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A hybrid technique for short-term wind speed prediction

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ABSTRACT

This study proposes a hybrid forecasting approach that consists of the EWT (Empirical Wavelet Transform), CSA (Coupled Simulated Annealing) and LSSVM (Least Square Support Vector Machine) for enhancing the accuracy of short-term wind speed forecasting. The EWT is employed to extract true information from a short-term wind speed series, and the LSSVM, which optimizes the parameters using a CSA algorithm, is used as the predictor to provide the final forecast. Moreover, this study uses a rolling operation method in the prediction processes, including one-step and multi-step predictions, which can adaptively tune the parameters of the LSSVM to respond quickly to wind speed changes. The proposed hybrid model is demonstrated to forecast a mean half-hour wind speed series obtained from a windmill farm located in northwestern China. The simulation results suggest that the developed forecasting method yields better predictions compared with those of other popular models, which indicates that the hybrid method exhibits stronger forecasting ability.

1. Introduction

Wind energy has become one of the most popular and fastest-growing renewable energy resources around the world. Over the past five years, wind energy has experienced rapid growth at an average rate of 31%. As of June 2013, the installed wind power capacity has amounted to 296,255 MW globally, and the installed wind turbine generators globally can generate approximately 3.5% of the global electricity demand [1]. However, the penetration of large amounts of the newly increased wind power capacity poses many challenges to electricity energy system operations, including the management of the variability of wind power generation, market integration, interconnection standards, power quality and power system stability and reliability [1,2].

Wind power generation is closely related to a significant factor-wind speed (the nonlinear relationship (i.e., basically cubic) between wind power and wind speed). Wind speed forecasting can be implemented according to the time scales of wind speed data and the purpose of the forecast. Short-term prediction, as one important type of wind speed forecasting, is instrumental in the planning of economic load dispatch and load increment/decrement decisions made with respect to the management of a significant amount of wind power. To forecast short-term wind speed, various methods and approaches have been proposed in the literature, such as persistence methods, physical modeling methods, time series models and soft computing approaches, over the past decades. The persistence method, which is generally employed as a benchmark for comparison with other tools [3], utilizes recent wind speed data for forecasting. The physical models make use of various weather data to forecast wind speed. The Numerical Weather Prediction [4–6] model represents a typical physical approach to producing wind forecasts for large-scale areas.

Time series models are widely used tools in the field of forecasting and have also been proposed for short-term wind speed forecasting. The models are established using historical data to tune the model parameters and by examining whether the fitting residuals possess the characteristics of a random walk process. Typical examples of time series models include the ARMA (autoregressive moving average) [7], the ARIMA (autoregressive integrated moving average) [8], the FARIMA (fractional autoregressive integrated moving average) [9], exponential smoothing techniques [10] and grey predictors [11].

Soft computing methods are extensively utilized by scholars to forecast wind speed because such methods provide suitable performance capabilities, especially in tackling nonlinear problems. ANNs (Artificial neural networks) are the most popular approaches

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Nomenclature

Λ_n	the nth segment in $[0,\pi]$
ω_n	the nth detected maxima of Fourier spectrum
$\forall$	randomly assign
$\hat{\phi}_n(w)$	the empirical scaling function
$\hat{\varphi}_n(w)$	the empirical wavelets
λ	the real number belong to the interval [0,1]
$\langle\rangle$	inner product
$f(t)$	the signal
$\overline{\varphi_n(\tau-t)}$	the conjugate of the empirical wavelets
$w_f^\varepsilon(n,t)$	The detail coefficients
$P(x\rightarrow y)$	the probability of transitioning from the current state x to y
T_k	the generation temperature
T_k^{ac}	the acceptance temperature
$E(x)$	the energy of the current state
$G(x\rightarrow y)$	the generation probability
$A(x\rightarrow y)$	the acceptance probability
$U(T_k,k)$	the generation temperature schedules
$V(T_k^{ac},k)$	the acceptance temperature schedules
W	the weight vector
b	the bias term
$\Phi(x)$	the nonlinear mapping function
e_i	the error variable
α_i	the Lagrange multiplier
EWT	empirical wavelet transform
CSA	coupled simulated annealing
PACF	partial autocorrelation function
BPNN	back-propagation neural network
RBFNN	radial basis function neural network
ANNs	artificial neural networks
WT	wavelet transform (WT),
GA	genetic algorithm (GA)
EMD	empirical mode decomposition
SVM	support vector machine
LSSVM	least square support vector machine
PSO	particle swarm optimization algorithm,

Definition

Multistep ahead forecast suppose that we are at the time index h and are interested in forecasting $\hat{r}_{h+l}$, where $l\geq 1$. The time index h is called the forecast origin and the positive integer l is the forecast horizon. Let $\hat{r}_h(l)$ be the forecast of r_{h+l}, we refer to $\hat{r}_h(l)$ as the l-step ahead forecast of r_t at the forecast origin h when $l=1$, we refer to $\hat{r}_h(1)$ as the **one-step ahead forecast** of r_t at the forecast origin h.

among soft computing methods, which are based upon empirical risk minimization and asymptotic theories. Typical examples of artificial neural networks include the BPNN (Back-Propagation Neural Network) [12,13], the recurrent neural networks [14], the RBFNN (Radial Basis Function Neural Network) [15], the Elman neural network [16], the GRNN (General Regression Neural Network) [17], the ANFIS (Adaptive Neuro Fuzzy Inference System) [18,19] and MLP (Multi-Layer Perceptron network) [20,21]. SVM (Support Vector Machine) [22–27] is another type of soft computing methods, which is based on a statistical learning theory and the structural risk minimization principle.

In recent years, hybrid approaches to wind speed forecasting have become increasingly popular. A hybrid model consisting of a WT (Wavelet Transform), GA (Genetic Algorithm) and SVM was put forward to enhance the accuracy of short-term wind speed forecasting [22]. In the literature [23], a hybrid model was proposed to forecast wind speed for a Spanish wind farm, in which two different evolutionary computation techniques (an EP (Evolutionary Programming) algorithm and a PSO (Particle Swarm Optimization) algorithm) were used to tackle the hyper-parameters estimation problem in SVM. Guo et al. [28] reported a hybrid model which integrated EMD (empirical mode decomposition) with feed-forward neural network for the wind speed forecasting. Haque et al. [29] presented several hybrid approaches that combined a similar days method with soft computing models (a BPNN, a RBFNN, and an adaptive neuro-fuzzy inference system) for short-term wind speed prediction. Li et al. [30] proposed a combinational approach which combined three types of artificial neural network models that were independently used for prediction through weights determined by a Bayesian combination algorithm. Blonbou [31] suggested an adaptive short-term wind power prediction scheme using neural network predictors along with adaptive Bayesian learning and Gaussian process approximation. Recently, Bhaskar and Singh [32] proposed a hybrid forecasting approach involving a WT technique and an adaptive wavelet neural network for wind speed prediction, in which the wavelet technique is employed to decompose wind series, and the adaptive wavelet neural network predicts wind speed for each decomposed subseries. Nima Amjady et al. [33] attempted to apply a hybrid strategy consisting of a feature selection component and a forecasting engine for wind power forecasting. The feature selection component utilized two filters to eliminate irrelevant features and redundancy from the set of candidate inputs, and the forecasting engine, a hybrid neural network optimized by a new, enhanced particle swarm optimization algorithm, provided wind power predictions.

This study utilizes the concept of hybrid prediction and proposes a hybrid forecasting approach for more accurately estimating short-range wind speed. The developed hybrid method is examined by one-step ahead and multi-step ahead forecasting of the mean 30-min wind speed of the observation site located in northwestern China. The simulation results reveal that the hybrid forecasting method outperforms other popular algorithms.

The remainder of this paper is organized as follows. Section 2 discusses the drawbacks of existing models and the contributions of the proposed model, and section 3 introduces the required individual models and describes the developed hybrid model. In section 4, the wind speed predictions and advantages of the developed strategy are analyzed and discussed through comparisons with other benchmark models. Finally, the conclusions of the study are presented in section 5.

2. Contribution

Time series models mentioned in section 1 are established on the linear assumption. They can cope with the wind speed forecasting problem when the wind speed series presents the linearity characteristic [34]. However, in most situations, wind series does not always change in a linear manner, thus affecting the accuracy of predictions. Therefore, soft computing methods are proposed by scholars to tackle the problems. ANNs have advantages over traditional statistical models when approximating complex nonlinear functions, weak data dependence and fault tolerance. However, a well-trained ANN model may result in poor forecasting performance for new observations because its generalization ability is not guaranteed. Furthermore, ANNs are more time-consuming compared with the time series models, because the parameters of the neural networks are estimated based on an iterative training procedure while the parameters of the traditional statistical models are estimated directly without training. In addition, ANNs occasionally have problems with local minima and over-fitting [30] and they are sensitive to the initial parameter selection [30]. SVM shows many unique advantages in addressing small samples and nonlinear or high dimension pattern recognition problems. The SVM has been used extensively for classification, regression and pattern recognition. However, individual SVM does not show good performance in forecasting wind speed.

More recently, the proposed hybrid approaches can generate more accurate and reliable wind speed predictions than individual models to some extent. The SVM-based approaches are the typical examples of these hybrid approaches, which usually combine the SVM with the data preprocessors such as the WT or EMD techniques to exploit the advantages of each individual component and obtain good prediction accuracy. However, the WT lacks the ability of self-adaptive data processing and needs to specify wavelet basis and parameters beforehand, while the EMD is sensitive to noise and sampling and lack of mathematical theory. The EWT method remedies the drawbacks of the aforementioned decomposition methodologies to some extent. It can adaptively represent the processed signal and then decomposes the signal into a finite number of modes.

When utilizing the hybrid forecasting approaches for the prediction including the wind speed prediction and the other predictions in other fields, the parameters of forecasting components e.g. soft computing methods (including ANNs and SVM), are often optimized by the widely used GA and PSO [23,24–27]. The two optimization algorithms are advantageous on the dealing with complex problems and parallelism. Nevertheless, the algorithms require a large amount of cost-function evaluations to reach the globally optimal solution. They are sensitive to the initialization parameters, i.e., it lacks robustness when the initialization parameters take different values. The CSA (Coupled Simulated Annealing) algorithm remedies these disadvantages to reach the globally optimal solution. Specifically, the algorithm creates cooperative behavior via information exchange to help the decision of whether uphill moves will be accepted. The coupling and the variance control of the acceptance probabilities in the CSA can provide information that can be used online to steer the overall optimization process toward the global optimum, thus reduce the overall number of cost-function evaluations. In addition, the coupling and the variance control of the acceptance probabilities reduce the sensitivity of the algorithm to initialization parameters, while guiding the optimization process to quasioptimal runs.

Because the range of short-term predictions is usually considered to be 30 min to 6 h ahead according to time horizons and the forecasting of short-term wind speed (one-step and multi-step ahead forecasting) is instrumental in the planning of economic load dispatch and load increment/decrement decisions made with respect to the management of a significant amount of wind power [35], this article proposes a new hybrid approach that combines an EWT technique, a CSA algorithm and the LSSVM model for accurately forecasting the mean 30-min wind speed. The main contributions of this study with respect to those offered by other studies in the same area of research can be summarized as follows:

(1) The model takes advantage of hybrid algorithms that can enhance prediction precision. The hybrid approach is proposed not only to remedy the deficiencies of classical time series-based techniques and artificial intelligence algorithms but also to tackle the characteristics of wind speed series.
(2) A LSSVM model with inappropriate parameters may lead to over-fitting or under-fitting in the training phase of modeling. Thus, the parameters of the LSSVM model should be optimized for accurate wind speed prediction. This study employs the CSA (Coupled Simulated Annealing), to determine the model parameters without a significant decrease in convergence speed.
(3) Considering that wind speed series exhibit uncertainty and randomness, the EWT, which is a novel signal process tool, is adopted to eliminate these characteristics from the original time series. EWT extracts only the meaningful components from the wind speed series.
(4) Due to the randomness and instability of wind series, the model parameters are adaptively adjusted by the rolling operation method in these prediction processes to respond quickly to wind speed changes and to better reflect the actual forecasting environment.

3. Methodology

This study adopts a strategy involving decomposition and forecasting components. Specifically, the EWT decomposes the wind speed series into several modes and a residual. Then, the residual, which contains noisy information, is discarded as noisy data. The decomposed modes are then reconstructed into new wind speed series. The LSSVM, whose parameters are optimized by the CSA algorithm, utilizes the reconstructed wind series to provide the prediction.

Before applying the proposed hybrid approach, it is necessary to introduce the required components. Thus, the operating principles of the individual models, including the EWT algorithm, CSA algorithm and the LSSVM, are presented. Then, the hybrid method is illustrated.

3.1. EWT (Empirical Wavelet Transform)

The EWT (Empirical Wavelet Transform) proposed by Jerome Gilles [36] identifies and extracts the different intrinsic modes of a time series. The algorithm relies on robust preprocessing for peak detection, then performs spectrum segmentation based on detected maxima, and constructs a corresponding wavelet filter bank.

The empirical wavelets can be defined as bandpass filters on each Λ_n, where Λ_n denotes each segment $\Lambda_n = [w_{n-1}, w_n]$, and $\cup_{n=1}^{N} \Lambda_n = [0, \pi]$. $\forall_n > 0$ the empirical scaling function and the empirical wavelets are defined by equations (1) and (2), respectively.

$$\widehat{\phi}_n(w) = \begin{cases} 1 & if\,|w| \le (1-\gamma)w_n \\ \cos\left[\frac{\pi}{2}\beta\left(\frac{1}{2\gamma w_n}(|w|-(1+\gamma)w_n)\right)\right] & if\,(1-\gamma)w_n \le |w| \le (1+\gamma)w_n \\ 0 & otherwise \end{cases} \tag{1}$$

and

$$\widehat{\varphi}_n(w) = \begin{cases} 1 & if (1+\gamma)w_n \le |w| \le (1+\gamma)w_{n+1} \\ \cos\left[\frac{\pi}{2}\beta\left(\frac{1}{2\gamma w_{n+1}}(|w| - (1-\gamma)w_{n+1})\right)\right] & if (1-\gamma)w_{n+1} \le |w| \le (1-\gamma)w_{n+1} \\ \sin\left[\frac{\pi}{2}\beta\left(\frac{1}{2\gamma w_n}(|w| - (1-\gamma)w_n)\right)\right] & if (1-\gamma)w_n \le |w| \le (1-\gamma)w_n \\ 0 & otherwise \end{cases} \tag{2}$$

where $0 < \gamma < 1$. If

$$\gamma < \min_n \left(\frac{w_{n+1} - w_n}{w_{n+1} + w_n}\right), \tag{3}$$

then the set $\{\phi_1(t), \{\varphi_n(t)\}_{n=1}^N\}$ is a tight frame of $L^2(R)$.The function $\beta(x)$ is an arbitrary $C^k([0,1])$ function that satisfies the following properties:

$$\beta(x) = \begin{cases} 0 & if \;\; x \le 0 \\ 1 & if \;\; x \ge 0 \end{cases} \text{and} \;\; \beta(x) + \beta(1-x) = 1 \;\; \forall_x \in [0,1]$$

Because the appropriate frame set of empirical wavelets is established, the EWT can be implemented in the same way as in the classic wavelet transform. The detail coefficients are obtained from the following inner products between the signal and the empirical wavelets:

$$w_f^\varepsilon(n,t) = \langle f, \varphi_n \rangle = \int f(\tau)\overline{\varphi_n(\tau - t)} d\tau \tag{4}$$

and the approximation coefficients are calculated by the following inner products with the scaling function:

$$w_f^\varepsilon(0,t) = \langle f, \phi_1 \rangle = \int f(\tau)\overline{\phi_1(\tau - t)} d\tau \tag{5}$$

where $\varphi_n(w)$ and $\phi_1(w)$ are defined by formulas (5) and (4), respectively. The reconstruction is obtained by

$$f(t) = w_f^\varepsilon(0,t)*\phi_1(t) + \sum_{n=1}^{N} w_f^\varepsilon(n,t)*\varphi_n(t) \tag{6}$$

Following this formalism, the empirical modes are given by

$$f_0(t) = w_f^\varepsilon(0,t)*\phi_1(t) \tag{7}$$

$$f_k(t) = \sum_{n=1}^{N} w_f^\varepsilon(n,t)*\varphi_n(t) \tag{8}$$

3.2. CSA (Coupled Simulated Annealing)

The CSA (Coupled Simulated Annealing) algorithm [37] is an advanced version of the SA (Simulated Annealing) algorithm and is characterized by a series of parallel SA processes. SA suffers from the problems of the premature and the sensitivity of the initialization parameters. The CSA is designed to upgrade the quality of solutions at the minimal cost of decreasing the convergence speed. In each optimization process of CSA, each single current state is performed separately and behaves as a single classical SA process. The main difference between SA and CSA lies in the acceptance probabilities.

The SA process adopts the importance sampling technique to choose sample states of a particle system model to efficiently estimate physical quantities that are related to the system. In terms of the master equation of a thermodynamic system, this principle states that

$$\frac{P(x \to y)}{P(y \to x)} = \frac{\exp(-E(y)/T)}{\exp(-E(x)/T)} \tag{9}$$

where $P(x \to y)$ denotes the probability of transitioning from the current state x to a candidate state y, T is the setting temperature, $E(x)$ and $E(y)$ denote the energy of the current state x and current state y, respectively. The transfer probability can be represented as the product of a generation probability and an acceptance probability, i.e., $P(x \to y) = G(x \to y)A(x \to y)$. If all candidate states take equal probabilities, i.e., the generation probability $G = 1/n$ with n denoting the number of possible states, then formula (11) can be simplified as follows:

$$\frac{A(x \to y)}{A(y \to x)} = \frac{\exp(-E(y)/T)}{\exp(-E(x)/T)} \tag{10}$$

The most common functions for acceptance probability are the Metropolis rule

$$A(x \to y) = \exp\left(\frac{E(x) - E(y)}{T_k^{ac}}\right) \tag{11}$$

and the rule

$$A(x \to y) = \frac{1}{1 + \exp\left(\frac{E(x) - E(y)}{T_k^{ac}}\right)} \tag{12}$$

SA only considers the current solution for the acceptance decision of the probing state, whereas CSA considers several current states and accepts a probing state based not only on the corresponding current state but also on the coupling term. The coupling can not only interchange information and produce cooperative behavior contributing to the decision of whether uphill moves are accepted but also provide information for the entire optimization process toward the globally optimal solution.

The framework of the algorithm is shown in Fig. 1, and the algorithm is carried out as follows:

1) Initialization: Randomly generate initial solutions in the set Θ. Evaluate the cost functions $E(x_i)$, $\forall x_i \in \Theta$, and assess the coupling term λ. Initialize the temperatures $T_k = T_0$ and $T_k^{ac} = T_0^{ac}$. Set the time index to $k = 0$.

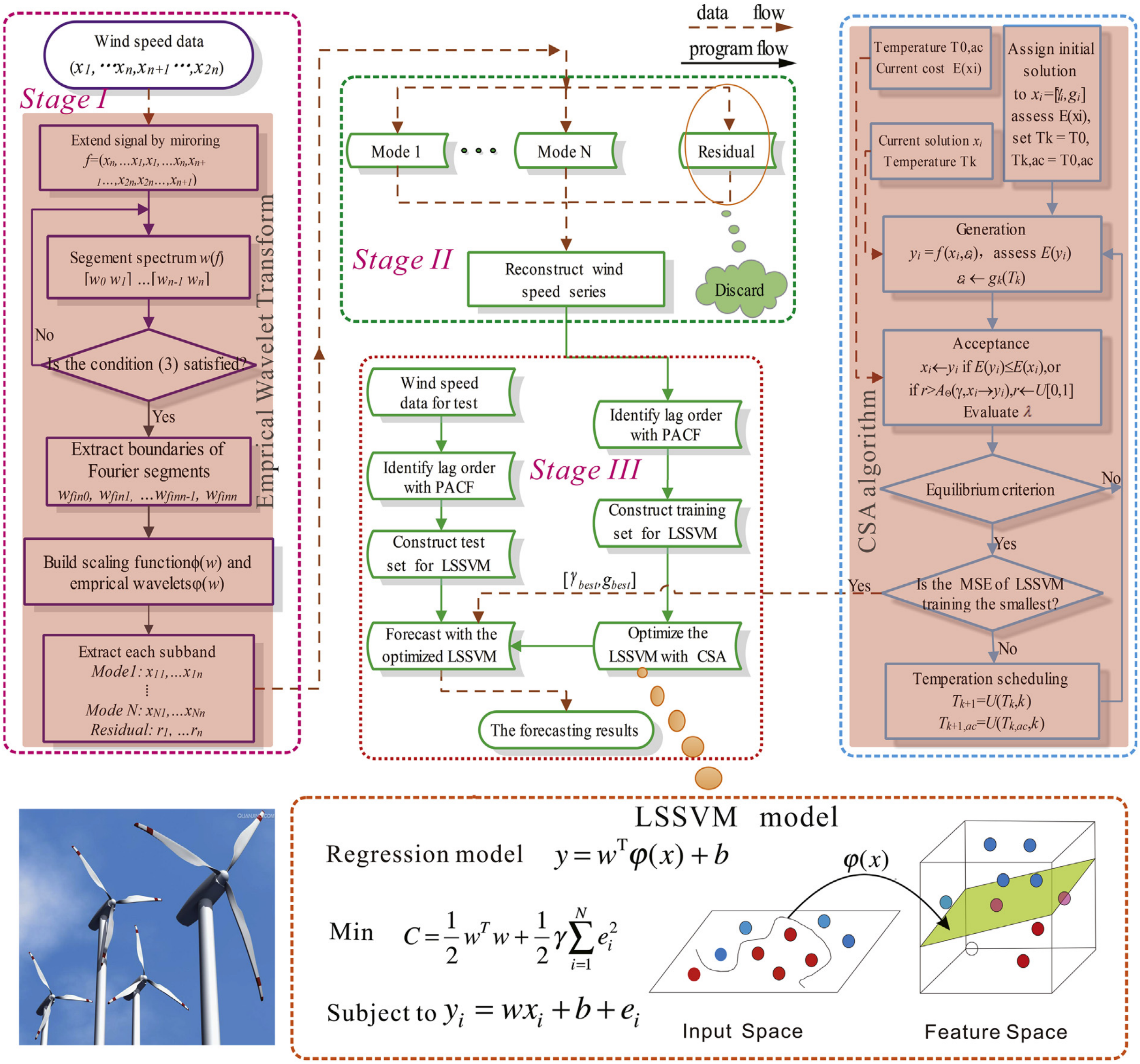

Fig. 1. The overall framework of the hybrid EWT-CSA-SVM model.

2) Produce anew solution y_i for each element of the set Θ according to the formula $y_i = x_i + \varepsilon_i$, $\forall x_i \in \Theta$, where ε_i is a random variable that obeys a given distribution $g(\varepsilon_i, T_k)$. Evaluate the costs for these new solutions: $E(x_i), i = 1\ldots m$.
3) For each $i \in 1\cdots m$, accept the solution y_i with probability1 if $E(y_i) \le E(x_i)$; otherwise, accept the solution with probability $A_\Theta(l, x_i \to y_i)$, i.e., make $x_i := y_i$ only if $A_\Theta > r$, where r is a random variable derived from a uniform distribution [0, 1]. Assess l, and go to Step 2 for N inner iterations (equilibrium criterion).
4) Lower the temperature in terms of the schedule $U(T_k, k)$ and $V(T_k^{ac}, k)$. Increase k.
5) Stop this algorithm if the termination criterion is satisfied; otherwise, go to Step 2.

3.3. LSSVM (Least Squares Support Vector Machine)

The modified version of SVM called LSSVM [38] resulted in a set of linear equations instead of a quadratic programming problem. The brief reviews of the LSSVM algorithm for regression problems are show as follows. Given a training set $\{x_i, y_i\}, i = 1,2\cdots N$, the regression formula can be constructed as follows,

$$y = W^T\Phi(x) + b \tag{13}$$

where W denotes the weight vector and b is the bias term. $\Phi(x)$ is the nonlinear mapping function that transfers the input to a higher-dimensional feature space. The weight vector W of the regression can be calculated by optimizing the following cost function (C) containing a penalized regression error:

$$C = \frac{1}{2}W^TW + \frac{1}{2}\gamma\sum_{i=1}^{N}e_i^2 \tag{14}$$

subject to

$$y_i\left(W^T\Phi(x_i) + b\right) = 1 - e_i \tag{15}$$

where e_i is the error variable at time t and γ is a regulation constant. Based on the subjections, the Lagrange function is constructed as follows:

$$L(W,b,e,\alpha)=\frac{1}{2}\|W\|^2+\gamma\frac{1}{2}\sum_{i=1}^{N}e_i^2-\sum_{i=1}^{N}\alpha_i\left(W^T\Phi(x_i)+b+e_i-y_i\right) \tag{16}$$

where α_i are Lagrange multipliers. The solution of Eq. (16) can be obtained by partially differentiating with respect to W, b, α_i and e_i. And then, the following result is obtained:

$$y=\sum_{i=1}^{N}\alpha_i\Phi(x_i)\Phi(x)+b=\sum_{i=1}^{N}\alpha_i\langle\Phi(x_i)\Phi(x)\rangle+b \tag{17}$$

If the function meets Mercer's condition, then a positive definite kernel function is defined as follows:

$$k(x_i,x_j)=\Phi(x_i)\Phi(x_j) \tag{18}$$

Substituting the result of Eq. (18)into Eq. (17) leads to the following nonlinear regression function:

$$y=\sum_{i=1}^{N}\alpha_i k(x_i,x)+b \tag{19}$$

3.4. The hybrid EWT-CSA-LSSVM model

The Least Squares version of SVM only considers equality constraints instead of inequalities from the SVM model. The LSSVM is comparable to SVM in terms of generalization performance. However, when the individual LSSVM approach is employed to forecast wind speed, it can not provide good predictions owing to the complexity of short-term wind speed series. Hence, a hybrid approach consisting of EWT, CSA and LSSVM is proposed. The EWT, as a novel and self-adaptive decomposition algorithm, decomposes short-term wind speed series into several independent modes. LSSVM is adopted as a forecasting engine in the proposed approach because the LSSVM algorithm can efficiently handle nonlinear problems with high computation speed. In addition, to avoid the defects and deficiencies of the LSSVM algorithm, such as trapping in local optima and over-fitting, the parameters of LSSVM are optimized by the CSA algorithm, thereby imparting a good generalization ability and outreach capacity to LSSVM. Fig. 1 shows the general structure of the proposed hybrid wind speed forecasting method.

The hybrid approach mainly includes three stages; the general task in each stage is described as follows:

Stage I: Utilize the EWT algorithm to divide the original short-term wind speed series into several independent modes and one residual series. In this stage, the wind speed series is firstly extended by mirroring, then the extended wind speed series is computed by Fourier transform, after that, by segmenting of the Fourier spectrum based on detected maxima, the empirical wavelet filter bank are established when the condition (3) is satisfied, finally, filter the signal to extract each subseries by the filter bank.

Stage II: Discard the residual series to de-noise and smooth the original short-term wind speed data and make preparations for the following forecasting. The decomposed modes possess different meanings at any point, e.g., the mode in the lowest frequency band signifies the central tendency of the time series. The decomposed residual series are discarded because the residual is small and can be regarded as an uncorrelated white noise series; the rest decomposed modes are aggregated into the new data series. This process de-noises the original data to improve the prediction accuracy.

Stage III: forecast the wind speed in different forecasting horizons (one-step ahead prediction or multi-step ahead prediction). Specifically, prior to using the LSSVM model for short-term wind speed prediction, the PACF (Partial Autocorrelation Function)[38],a widely used lag identification method in the AR (auto-regressive) (p) model, is employed to compute the correlation coefficients between inputs, When the sample PACF values at lags greater than p are approximately independent N (0, 1/n) random variables, the lag order can be determined as p, thereby confirming and identifying the inputs of the LSSVM. Then the CSA algorithm is used to optimize the parameters of LSSVM with the confirmed inputs. Finally, the well-trained LSSVM is utilized model to predict the wind speed in different forecasting horizons.

When decomposing to the wind speed series, the EWT is implemented with the established frame set of empirical wavelets in the same way as in the classic wavelet transform. Thus, the decomposition levels of the wavelet decomposition can serve as a reference for the EWT. Numerous empirical studies in electricity price [39], wind power predictions [40] and wind speed [21] demonstrated that the three-level decomposition with wavelet transform is enough to extract the meaningful signal. Therefore, the study decomposes the wind speed series in three-level, similar to the literature [21], thereby obtaining three modes and one residual.

It is essential to eliminate dimensions of the input for forecasting accuracy. Thus, the inputs are normalized by an appropriate method such as maximum and minimum normalization. Additionally, to respond quickly to wind speed changes, hybrid prediction with a rolling mechanism for short-term wind speed is adopted in these prediction processes, i.e., the parameters of the LSSVM model are estimated using all observations through a given forecasting origin. Next, the forecasts are generated for this origin. This procedure is then repeated for all forecasting origins in the period of interest. The following simulation will manifest the availability of the proposed model. This developed hybrid model can be applied to obtain multi-step ahead forecasts that are generated by the rolling forecast method.

4. Case study

4.1. Data collection

NWPs are generally accepted as the most accurate technique for the longer forecasts that might be required for wind speed prediction while statistical methods based on observations perform more accurately over the shorter forecast ranges [41]. The study proposes the hybrid approach with the observations to predict the short-term wind speed. The wind speed observations were collected from the Chengde wind farm in Hebei Province in China (shown in Fig. 2) to verify the proposed hybrid approach.

So far, there is no unified standard and clear definition with respect to the selection of data quantity for the model verification. The data sample size can be ranged from small sample sets (like 48 samples in literature [28] and 72 data in literature [44]) to large sample sets (like 744 data in literature [16], 1437 data in literature [22] and 3936 data in literature [6]). The selection of the training data from sample sets in the aforementioned literatures depended on the specific circumstances. This study selects 100 mean half-hour wind speed observations as the training set based on the following considerations. Firstly, the LSSVM is expert in addressing small sample problems, thus the small number of samples applied to the LSSVM training is available. Secondly, the mean half-hour wind speed observations in two days (i.e.96 mean 30-min wind

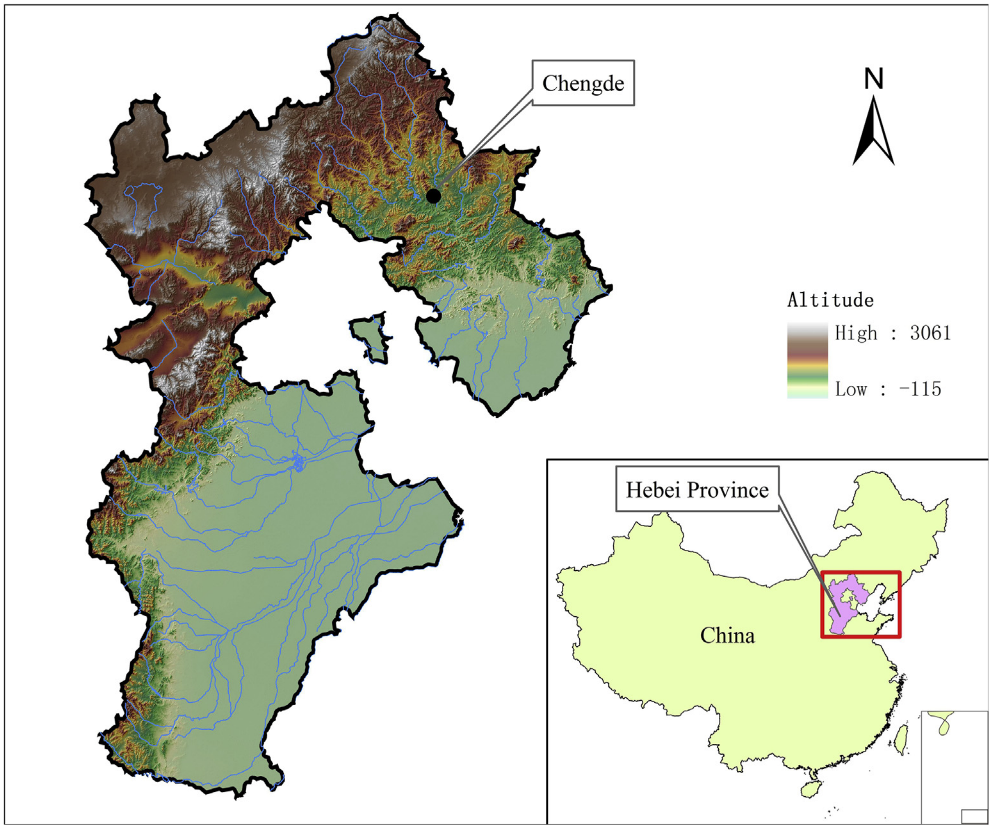

Fig. 2. The location of the Chengde wind farm in China.

speed observations) are collected as the main part of the training set, for that the current wind speed would be affected by the wind speed in the past 48 h in the short term weather prediction with the NWP. Specifically, the short term weather forecasting (up to 48 h, the short term weather forecasting is classified from a meteorological point of view) including the wind speed conditions provided by the NWP is based on fluid dynamics and thermodynamics models under certain initial and boundary value conditions (weather conditions) [42], thus, it can be roughly inferred that the current wind speed can be affected by the weather including wind speed in the past 48 h in the short term weather prediction. Thirdly, the correlation between the wind speed series is considered in building LSSVM. It can be identified from the Fig. 4 that the time lag is four. Therefore, the training set is set as 100 samples (96 mean half-hour wind speed observations plus 4 mean half-hour wind speed observations). In practical terms, it is common to use the remaining two-thirds for training and hold out one-third of the data for testing [43], i.e. the test set accounts for 50% of the training set. Thus, the amount of the test data is 50 samples, and then the number of the mean half-hour wind speed data selected in this

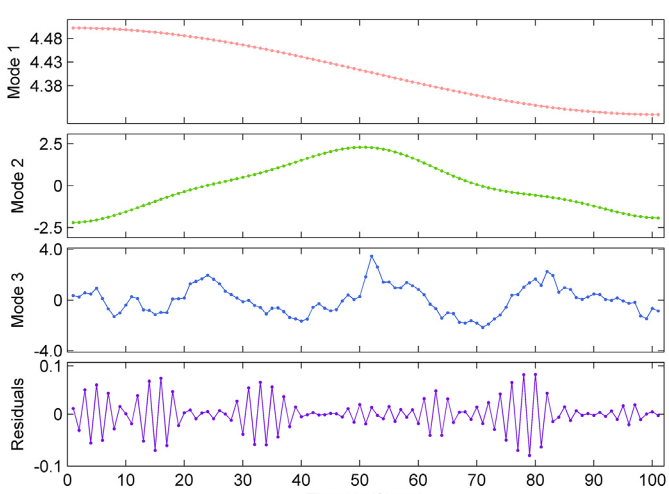

Fig. 3. The decomposed subseries of the mean 30 min wind speed by EWT.

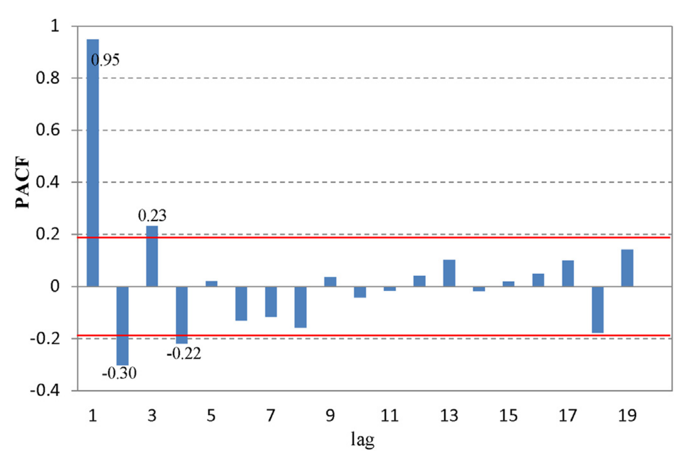

Fig. 4. The PACF of the reconstructed series.

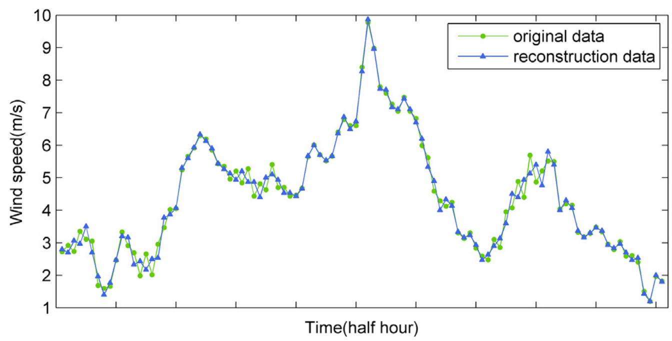

Fig. 5. Comparison of the original mean half-hour wind speed series and the reconstructed wind series.

study is 150 samples. Meanwhile, the leave-one-out cross validation method is adopted during the LSSVM modeling phase. And the literature [44] demonstrated the effectiveness in the least square SVM modeling with no more than 100 samples (60 samples). Therefore, the amount of the whole set (150 samples) is sufficient to ensure the validity of model.

4.2. Evaluation indices for forecasting performance

To evaluate the generation capacity of the proposed hybrid approach, three statistical indices are utilized to measure the forecasting accuracy. These indices are the MAE (mean absolute error), RMSE (root mean square error) and MAPE (mean absolute percent error), for which small values indicate high forecast performance. These indices are defined as follows:

$$\mathrm{MAE} = \frac{1}{T}\sum_{i=1}^{T}\left|p_i^{\mathrm{true}} - p_i^{\mathrm{forecast}}\right| \tag{20}$$

$$\mathrm{MAPE} = \frac{1}{T}\sum_{i=1}^{T}\frac{\left|p_i^{\mathrm{true}} - p_i^{\mathrm{forecast}}\right|}{p_i^{\mathrm{ture}}} \times 100\% \tag{21}$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{T}\sum_{i=1}^{T}\left|p_i^{\mathrm{true}} - p_i^{\mathrm{forecast}}\right|^2} \tag{22}$$

where p_i^{true} is the observed value for the time period t and p_i^{forecast} is the predicted value for the corresponding period. The MAE reveals how similar the predicted values are to the observed values, whereas the RMSE measures the overall deviation between the predicted values and the observed values. The MAPE is a unit-free measure of accuracy for the predicted wind series and is sensitive to small changes in the data.

The MAE, MAPE, and RMSE are selected as prediction criteria based on the following considerations. (1) Wind speed forecasting has a character of the inherent uncertainty, which means that model forecasting can not ever be exact. Due to the inherent uncertainty, the popular and widely used way to describe the uncertainty is to adopt statistical indices. The statistical indices are commonly used to evaluate the error measures on data that have not been used to build the prediction model. (2) At present, the existing literatures on wind speed forecasting adopt the statistical indices like MAE, MAPE, and RMSE as prediction criteria to access the model performance. The study also adopts the evaluation criteria to evaluate our proposed model in the same way as the existing literatures.

In addition, these prediction criteria on wind speed forecasting are not suitable to apply directly to the management of connected electric power systems. This is because that wind speed forecasting is not exactly equivalent to the wind power foresting. The relationship between wind speed and wind power is established on certain conditions. In reality, the generated power is not always obey the rules (the wind power in proportion to the cubic wind speed) because of the change of conditions. Specifically, wind speed is one of the most significant factors of wind power generation and the accuracy of wind speed prediction directly influences the management of wind generator for power system real-time scheduling. However, the wind power management is also influenced by other factors such as the cut-in and cut-out wind speeds of wind turbines, wind turbine wakes and the mutual effect between turbines etc. Therefore, the prediction error of the generated wind power could not be fully evaluated, if the objective of the wind speed prediction in this work is the management of connected electric power systems.

Because the wind power forecasting also has a character of the inherent uncertainty like wind speed forecasting, the existing literatures utilize the criteria listed in literature [45] for wind power prediction. The criteria of the generated power differ from the prediction errors which are in proportion to the cubic wind speed prediction errors. Therefore, the evaluation indices of wind speed forecasting are not directly applied to the management of connected electric power systems.

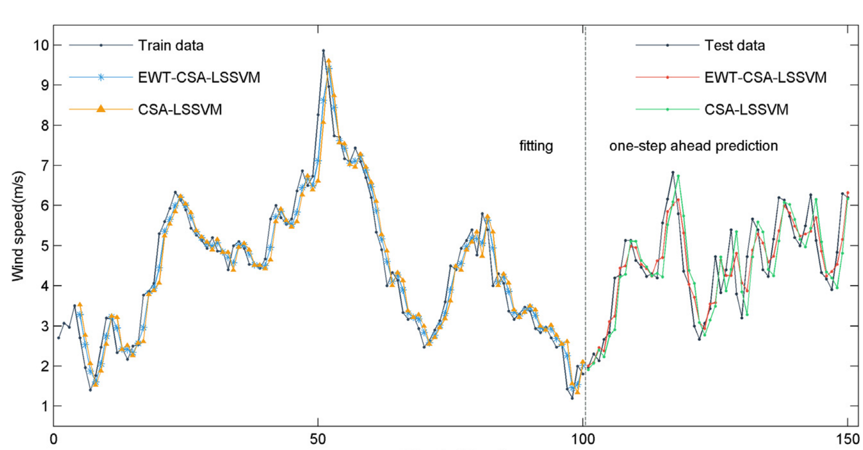

Fig. 6. Comparison between the actual data and the fitting and one-step ahead forecasting results.

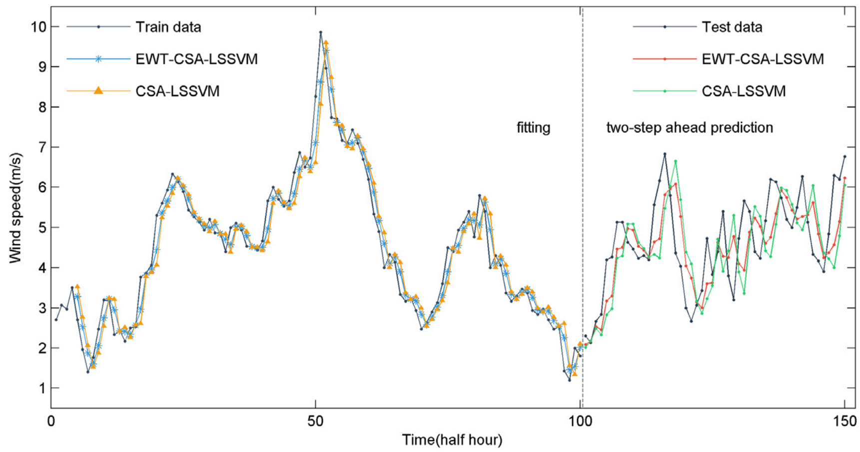

Fig. 7. Comparison between the actual data and the fitting and two-step ahead forecasting results.

4.3. Simulation

The simulation submits the wind series shown in Fig. 5 to the proposed hybrid approach to obtain the predicted outcomes. In Stage I, the original wind series presents high fluctuation and non-stationarity. Utilizing the EWT algorithm, the wind speed series is broken down into three uncorrelated modes (shown in Fig. 3) and one residual. The instantaneous frequency of each mode is meaningful at any point, and different modes possess different characteristics, e.g., mode 1 is the lowest frequency band and denotes the central tendency of the short-term wind speed, whereas mode 3 is the highest frequency band and mainly contains high-frequency signals. In stage II, to improve the forecasting quality of the short-term wind speed, the following strategy is adopted to prepare for the final prediction. The residual is discarded because it mainly contains noisy signals. This process plays a role in de-noising the wind speed series, and all of the modes are reconstructed into the new series to be used for forecasting. As shown in Fig. 5, there is little difference between the original and reconstructed wind speed data in the gently fluctuated area, while the difference is obvious in the wildly fluctuated area. In stage III, prior to the forecasting process performed by the LSSVM model, the PACF is employed to identify the correlations among the reconstructed series such that the relationship between the inputs and outputs of the LSSVM model can be determined (shown in Fig. 4). It can be confirmed from Fig. 4 that the sample PACF values at lags greater than four falls in the area between the upper and lower boundaries (red lines (in web version)). Thus, the lag order of the autoregressive process is determined as four. In addition, after obtaining the correlations, the CSA algorithm is utilized to determine the best parameters for the LSSVM model such that the LSSVM model has the smallest errors and good generation capability. Moreover, to overcome the saturation phenomenon and provide better conditions for LSSVM training, the input and output variables of each LSSVM are linearly normalized to the range [0, 1]. Then, by employing the LSSVM technique optimized by the CSA algorithm, the forecasting results of the combined series are achieved as shown in Figs. 6–8. Fig. 6 shows that the one-step forecasting results of the hybrid EWT-CSA-LSSVM model match the original short-term wind series well. It can also be seen from Figs. 6–8 that the forecasting performance of the employed approaches declines to some extent with the raise of forecasting time horizon, which means that the stochastic uncertainty of wind speed increase, resulting in the poorer prediction accuracy.

Additionally, other models are established to compare with the proposed model and highlight the advantages of the proposed model. Several popular individual forecasting models proposed in recent studies on short-term wind speed forecasting are selected as benchmarks. These models are types of time-series-based techniques and artificial intelligence algorithms. The AR (auto-regressive) model is selected from the time series techniques, and a single LSSVM is chosen from among the artificial intelligence algorithms.

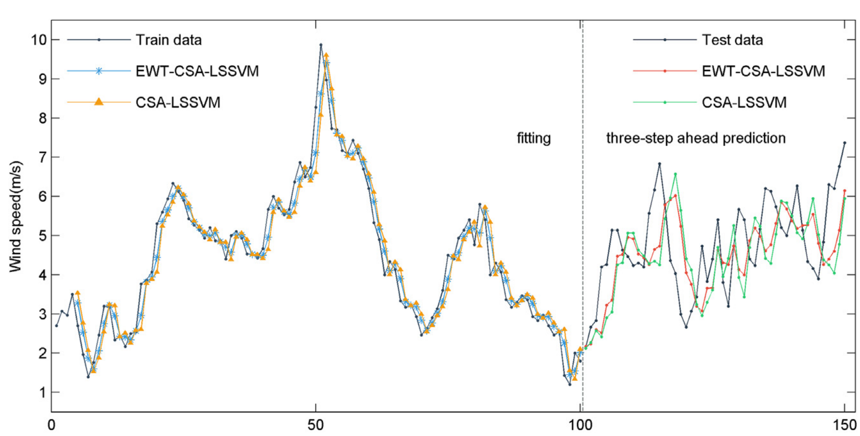

Fig. 8. Comparison between the actual data and the fitting and three-step ahead forecasting results.

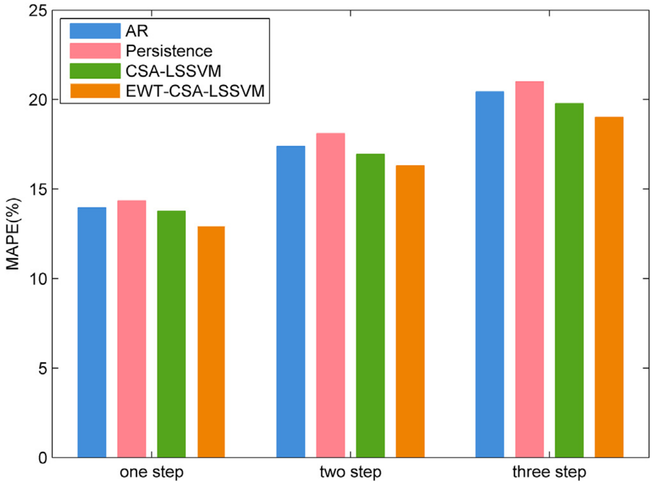

Fig. 9. MAPE comparisons among different models for various forecasting horizons.

Furthermore, the persistence method is employed as a benchmark to compare with other forecasting models to baseline the performance. All of the aforementioned simulations are implemented in matlab 7.11.0.

4.4. The comparisons and analysis

We first compare and discuss the one-step forecasting results obtained from the aforementioned models in detail. Then, we analyze the multi-step forecasting results in a similar manner. For one-step forecasting, we make comparisons between the AR, CSA-LSSVM (linear kernel), persistence method and hybrid EWT-CSA-LSSVM (linear kernel) model.

The one-step ahead predicted outcomes of the different models are presented in Fig. 9 and in Table 1. It is also clear from Table 1 and Fig. 9 that the three one-step forecasting evaluation indices (MAE, RMSE and MAPE) obtained through the proposed hybrid strategy are smaller than those obtained from other models. The comparison of the predictions shows that the integration of the EWT algorithm and the LSSVM model is an effective method for short-term wind speed prediction and that the hybrid model can provide good forecasts based on the properties of the short-term wind series because the EWT is a self-adaptive method and the LSSVM is established in terms of wind speed data.

To further evaluate the established approaches, the models are submitted to further analyses. First, because the persistence method is used as a benchmark to baseline the forecasting performance, other models are compared with it. Table 1 show that the AR, CSA-LSSVM (linear kernel) and hybrid EWT-CSA-LSSVM (linear kernel) perform better than the persistence method, which reveals that the short-term wind speeds have a strong linear relationship. This is the reason that numerous studies have proposed a linear model or modified linear model to tackle short-term wind speed problems. Second, the comparison and analysis of forecasting results between the persistence method and EWT-CSA-LSSVM reveal that the proposed model leads to reductions of 10.2% in MAPE and 9.1% in MAE. In conclusion, the model comparisons show that the proposed hybrid EWT-CSA-LSSVM model achieves good forecasting performance based on analyses of the prediction results.

The proposed hybrid EWT-CSA-LSSVM model also performs well when applied to multi-step forecasting. With respect to the method of analysis, we can obtain the same conclusion from the forecasts yielded by these models, as revealed in Table 2 and in Fig. 9. We also find that the hybrid EWT-CSA-LSSVM (linear kernel) exhibits better performance than the AR model, which reveals that the models that use support vectors to handle the linear problem outperform the linear models, although the former are more complex and unintelligible than the latter. In addition, compared with the CSA-LSSVM model, the EWT-CSA-LSSVM model leads to a 3.78% reduction in the total MAPE for two-step prediction and a 4.06% reduction in the total MAPE for three-step ahead prediction, which demonstrates that the preprocessing methods are effective in boosting the forecasting accuracy of short-term wind speed prediction. The hybrid models adequately make use of data preprocessing methods and the LSSVM model and fully exploit their advantages. In addition, we can draw the conclusion that the forecast accuracy of each model decreases with the increase in the number of horizon steps.

The comparisons between the predicted data and the actual data in Figs. 6–8 convey the information on the time lag of the predicted data against the actual data. This can be illustrated with the Sample PACF (Fig. 4). The subsection 4.2 mentioned that the lag order of the autoregressive process is four. The PACF value at lag 1 is up to 0.95 while the PACF values at lag 2–4 are −0.30, 0.23 and −0.22, respectively, which means that the actual data at time t severely affects the corresponding multistep ahead prediction whereas the effect of the actual data at time $t-l$ to the multistep ahead prediction is not so obvious, where l is lag order. Therefore, the correlation leads to the time lag of the predicted data against the actual data in visual way. The time lag of prediction affects the predictive control of wind turbines and real-time optimization of wind farm operation, and then affects economic load dispatch planning and load increment/decrement decisions. Good prediction system should reduce the time lag of prediction. It can be seen from the horizontal perspective in the Figs. 6–8 that the proposed method achieves an improvement in the time lag of the predicted data against the actual data. Compared with the predictions provided by the CSA-LSSVM, the time lag of the predicted data offered by proposed approach is smaller and the forecasting results are closer to the actual data series. This is because the EWT extracts meaningful information from the short-term wind speed series and eliminates some disturbing factors. Specifically, the EWT firstly extracts three meaningful modes (the top three sub-graphs in Fig. 3) from the wind speed series, and isolates the meaningless residual (shown at the bottom of the Fig. 3), and then the residual is discarded. The foregoing operations make the forecast engine

Table 1
The performance evaluations of different models for one-step horizon.

Forecasting horizon	Indicators	Forecasting models			
		AR	Persistence	CSA-LSSVM	EWT-CSA-LSSVM
One-step	RMSE	0.65	0.67	0.61	0.57
	MAE	0.65	0.67	0.61	0.57
	MAPE	13.97	14.35	13.44	12.89

Table 2
The performance evaluations of different models for multi-step horizon.

Forecasting horizon	Indicators	Forecasting models			
		AR	Persistence	CSA-LSSVM	EWT-CSA-LSSVM
Two-step	RMSE	0.85	0.87	0.83	0.79
	MAE	0.79	0.82	0.77	0.74
	MAPE	17.40	18.11	16.95	16.31
Three-step	RMSE	1.06	1.08	1.03	0.99
	MAE	0.96	0.98	0.93	0.89
	MAPE	20.43	21.00	19.19	18.41

Table 3
The performance evaluations of the LSSVM models with different kernels for various forecasting horizons.

Prediction horizon	Indicators	EWT-CSA-LSSVM Model			CSA-LSSVM Model		
		Linear	Gaussian	Polynomial	Linear	Gaussian	Polynomial
One-step	RMSE	0.57	0.58	0.57	0.61	0.61	0.61
	MAE	0.57	0.58	0.57	0.61	0.61	0.61
	MAPE	12.89	12.94	12.64	13.44	13.44	13.55
Two-step	RMSE	0.79	0.81	0.81	0.83	0.83	0.85
	MAE	0.74	0.75	0.75	0.77	0.77	0.79
	MAPE	16.31	16.53	16.49	16.95	16.92	17.24
Three-step	RMSE	0.99	0.98	0.96	1.03	0.98	1.01
	MAE	0.89	0.88	0.86	0.93	0.89	0.91
	MAPE	18.41	19.29	18.69	19.19	19.25	19.71

easier to capture the internal relationship embedded in the wind speed series, thereby decreasing the deviation between the predicted data and the actual data and improving the prediction accuracy. In addition, with the forecasting horizon increasing, the time lag of the predicted data against the actual data also arises.

Though the proposed EWT-CSA-LSSVM approach generates slightly better results in comparison with other models, the operation on the proposed model is a little more complex owing to the data preprocessing and the parameter optimization. In addition, the computation time required by the proposed approach is more than the ones cost by the other models. Specifically, the persistence method and AR model cost no more than 1 s to accomplish the forecasting task, while the computation time required by the proposed approach is about 22 s, which is a little more than the computation time required by the CSA-LSSVM methods (about 21 s) owing to the data preprocess. All these computations are conducted on the computer (the Computer Configuration is shown as follows. CPU: Intel(R) Core(TM) i5-3470 cpu@3.2 GHz 3.2 GHz; RAM: 8.00 GB; System type: 64bit). Compared with the persistence method and AR model, the proposed EWT-CSA-LSSVM approach costs much more time to accomplish the whole forecasting process. However, the whole computing time is no more than 1 min, which is acceptable for the cost on the modeling and computing in practice. Thus, the EWT-CSA-LSSVM approach should be promoted thanks to the small amount of sample data and the progress of computer technology.

In applying the proposed predictor LSSVM in the CSA-LSSVM and EWT-CSA-LSSVM models to short-term wind speed prediction, we compare the forecasting results obtained with different mapping functions, i.e., the kernel functions. The forecasting results obtained with different mapping functions are shown in Table 3. Overall, the LSSVM with a linear kernel exhibits the best performance in terms of forecasting accuracy, whereas the LSSVM with a Gaussian kernel exhibits the worst performance because there are linear patterns hiding in the data (shown in Fig. 10). Based on the forecasting results, we find that the forecasting performances of the models with different mapping functions are subtly different. We recommend using the linear kernel function when time series show more linearity than nonlinearity.

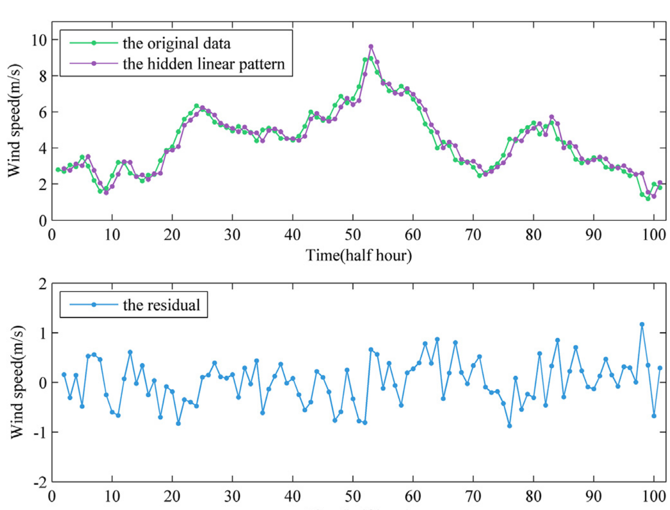

Fig. 10. The linear patterns hiding in the data.

5. Conclusions

Because they are affected by various environmental factors, wind speed data present high fluctuations, autocorrelation and stochastic volatility, making it is difficult to forecast wind speed using a single model. Herein, a hybrid EWT-CSA-LSSVM model for short-term wind speed prediction is presented. The EWT is exploited to eliminate the stochastic volatility in wind speed series. The parameters in the LSSVM are tuned and optimized by the CSA algorithm. This study generates wind speed predictions over two different forecasting horizons: one-step ahead prediction and multi-step ahead prediction. The two forms of prediction involve a rolling operation method, and this study investigates the effects of the kernel function in the LSSVM on the prediction accuracy. The test results obtained for different forecast horizons suggest that the developed hybrid wind speed forecasting approach based on the LSSVM model integrated with the EWT algorithm and CSA algorithm has the ability to yield good wind speed predictions.

Acknowledgments

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