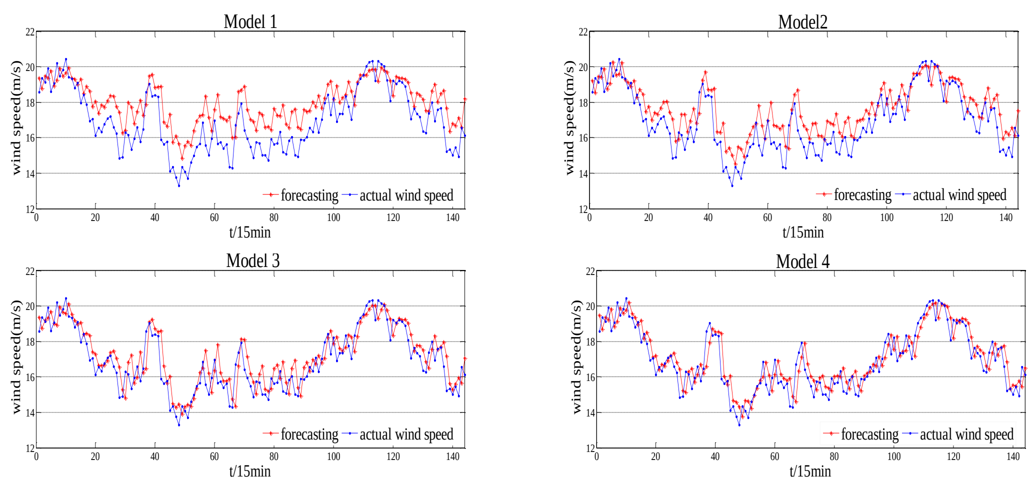

Figure 5 **Wind Speed in January.**

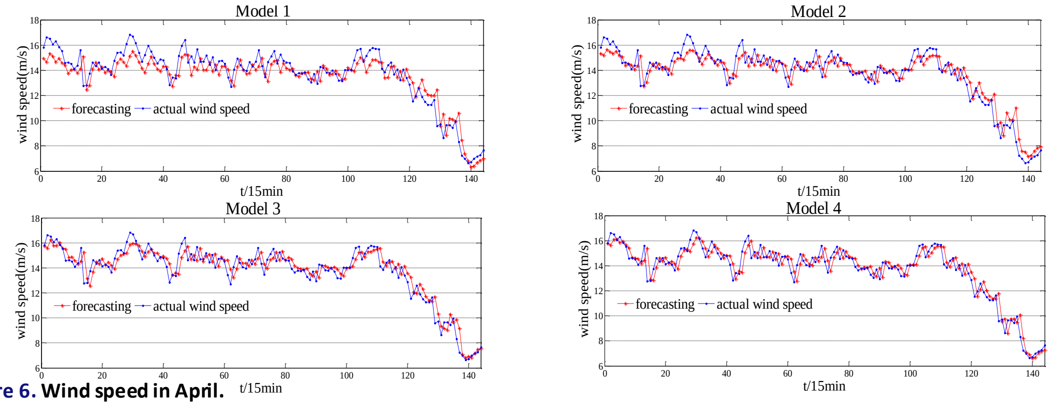

Figure 6. Wind speed in April.

Table 3. The Mean Squared Error (MSE) and Regression Coefficient (R2) for the Models.

	Model	*MSE*	R^2
January	1	0.6501	0.8812
	2	0.7417	0.8461
	3	0.6596	0.8791
	4	0.6337	0.9279
April	1	0.5211	0.8986
	2	0.5077	0.9015
	3	0.5121	0.9003
	4	0.4981	0.9030
July	1	0.5320	0.8615
	2	0.5824	0.8391
	3	0.4617	0.8830
	4	0.6256	0.9319
October	1	1.1212	0.8093
	2	0.8440	0.8927
	3	0.8852	0.8876
	4	0.7682	0.9378

6 CONCLUSION

CONSIDERING the unique natural conditions and seasonal differences of the Dabancheng, the WNNs were used to predict wind speed for the different seasons. The WNN models combined the wavelet analysis and a multi-layer perceptual neural network to predict short-term wind speed. Four different WNNs were established with different numbers of hidden neurons, trained on real data from the region, and used to predict the wind speed for the four seasons. The outcomes are summarized below. The number of hidden layers can be used to adjust the prediction accuracy of the wind speed. As the number of neurons in the hidden layer increases, the prediction accuracy is improved, but the computing time increases. Model 4, which had the largest number of hidden neurons, provided the best prediction accuracy with R^2 = 0.9279, 0.9030, 0.9319, 0.9378; and *MSE* =0.6337, 0.4981, 0.6256, 0.7682 for January, April, July, and October, respectively. The preferred model (Model 4) provides good accuracy for the short-term wind speed prediction and has good prospects for the practical engineering application.

7 ACKNOWLEDGMENT

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9 DISCLOSURE STATEMENT

No potential conflict of interest was reported by the authors.

10 NOTES ON CONTRIBUTORS

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