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A hybrid model based on smooth transition periodic autoregressive and Elman artificial neural network for wind speed forecasting of the Hebei region in China

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ABSTRACT

Wind energy, one of the most promising renewable and clean energy sources, is becoming increasingly significant for sustainable energy development and environmental protection. Given the relationship between wind power and wind speed, precise prediction of wind speed for wind energy estimation and wind power generation is important. For proper and efficient evaluation of wind speed, a smooth transition periodic autoregressive (STPAR) model is developed to predict the six-hourly wind speeds. In addition, the Elman artificial neural network (EANN)-based error correction technique has also been integrated into the new STPAR model to improve model performance. To verify the developed approach, the six-hourly wind speed series during the period of 2000–2009 in the Hebei region of China is used for model construction and model testing. The proposed EANN-STPAR hybrid model has demonstrated its powerful forecasting capacity for wind speed series with complicated characteristics of linearity, seasonality and nonlinearity, which indicates that the proposed hybrid model is notably efficient and practical for wind speed forecasting, especially for the Hebei wind farms of China.

KEYWORDS

Elman artificial neural network (EANN); error correction; smooth transition periodic autoregressive (STPAR); wind energy; wind speed forecasting

Introduction

As a developing country, it is important for China to maintain a balance among the economy, energy, and environment during its modernization process (Xu, He, and Zhao 2010). Therefore, the Chinese government is paying considerable attention to the utilization of renewable energy, especially wind energy, which is rapidly emerging as a critical energy source (Liu, Shi, and Erdem 2013). Wind energy, as an inexhaustible renewable energy source, can provide significant amounts of energy to support the demands of a country (Bagiorgas, Mihalakakou, and Matthopoulos 2008). According to the World Energy Outlook 2009, fossil fuels remain the dominant source of primary energy worldwide, accounting for more than three-quarters of the overall increase in energy use between 2007 and 2030 (World energy outlook 2009). However, the rapid depletion of fossil fuel reserves and increasing environmental problems encouraged policy makers and planners to search for substitutes among renewable energy sources (Shamshad et al. 2005). Recently, wind energy has been given considerable attention due to the increasing focus on renewable energies (Kavak Akpinar and Akpinar 2004). Over the past several years, China has become one of the fastest-growing wind energy markets around the world. At the end of 2010, the latest statistic indicated that the cumulative wind energy installed capacity of China had reached 42,287 MW and had surpassed the USA for the first time, ranking first in the world (Nation Master Net 2010).

Wind energy is one of the most promising renewable energy sources that primarily include wind, solar, water, geothermal energy, biomass energy and ocean energy. However, wind speeds, which are vulnerable to the influence of the weather, can easily make a negative impact on power grid security, power system operation and market economics due to its intermittent nature, especially in areas with wind power penetration (Guo et al. 2011a; Shi, Qu, and Zeng 2011). A sudden cut-off of wind power due to excessive wind speeds may induce unacceptable shocks in the conventional power units (Pourmousavi Kani, Riahy, and Mazhari 2011), which makes it challenging to keep the load and generation balanced and poses a threat to grid reliability (Das, Bishal, and Mazumdar 2013). Moreover, in an electricity market, a 10% deviation in wind speed forecasts leads to a 30% deviation in wind power generation (Ackermann and Soder 2000). Hence, accurate modeling and forecasting of wind speed has been recognized as key to the optimal distribution of wind energy and to the efficient and safe operation of wind turbines (Mandic et al. 2009). Moreover, precise wind speed forecasting is crucial not only for shipping, aviation, agriculture and environmental planning but also for scheduling, maintenance, control and resource planning. Thus, examining and conducting wind speed forecasting is important and meaningful.

Many forecasting methods have been carried out for wind speed forecasting. These methods can be divided into four categories (Ma et al. 2009): (a) physical models; (b) spatial correlation models; (c) conventional statistical models; and (d) artificial intelligence and new models. Physical models use physical data such as temperature, pressure and topography information to predict the future wind speed (Alexiadis et al. 1998; Landberg

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Color versions of one or more of the figures in the article can be found online at www.tandfonline.com/ljge.

1999; Negnevitsky and Potter 2006), while spatial correlation models take into account the spatial relationship of wind speed at different sites (Focken et al. 2002; Barbounis and Theocharis 2007). Both methods are in close contact with additional meteorological factors, which are difficult to measure. A statistical method, which aims at finding the relationship of the online measured power data (Mantas, Vladislovas, and Andrius 2008), uses only historical wind speed data recorded at the observation site to build statistical models from which the forecasts can be derived. Techniques commonly used for average wind speed forecasting are time series analysis or time series analysis combined with an artificial neural network (Yang, Xiao, and Chen 2005; Cai et al. 2008; Du et al. 2008; Sun, Wang, and Li 2008; Wu, Zhou, and Huang 2008). Sancho and Angel proposed a method for accurate short-term wind speed prediction by exploiting the diversity in input data using numerous artificial neural networks, which yields much better results compared with those determined from a model using a single neural network (Sancho et al. 2009). Riahy and Abedi suggested a new linear model of utilizing a linear prediction method in company with the filtering of a wind speed waveform to forecast short-term wind speed (Riahy and Abedi 2008). Haque and Meng proposed a novel approach for short-term wind speed forecasting using the Fuzzy ARTMAP technique (Haque and Meng, 2011). Barbounis and Theocharis introduced a local feedback dynamic fuzzy neural network (LF-DFNN) model utilizing spatial wind speed information from remote measurement stations at wind farms to estimate multi-step wind speeds from 15 min to three hours ahead (Barbounis and Theocharis 2007). Mohandes et al. proposed a support vector machines (SVM) algorithm for wind speed prediction (Mohandes et al. 2004). This algorithm performed far better when compared with multilayer perceptron (MLP) neural networks. A new strategy in wind speed forecasting based on fuzzy logic and artificial neural networks was proposed by Mohammad, Hasan, and Hossein (2009). The experimental results showed that the proposed method not only provided significantly less rule base but also increased the forecasting wind speed accuracy when compared with the traditional fuzzy and neural methods. Recently, the Grey Theory has also been used in short-term wind speed prediction (Li et al. 2010; Shun and Shu 2010), which focuses on model uncertainty and information insufficiency via research on conditional analysis, forecasting and decision making.

Considering the complexities of wind speed patterns, it is difficult to obtain accurate forecasts using a single conventional statistical model because wind speed series consist of complex seasonal, linear, and nonlinear patterns. However, a hybrid model, applying different models through integration, can take advantage of the different techniques while mitigating the restrictions of each model. Lately, hybrid models for wind speed forecasting are also increasingly popular. Guo et al. proposed a corrected hybrid approach by combining the Seasonal Auto-Regression Integrated Moving Average (SARIMA) method and the Least Squares Support Vector Machine (LSSVM) method for wind speed prediction (Guo et al. 2011b). This hybrid model can successfully capture the seasonality and nonlinearity components of the wind speed time series. Guo et al. also introduced a new hybrid wind speed forecasting method based on a back-propagation (BP) neural network and the idea of eliminating seasonal effects from actual wind speed datasets using a seasonal exponential adjustment (Guo et al. 2011b). Simulation results indicated that the method can significantly improve the predictive accuracy compared with a method that used a single BP network without seasonal adjustment. In the literature (Pourmousavi Kani, Riahy, and Mazhari 2011), an innovative hybrid algorithm is introduced for very short-term wind speed prediction in a wind turbine application, and the final prediction has been significantly improved with the forecasting horizon. A hybrid EMD-ANN model based on Empirical Model Decomposition (EMD) and Artificial Neural Networks (ANN) models was presented by Liu et al., which was robust in addressing jumping samples in nonstationary wind speed series (Liu et al. 2012). Haque et al. presented short-term wind speed forecasting methods by considering various soft computing models (SCMs), including a combined SCM and similar days approach for data pre-processing (Haque et al. 2012).

According to the prediction horizon, as well for as the purpose of forecasting, wind speed predictive methods can be classified into three categories (Pourmousavi Kani and Aredhali 2011): short-term forecasting, medium-term forecasting and long-term forecasting. Short-term forecasting (over minutes, hours or days) is generally utilized in the control of wind turbines, real-time grid operations, regulation, economic load dispatch planning, reasonable load decisions and operational security in the electricity market. Medium-term forecasting (over weeks to months) is primarily utilized in maintenance planning, operation management and optimizing operating costs. Long-term forecasting (over years) is usually utilized in wind farm design and calculating the annual generating capacity of wind farms. With the increased integration of wind energy into power networks, accurate wind speed forecasts are critical to reducing uncertainty and improving both grid planning and the integration of wind into power systems (Foley et al. 2012). Up to now, many studies have been conducted on wind speed forecasting of different time-scales, but most focus on short-term forecasting, despite growing awareness of the significance of medium-term and long-term wind prediction.

Although the above models have shown their admirable forecasting performance with different forecasting horizons, there is still no single perfect approach for wind speed forecasting because a wind speed time series is a complex system with seasonal and nonlinear (and sometimes linear) characteristics. Moghram and Rahman reviewed five forecasting methods (Moghram and Rahman 1989): (a) multiple linear regression; (b) time series; (c) general exponential smoothing; (d) state space and Kalman filtering; and (e) knowledge-based approaches. Each method was described briefly and implemented to forecast the hourly load of a southeastern utility. Winter and summer loads were modeled separately, and the results were compared in terms of the percent error. No method was determined to be superior. The transfer function approach was best predictor over the summer months, but it was the second worst predictor over the winter months. Thus, the authors concluded that due to its strong dependence on historical data, the transfer function approach did not respond as well to abrupt changes as did the knowledge-

based approaches. The finding suggested that model performance under specific conditions should be analyzed and incremental improvements should be made based on the knowledge gained.

This aforementioned phenomenon can be attributed to wind speed patterns, which can be quite different between wind farms and can be different even in the same farm at different times or heights. Wind speed is easily influenced by many factors that are difficult to control and location specific (Guo et al. 2011b). Therefore, new efficient forecasting approaches are continually studied and developed to improve the wind forecasting accuracy.

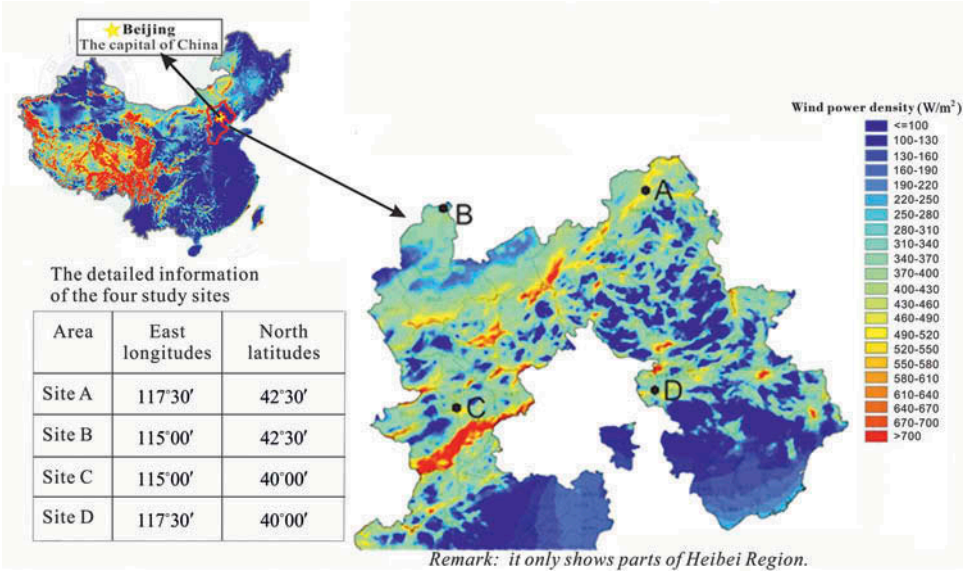
This paper proposed an EANN-STPAR model, which is based on the smooth transition autoregressive periodic regressive method (STPAR) and Elman artificial neural network technique (EANN). The STPAR model can capture the features of a wind speed series with seasonality and linearity well, while the EANN model can successfully describe a wind speed with a nonlinear pattern. The proposed hybrid model is used for six-hourly wind speed forecasting over a short period of time in advance, such as one week ahead. As an applicative case of the proposed method, a six-hourly wind speed data series was collected from 1 January 2000 to 31 December 2009 in the Hebei wind farms. The simulation results show that the proposed hybrid model can capture specific components of the wind speed time series well, and it is quite practical and reliable for wind speed forecasting, especially in the Hebei wind farms of China.

The rest of this paper is organized as follows. Section 2 presents the study area and available data, and the forecasting problem is defined. Section 3 describes the proposed methods in detail, including the STPAR and EANN models. Forecasting results and model comparisons are presented and discussed in section 4. After this, conclusions are presented in section 5. Finally, acknowledgments and references are presented.

Study area and available data

The Hebei region, located in North China, has abundant wind resources due to its geographical characteristics with the mountains and sea. As shown in Figure 1, wind resources are mainly distributed in Zhangjiakou, north and east of Chengde, the Tangshan coastal area and the Cangzhou coastal area. According to the National Climate Centre of China, wind energy resources in the Hebei region at the level of 3 (300 ~ 400 W/m^2) and above occupy an area of 34,400 km^2, and the potential development quantity and installed capacity is approximately 79.3 million KW and 23.79 million KW, respectively. Among these factors, wind energy resources at level 3 (300 ~ 400 W/m^2) share an area of 23,500 km^2, and the potential developed quantity is approximately 57.9 million KW and installed capacity approximately 17.37 million KW. Meanwhile, the potential developed quantity of wind energy resources at level 4 (≥400 W/m^2) is approximately 21.4 million KW, and the installed capacity is approximately 6.42 million KW (NCC.net, 2013).

However, according to the reports, seven of China's top 10 heavily polluted cities are located in the Hebei Province, and the reasons for this observation are complicated. For instance, most cities in the Hebei Province lie to the east of Mount Taihang and Mount Yan, which block the air moving from the east to the north, leading to the "Safe haven" effect where pollution is difficult to dilute and spread. However, the most fundamental reason is the heavy emissions of pollutants from the heavy chemical industrial structure, which have imposed tremendous stress on the environment. Hence, high energy consumption and heavy pollution have been one of the large challenges faced by the Hebei Province (HEXUN.COM 2013). Therefore, the ecological environment should be given priority under the development of new energy industries. Green and low-carbon industries that consider environmental protection should be vigorously developed to embody the action of scientific development and sustainable development. In the Hebei region, new clean energy will be largely developed and cultivated, especially wind power,



Area	East longitudes	North latitudes
Site A	117°30′	42°30′
Site B	115°00′	42°30′
Site C	115°00′	40°00′
Site D	117°30′	40°00′

Figure 1. Distribution of wind energy resources and the detailed location of the study sites in the Hebei region of China.

and in the future this region will be built into one of the most important comprehensive clean energy supply bases for Beijing, the capital of China.

To investigate actual wind power potential, it is therefore highly desirable to forecast wind speed in advance, such as a week ahead of time. With the aim of developing an effective forecasting method for wind speed, data used in this paper are collected from four observation sites in the Hebei region during the period of 2000–2009. The detailed longitudes, latitudes and geological locations of the four sites are provided in Figure 1 In this paper, the forecasting methods under development will predict the six-hourly wind speeds for a period of time, such as a week in 2009, in advance by using the historic wind speed data of the corresponding weeks from 2000 to 2008. The wind speed series in the corresponding week used for model construction and model testing are plotted in Figure 2.

Methodology

Smooth transition periodic autoregressive model (STPAR)

STPAR model construction

In recent times, the utility of periodic models to construct seasonal time series has increased notably, such as the periodic autoregressive model (PAR). Several applied research studies use this modeling method (Lund and Basawa 2000; Ghysels and Osborn 2001; Basawa and Lund 2002). Periodic models have demonstrated their efficiency in forecasting electricity demand up to a day ahead (Taylor, Menezes, and McSharry 2006), especially the periodic seasonal Reg-ARFIMA-GARCH models for daily electricity spot prices (Koopman, Ooms, and Carnero 2007).

A notable characteristic of these models is that the autocorrelation at a particular lag of one half-hour varies across the week. This behavior is not captured by a seasonal ARMA model. According to Taylor, Menezes, and McSharry (2006), the linear model for wind speed forecasting is as follows:

$$\begin{aligned} y_t &= \beta_0 + \beta_1 y_{t-1} + \ldots + \beta_p y_{t-p} + \varepsilon_t \\ \beta_i &= \alpha_i + \sum\nolimits_{j=1}^{h} \{\lambda_{ij} \sin(2j\pi \frac{D(t)}{4}) + \tau_{ij} \cos(2j\pi \frac{D(t)}{4})\} \end{aligned} \tag{1}$$

where $i = 0, 1, \ldots, p, j = 1, \ldots, h$, and $D(t)$ is repeating step function that numbers the periodicity. For six-hourly wind speed data, $D(t) = 1, 2, 3, 4$, with h representing the number of harmonics. So it follows that a Fourier form would represent the daily and weekly periodic. As it stands, Eq. (1) does not contain the variable information that is relevant to the modeling process. Furthermore, the relationship between the dependent variables and independent variables may be asymmetric. The best solution to such an asymmetric problem is to substitute typical linear time series models for nonlinear models, without or with the explain variables incorporated.

The nonlinear model can be defined as a Smooth Transition Periodic Autoregressive (STPAR) model. It is followed that

$$\begin{aligned} y_t &= \beta_{1,0} + \beta_{1,1} y_{t-1} + \ldots + \beta_{1,p} y_{t-p} + \\ &\{(\beta_{2,0} + \beta_{2,1} y_{t-1} + \ldots + \beta_{2,p} y_{t-p}) \times F(\gamma(s_{t-d} - c))\} + \varepsilon_t \\ \beta_{R,i} &= \alpha_{R,i} + \sum\nolimits_{j=1}^{h} \{\lambda_{R,ij} \sin(2j\pi \frac{D(t)}{4}) + \tau_{R,ij} \cos(2j\pi \frac{D(t)}{4})\} \end{aligned} \tag{2}$$

where $i = 0, 1, \ldots, p$ and $j = 1, \ldots, h$. The number of regimes is R, where $R = 1, 2$ and the random error term is $\varepsilon_t \sim NID(0, \sigma^2)$. $F(\cdot)$is the logistic function defined by:

$$F(\gamma(s_{t-d} - c) = (1 + \exp\{-\gamma(s_{t-d} - c)\})^{-1}, \gamma > 0. \tag{3}$$

The parameter γ determines the smoothness of the change in the value of the logistic function and is therefore a measure of the smoothness of the transition from one regime to the other.c is a location parameter embedded in the transition

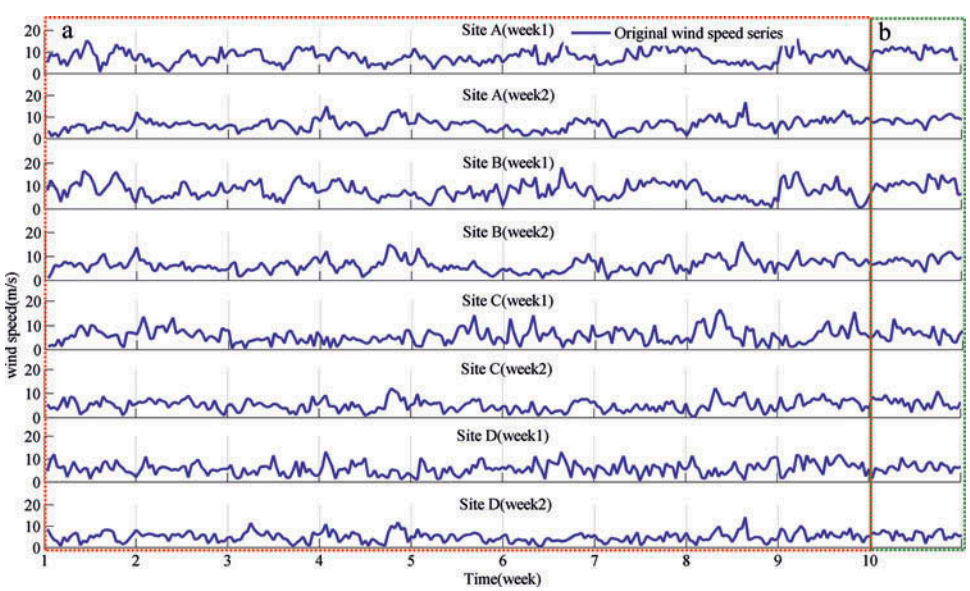


Figure 2. Original wind speed series. (a) shows the original wind speeds of the corresponding week over the period of 2000–2008 for model construction, while (b) gives the wind speeds of the corresponding week in year 2009 for model testing.

function and only indicates the location of the transition. In addition, s_{t-d} is a transition variable that can be represented by a lag value of the dependent variable y_{t-d}. The delay parameter d of the transition variables can take values in the range of $1 \leq d \leq p$.

The smooth transition autoregressive model (STAR) was first introduced by Chan and Tong (1986) and further developed by Teräsvirta (1994). It involves a smooth transition between two or more regimes. Each regime is modeled as an autoregressive process of order p with a transition function that determines the data composition of each regime. In the new model proposed here, periodic behavior will be incorporated into a STAR model framework.

STPAR model estimation

In this paper, the dependent variable y is taken as a transition variable. Once h and d have been selected, then the estimation of the parameters in Eq. (2) will be conducted by nonlinear least squares. Therefore, the vector of parameters ψ can be estimated as

$$\hat{\psi} = \arg\min Q_n(\psi) = \arg\min \sum_{t=1}^{n} (y_t - G(\omega_t, s_t; \psi))^2 \quad (4)$$

Where $\omega_t = [1, y_{t-1}, \ldots, y_{t-p}]'$, and $G(\cdot)$ is the function on the right-hand side of Eq. (2).

According to this procedure, the parameter vector $\hat{\psi}$ can be obtained by the nonlinear least square method, after the forecasting series $\hat{y}$ is obtained.

To verify the predicting efficiency, two evaluation criteria are applied here. The first one is the mean absolute error (*MAE*) which is a measure of the average error for all points (Lin, Lee, and Chang 2009) and is given as

$$MAE = \frac{1}{n}\sum_{t=1}^{n} |y_t - \hat{y}_t|. \quad (5)$$

The second one is the mean absolute percentage error (*MAPE*), which is a relative evaluation criterion and is defined as (Pourmousavi Kani, Riahy, and Mazhari 2011)

$$MAPE = \left(\frac{1}{n}\sum_{t=1}^{n} \left|\frac{y_t - \hat{y}_t}{y_t}\right|\right) \times 100\%. \quad (6)$$

where $\hat{y}_t$ is the output variable to be predicted and y_t is the respective actual one. The lower the *MAE* and *MAPE* values, the better the prediction.

The proposed model construction

In addition to modifying the model of STPAR, the Elman artificial neural network technique is also adopted to reduce the stochastic residual error. The detailed residual error modifications are presented as follows.

Elman artificial neural network (EANN)

Artificial neural network (ANN) is a computational model that attempts to imitate the way that human biological neural networks work. The Elman artificial neural network (EANN), first proposed by Elman in 1990 (Elman 1990), is a partial recurrent network model and lies somewhere between a classic feed-forward perception and a pure recurrent network. Recurrent neural networks have a superior temporal and spatial behaviors, such as stable and unstable fixed points and limits cycles, and chaotic behaviors. These behaviors can be utilized to model certain cognitive functions, such as associative memory, unsupervised learning, self-organizing maps, and temporal reasoning (He 1999). The classic feed-forward loop consists of the input layer, hidden layer, and output layer, in which the weights connecting two neighboring layers are variables. Elman's definition of a context revolved around prior internal states, and thus a layer of "context units," which is sensitive to the history of input data, was added to the classic feed-forward net. In this way, the states of the hidden units could be fed back into the hidden units during the next stage of input. The process can be described as the following: both the input units and context units activate the hidden units; then the hidden units feed forward to activate the output units and also feedback to activate the context units, which constitutes the forward activation.

For the application under consideration, the input data correspond to the plant measurement at a given time step and the target value are the plant measurement at the next time step. The number of hidden nodes is equal to the number of context nodes and must be adjusted to fit the problem at hand. The input layer and hidden layer had one bias node each, and Gaussian activation functions were used throughout the network. Most recurrent and ordinary feed-forward networks used today are trained using some form of back-propagation, which is a form of gradient descent, and a good derivation can be found in the literature (Hertz, Krogh, and Palmer 1991). The goal is to minimize the squared error between the actual network and outputs and the targets values by adjusting the weights in the network for all the output nodes

$$\min(E(\omega)) = \sum_{k=1}^{n} (y_k(\omega) - \tilde{y}_k(\omega))^2 \quad (7)$$

where $y_k(\omega)$ is an input vector and $\tilde{y}_k(\omega)$ is a target output vector.

The recurrent Elman architecture was chosen for this work due to its nonlinear mapping ability, which can describe the wind speed nonlinear pattern well. A simple Elman artificial neural network structure is described in Figure 3. Because the dynamic characteristics of the Elman network are provided by internal connections, it does not need to use the state as input or training signal, which makes EANN superior to static feed-forward network and explains why it is widely used in dynamic system identification.

The proposed EANN-STPAR model

Both EANN and STPAR models have achieved success in their own nonlinear, seasonal, and linear domains. However, neither is a universal model that is suitable for all circumstances. The nonlinear approximation of the EANN model may not be adequate for complex seasonal and linear problems. As for the single STPAR model, it is suitable to obtain

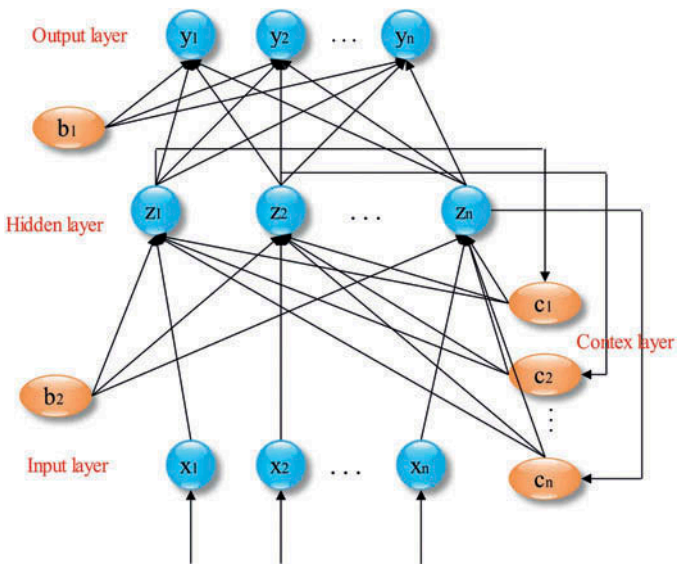


Figure 3. Elman artificial neural network structure.

satisfactory prediction results for a time series with linearity characteristics but not for that with nonlinearity. Nonetheless, the behavior and pattern of wind speeds are too complicated to be easily captured. Therefore, a hybrid strategy that contains nonlinear, seasonal and linear modeling abilities is a quite reasonable alternative for forecasting wind speed. Both the EANN and STPAR models have different capabilities to capture data characteristics of wind speed. In comparison with other methods, the hybrid model developed in this study is composed of the EANN component and the STPAR component. Through experiments with an actual case, the hybrid model can construct nonlinear, seasonal and linear patterns with improved overall prediction performance. The combining methodology consists of the following three steps.

Step 1: STPAR model is constructed and tested by using the wind speed series from four observation sites.
Step 2: EANN is developed to describe the residual series from the STPAR model.
Step 3: Error correction and analysis is conducted for the prediction results.

Case study and analysis

Forecasting results based on the STPAR model

The first step is to determine the parameters in the STPAR model. The order of the autoregressive model was determined according to the autocorrelation function together with the Akaike information criterion (AIC) and the Schwartz information criterion (BIC), suggesting the use of lags 1, 4 (day), and 28 (week). The choice of the values of d and h was determined according to the forecasting performance for each pair (h,d) tried in the model formulation. A comparison of the *MAPE* indicates that when the values of h and d are equal to 3 and 1, respectively, the model is quite suitable. Therefore, the selected model is given by:

$$\begin{aligned} y_t &= \beta_{1,0} + \beta_{1,1}y_{t-1} + \beta_{1,4}y_{t-4} + \beta_{1,28}y_{t-28} \\ &+ \{(\beta_{2,0} + \beta_{2,1}y_{t-1} + \beta_{2,4}y_{t-4} + \beta_{2,28}y_{t-28}) \times F(\gamma(y_{t-1} - c))\} + \varepsilon_t \\ \beta_{R,i} &= \alpha_{k,i} + \sum\nolimits_{j=1}^{3} \{\lambda_{R,ij}\sin(2j\pi\frac{D(t)}{4}) + \tau_{R,ij}\cos(2j\pi\frac{D(t)}{4})\} \end{aligned} \tag{8}$$

Next, the candidate model is estimated by the nonlinear least squares method. The STPAR model is applied to forecast the wind speed of the Hebei region in 2009, and the data during the corresponding weeks from 2000 to 2008 are used to train the STPAR model. The forecasting results together with forecasting errors of the four observation sites are shown in Figure 4. It can be clearly seen from Figure 4 that the forecasting values are a little lower or higher than the original series over the prediction horizon, which indicates the forecasting accuracy of STPAR model is unsatisfactory and needs to be improved.

In the STPAR model, the residual series are expected to be independently and identically distributed as normal random variables. Figure 5 shows the autocorrelation function (ACF) and partial autocorrelation function (PACF) of the residual series with 95% confidence limits for the four observation sites. It can be observed from Figure 5 that there are only several lags of ACF and PACF with large values, which indicates that the residual series are randomly strong, and the STPAR model can describe the approximate wind speed time series well. However, the individual lags with strong ACF and PACF also imply that the STPAR model cannot comprehensively generalize the characteristics of wind speed series.

Because a wind speed time series is a complex system, a single statistical model cannot describe it comprehensively. In the next section, Elman artificial neural network will be used for error correction, and the hybrid model (EANN-STPAR) will obtain a better forecasting performance.

Error correction by EANN

In the previous section, the forecasting results obtained by the STPAR model are shown in Figure 4. As the results shown, the STPAR model can describe the wind speed time series characteristics well, but it cannot describe and forecast the wind speed series comprehensively. Although the values of *MAE* and *MAPE* listed in Figure 4 are acceptable, they are still a little high. Thus the model needs to be improved to make the forecasting performance better.

In this section, to improve the forecasting accuracy, the Elman artificial neural network technique (EANN) is used for further error correction. The hybrid model (Y_t) is represented as follows:

$$Y_t = N_t + S_t \tag{9}$$

Where N_t is the nonlinear component and S_t is the seasonal and linear component of the hybrid model. Both N_t and S_t have to be estimated from the data set. First, the STPAR is used to model the seasonal and linear part. Let N_t denote the residual at time t, which can be given by:

$$N_t = Y_t - \hat{S}_t \tag{10}$$

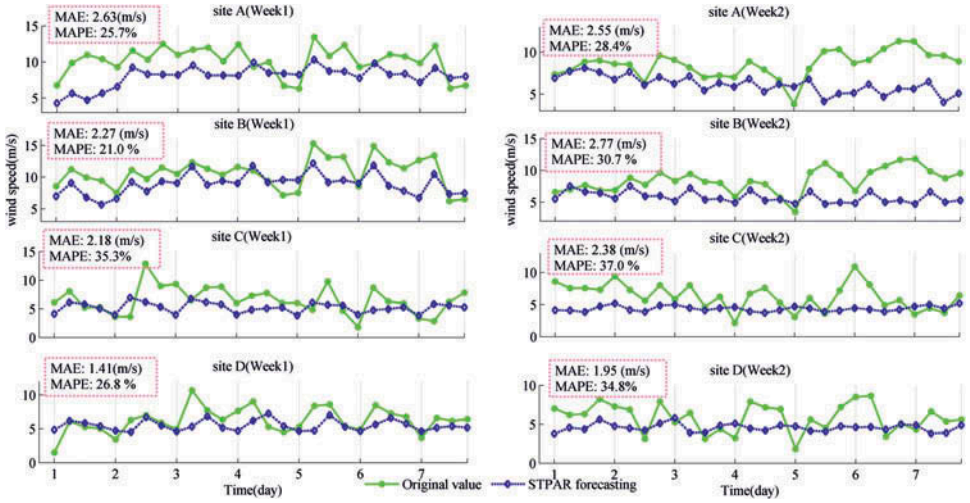


Figure 4. STPAR forecasting results together with forecasting errors for the four study sites.

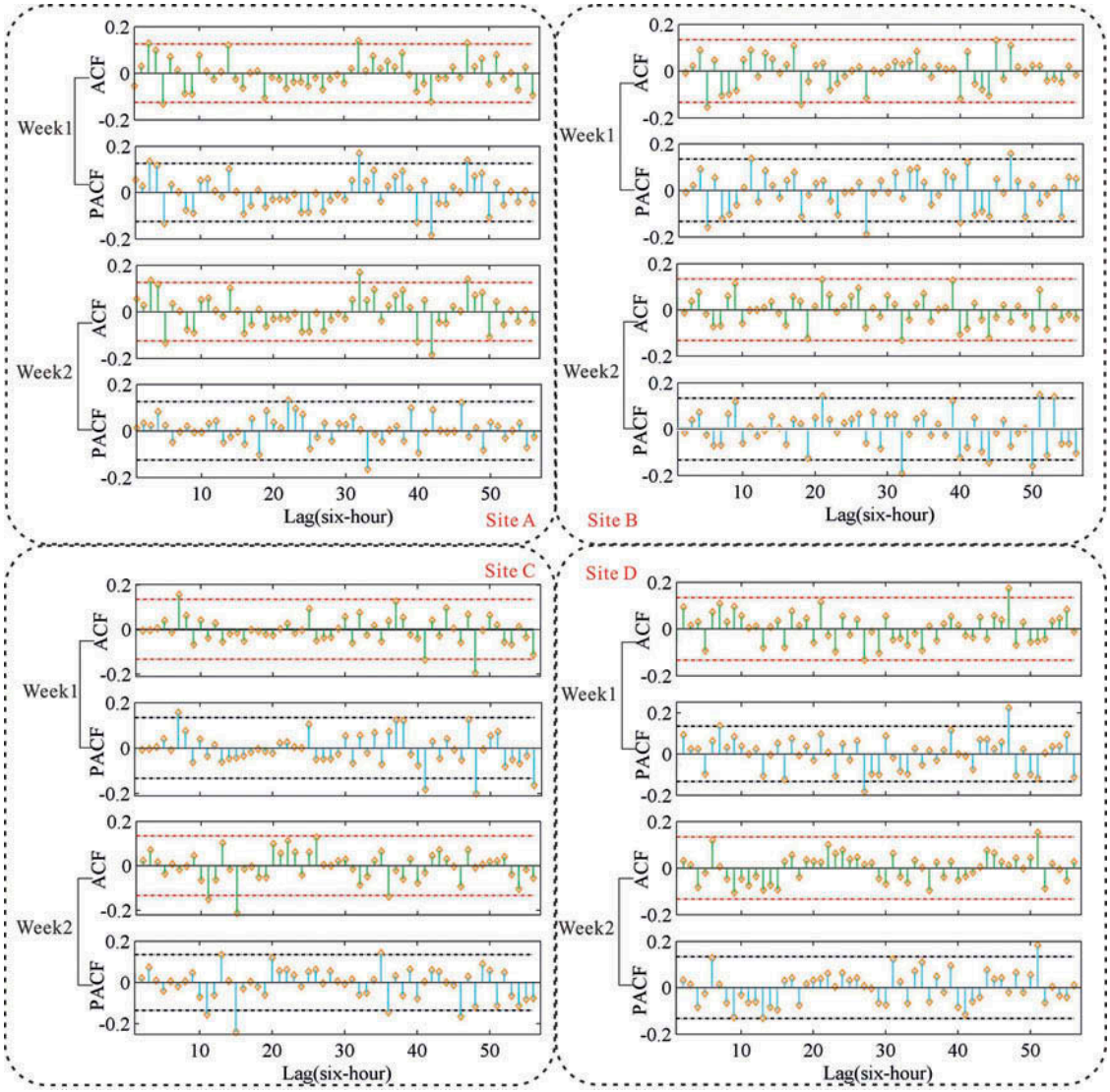


Figure 5. ACF and PACF of the residual series generated by the STPAR model.

where $\hat{S}_t$ is the fitting value of the STPAR model at time t over the periods from year 2001 to 2008.

The residual N_t is modeled and forecasted by the EANN model. Thus,

$$\hat{Y}_t = \hat{S}_t + \hat{N}_t \tag{11}$$

where $\hat{N}_t$ and $\hat{Y}_t$ represent the forecasting value of the EANN model and the proposed hybrid model at time t over the prediction horizon, respectively.

Combining the STPAR model with the EANN technique, the flowchart of the developed EANN-STPAR hybrid model can be described as Figure 6. The error correction results for the four observation sites are provided in Tables 1–4, and the hybrid EANN-STPAR prediction results over the forecasting horizon are shown in Figure 7.

As shown in Figure 7, over the predictive horizon, the synchronicity and range of the vibration of the forecasting series are approximate to the factual series. In Figure 4, it can be clearly observed that the prediction results of STPAR are much lower than the corresponding real wind speed values. Therefore, when compared with the STPAR prediction results shown in Figure 5, the hybrid EANN-STPAR model performs much better for the four observation sites over the prediction horizon. The error correction can describe the nonlinearity of the wind speed time series well, and thus the forecasting accuracy can be improved. All the statistical errors (*MAE* and *MAPE*) listed in Figure 7 are much better than those obtained by the single STPAR model. Specifically, for week1 at the four observation sites A, B, C and D, the value of *MAE*/*MAPE* has been improved up to 1.99(m/s)/19.7%, 1.88(m/s)/19.5%, 2.12(m/s)/33.4%, and 1.19 (m/s)/25.3%, with 0.64(m/s)/6%, 0.39(m/s)/1.5%, 0.06(m/s)/2.1%, and 0.22(m/s)/1.5% improvement when compared to that generated by the STPAR model, respectively. For week2 at the four observation sites A, B, C and D, the value of *MAE*/*MAPE* has been

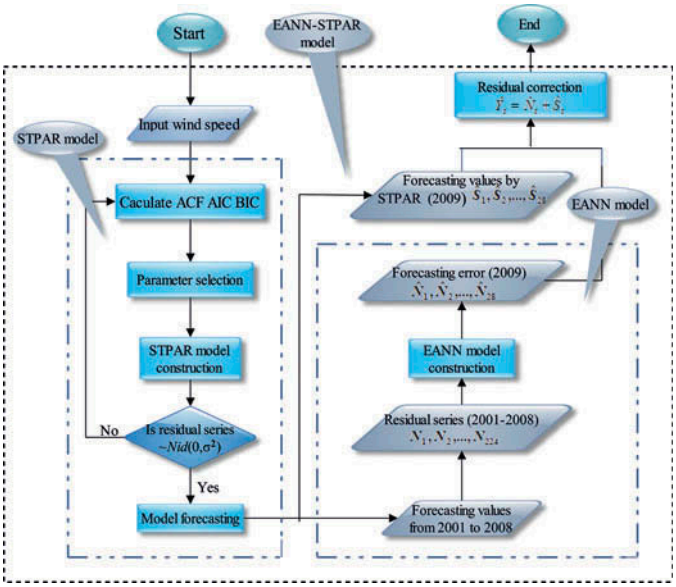


Figure 6. Flowchart of the developed EANN-STPAR hybrid model.

Table 1. Error correction results by using the EANN in observation site A.

Observation Site A						
Time	Week 1			Week 2		
(Day)	STPAR[a]	EANN[b]	EANN-STPAR[c]	STPAR	EANN	EANN-STPAR
1	4.29	2.46	6.75	6.92	2.27	9.19
	5.65	−1.45	4.20	7.71	0.54	8.25
	4.71	0.10	4.81	8.12	1.72	9.84
	5.69	1.72	7.41	7.61	2.08	9.69
2	6.59	−0.88	5.71	6.74	−0.38	6.36
	9.25	−1.39	7.86	7.64	−0.68	6.96
	8.31	0.89	9.20	6.09	1.52	7.61
	8.25	1.82	10.1	7.04	1.16	8.20
3	8.20	2.94	11.1	6.23	1.16	7.39
	9.55	2.48	12.0	7.13	2.41	9.54
	8.14	−1.29	6.85	5.42	2.22	7.64
	8.15	−0.68	7.47	6.34	−0.79	5.55
4	8.11	−1.37	6.74	5.86	1.11	6.97
	9.93	1.03	11.0	6.83	−1.54	5.29
	8.50	1.61	10.1	5.28	2.10	7.38
	8.40	−0.51	7.89	6.17	1.25	7.42
5	8.23	−0.31	7.92	5.85	0.38	6.23
	10.30	4.37	14.7	6.76	3.15	9.91
	8.73	1.33	10.1	4.12	0.40	4.52
	8.70	2.95	11.7	5.06	2.86	7.92
6	7.79	2.45	10.2	5.14	2.56	7.70
	9.83	−0.35	9.48	6.17	2.78	8.95
	8.25	0.73	8.98	4.67	1.87	6.54
	8.37	3.05	11.4	5.65	1.27	6.92
7	7.17	1.34	8.51	5.63	1.25	6.88
	9.16	2.64	11.8	6.47	3.39	9.86
	7.77	1.16	8.93	4.03	−0.09	3.94
	8.00	−0.55	7.45	5.08	1.34	6.42

a: Forecasting wind speeds by STPAR model.
b: Forecasting errors by EANN model.
c: Error correction results, namely the forecasting results obtained by the proposed EANN-STPAR model.

Table 2. Error correction results by using the EANN in observation site B.

Observation Site B						
Time	Week 1			Week 2		
(Day)	STPAR[a]	EANN[b]	EANN-STPAR[c]	STPAR	EANN	EANN-STPAR
1	7.00	4.73	11.73	5.50	1.11	6.61
	9.07	1.55	10.62	7.51	−0.06	7.45
	6.81	2.38	9.19	6.63	−2.46	4.17
	5.66	2.36	8.02	6.42	−1.29	5.13
2	6.58	3.68	10.26	5.55	1.92	7.47
	9.26	2.23	11.49	7.53	−0.53	7.00
	7.77	3.58	11.35	5.93	−0.70	5.23
	9.35	0.66	10.01	5.98	0.65	6.63
3	9.05	1.18	10.23	5.16	2.38	7.54
	11.7	1.91	13.6	7.20	0.03	7.23
	8.79	−0.79	8.00	5.37	1.35	6.72
	9.39	0.90	10.3	5.54	−2.32	3.22
4	9.01	1.93	10.9	4.88	−0.06	4.82
	11.8	1.80	13.6	6.87	1.41	8.28
	9.17	1.23	10.4	5.25	1.80	7.05
	9.58	1.14	10.7	5.44	0.28	5.72
5	9.53	0.91	10.4	4.74	−0.34	4.40
	12.2	2.19	14.4	6.68	1.79	8.47
	9.19	2.83	12.0	4.71	1.60	6.31
	9.52	2.36	11.9	4.94	1.54	6.48
6	9.02	2.26	11.3	4.81	0.05	4.86
	11.8	−0.11	11.7	6.72	2.85	9.57
	8.63	3.00	11.6	4.97	1.59	6.56
	7.82	1.53	9.35	5.27	0.55	5.82
7	6.73	0.33	7.06	4.71	1.86	6.57
	10.5	0.95	11.4	6.64	1.66	8.30
	7.33	0.91	8.24	4.98	1.74	6.72
	7.47	2.21	9.68	5.28	0.10	5.38

a: Forecasting wind speeds by STPAR model.
b: Forecasting errors by EANN model.
c: Error correction results, namely the forecasting results obtained by the proposed EANN-STPAR model.

Table 3. Error correction results by using the EANN in observation site C.

Observation Site C						
Time	Week 1			Week 2		
(Day)	STPAR[a]	EANN[b]	EANN-STPAR[c]	STPAR	EANN	EANN-STPAR
1	4.11	−2.11	2.00	4.11	2.49	6.60
	6.14	−0.30	5.84	4.08	2.57	6.65
	5.81	−2.62	3.19	3.82	−2.15	1.67
	5.06	−0.41	4.65	4.73	−0.13	4.60
2	3.94	−0.17	3.77	5.19	0.03	5.22
	6.95	−1.67	5.28	4.17	0.66	4.83
	6.20	0.01	6.21	3.89	1.69	5.58
	5.35	−0.24	5.11	4.85	−0.08	4.77
3	3.95	2.03	5.98	4.98	−1.34	3.64
	6.77	−1.29	5.48	4.48	0.23	4.71
	6.16	−0.58	5.58	4.09	0.69	4.78
	5.77	0.02	5.79	4.43	0.50	4.93
4	3.99	0.26	4.25	4.60	−0.36	4.24
	4.83	0.41	5.24	3.95	−0.09	3.86
	5.08	1.04	6.12	3.70	1.40	5.10
	5.23	−0.07	5.16	4.12	0.10	4.22
5	3.85	−0.43	3.42	4.69	−0.98	3.71
	6.10	−0.64	5.46	4.40	1.52	5.92
	5.68	1.96	7.64	3.87	0.41	4.28
	5.59	−0.05	5.54	4.06	1.01	5.07
6	3.99	−0.33	3.66	4.45	1.53	5.98
	4.78	−0.40	4.38	4.26	0.40	4.66
	4.95	1.10	6.05	3.92	1.08	5.00
	5.28	−0.81	4.47	4.21	0.98	5.19
7	3.84	−0.30	3.54	4.69	−0.38	4.31
	5.84	−0.42	5.42	4.98	−1.09	3.89
	5.58	0.88	6.46	4.38	0.98	5.36
	5.25	−1.43	3.82	5.19	0.03	5.22

a: Forecasting wind speeds by STPAR model.
b: Forecasting errors by EANN model.
c: Error correction results, namely the forecasting results obtained by the proposed EANN-STPAR model.

Table 4. Error correction results by using the EANN in observation site D.

Observation Site D						
Time	Week 1			Week 2		
(Day)	STPAR[a]	EANN[b]	EANN-STPAR[c]	STPAR	EANN	EANN-STPAR
1	4.85	0.57	5.42	3.79	3.38	7.17
	6.18	−0.48	5.70	4.57	0.70	5.27
	5.85	0.53	6.38	4.38	1.11	5.49
	5.40	−0.25	5.15	5.63	1.63	7.26
2	4.72	−0.26	4.46	4.77	2.57	7.34
	4.51	0.65	5.16	4.50	1.15	5.65
	6.73	0.10	6.83	4.24	2.46	6.70
	5.49	0.62	6.11	5.13	−1.44	3.69
3	4.61	0.79	5.40	5.81	−0.27	5.54
	5.33	2.55	7.88	3.93	1.84	5.77
	6.86	0.17	7.03	3.96	−1.49	2.47
	5.17	1.93	7.10	4.85	0.94	5.79
4	4.70	−0.39	4.31	5.11	−1.62	3.49
	6.22	1.64	7.86	4.47	0.62	5.09
	7.28	−0.61	6.67	4.22	−2.52	1.70
	5.39	0.39	5.78	4.87	2.30	7.17
5	4.66	1.05	5.71	4.75	−1.35	3.40
	4.74	0.66	5.40	4.17	−2.88	1.29
	7.03	0.70	7.73	4.04	−0.41	3.63
	5.30	0.33	5.63	4.76	0.28	5.04
6	4.67	1.12	5.79	4.63	2.72	7.35
	5.65	1.04	6.69	4.65	5.44	10.1
	6.59	0.82	7.41	4.33	2.10	6.43
	5.76	0.69	6.45	4.99	2.38	7.37
7	4.65	−0.84	3.81	5.00	−0.17	4.83
	5.16	0.51	5.67	3.83	3.88	7.71
	5.38	−1.82	3.56	3.91	1.39	5.30
	5.18	−0.73	4.45	4.89	−0.99	3.90

a: Forecasting wind speeds by STPAR model.
b: Forecasting errors by EANN model.
c: Error correction results, namely the forecasting results obtained by the proposed EANN-STPAR model.

improved up to 1.97(m/s)/22.8%, 2.13(m/s)/23.8%, 1.91(m/s)/29.8%, and 1.57(m/s)/30.5%, with predictive accuracy increased by 0.58(m/s)/5.6%, 0.64(m/s)/6.9%, 0.47(m/s)/7.2%, and 0.38(m/s)/4.3% when compared to that generated by the STPAR model, respectively. The forecasting results indicate that the combination of the STPAR method and the EANN technique is an available and effective method. Model comparisons are presented in the next section to provide convincing proof of the strong prediction capacity of the developed hybrid model.

Model comparisons

In this section, to measure the forecasting performance of the hybrid model EANN-STPAR, model comparisons are taken among the Seasonal autoregressive integrated moving average (SARIMA), STPAR model, EANN model and the proposed hybrid model. The prediction results of different forecasting models are shown in Figure 8, while the error comparisons are provided in Table 5.

In Figure 8, it is clearly shown that the developed hybrid EANN-STPAR model performs much better than the other three models not only in synchronicity of the vibration but also the range of vibration. Lower values of *MAPE* indicate less deviation between the predicted and the actual values. The *MAPE* value of wind speed forecasting usually ranges from 25% to 40% (Yang, Xiao, and Chen 2005). Considering the results listed in Table 5, we can see that the *MAPE* of the EANN, STPAR and EANN-STPAR models are less than 40%, which indicates that these models can be regarded as having reasonable forecasting ability for wind speeds. For the four observation sites, the highest, average and lowest value of *MAPE* obtained by the proposed hybrid model are 33.4%, 25.6%, and 19.5%, which implies the proposed model offers highly accurate forecasting ability. However, as seen from Table 5, the forecasting accuracy for observation site B in week 2 obtained by the SARIMA model is much lower than that obtained by the EANN-STPAR model. Nonetheless, for the rest of the study sites over the forecasting horizon, the accuracy of the predictive results obtained by using the hybrid model EANN-STPAR is much better than that obtained by the other three single models, which indicates that the developed hybrid model has stronger robustness and universality when compared with the other models. Furthermore, the developed hybrid model is notably simple and efficient in actual application. In a word, the proposed model can be easily performed and can obtain more accurate wind speed prediction values.

The model comparisons have shown the powerful forecasting ability of the developed EANN-STPAR hybrid model through analysis of the prediction results. However, there is no one best prediction approach for different forecasting problems; model performance under specific conditions should be analyzed and understood, and incremental improvements should be made based on knowledge gained (Palm and Zellner 1992). For the topic discussed in this paper, the wind speed time series are closely related to the climate conditions

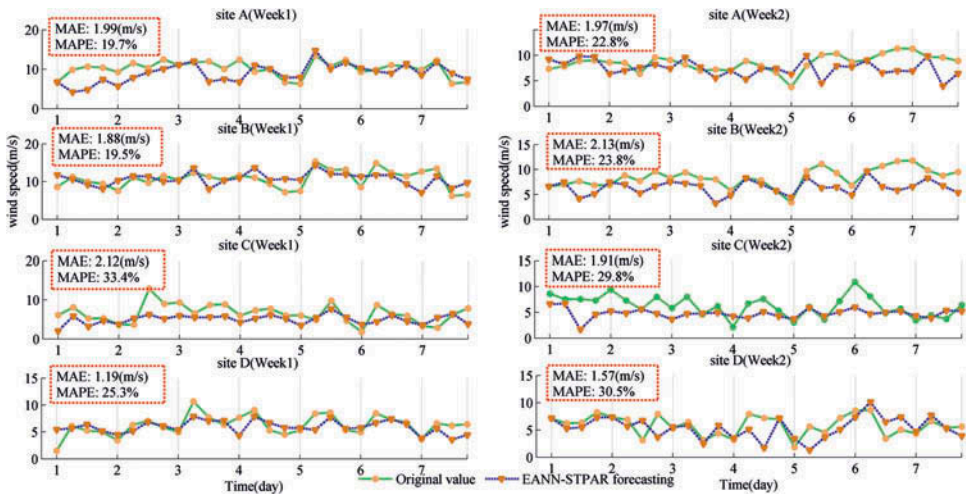


Figure 7. Hybrid EANN-STPAR forecasting results over the prediction horizon.

and geomorphic characteristics. Therefore, different regions have different change features impacting wind speed time series. In this paper, the aim is to predict six-hourly wind speeds in the Hebei region. Undeniably, a perfect predictive model applied for all situations does not exist. However, improved prediction accuracy is obtained by using the developed hybrid model with historical data analysis and research when compared with other conventional forecasting methods.

Conclusions

Wind energy, a renewable energy source, is becoming more significant for sustainable energy development and environmental protection. Rational exploitation of wind energy can contribute to environmental protection and economic development. Numerous statistical forecasting models have been proposed to improve the accuracy of wind speed forecasting. However, these models cannot acquire satisfactory results in every case for different wind speed time series. Thus, different forecasting models should be proposed and developed for different wind speed time series. In this paper, a new hybrid model EANN-STPAR is developed to forecast six-hourly wind speed in the Hebei region of China. The prediction results of the proposed model are far better than the single STPAR model and EANN model. Wind speed prediction remains a quite challenging problem, and the mean absolute percentage errors (*MAPE*) associated with such forecasting usually range from 25% to 40% (Yang, Xiao, and Chen 2005). With the proposed hybrid model over the prediction horizon, the average mean absolute percentage error (*MAPE*) for the four observation sites is 25.6%, which indicates the predictive results are satisfactory. Thereby, this simulation of results demonstrated that the developed hybrid model can be successfully applied to forecast wind speed, especially in the Hebei wind farms of China.

The hybrid model proposed in this paper does well in the study case and has several advantages. First of all, the proposed hybrid model can be a new method for six-hourly wind speed prediction. The combination of the STPAR model and EANN technique has not been used for wind speed forecasting previously in the literature. Thus, it is a development that applies the proposed hybrid forecasting method to six-hourly wind speed prediction. In addition, the prediction results verify that the proposed hybrid model is considerably suitable for wind speed forecasting in the Hebei wind farms. In addition, this proposed hybrid model can describe the wind speed time series comprehensively when compared with the traditional forecasting models. Different forecasting models have different characteristics, information and application fields because they do not have generality. A single conventional statistical model cannot describe wind speed well because wind is a complex system with seasonality, linearity and nonlinearity. Meanwhile, a hybrid model combining several advantages from each individual model can be utilized to improve the forecasting performance. In the developed hybrid model, the smooth transition periodic autoregressive method was used preliminary to establish the STPAR model, which can capture the linear and seasonal patterns of wind speed. Then, EANN is employed to describe the nonlinearity by correcting residual series. Consequently, satisfactory prediction accuracy has been achieved. All of these advantages indicate that this proposed hybrid model is a significant improvement over the conventional forecasting models. Although this hybrid model is simple, it is rather efficient and practical for wind speed prediction, especially for the six-hourly wind speed predictive problem in the Hebei region of China.

Acknowledgments

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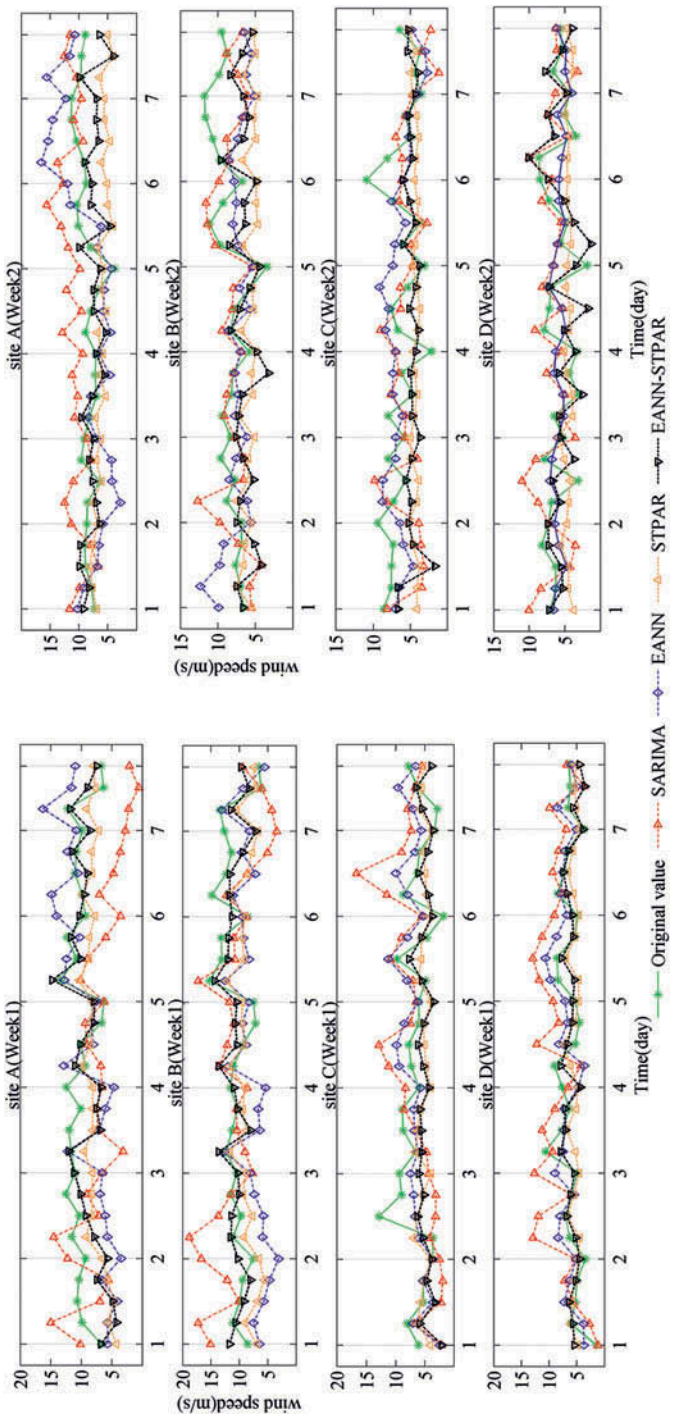

Figure 8. Prediction comparison among different forecasting models.

Table 5. Error comparison among several forecasting models.

Area	Models	Week 1		Week 2	
		MAE(m/s)	*MAPE*(%)	*MAE*(m/s)	*MAPE*(%)
Site A	SARIMA	4.40	43.7	2.96	39.0
	EANN	3.50	35.4	2.67	30.4
	STPAR	2.63	25.7	2.55	28.4
	EANN-STPAR	1.99	19.7	1.97	22.8
Site B	SARIMA	3.58	35.0	1.83	22.4
	EANN	3.10	29.6	2.37	28.4
	STPAR	2.27	21.0	2.77	30.7
	EANN-STPAR	1.88	19.5	2.13	23.9
Site C	SARIMA	3.24	57.9	2.30	41.3
	EANN	2.00	38.6	1.94	38.3
	STPAR	2.18	35.3	2.38	37.0
	EANN-STPAR	2.12	33.4	1.91	29.8
Site D	SARIMA	3.12	53.6	2.07	46.7

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