Ultra Short Term Wind Speed Combination Forecasting Based on Wind Tower Neural Network and Wavelet Analysis

Zhong Hong-yu¹², Gao Yang², Whang Xiu-ping², Qu Chun-yu², Xing Jing³, Zhang Qian-ran⁴, Cong Jing⁵, Li Guang-shan⁶

¹. State Grid Jilin Power Supply Company of Tonghua, Jilin Province of China
². School of Electrical Engineering, Shenyang Institute of Engineering, Liaoning Province of China
³. State Grid Jilin Power Supply Company of Changchun, Jilin Province of China
⁴. State Grid Neimenggu Electric Power Science Research Institute, Neimenggu Province of China
⁵. State Grid Liaoning Power Supply Company of Yingkou, Liaoning Province of China
⁶. State Grid Xinjiang Electric Power Science Research Institute, Xinjiang Province of China

E-mail: ¹313440302@qq.com, ²657080195@qq.com, ³13918678@qq.com

Abstract: This paper has taken neural network and wavelet analysis into combination, and proposes a novel technique of super short term wind speed forecasting based on the wind tower network and wavelet analysis. It aims to perform the wind speed forecasting in wind farm by employing the nonlinear learning ability of neural network and the multi-resolution analysis ability of wavelet theory, and provide a reliable protection for the stable operation of the power grid. Firstly, setting up the physical model of wind tower neural network, which is utilized to forecast wind speed signal at the hub of the wind turbine. Secondly, wavelet multi-resolution can be employed to decompose the wind speed signal and filter out high-frequency component for obtaining decisive role of the low frequency component for the wind speed forecast. Finally, a wind speed curve comparison chart of the method, conventional sustained wind speed model and real measured wind speed is simulated to make the proposed method have a positive contrast, then we can safely come to a conclusion that the proposed combined forecasting method in this paper based on wind tower neural network and wavelet analysis is closer to the real measured wind speed, which has a better forecasting effect on the ultra short term wind speed forecasting.

Keywords: neural network; wavelet analysis; wind speed forecasting; high frequency; low frequency.

1. Introduction

Wind energy, as a renewable and clean energy, has attracted worldwide attention in recent years. Wind energy possesses the characteristics of volatility, intermittent, low energy density, uncontrollable, so large-scale wind power connected to grid, which has brought challenge of a certain degree for the security and stability of the power system. Therefore, ultra short term wind speed forecasting of wind farm has been widely concerned by scholars both at home and abroad. Ultra short term wind farm wind speed forecasting is to forecast future within 4H, and the accurate ultra-short term wind speed forecasting can reduce the spinning reserve capacity, reduce the cost of wind power generation systems, provide a reliable basis and guarantee for the operation of power grid [1-4].

Conventional wind speed forecasting methods, such as time series method [5], exponential smoothing method [6], rough set theory method [7], chaos theory method [8], grey forecasting method [9], wavelet analysis method [10], neural network method [11], ant colony algorithm [12], ARMA model method [13] and so on, which are mostly limited to single mathematical model or physical model, being lack of deep understanding of wind speed forecast and lack the consideration of physical characteristics of the wind speed. The relevant literature shows that: wind speed forecasting average mean relative error (MRE) of wind farm is between 20% and 40% [14]. Wind speed forecasting error directly led to wind power forecasting error and forecasting precision can’t achieve ideal forecasting effect.

In all of the above forecasting methods, neural network is familiar with popular scholars by its good fault tolerance and nonlinear learning capacity, nonlinear organizational capacity, nonlinear mapping ability and so on, which is widely used in the wind speed forecasting. For example, combining neural network with time series method to forecast the wind speed, has been a good improvement effect (MRE after improved is about 15%) compared to a single time series method (MRE is 20%-25%) in the literature [15]. However, the time series method only emphasizes the role of time factor in the wind speed forecasting signal and ignores the causal relationship between the forecasting object and the influencing factors, so the forecasting accuracy is not ideal.
Wavelet analysis can divide space into several levels by using the characteristics of multi-resolution analysis, and then carry out layers of decomposition, which can extract more detailed information on time – frequency. The generalization ability is better than time series method, which is often used to forecast the wind speed. For example, the ultra short term wind speed forecasting is carried out using wavelet analysis in the literature [16], although the forecast effect is improved compared with the time series method, but it is still not satisfactory. A wind speed forecasting synthetic model based on wavelet analysis is put forward in the literature [17], which has achieved a good forecasting effect in a large extent (MRE is about 10%). It can be seen that the wind speed forecasting of the wind farm is a very complicated nonlinear process, and it is difficult to achieve a good forecasting effect by using a single forecasting model.

In terms of this, in order to further improve the accuracy of wind speed forecasting, this paper presents a forecasting method based on the combination of wind tower neural network and wavelet analysis. First, a wind tower neural network model is established by using neural network nonlinear learning ability to forecast wind speed signal at the hub of wind turbine. Then, the multi resolution analysis of wavelet theory is employed to decompose the wind speed signal. Extracting low-frequency components that have a decisive role in wind speed forecasting. Finally, through the simulation, by the comparison with conventional sustained wind speed model and the real measured wind speed, a conclusion could be obtained: the proposed method in this paper is closer to real measured wind speed, which has a good forecasting effect for ultra short term wind speed forecasting.

2. Wind speed forecasting model of scheme design based on wind tower neural network and wavelet analysis

2.1 Neural network review

Neural network is a kind of algorithm developed according to the process of human cognition. Neural network is a kind of information processing system that imitates the structure and function of human brain, which is a simple, abstract and simulation of the biological neural network of human brain. It has good fault tolerance, nonlinear learning ability, nonlinear organizational ability, nonlinear mapping ability and super strong generalization ability [18-21].

The radial basis function neural network (RBF) is used in this paper, and the radial basis function neural network is proposed by the end of 1980s, Modi (J. Moody) and Daken (C. Darken) [22]. Radial basis function is one of the main fields in the numerical analysis. Compared with BP neural network, RBF neural network is mainly reflected in the different input way of network hidden layer neurons, BP neural network uses inner, RBF neural network uses the distance, RBF neural network is a kind of partial approximation network, it only has a few connection influencing network output for a partial region of input space, for each input - output data, only a small number of connection weights need to be adjusted, so that it has the characteristics of fast learning speed and better ability of nonlinear mapping and learning. Its structure diagram is shown in Figure 1.

![Fig.1 Structure of RBF neural network](image)

In the diagram, N1, N2, …Nn represents the value of wind speed of different height of wind tower of wind farm respectively, and the unit is m/s.

2.2 Wavelet theory review

Wavelet analysis is established on the basis of Fourier transform, which makes up for the shortcomings of Fourier series, and it is able to change the Fourier series of sine wave into square integral space of some orthogonal bases by using the base to represent some of the functions, which is widely used to analyze the signal. With its characteristics of multi-resolution analysis, signal in space is divided into several hierarchical levels, wherein wavelet coefficients in different levels are explored and utilized to discuss the physical signal, and more detailed information can be obtained in time and frequency. Wavelet transform which is a partial transformation of space (time) and frequency could effectively extract important information from the signal, that is widely used to make a signal forecasting [23-24].

2.3 Scheme design
Wind tower neural network, namely by use of wind tower real measuring at different heights, in which wind speed signal of wind farm is as the input samples and wind speed signal at the hub of the wind turbine is as output sample for establishing the neural network model. Therefore, we create the design as follows:

The first step, measuring wind speed at different heights of wind farm by tower as a historical wind speed, regarding the wind speed of height as input of the wind tower neural networks (neural networks using RBF) and the historical wind speed of wind turbine hub is as the output of the wind tower neural network to train the neural network model, and the model is used to forecast the wind speed of wind turbine hub.

The second step, using multi resolution analysis of wavelet theory to decompose wind speed forecasting signal of wind turbine hub and filter out the high frequency signal, then extracting low frequency signal, which plays a decisive role in the wind speed forecasting.

The third step, the combination forecasting method proposed in this paper is compared with the conventional continuous method and the real measured data to verify the validity of the method.

The scheme design block diagram is shown in Figure 2:

![Fig.1 Block diagram of wind speed forecasting on modeling scheme design of based on Wind Tower Neural Network and Wavelet Analysis](image)

3. Wind speed forecasting scheme modeling based on wind tower neural network and wavelet analysis

3.1 Wind speed forecasting at the hub of wind turbine of wind tower neural network

According to the first step in the design scheme in Section 2.3, train wind tower the neural network model. The methods used are as follows:

Step 1: mark number for all the wind machine, the number were 1, 2, 3, ...

Step 2: wind speed history data at different heights (including 10m, 20m, 30m and 50m, 70m) of wind tower (the wind tower adopt a wind farm of china - hereinafter referred to as "Y wind farm"), the wind speed history data at the height of wind turbine hub of single is used as output, respectively. Training and establishing of wind speed wind tower neural network model for each wind turbine, the model is used to forecast wind speed at the hub of wind turbine, the physical model is shown in Figure 3.

![Fig.3 Wind Tower Neural network prediction model of wind speed](image)

3.2 Wavelet analysis decomposes wind speed forecasting signal of the wind turbine hub

According to the second step of Section 2.3, to carry on the multiresolution analysis to wind speed forecasting signal at hub of wind turbine by wind tower neural network, to extract low frequency signal that play a decisive role in the wind speed forecasting.

Take the following steps:

Step 1: multi resolution analysis
Taking the signal $x(t)$ orthogonal projection to the space $V_j$ and $W_j$, can obtain discrete approximation signal $c_j(t)$ of $x(t)$ in resolution $j$ and discrete detail signal $d_j(t)$. Make $j$ to be increased from zero step by step, and it can be realized step by step signal decomposition. Each level decomposition result will last through the decomposition of the low frequency signal which is further broken down into two parts: low frequency and high frequency. Besides, high frequency signal can be ignored and low-frequency component contains main energy in the air fluid, which has a decisive role in accuracy of wind speed forecasting. As shown in Figure 4 and Figure 5.

Fig.4 Analysis of spatial resolution

Fig.5 Decomposition process of multi resolution analysis

Step 2: selected wavelet theory function

In order to apply wavelet theory to extract low frequency components of the wind tower neural network forecasting wind speed signal effectively, we must choose a suitable wavelet function, because of various wavelet functions and with application of different wavelet analysis will have different results for same engineering problems, so selection of function of wavelet theory is very important.

Step 3: select the filter

Wind tower real measured wind speed date may be ill conditioned data, resulting in wind tower neural network model forecasting wind speed data that is less than 0. So it is necessary to filter the wind speed time series, and to eliminate the influence of pathological data.

4. Example analysis

Select real measured wind speed time series of Y wind farm in 2014, fitting a Weibull distribution curve of wind speed, as shown in Figure 6.

Fig.6 Wind speed distribution of Y wind farm in 2014

4.1 Forecasting Of Wind Speed Simulation of Wind Turbine Hub by Wind Tower Neural Network

According to the first step of 2.3 section of scheme design to do simulation forecasting. Selecting wind
speed historical time series of Y wind farm of January and February in 2014 as input, and selecting wind speed of wind turbine hub as the output, trained by wind tower neural network physical model. Taking wind speed data of "Y wind farm" March in 2014 (only extracted part) as the forecast input samples, through simulation and forecasting, the real measured wind speed, NWP wind speed, wind tower neural network forecast wind speed for comparison, as shown in Figure 7. From figure 7, we can see that compared with the real measured wind speed, wind tower neural network wind speed forecasting shows the synchronization and stability of wind series than NWP wind speed.

Fig.7 Comparison of wind speed curve of wind speed of real measured, wind speed of NWP and forecasting wind speed wind Tower neural network method

4.2 Multi resolution analysis and Simulation of wind speed forecasting at the wind turbine hub by wavelet analysis

According to the second step of scheme design of 2.3 section to do simulation forecasting. Its flow chart is shown in Figure 8. The forecasting process mainly includes multi resolution analysis (in the 3.2 step, a detailed introduction), the selected wavelet theory function, the selected of the wavelet N, the selected filter.

(1) The selected wavelet theory function

We choose dbN wavelet, because the wavelet has the following characteristics, can be used to analyze the time series in this paper:

(a) Good tight support: that is, the wavelet function is zero all the time in the interval [a, b].
(b) R value vanishing moments of wavelet function is as high as possible: if satisfied:

\[ \int_{-\infty}^{\infty} t^r \psi(t) dt = 0, (r = 0, 1, \ldots, R-1), \]

Called wavelet to have R order vanishing moments. The larger the vanishing moment, the longer the support length is, the smoother the corresponding filter is, the more zeros of smooth function after wavelet expansion is, the smaller the frequency coefficient is.

(c) Good regularity: that is, shown the micro or smooth of the wavelet basis in the mathematical performance, the higher the regularity, the higher the higher the vanishing moment for most of the orthogonal basis.

At the same time, the Pearson product moment correlation coefficient \(^{[25]}\) is used as the criterion for the linear correlation of the dbN wavelet. The correlation coefficient of Pearson product moment correlation is expressed by R, and its basic formula is shown as formula (1):

\[ R = \frac{E(XY) - E(X)E(Y)}{\sqrt{E(X^2) - E(X)^2} \sqrt{E(Y^2) - E(Y)^2}} \]  

Absolute value R is divided into three levels generally: \(|R|<0.4\) is low linear correlation; \(0.4 \leq |R| < 0.7\) is significantly correlated; \(0.7 \leq |R| < 1\) is highly linear correlation.

(2) The selected of the wavelet N
Using db2, db3, db4, db5 to decompose forecasting wind speed by wind tower neural network and real measured wind of Y wind farm in March 2014 by 3 to 6 layers, and calculating the Pearson correlation coefficient between two low frequency components, as shown in Table 1.

<table>
<thead>
<tr>
<th>Tab.1 Pearson correlation coefficient</th>
</tr>
</thead>
<tbody>
<tr>
<td>M layer</td>
</tr>
<tr>
<td>-----------</td>
</tr>
<tr>
<td>db2</td>
</tr>
<tr>
<td>db3</td>
</tr>
<tr>
<td>db4</td>
</tr>
<tr>
<td>db5</td>
</tr>
</tbody>
</table>

When m is less than or equal to 4, Pearson product moment correlation coefficient R were less than 0.9, which illustrated that low frequency part of forecasting wind speed and low frequency part of real measured wind speed is poor linear correlation; when m = 5, R of db3 wavelet is maximum, whose linear correlation degree is better. So select db3 wavelet, decomposition of the number of layers M selected 5.

(3) The selected filter
Using Butterworth filter to filter the forecasting of wind speed by the neural network model, design parameters: passband edge frequency is 0.1π, stopband edge frequency is 0.3π, band ripple is 3 dB, and stop band attenuation is 19dB.

4.3 Algorithm verification simulation
(1) Error evaluation
In order to make the forecasting accuracy have a good evaluation, this paper uses the average relative error (MRE) to evaluate the model, and its mathematical model formula (2) is shown in this paper:

\[ MRE = \frac{1}{N} \sum_{i=1}^{N} \frac{|x_i - x_{i,\text{pre}}|}{x_i} \] (2)

In the formula (2), N is forecasting sample length, \(x_i\) is sample real value, and \(x_{i,\text{pre}}\) is sample forecasting value.

Using MATLAB to have simulated the average relative error curve of the linear wavelet (no filtering) and linear wavelet (with filter) and take average relative error curve of single forecasting of wind speed of sustainable model and NWP wind speed as the measured standard of forecasting effect. As shown in Figure 10.

![Fig.10 Comparison of the average relative error curves of the three models and NWP](image)

It can be seen from the Figure 10: the forecasting curve of wavelet linear (including filtering) is smoother, more stable, and better forecasting results.

(2) Judge of forecasting scale
Usually judge for ultra-short term to <4h to forecast, short term to >4h to forecast, in order to make the forecasting scale has a positive judgment, this paper has simulated average relative error curve that forecast period is 1h–24h of linear wavelet (with filter). As shown in Figure 11.
From figure 11 it can be seen: when the forecast period is less than 4h, linear wavelet (with filter) model is utilized to forecast the effect is relatively stable, when the forecast period is more than 4h, wavelet linear (with filter) model to forecast the effect is poor, which is because when the forecasting period is more than 4 hours, the system error sequence of linear correlation of the forecasting periods is lower. So we can draw the conclusion that the wind speed signal could be obtained by the wind tower neural network to forecast, then wind speed forecasting scale by the wavelet multiresolution analysis is applicable to ultra-short-term.

(3) Combination forecast verification

Use the combination method of wind tower neural network and wavelet analysis to forecast wind speed time series of March 3 to March 9 of Y wind farm in 2014 by MATLAB simulation, the results are as shown in Figure 12 and the MRE as shown in Table 2.

As can be seen from Figure 12, a combination forecasting method of this paper put forward is closer to the real measured wind speed.

<table>
<thead>
<tr>
<th>Forecasting model</th>
<th>MRE/%</th>
</tr>
</thead>
<tbody>
<tr>
<td>NWP wind speed</td>
<td>25.74</td>
</tr>
<tr>
<td>Sustainable model</td>
<td>20.32</td>
</tr>
<tr>
<td>Combined forecasting</td>
<td>10.58</td>
</tr>
</tbody>
</table>

As can be seen from Table 2, the MRE value of the combined forecasting model proposed in this paper is 10.58%, which has reached a very good prediction accuracy.

5. Conclusions

This paper has performed the ultra-short term wind speed combination forecasting model based on the wind tower neural network and wavelet analysis by building wind tower neural network physical model to forecast wind speed of wind turbine hub, then employing a wavelet multi resolution analysis to decompose wind speed forecasting signal of wind turbine hub, which is used to extract the low frequency signal (this low
frequency signal has a decisive effect on wind speed). Simulation results show that when the prediction time > 4h, forecasting error increases gradually; when the forecast period < 4h, forecasting error is relatively stable, which is suitable for the ultra-short term wind speed forecasting. Finally, the conclusion is obtained: combined method based on the wind tower neural network and wavelet analysis is applicable to ultra short term wind speed forecasting, and through the comparison of a single continuous model forecasting wind speed and real measured wind speed, the combination forecasting method is closer to the real measured wind speed, which affirmed the effectiveness of the combination forecasting method.

6. Acknowledgement

The authors acknowledge the financial support of the National Nature Science Foundation, project NO. 60972164, 61273029, 60904101, 61203086, the Key Project of Chinese Ministry of Education, project NO. 212033, the Program for Liaoning Excellent Talents in University, project NO. LJQ2014136.

7. References


