Applied Soft Computing 23 (2014) 452–459

Contents lists available at ScienceDirect

Applied Soft Computing

journal homepage: www.elsevier.com/locate/asoc

Forecasting wind speed using empirical mode decomposition and Elman neural network

Jujie Wang [a,b], Wenyu Zhang [b,*], Yaning Li [c], Jianzhou Wang [c], Zhangli Dang [b]

[a] School of Economics and Management, Nanjing University of Information Science and Technology, Nanjing 210044, China
[b] Key Laboratory for Semi-Arid Climate Change of the Ministry of Education, College of Atmospheric Sciences, Lanzhou University, Lanzhou 730000, China
[c] School of Mathematics and Statistics, Lanzhou University, Lanzhou 730000, China

ARTICLE INFO

Article history:
Received 30 July 2013
Received in revised form 26 April 2014
Accepted 18 June 2014
Available online 27 June 2014

Keywords:
Wind speed prediction
EMD
Elman neural network
PACF
Hybrid model

ABSTRACT

Because of the chaotic nature and intrinsic complexity of wind speed, it is difficult to describe the moving tendency of wind speed and accurately forecast it. In our study, a novel EMD–ENN approach, a hybrid of empirical mode decomposition (EMD) and Elman neural network (ENN), is proposed to forecast wind speed. First, the original wind speed datasets are decomposed into a collection of intrinsic mode functions (IMFs) and a residue by EMD, yielding relatively stationary sub-series that can be readily modeled by neural networks. Second, both IMF components and residue are applied to establish the corresponding ENN models. Then, each sub-series is predicted using the corresponding ENN. Finally, the prediction values of the original wind speed datasets are calculated by the sum of the forecasting values of every sub-series. Moreover, in the ENN modeling process, the neuron number of the input layer is determined by a partial autocorrelation function. Four prediction cases of wind speed are used to test the performance of the proposed hybrid approach. Compared with the persistent model, back-propagation neural network, and ENN, the simulation results show that the proposed EMD–ENN model consistently has the minimum statistical error of the mean absolute error, mean square error, and mean absolute percentage error. Thus, it is concluded that the proposed approach is suitable for wind speed prediction.

Introduction

With the deterioration of the environment and depletion of conventional resources, increasing attention has turned to renewable energy. As one of the cleanest forms of renewable energy, wind energy is in rapid development around the world [1]. In China alone, wind energy is growing at 114%, and the total installed capacity of wind power was 25805.3 MW in 2009 [2–4]. In the past 3 years, the total installed capacity of wind power has been doubled, and this trend is expected to continue [5]. With the increasing utilization of wind power, it is becoming increasingly important to integrate wind power into electricity grids [6]. However, because of the intermittent and intrinsic complexity of wind, the integration efficiency of wind power into electricity grids is limited, and the integration cost is high [7]. To improve the utilization efficiency of wind power and reduce the integration cost of wind energy, the accurate prediction of wind speed is indispensable [8].

To improve wind speed prediction accuracy, many approaches have been developed in the past 30 years. Generally, these approaches can be divided into four categories: (a) physical approaches; (b) statistical approaches; (c) hybrid physical-statistical approaches; and (d) artificial intelligence (AI) techniques [9–11]. Physical approaches try to use physical considerations, such as the topography, roughness, and obstacles, to achieve the most accurate forecast of wind speed. They are very expensive and complicated approaches and are not reliable for short-term prediction [12,13]. Statistical approaches for wind speed prediction use statistical equations to describe the statistical regularities of wind speed [14–17]. These approaches have certain advantages, such as simplicity; they are easy to model and do not require any data beyond historical wind speed data. However, the forecasting accuracy of these approaches drops rapidly when the nonlinear characteristics of wind speed series are prominent. Normally, physical and statistical methods are used in combination, where the results of the physical approaches are used as input to the hybrid system, which is trained according to the statistical theories [1,42]. With

* Corresponding author at: College of Atmospheric Sciences, Lanzhou University, Lanzhou 730000, China. Tel.: +86 931 8911031; fax: +86 931 8914278.
E-mail address: zhangwy@lzu.edu.cn (W. Zhang).

http://dx.doi.org/10.1016/j.asoc.2014.06.027
1568-4946/

the development of AI techniques, certain novel approaches based on AI have been developed, mainly including the Artificial Neural Network (ANN), fuzzy logic method, and support vector machine [18–23].

As a novel machine-learning tool, ANN can be a useful technique for wind speed prediction. It can map random input vector(s) to the corresponding random output vector among the empirical data even with no a priori assumption about the properties of the empirical data and can use this information to forecast future values [24–26]. Normally, ANNs can be divided into two categories: (a) forward networks and (b) recurrent networks. In forward networks, there are no delay or feedback elements, and in recurrent networks, the output depends on the current and previous inputs or outputs of the network [27]. In previous studies, forward networks have frequently been used for wind speed prediction, while recurrent networks have rarely been used. However, unlike forward networks, recurrent networks can make use of internal memory to exhibit temporal behavior and handle arbitrary input data series [28]. This ability makes them applicable to time series prediction with satisfactory prediction results [29]. As a special recurrent neural network, the Elman neural network (ENN) has been widely used in the field of time series prediction [30,31]. However, ENN is rarely used for wind speed prediction. Therefore, we are motivated to use ENN to forecast wind speed in this paper.

When using models for wind speed forecasting, the original wind speed datasets are usually applied directly to build prediction models. However, because of the chaotic nature and intrinsic complexity of wind speed, it is difficult to describe the moving tendency of wind speed and accurately forecast it. To construct a suitable prediction model, the original dataset features of wind speed need to be fully considered and analyzed. As a weather-driven renewable resource that depends on climate, wind has specific cycles such as year, month, week, and day, and these cycles are nested in each other. Therefore, the wind speed series can be considered as a combination of sub-series characterized by different frequencies. Each sub-series corresponds to a range of frequencies and shows much more regularities and hence they are predicted more accurately than the original wind speed series. To improve the prediction accuracy, the multi-scale decomposition of the original wind speed is indispensable. As a special signal processing technique, empirical mode decomposition (EMD) has certain advantages regarding multi-scale signal decomposition, and it can decompose a complex signal into a collection of intrinsic mode functions (IMFs) and a residue, which are relatively stationary sub-series and can be readily modeled [32,33]. Due to the complex nonlinear characteristics of original wind speed datasets, EMD is applied to decompose the original datasets in this study.

In this study, a novel EMD–ENN approach that hybridizes EMD and ENN is proposed to forecast wind speed. First, the original wind speed datasets are decomposed into a collection of IMFs and a residue by EMD, which are relatively stationary sub-series and can be readily modeled. Second, both the IMF components and the residue are used to establish the corresponding ENN models. Finally, the prediction values of the original wind speed datasets are calculated by summing the forecasting values of every sub-series. Moreover, in the ENN modeling process, the neuron number of the input layer is determined by a partial autocorrelation function (PACF). Four prediction cases of wind speed are used to test the performance of the proposed hybrid approach. Compared with the persistent model (PM), back-propagation neural network (BPNN), and ENN, the simulation results show that the proposed EMD–ENN model consistently has the minimum statistical error of the mean absolute error (MAE), mean square error (MSE) and mean absolute percentage error (MAPE). It is concluded that the proposed approach is an effective way to improve prediction accuracy.

The rest of this paper is organized as follows. Proposed approach presents the hybrid EMD–ENN approach for wind speed prediction. Experimental simulation provides the evaluation criteria and presents the numerical results from four real datasets. Finally, the last part outlines the conclusions.

Proposed approach

In this paper, an EMD–ENN model, which feeds EMD into ENN, is proposed for wind speed prediction. The algorithm is described below, and the flowchart is shown in Fig. 1. The methods used in the EMD–ENN approach are briefly introduced in the following sections.

Step 1: Use the EMD to decompose the original wind speed datasets into several sub-series, which have simpler frequency components and are relatively easy to model.
Step 2: Apply the PACF to determine the potential relationship between the input vector and the corresponding output vector, and determine the input number of neurons of the ENN models for each sub-series.
Step 3: Construct the ENN models for each sub-series, and apply the established ENN models to predict each sub-series.
Step 4: Aggregate the prediction results of each sub-series, and obtain the prediction values of the original datasets.

Empirical mode decomposition (EMD)

Compared with other signal decomposition techniques, the EMD method is relatively easy to understand and use. Its central idea is to use the Hilbert–Huang transform (HHT) to sift the non-stationary signal until the signal is stationary [32]. The foundation of the method is to decompose a complicated signal into a sum of several intrinsic mode functions (IMFs) and a residue, which are relatively stationary sub-series and can be readily modeled. In EMD, a function is called IMF if it satisfies the following two conditions: (1) in the whole dataset, the sum of the extrema and the sum of the zero crossings must be equal or must differ at most by one, and (2) the average of the envelope, which is defined by the local maxima and minima, must be zero at any point [33]. Let $\{y(t)\}$ be a given original wind speed time series, and then the EMD calculation can be described as follows:

$$y(t) = \sum_{i=1}^{n} f_i(t) + R_n(t) \tag{1}$$

where $f_i(t)\,(i = 1, 2, \ldots, n)$ represents the different IMF, and $\{R_n(t)\}$ is the residue after n IMFs are derived. The process of sifting alteration is used to extract the separate IMF. For convenience, we describe the sifting process as follows [32,34–36]:

Step 1: Identify all the local extrema of the original wind speed time series $\{y(t)\}$.
Step 2: Calculate its upper envelope $\{y_1(t)\}$, which can be derived by connecting all the local maxima using a cubic spline line. Similarly, we can obtain the lower envelope $\{y_2(t)\}$.
Step 3: Apply the upper and lower envelops to calculate the mean envelope $\{h(t)\}$, which can be presented as follows:

$$h(t) = \frac{[y_1(t) + y_2(t)]}{2} \tag{2}$$

Step 4: Find the IMF. Let $m(t) = y(t) - h(t)$. If $\{m(t)\}$ is an IMF, then set $f(t) = m(t)$ and meantime replace $\{y(t)\}$ with the residual $R(t) = y(t) - f(t)$. Otherwise, if $\{m(t)\}$ is not an IMF, replace $\{y(t)\}$ with $\{m(t)\}$, and repeat Steps 2–3 until the termination criterion is satisfied. The stop condition of the iterative process is as follows:

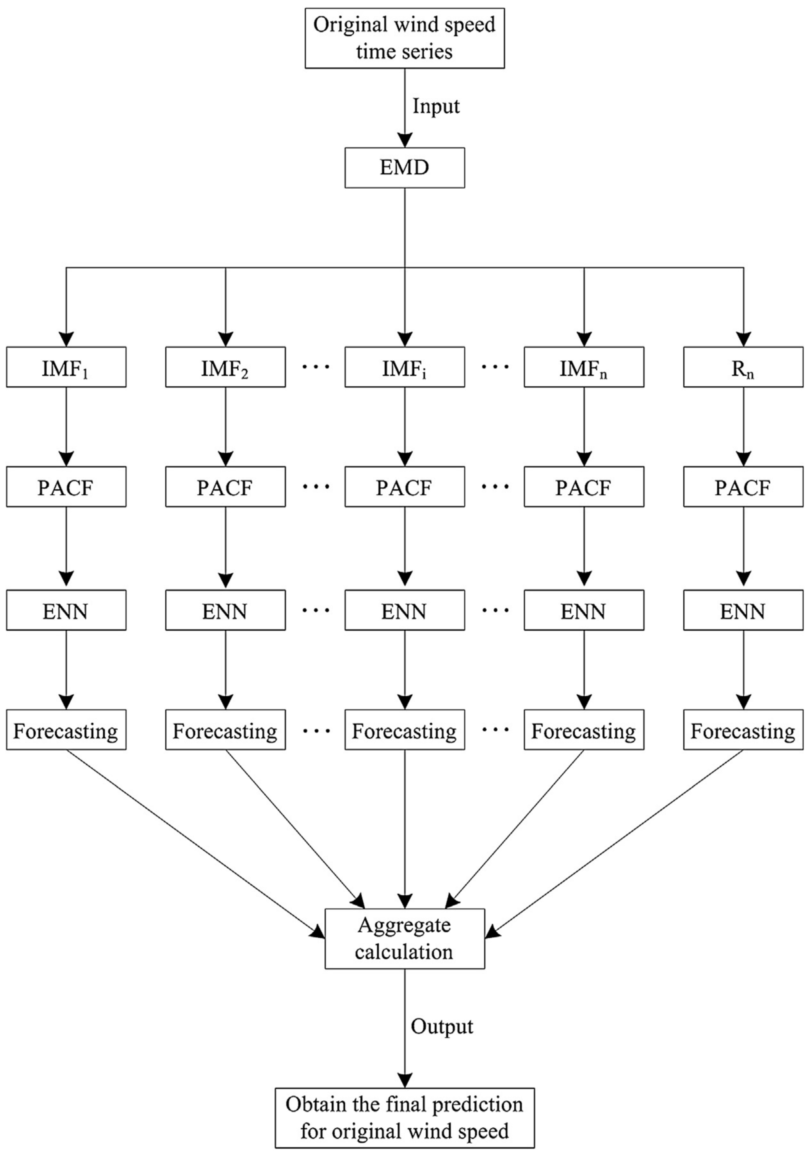

Fig. 1. EMD–ENN flowchart.

$$\sum_{t=1}^{l}\frac{[m_{i-1}(t)-m_i(t)]^2}{[m_{i-1}(t)]^2}\leq\delta \quad (i=1,2,\ldots;t=1,2,\ldots,m) \tag{3}$$

where l is the length of the signal; i denotes the number of iterative calculations, and δ is the terminated parameter, which is usually determined according to the practical application. In this paper, $\delta = 0.3$.

Step 5: Repeat steps 1–4 until all the IMFs are found.

Elman neural network (ENN)

The ENN, a simple recurrent neural network, was introduced by Elman in 1990 [37]. This type of network consists of an input layer, a hidden layer, and an output layer. In this sense, it is similar to a three-layer feed-forward neural network. However, it has a context layer that feeds back the hidden layer outputs in the previous time steps. The neurons contained in each layer are used to propagate information from one layer to another. The dynamics of the change in hidden state neuron activations in the context layer is as follows [30,31]:

$$S_i(t)=g\left(\sum_{k=1}^{K}V_{ik}S_k(t-1)+\sum_{j=1}^{J}W_{ij}I_j(t-1)\right) \tag{4}$$

where $S_k(t)$ and $I_j(t)$ denote the output of the context state and input neurons, respectively; V_{ik} and W_{ij} denote their corresponding weights; and $g(\cdot)$ is a sigmoid transfer function.

For example, a simple three-layer ENN is shown in Fig. 2. From Fig. 2, one can see that the network has two input neurons, two hidden neurons and a single output neuron. There are also two context neurons. The context neurons receive input from the hidden layers and pass their output to the hidden layers. The context layers always store the output from the hidden layer and relay this information in the next iteration. This behavior allows them to form a sort of short-term memory.

In this study, we adopt a three-layer network with the addition of a set of context units in the input layer. The ENN has hyperbolic tangent sigmoid transfer function neurons in its hidden (recurrent) layer and linear transfer function neurons in its output

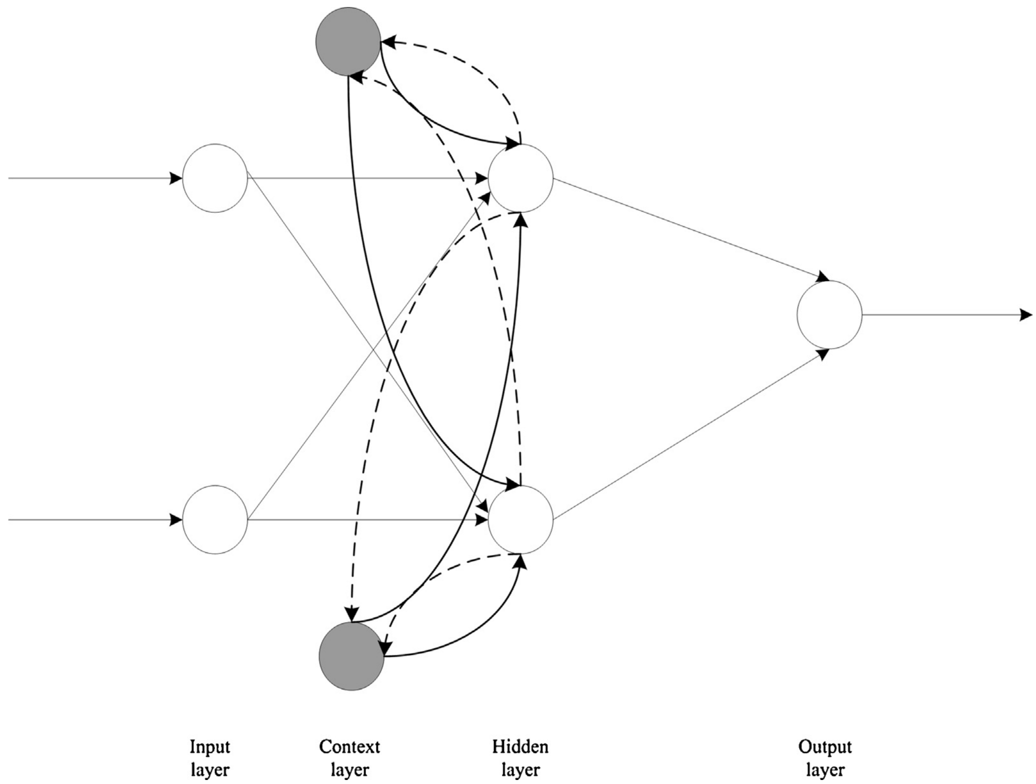

Fig. 2. ENN architecture.

layer. These connections between the hidden layer and the context units are fixed with a weight of one. The back-propagation learning algorithm is adopted, and the information of the input layer is propagated by a standard feed-forward network.

Partial autocorrelation function (PACF)

In ANN theory, the format of the training data directly impacts the performance of the network. In the same way, the format of sub-series attained by the calculation of the EMD can also affect the ENN. How to apply those sub-series to train ENN models is a challenging issue. To break through the limitation of ignoring the training data format, the PACF is utilized to determine the training data format [38]. Concretely, let $x(i)$ be a given output variable. If the partial autocorrelation at lag t is outside the 95% confidence interval, $[-1.96/\sqrt{N}, 1.96/\sqrt{N}]$, then $x(i-t)$ is one of the input variables. The description of PACF is as follows [39,40]:

$$\varphi(B)x(i) = \theta(B)a(i) \tag{5}$$

where $\varphi(B) = 1 - \varphi_1 B - \varphi_2 B^2 - \cdots - \varphi_p B^p$ and $\theta(B) = 1 - \theta_1 B - \theta_2 B^2 - \cdots - \theta_q B^q$.

Let $\{y(i)\}$ $(i = 1, 2, \ldots, n)$ be a time series, and let $\gamma(t)$ denote the covariance at lag t. Then the estimate $\hat{\gamma}(t)$ of $\gamma(t)$ is derived as follows:

$$\hat{\gamma}(t) = \frac{1}{n}\sum_{i=1}^{n-t}(y(i)-\bar{y})(y(i+t)-\bar{y}), \quad t = 0, 1, \cdots, m \tag{6}$$

where $\bar{y}$ is the average of the time series $\{y(i)\}$, and $m = n/4$ is the maximum lag. It is clear that $\hat{\gamma}(-t) = \hat{\gamma}(t)$.

With $\rho(t)$ defined as the autocorrelation function (ACF) at lag t, then the estimation value $\hat{\rho}(t)$ of $\rho(t)$ is derived as follows:

$$\hat{\rho}(t) = \frac{\hat{\gamma}(t)}{\hat{\gamma}(0)} \tag{7}$$

Now, the estimation value $\hat{\alpha}(t, t)$ of the PACF at lag t is derived as follows:

$$\hat{\alpha}(1, 1) = \hat{\rho}(1) \tag{8}$$

$$\begin{aligned} \hat{\alpha}(t+1, t+1) &= \frac{\hat{\rho}(t+1) - \sum_{j=1}^{t}\hat{\rho}(t+1-j)\hat{\alpha}(t, j)}{1 - \sum_{j=1}^{t}\hat{\rho}(j)\hat{\alpha}(t, j)} \\ \hat{\alpha}(t+1, j) &= \hat{\alpha}(t, j) - \hat{\alpha}(t+1, t+1)\cdot\hat{\alpha}(t+1, t-j+1) \\ & (j = 1, 2, \cdots, t) \end{aligned} \tag{9}$$

where $t = 1, 2, \cdots, m$.

In the modeling process of BPNN, ENN, and EMD–ENN, the PACF is adopted to find the relationship between the input(s) and output(s) of the training data and to determine the number of inputting neurons in the ENN models.

Experimental simulation

Error measures

To assess the performance of the prediction models, three error measures, the mean absolute error (MAE), mean square error (MSE), and mean absolute percentage error (MAPE), are used for model comparison. These measures are defined as follows:

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{m}\left|e(i)\right|, \tag{10}$$

$$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{m}e(i)^2, \tag{11}$$

$$\mathrm{MAPE} = \frac{1}{n}\sum_{i=1}^{m}\left|\frac{e(i)}{y(i)}\right|, \tag{12}$$

Table 1
Statistical analysis of four wind speed datasets.

	Mean (m/s)	Std. dev. (m/s)	Maximum (m/s)	Median (m/s)	Minimum (m/s)
Spring	5.87	3.66	17.10	5.00	0.40
Summer	4.52	2.71	15.10	3.90	0.50
Fall	4.14	2.13	11.20	3.80	0.40
Winter	3.75	2.25	12.30	3.25	0.00

where $e(i) = x(i) - p(i)$; n is the sample size; and $x(i)$ and $p(i)$ are the actual and forecast values at time period i, respectively.

Wind speed datasets

To test the validity of the proposed hybrid approach, the wind speed data from a wind observation site located in the province of Gansu, China are employed. These data consist of actual hourly wind speed data from January 1, 2010 to March 31, 2011. To reduce the influence of seasonal patterns on wind speed prediction, the following months are randomly selected: March 2010, July 2010, October 2010, and February 2011, corresponding to the four seasons of the year. Fig. 3 shows four wind speed datasets corresponding to the four seasons. To further evaluate the prediction accuracy, every dataset is partitioned into a training data set (80%) and a validation data set (20%). The training data set can be applied to establish the prediction model, and the validation data set can be applied to validate the effectiveness of the established model. Table 1 shows the statistical analysis results of four wind speed datasets. In Table 1, it is shown that the statistical measures are different for the four wind speed datasets. The basic idea of the selection is to determine whether it can be used for different conditions.

EMD of wind speed time series

Most previous prediction studies only directly attempt to bring the fitting values as close as possible to the real values through the experimental method, even though the experimental method is repetitive and time consuming. However, due to the chaotic nature and intrinsic complexity of the original wind speed datasets, it is very difficult to directly describe the moving tendency of wind speed using the proposed prediction models. To improve the prediction accuracy, in this study, EMD is applied to decompose the original wind speed datasets.

IMFs are obtained from the original wind speed datasets by the EMD. Fig. 4 show the decomposition process of the original wind speed datasets in Spring. From Fig. 4, it can be observed that the original wind speed dataset has been decomposed into several sub-series, which have simpler frequency components and are relatively easy to model. Then, each sub-series can be applied to establish the corresponding ENN model. Similarly, the original wind speed datasets in other seasons can be decomposed by EMD. The decomposition results can be shown in Table 2. In the next section, the PACF will be applied to determine the input neuron number of the ENN models, and Kolmogorov's theorem will be used to determine the hidden neuron number of the ENN models.

Table 3
The prediction results using PM, BPNN, ENN, and EMD–ENN.

Case	Errors	PM	BPNN	ENN	EMD–ENN
Spring	MAE	1.06	0.94	0.81	0.70
	MSE	1.41	1.28	0.97	0.93
	MAPE	0.49	0.39	0.32	0.27
Summer	MAE	0.96	0.85	0.71	0.64
	MSE	0.75	0.58	0.56	0.47
	MAPE	0.42	0.39	0.25	0.19
Fall	MAE	0.79	0.61	0.56	0.37
	MSE	1.15	0.87	0.82	0.44
	MAPE	0.36	0.28	0.23	0.12
Winter	MAE	1.29	1.13	0.91	0.76
	MSE	1.55	1.40	1.02	0.85
	MAPE	0.46	0.41	0.34	0.22

Model structure determination

When modeling with ENN, there is another limitation that sometimes leads to a slow convergence speed and low prediction accuracy: the relationship between the input value and output value is ignored, or certain previous values of the original datasets are empirically selected as inputs. To break through this limitation, the PACF is utilized to find the relationship between the input and output and to determine the inputting neuron number of ENN. Fig. 5 plots PACF against the lag length in Spring. According to the potential relationship between the sub-series and their lags, the inputting neuron number of each ENN is determined. Similarly, the relationship between the input value and output value in other seasons can be decomposed by PACF. The results can be shown in Table 2.

Choosing the number of hidden neurons is also an important step in the modeling process of ENN. According to Kolmogorov's theorem, $2n+1$ hidden neurons are sufficient to map any function for n inputs [41], and this approach is adopted in this paper. Table 2 lists the optimal network structure for all the original series and sub-series.

Table 2
The optimal network structure of all the original series and sub-series.

Case	Nodes number	Series									
		Original	IMF1	IMF2	IMF3	IMF4	IMF5	IMF6	IMF7	IMF8	Residue
Spring	Input layer	3	3	6	6	7	6	6	6	–	6
	Hidden layer	7	7	13	13	15	13	13	13	–	13
	Output layer	1	1	1	1	1	1	1	1	–	1
Summer	Input layer	2	3	5	5	6	6	6	6	–	6
	Hidden layer	5	7	11	11	13	13	13	13	–	13
	Output layer	1	1	1	1	1	1	1	1	–	1
Fall	Input layer	2	2	5	5	7	6	7	6	–	6
	Hidden layer	5	5	11	11	15	13	15	13	–	13
	Output layer	1	1	1	1	1	1	1	1	–	1
Winter	Input layer	2	2	7	5	7	6	6	6	7	6
	Hidden layer	5	5	15	11	15	13	13	13	15	13
	Output layer	1	1	1	1	1	1	1	1	1	1

'–' denotes a null set.

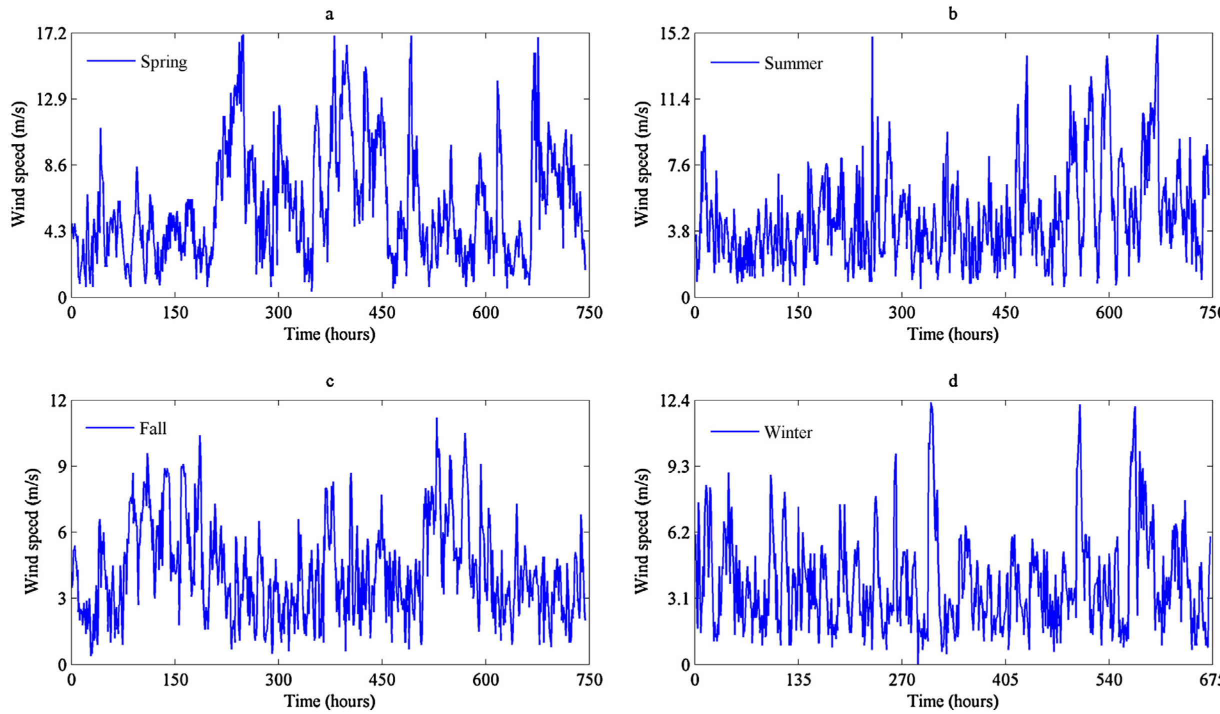

Fig. 3. Original wind speed series for the four seasons: (a) Spring, (b) Summer, (c) Fall, and (d) Winter.

Forecasting results

In the previous section, the original wind speed datasets are decomposed into a collection of different sub-series by EMD, and each sub-series is used to build the corresponding ENN model. In this section, each ENN is applied to forecast the corresponding sub-series, and the final prediction of the original wind speed is obtained by aggregating the prediction results of each sub-series. The one-step-ahead forecast is adopted in this study. Fig. 6 shows the prediction results for the four original wind speed datasets based on the proposed approach.

As a naive predictor, the persistent model (PM) is often used as a benchmark to evaluate other models in the field of prediction. In general, a novel prediction method is first compared with the PM to evaluate its performance. In this paper, to assess the performance of the novel hybrid model in wind speed prediction, the EMD–ENN is compared with PM, BPNN, and ENN. The results of these comparisons are shown in Table 3, and it can be clearly observed that the

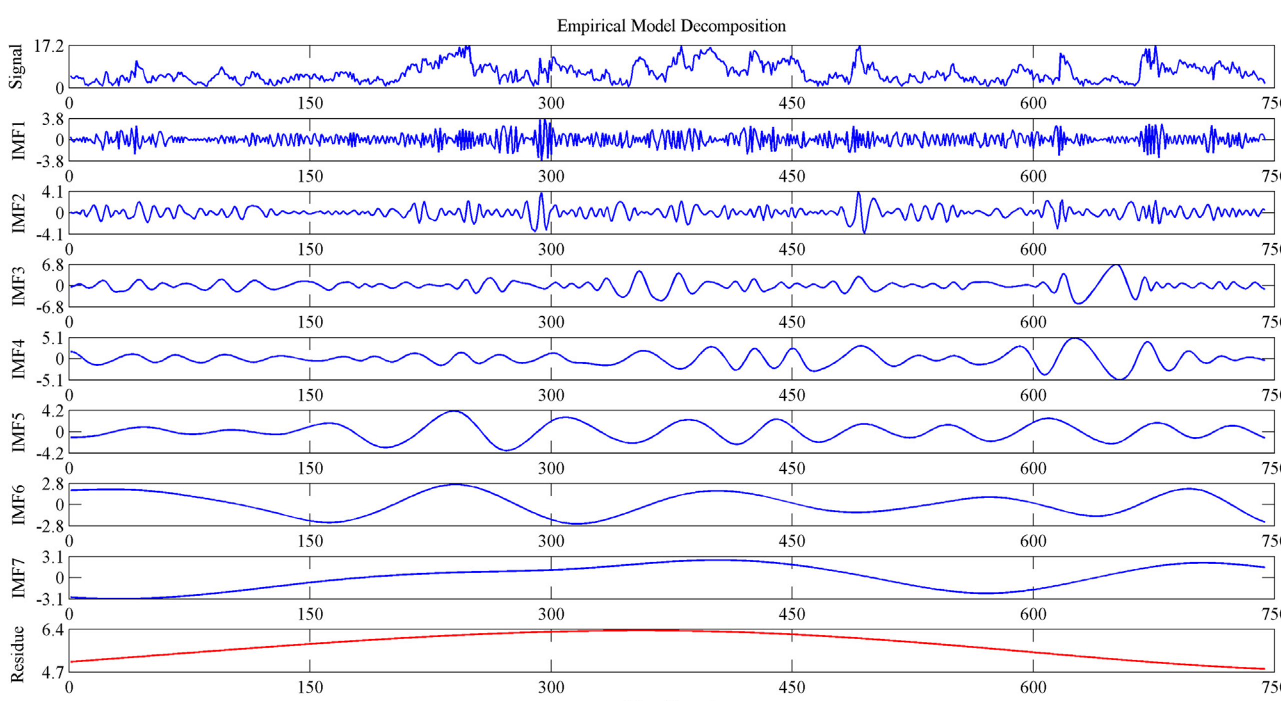

Fig. 4. EMD results in Spring.

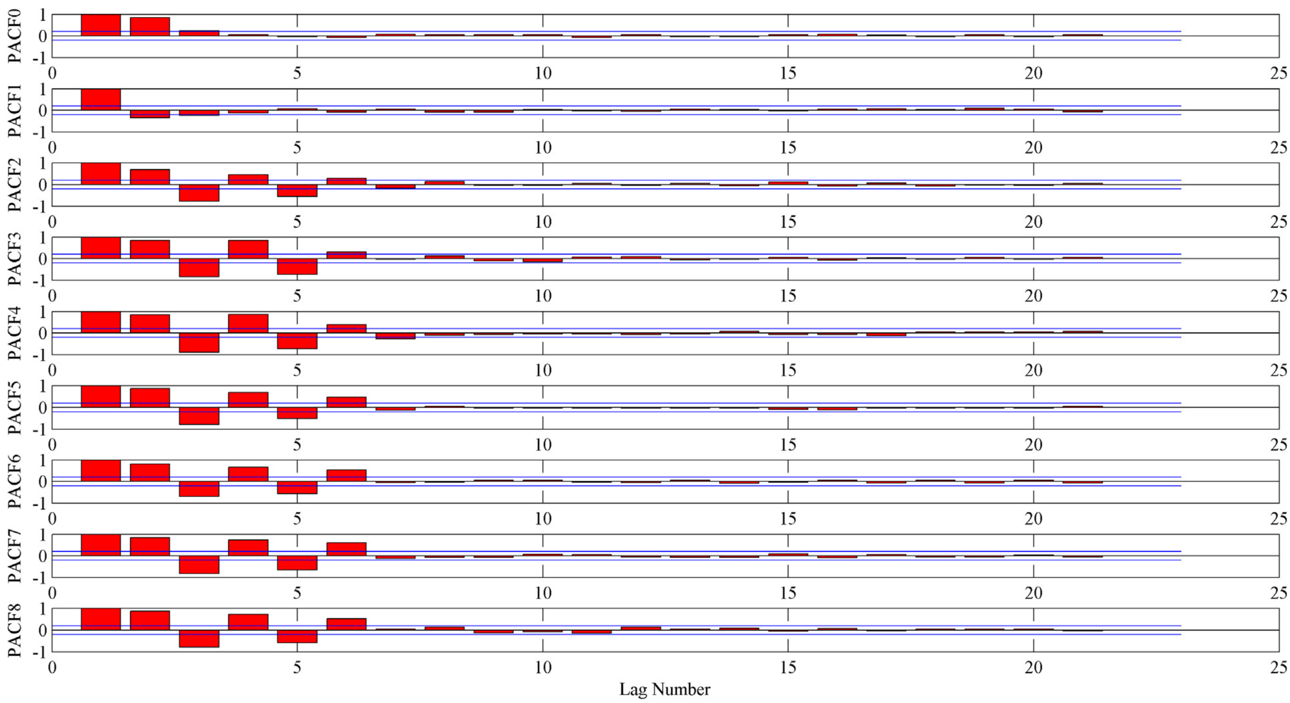

Fig. 5. Plots of PACF against the lag length in Spring.

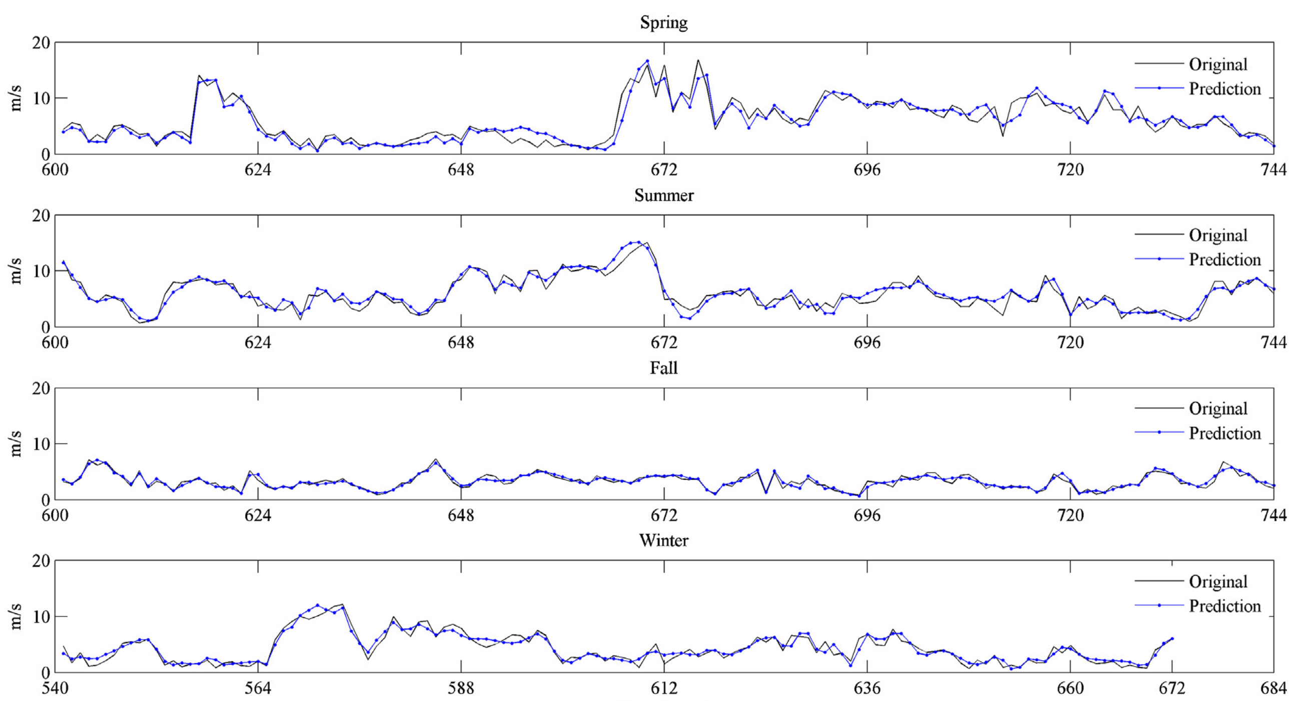

Fig. 6. Prediction results of the original wind speed series according to the proposed approach.

proposed approach consistently has the minimum statistical error according to MAE, MSE and MAPE. It is concluded that the proposed approach is effective and can improve the forecasting performance.

Conclusions

Accurate wind speed prediction can be very useful for the operation and management of wind farms. For this purpose, a novel EMD–ENN approach, which combines empirical mode decomposition (EMD) and the Elman neural network (ENN), is proposed to forecast wind speed. First, the original wind speed datasets are decomposed into a collection of IMFs and a residue by EMD, which are relatively stationary sub-series and can be readily modeled. Second, both the IMF components and the residue are used to establish the corresponding ENN models. Then, each sub-series is predicted by the corresponding ENN. Finally, the prediction values of the original wind speed datasets are calculated by summing the forecasting values of every sub-series. Moreover, in the ENN modeling process, the neuron number of the input layer is determined by the partial autocorrelation function. Four wind speed prediction cases are used to test the performance of the proposed hybrid approach. Compared with the persistent model, back-propagation neural network, and ENN, the simulation results show that the proposed EMD–ENN model consistently has the minimum statistical error in terms of mean absolute error, mean square error, and mean absolute percentage error. It is concluded that the proposed approach is an effective way to improve the prediction accuracy.

Acknowledgments

This research was supported by the National Basic Research Program of China '973' Program (Grant No. 2012CB956200) and the Opening Fund of Key Laboratory for Land Surface Process and Climate Change in Cold and Arid Regions, Chinese Academy of Sciences (No. LPCC201201). In addition, the authors also thank the editor, associate editor, and the six anonymous reviewers for their valuable comments that greatly improved the quality of this paper.

References

[1] L. Ma, S.Y. Luan, C.W. Jiang, H.L. Liu, Y. Zhang, A review on the forecasting of wind speed and generated power, Renew. Sustain. Energy Rev. 13 (2009) 915–920.
[2] A. Shiu, P.L. Lam, Electricity consumption and economic growth in China, Energy Policy 32 (1) (2004) 47–54.
[3] J.J. Chen, Development of offshore wind power in China, Renew. Sustain. Energy Rev. 15 (9) (2011) 5013–5020.
[4] Z.H. Guo, J. Zhao, W.Y. Zhang, J.Z. Wang, A corrected hybrid approach for wind speed prediction in Hexi Corridor of China, Energy 36 (3) (2011) 1668–1679.
[5] E. Erdem, J. Shi, ARMA based approaches for forecasting the tuple of wind speed and direction, Appl. Energy 88 (2011) 1405–1414.
[6] H. Liu, H.Q. Tian, Y.F. Li, Comparison of two new ARIMA-ANN and ARIMA-Kalman hybrid methods for wind speed prediction, Appl. Energy 98 (2012) 415–424.
[7] M. Khalid, A.V. Savkin, A method for short-term wind power prediction with multiple observation points, IEEE Trans. Pow. Syst. 27 (2) (2012) 579–586.
[8] H.P. Liu, J. Shi, E. Erdem, Prediction of wind speed time series using modified Taylor Kriging method, Energy 35 (2010) 4870–4879.
[9] A. Costa, A. Crespo, J. Navarro, G. Lizcano, H. Madsen, E. Feitosa, A review on the young history of the wind power short-term prediction, Renew. Sustain. Energy Rev. 12 (6) (2008) 1725–1744.
[10] J.M. Morales, R. Mínguez, A.J. Conejo, A methodology to generate statistically dependent wind speed scenarios, Appl. Energy 87 (3) (2010) 843–855.
[11] D.A. Fadare, The application of artificial neural networks to mapping of wind speed profile for energy application in Nigeria, Appl. Energy 87 (3) (2010) 934–942.
[12] L. Landberg, Short-term prediction of the power production from wind farms, J. Wind Eng. Ind. Aerodyn. 80 (1–2) (1999) 207–220.
[13] L. Landberg, A mathematical look at a physical power prediction model, Wind Energy 1 (1) (1998) 23–28.
[14] G.H. Riahy, M. Abedi, Short term wind speed forecasting for wind turbine applications using linear prediction method, Renew. Energy 33 (1) (2008) 35–41.
[15] R.G. Kavasseri, K. Seetharaman, Day-ahead wind speed forecasting using f-ARIMA models, Renew. Energy 34 (2009) 1388–1393.
[16] K. Lalarukh, Z.J. Yasmin, Time series models to simulate and forecast hourly averaged wind speed in Quetta: Pakistan, Solar Energy 61 (1) (1997) 23–32.
[17] J.L. Torres, A. García, M. De Blas, A. De Francisco, Forecast of hourly average wind speed with ARMA models in Navarre, Sol. Energy 79 (1) (2005) 65–77.
[18] P. Flores, A. Tapia, G. Tapia, Application of a control algorithm for wind speed prediction and active power generation, Renew. Energy 30 (4) (2005) 523–536.
[19] S. Salcedo-Sanz, A.M. Pérez-Bellido, E.G. Ortiz-García, A. Portilla-Figueras, L. Prieto, D. Paredes, Hybridizing the fifth generation mesoscale model with artificial neural networks for short-term wind speed prediction, Renew. Energy 34 (6) (2009) 1451–1457.
[20] E. Cadenas, W. Rivera, Short term wind speed forecasting in La Venta: Oaxaca, México, using artificial neural networks, Renew. Energy 34 (1) (2009) 274–278.
[21] A. Sfetsos, A comparison of various forecasting techniques applied to mean hourly wind speed time series, Renew. Energy 21 (1) (2000) 23–35.
[22] T.G. Barbounis, J.B. Theocharis, A locally recurrent fuzzy neural network with application to the wind speed prediction using spatial correlation, Neurocomputing 70 (7–9) (2007) 1525–1542.
[23] M.A. Mohandes, T.O. Halawani, S. Rehman, A.A. Hussain, Support vector machines for wind speed prediction, Renew. Energy 29 (2004) 939–947.
[24] Y. Chauvin, D.E. Rumelhart, Backpropagation: Theory, Architectures, and Applications, Lawrence Erlbaum Associates, New Jersey, 1995.
[25] S. Haykin, Neural Network: a Comprehensive Foundation, Prentice-Hall, Englewood Cliffs, NJ, 1999.
[26] P.D. McNelis, Neural Networks in Finance: Gaining Predictive Edge in the Market, Academic Press, New York, 2004.
[27] M.T. Hagan, H.B. Demuth, M.H. Beale, Neural Network Design, PWS Publishing, Boston, 1996.
[28] A. Graves, M. Liwicki, S. Fernandez, R. Bertolami, H. Bunke, J. Schmidhuber, A novel connectionist system for unconstrained handwriting recognition, IEEE Trans. Pattern Anal. Mach. Intell. 31 (5) (2009) 855–868.
[29] M. Ardalani-Farsa, S. Zolfaghari, Chaotic time series prediction with residual analysis method using hybrid Elman–NARX neural networks, Neurocomputing 73 (2010) 2540–2553.
[30] R. Chandra, M.J. Zhang, Cooperative coevolution of Elman recurrent neural networks for chaotic time series prediction, Neurocomputing 86 (2012) 116–123.
[31] M. Cacciola, G. Megali, D. Pellicano, F.C. Morabito, Elman neural networks for characterizing voids in welded strips: a study, Neural Comput. Appl. 21 (2012) 869–875.
[32] N.E. Huang, Z. Shen, S.R. Long, M.C. Wu, H.H. Shih, Q.N. Zheng, et al., The empirical mode decomposition and the Hilbert spectrum for nonlinear and non-stationary time series analysis, Proc. R. Soc. Lond. A – Math. Phys. Eng. Sci. 454 (1998) 903–995.
[33] C.F. Chen, M.C. Lai, C.C. Yeh, Forecasting tourism demand based on empirical mode decomposition and neural network, Knowl. Based Syst. 26 (2012) 281–287.
[34] J.S. Cheng, D.J. Yu, Y. Yang, A fault diagnosis approach for roller bearings based on EMD method and AR model, Mech. Syst. Signal Process. 20 (2) (2006) 350–362.
[35] X. Zhang, K.K. Lai, S.Y. Wang, A new approach for crude oil price analysis based on Empirical Mode Decomposition, Energy Econ. 30 (3) (2008) 905–918.
[36] H.L. Liang, S.L. Bressler, R. Desimone, P. Fries, Empirical mode decomposition: a method for analyzing neural data, Neurocomputing 65–66 (2005) 801–807.
[37] J. Elman, Finding structure in time, Cognitive 15 (1990) 179–211.
[38] E. Cadenas, W. Rivera, Short term wind speed forecasting in La Venta, Oaxaca, México, using artificial neural networks, Renew. Energy 34 (2009) 274–278.
[39] H. Wang, W. Zhao, ARIMA model estimated by particle swarm optimization algorithm for consumer price index forecasting, lecture notes in computer Science, Artif. Intell. Comput. Intell. 5855 (2009) 48–58.
[40] Z.H. Guo, W.G. Zhao, H.Y. Lu, J.Z. Wang, Multi-step forecasting for wind speed using a modified EMD-based artificial neural network model, Renew. Energy 37 (2012) 241–249.
[41] A.P. Plumb, R.C. Rowe, P. York, M. Brown, Optimisation of the predictive ability of artificial neural network (ANN) models: a comparison of three ANN programs and four classes of training algorithm, Eur. J. Pharm. Sci. 25 (2005) 395–405.
[42] V.N. Vapnik, Statistical Learning Theory, John Wiley & Sons, Inc., Canada, 1998.