Wind speed forecasting using wavelet network based on a structure optimization method

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Abstract. Accurate forecasting of wind speed is significant to the safe and stable operation of wind power system. In this paper, a structure optimization method is proposed and used to improve the accuracy of wavelet network wind speed forecasting model. In the training process of wavelet network, grey correlation pruning method is applied to optimize the hidden layer nodes firstly, until the grey correlation pruning coefficients of the remaining hidden nodes are greater than grey correlation pruning threshold. Secondly, contribution pruning method is applied to optimize the hidden layer nodes, until the contribution pruning coefficients of the remaining hidden nodes are greater than contribution pruning threshold. Finally wind speed forecasting model is built with optimized wavelet network. Experiment results show that using the grey correlation-contribution pruning method to optimize wavelet network can simplify the network structure, and the performances of the optimized wind speed model have been improved obviously compared with the wavelet network without structure optimization.

Introduction

In recent years, with the aggravation of the energy crisis, countries around the word have increasingly focused on wind power [1]. However, wind power is always intermittent and fluctuating, which brings severe challenges to power system, especially in aspects of stable operation and reasonable dispatch. Wind speed forecasting is a key technology that could be applied to alleviate the adverse effects[2]. Therefore, the accurate forecasting of wind speed is crucial for the wind power generation.

Wavelet network is a combination of wavelet analysis and artificial neural network, and has the advantages of strong function approximation capacity and fast convergent speed. However, the number of the hidden layer nodes is generally determined by experience of designer, which may be not suitable for application. Generally, when there are too many hidden nodes, the training time will become longer and it is easily for wavelet network to fall into local optimal solution; when there are too few hidden nodes, wavelet network has lower data handing capacity and fitting capacity [3]. So, some approaches have been proposed to optimize the structure of the wavelet network. A structure optimization method based on Sanger Algorithm [4] is proposed to solve the problem like too many nodes. However, feature value and feature vector are requested to calculate. In reference [5], grey correlation pruning method is used to optimize the structure of network. However, there are problems like deleting hidden nodes by mistake and failing to delete redundant hidden nodes completely, when the grey correlation threshold is not suitable.

In this paper, the grey correlation-contribution pruning method is proposed to optimize the structure of the wavelet network and determine the number of hidden nodes. A wind speed forecasting model is built with the optimized wavelet network. The forecasting results indicate the effectiveness and feasibility of the approach.

Wind Speed Forecasting Model based on Wavelet Network

Input of forecasting model. Study has shown that the historical wind speed and meteorological factors are closely related to wind speed [6]. And these factors are used to determine the input of forecasting model. The experimental data are collected from a wind farm in Shanxi Province in 2014, and involve some variables like wind speed (x_1), wind direction (x_2), temperature (x_3), humidity (x_4) and barometric pressure (x_5). The time interval is 15 minutes. There are 2016 data samples in each month, and the 1st~1920th samples of them are used to build forecasting model, the 1921st~2016th samples are applied to test the forecasting performance.

Analyzing the experimental data, it has been found that the meteorological factors are changed slowly within a short time, and the historical data of a moment before make major influence to forecasting wind speed. Auto-correlation technique is used to analyze the wind speed, and the result could be found that the historical wind speed $x_1(t)$ is important for the forecasting wind speed $x_1(t+1)$. According to these results, input of the forecasting model could be determined and shown in Table 1.

Table 1 Input of the wind speed forecasting model

Data sources	Input	Number
June	$x_1(t)$, $x_2(t)$, $x_3(t)$, $x_4(t)$, $x_5(t)$	5
July	$x_1(t)$, $x_2(t)$, $x_3(t)$, $x_4(t)$, $x_5(t)$	5

Wind speed forecasting model. In this paper, the wind speed forecasting model is based on wavelet network with three-layer structure: input layer, hidden layer and output layer, shown in Fig 1.

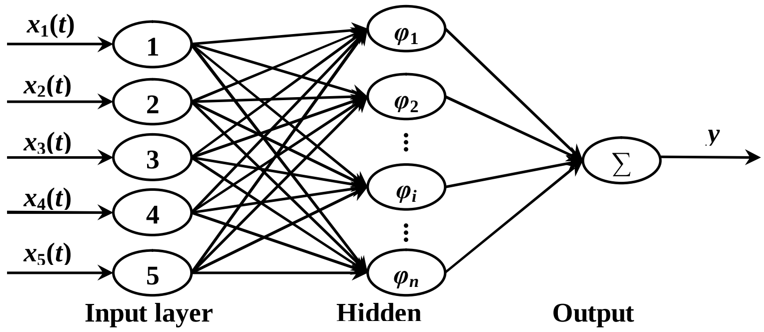

Fig 1. The structure of wind speed forecasting model

As shown in Fig 1, $x_1(t)$, $x_2(t)$, $x_3(t)$, $x_4(t)$, $x_5(t)$ are the input of model; y is the output of model; $\varphi_1,\varphi_2,\ldots,\varphi_i,\ldots,\varphi_n$ are activation functions of hidden nodes where n denotes number of hidden nodes, and here Morlet wavelet is used as activation function of hidden node, defined as:

$$j\,(x) = \cos(1.75x)e^{-x^2/2} \tag{1}$$

When giving input, the output of wind speed forecasting model is calculated as:

$$y = \sum_{i=1}^{n} w_i j\,((\sum_{j=1}^{5} w_{ij}x^j - b_i)/a_i) \quad i = 1, 2, \mathbf{L}, n \tag{2}$$

where j represents the j^{th} input node, w_i is the weight between the i^{th} hidden node and output node; w_{ij} is the weight between the j^{th} input node and the i^{th} hidden node; x^j is the input of the j^{th} input node; a_i is the scale coefficient of the i^{th} hidden node and b_i is the translation coefficient of the i^{th} hidden node.

Structure Optimization of Wind Speed Forecasting Model

To improve the performance of wind speed forecasting model, grey correlation-contribution pruning method is proposed and applied to optimize the structure of wind speed forecasting model. Assume $o_i=(o_i(1),o_i(2),\ldots,o_i(p),\ldots,o_i(N_1))(i=1,2,\ldots,n)$ is output of the i^{th} hidden node under N_1 training samples, $y=(y(1),y(2),\ldots,y(p),\ldots,y(N_1))$ is output of wavelet network under N_1 training samples.

Grey correlation degree. Grey correlation degree reflects the degree of correlation between output of hidden node and wavelet network output. The grey correlation degree of the i^{th} hidden node is defined as [7]:

$$r_i = \frac{1}{N_1}\sum_{p=1}^{N_1} x_i(p) \quad i = 1, 2, \mathbf{L}, n^{'} \tag{3}$$

where $n^{'}$ denotes the number of current hidden nodes and $\xi_i(p)$ is calculated as:

$$x_i(p) = \frac{\min_i \min_p |y(p) - o_i(p)| + l \times \max_i \max_p |y(p) - o_i(p)|}{|y(p) - o_i(p)| + l \times \max_i \max_p |y(p) - o_i(p)|} \tag{4}$$

where l is the distinguishing coefficient and usually l=0.5.

Contribution degree. Contribution degree reflects the contribution that hidden nodes make to the wavelet network output, and the contribution degree of the i^{th} hidden nodes is defined as [8]:

$$r_i = \frac{1}{N_1}\sum_{p=1}^{N_1} (S_i(p) - \overline{S_i})^2 \tag{5}$$

where $S_i(p)$ and $\overline{S_i}$ are calculated as:

$$S_i(p) = \frac{w_i o_i(p)}{y(p)} \ , \quad \overline{S_i} = \frac{1}{N_1}\sum_{p=1}^{N_1} S_i(p)$$

(6)

Grey correlation-contribution pruning method. This method is mainly divided into two steps. First, calculate the grey correlation degrees of hidden nodes, and delete the hidden nodes which have less grey correlation degrees. Second, calculate the contribution degrees of hidden nodes, and delete the hidden nodes which have less contribution degrees. Thus, the structure of forecasting model will be optimized. The flow chart of the grey correlation-contribution pruning method is shown in Fig 2.

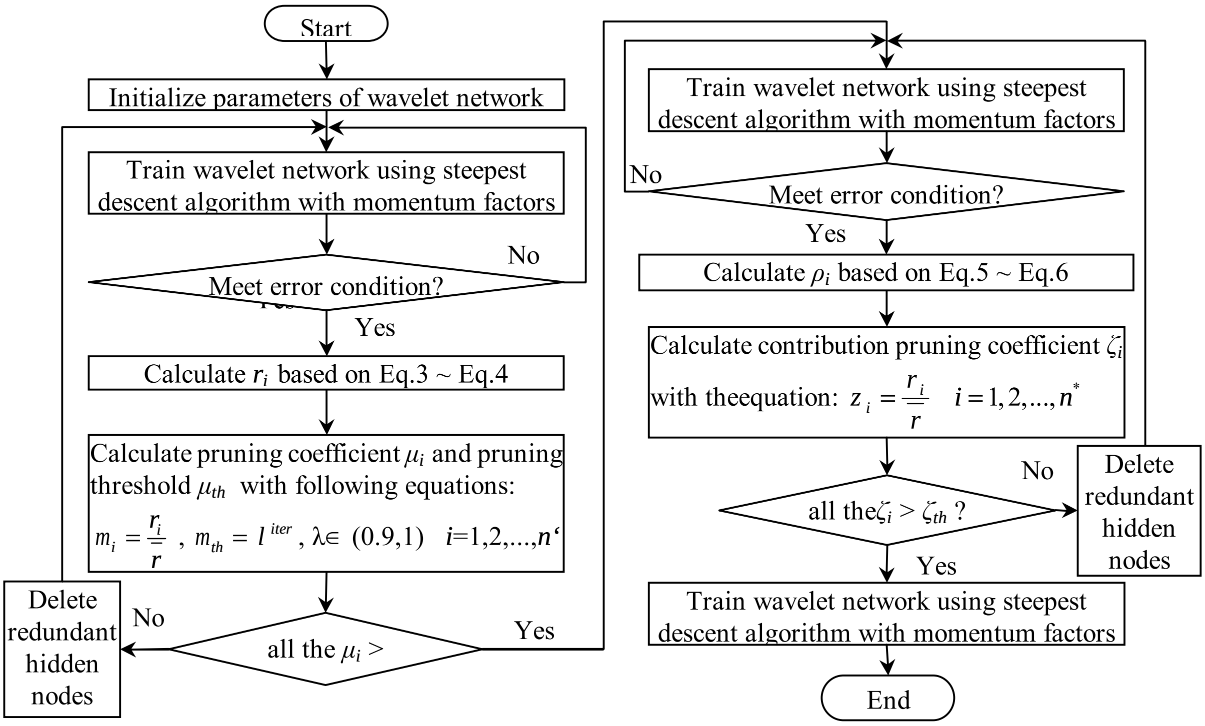

Fig 2. The flow chart of structure optimization based on grey correlation-contribution pruning method

Experimental Results and Analysis

To estimate the effectiveness and feasibility of the proposed approach, four different models based on grey correlation–contribution pruning method, grey correlation pruning method, contribution pruning method and basic wavelet network respectively are built to forecast wind speed, and they are marked as M1, M2, M3 and M4 respectively. The mean absolute percentage error (*MAPE*), the mean absolute error (*MAE*) and the root mean squared error (*RMSE*) are applied to evaluate forecasting accuracy.

To make a fair comparative analysis of the four models, the key training parameters of each model are kept the same. And these parameters are chosen as: (1) Number of input nodes: 5; (2) Number of output nodes: 1; (3) Initial number of hidden nodes: 26 (this value is calculated as $n=\max\left(2\times\left(\left\lceil\sqrt{5+1}\right\rceil+a\right)\right)\ a\in[1,10]$); (4) Initial weights, scale coefficient and translation coefficient: random number in a rang of [-0.1, 0.1]; (5) Maximal training times: 1000; (6) Learning rate of weights: 0.01; (7) Learning rate of scale coefficient and translation coefficient: 0.001; (8) Goal error of models: 0.0001; (9) Momentum factors: 0.1.

Fig 3and Fig 4 show the wind speed forecasting results at the 1921st~ 2016th samples of June and July in 2014. The evaluated results of these forecasting results are displayed in Table 2.

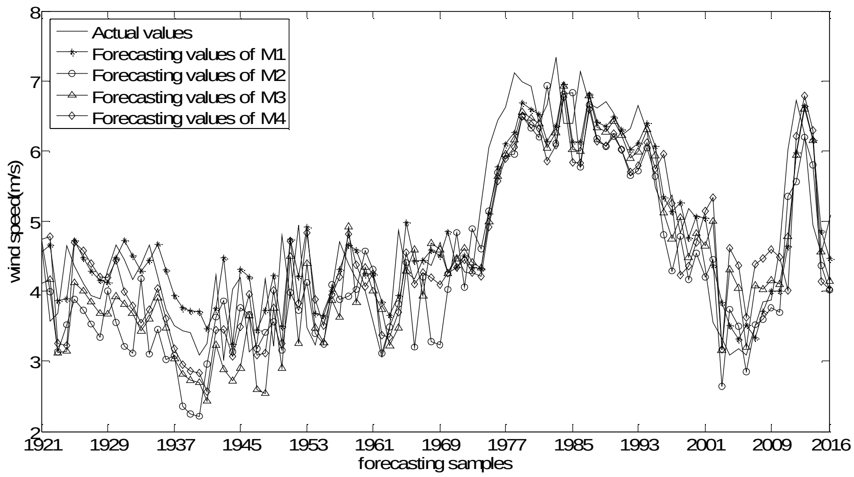

Fig 3. The forecasting results of June based on M1, M2, M3 and M4

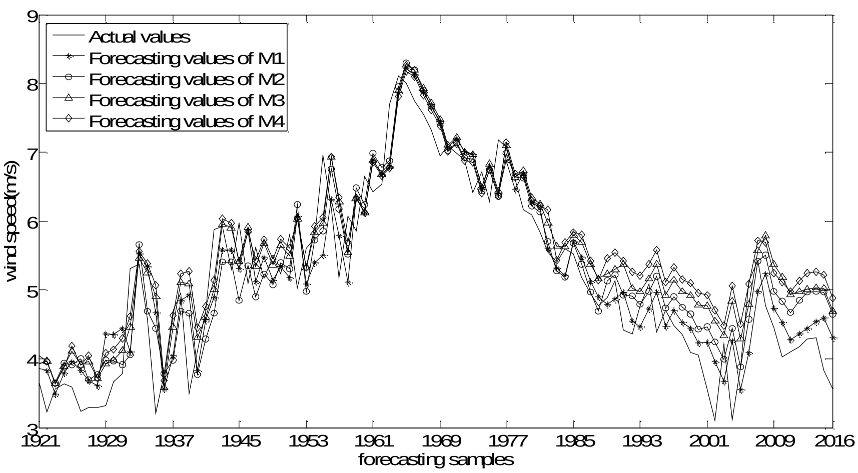

Fig 4. The forecasting results of July based on M1, M2, M3 and M4

Table 2 The evaluated results of wind speed forecasting results in June and July

Model		M1	M2	M3	M4
June	number of hidden nodes	7	21	14	26
	MAPE (%)	10.62	12.96	12.90	13.41
	RMSE (m/s)	0.5782	0.7108	0.5157	0.7383
	MAE (m/s)	0.4658	0.5900	0.5755	0.5994
July	number of hidden nodes	10	19	17	26
	MAPE (%)	9.67	10.13	11.88	13.07
	RMSE (m/s)	0.5553	0.5822	0.6548	0.7135
	MAE (m/s)	0.4497	0.4653	0.5312	0.5749

The above results indicate the following:

(1) The forecasting results of M4 are further away from actual values of wind speed, and the errors are maximal. After structure optimization, the performance of wind speed forecasting model is improved, the necessity of structure optimization is proved.

(2) The number of hidden nodes of M1 is minimal. When comparing M1with M2, M3 and M4 in sequence, *MAPE*, *RMSE* and *MAE* of M1 are minimal, the accuracy of M1is improved. These results show that using grey correlation-contribution pruning method, can not only retrench the structure of wavelet network, but also improve the performance of wind speed forecasting model. The effectiveness and feasibility of the proposed method are proved.

Conclusion

In order to further improve the accuracy of forecasting model, the grey correlation-contribution pruning method is proposed and has been used to optimize structure of wavelet network. The data from a wind farm in Shanxi Province are used to conduct experiments. The results demonstrate the necessity of optimizing the structure of wavelet network. And the proposed method can reasonably simplify the structure of wind speed forecasting model, which not only can improve the forecasting performance of wind speed model, but also make a guidance for determining optimal structure of wavelet network in the filed of wind speed forecasting modeling.

Acknowledgments

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References

[1] Y. Jiang, Z. Song, A. Kusiak, Very short-term wind speed forecasting with Bayesian structural break model, J. Renewable energy.50(2013): 637-647.

[2] X. C. Wang, P. Guo, X. B. Huang, A review of wind power forecasting models, J. Energy Procedia. 12(2011): 770-778.

[3] Y. B. Meng, J. H. Zou, G. H. Liu, Optimization method for hidden layer nodes of WNN based on rough set reduction, J. Control and Decision. 2014,29(6): 1091-1096. (In Chinese)

[4] S. S. Liu, S. L. Yu, Y. Ding, Structure optimal method of wavelet network based on sanger algorithm, J. Computer Engineering and Design. 2004,25(9): 1438-1440.

[5] W. M. Tang, The study of the optimal structure of BP Neural Network, J. Systems Engineering Theory and Practice. 2006,25(10): 95-100. (In Chinese)

[6] X.J. Liu, T. Y. Cen, W. S. Zheng, Z. Q. Mi, Neural Network Wind Speed Prediction Based on Fuzzy Rough Set and Improved Clustering, J. Proceedings of the CSEE.2014,34(19): 3162-3169. (In Chinese)

[7] X. M. Zhang, F. Wang, Y. X. Jin, Hidden layer structure optimization of BP Network based on grey incidence degree and sensitivity degree, J. Computer Measurement and Control. 2014,22(009): 3055-3057. (In Chinese)

[8] Y. J. Zhang, Fuzzy neural network optimization and system performance evaluation research. Lanzhou: Lanzhou University of Technology, 2013. (In Chinese)