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Wind speed prediction model using singular spectrum analysis, empirical mode decomposition and convolutional support vector machine

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ABSTRACT

Accurate wind speed forecasting is critical to the exploitation and utilization of wind energy. In this paper, a novel wind speed multi-step prediction model is designed based on the SSA (*Singular Spectrum Analysis*), EMD (*Empirical Mode Decomposition*) and CNNSVM (*Convolutional Support Vector Machine*). In the SSA-EMD-CNNSVM model, the SSA is used to reduce the noise and extract the trend information of the original wind speed data; the EMD is used to extract the fluctuation features of the wind speed data and decompose the wind speed time series into a number of sub-layers; and the CNNSVM is used to predict each of the wind speed sub-layers. To investigate the prediction performance of the proposed model, some models are used as the comparison models, including the SVM model, CNNSVM model, EMD-BP model, EMD-RBF model and EMD-Elman model. According to the prediction results of the four experiments, it can be found that the proposed model can have significantly better performance than the seven comparison models from 1-step to 3-step wind speed predictions with the MAPE of 42.85% average performance promotion, MAE of 39.21% average performance promotion, RMSE of 39.25% average performance promotion.

1. Introduction

With the development of industrialization, energy problem has been a major topic in the world. Since the fossil fuel resources are limited and they have the adverse impacts on air pollution and global warming, the renewable resources are becoming more and more important [1]. Wind energy is one of the most potential and practical renewable resources, the technologies related to the wind energy should be developed in depth. Since wind has the intermittent characteristic, the generation of wind power is unstable. The large-scale grid integration of wind power into electric power networks can challenge the energy conversion and management [2]. In order to address this problem, wind speed prediction is regarded as one of the most effective technologies. However, wind speed can be affected by multiple factors, the simple prediction models are challenging to catch the sophisticated features of the wind speed and obtain the accurate prediction results. Therefore, the high-precision wind speed prediction has received worldwide attention.

Over the past decades, numerical wind speed prediction models have been proposed, which can be classified into two groups as the physical models and statistical models [3]. The physical models can approximately simulate the wind speed by using some physical information, such as atmospheric pressure, local terrain and ambient temperature [4]. Since the physical models have the firm theoretical basis and excellent performance in wind speed prediction, these models are widely used in practice. However, the physical models require many physical equations and substantial computational costs, thus, these models are suitable for mid-long term wind speed prediction in large-scale areas, and less ideal for short-term wind speed prediction in small-scale areas. Recently, some interesting physical models have been designed. For example, Allen et al. [5] developed a boundary layer scaling model for forecasting long-term average near-surface wind speed; and Mughal et al. [6] proposed a physical based wind speed prediction model in complex terrain.

The statistical models can forecast the wind speed based on the historical data. With the rapid developing of the data science, the statistical models are becoming more and more popular. Generally, on the basis of the data source, the statistical models can be classified into two types as the multiple data models and single wind speed data models. The multiple data models can predict the wind speed by combining the numerous physical information with some statistical algorithms [7]. In some cases, the prediction performance of the multiple data models can be excellent, hence many scholars focus on these models. Hoolohan et al. [8] established a multiple data model by using Gaussian process regression and observed meteorological data. Zhao et al. [9] designed a

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probabilistic wind speed prediction model based on some non-parameter statistical algorithms and numerical weather prediction data. Wang et al. [10] built a wind speed prediction model based on copula method, and in their model, the data from the local wind farm and meteorological station were combined for analysis. Although the multiple data models can have good prediction results, sometimes the multiple data may increase the complexity and uncertainty of the prediction model. Compared to the multiple data, the single wind speed data is more accessible and stable, additionally, the single wind speed data models often have the low computational burden, thus the single wind speed data models are widely used in wind speed prediction, especially in short-term wind speed prediction [11].

To maximize the utilization of the single wind speed data, a lot of algorithms are used in designing the single wind speed data models, such as time series algorithms, signal processing algorithms, ANN (*Artificial Neural Networks*) algorithms, SVM (*Support Vector Machine*) algorithms, search algorithms, and other algorithms [12]. The time series algorithms belong to the classical wind speed prediction algorithms, which mainly contain the persistence algorithms, AR (*Auto-Regressive*) algorithms, ARMA (*Auto-Regressive Moving Average*) algorithms and ARIMA (*Auto-Regressive Integrated Moving Average*) algorithms [13]. The signal processing algorithms are used as the feature extraction algorithms in wind speed prediction, including WD (*Wavelet Decomposition*), WPD (*Wavelet Packet Decomposition*), EMD, EEMD (*Ensemble Empirical Mode Decomposition*), CEEMDAN (*Complete Ensemble Empirical Mode Decomposition*), SSA and others [14]. The ANN algorithms and SVM algorithms can have satisfactory nonlinear mapping and generalization abilities, so they are often used as the predictors in wind speed prediction [15]. The search algorithms, such as GS (*Grid Search*) algorithm, GA (*Genetic Algorithm*), and PSO (*Particle Swarm Optimization*) algorithm, can be used to search the optimal parameters of the predictors in wind speed prediction [16].

According to some studies, compared to the single algorithms, some hybrid algorithms can have better performance in wind speed prediction [17,18]. Presently, more and more single wind speed data models are proposed by mixing different algorithms. Wang et al. [19] proposed a short-term wind speed prediction model based on the ELM (*Extreme Learning Machine*), ICEEMDAN (*Improved Complete Ensemble Empirical Mode Decomposition*) and ARIMA, and their experimental results indicated that the ensemble algorithms, feature extraction algorithms and error correction algorithms could be useful for improving the performance of wind speed prediction. Santhosh et al. [20] designed a short-term wind speed prediction model by combing the EEMD with the adaptive wavelet neural network. Khosravi et al. [21] investigated the wind speed time series prediction by using a series of machine learning algorithms, including MLFFNN (Multilayer Feed-forward Neural Network), SVM, FIS (Fuzzy Inference System), ANFIS (Adaptive Neuro-fuzzy Inference System), GMDH (Group Method of Data Handling) type neural network, ANFIS-PSO algorithm and ANFIS-GA algorithm. Mi et al. [22] developed a multi-step wind speed prediction model based on the wavelet domain denoising, WPD, EMD, ARMA, ELM and outlier correction algorithm, in their model, the wavelet domain denoising was acted as the preprocessing, and the outlier correction algorithm was acted as the post-processing. Wang et al. [23] put up with an interesting multi-step ahead wind speed prediction model based on the heteroscedastic multi-kernel learning, variational Bayesian inference and matrix-variate Gaussian distribution. Jiang et al. [24] put forward a real-time wind speed prediction model by using the correlation-aided discrete wavelet transform, LSSVM (Least Squares Support Vector Machine) and GARCH (Generalized Autoregressive Conditionally Heteroscedastic). Li et al. [25] proposed the wind speed prediction models based on the EWT, LSTM and RELM. Song et al. [26] presented a short-term wind speed prediction model by using the ICEEMDAN, GWO (*Gray Wolf optimization*) and ANN. Li et al. [27] provided a multi-step short-term wind speed prediction model based on the VMD (Variational Mode Decomposition), GSO (Gram Schmidt Orthogonal) and ELM. Moreno et al. [28] introduced the SSA and ANFIS into wind speed forecasting.

The prediction algorithms are the core of the wind speed prediction models. Among the hybrid prediction models with single wind speed data, some novel and important prediction algorithms, for example, the deep learning algorithms, are introduced into wind prediction [29]. The deep learning algorithms, such as CNN (*Convolutional Neural Network*), RNN (*Recurrent Neural Network*) and DBN (*Deep Belief Network*), are regarded as the most powerful and promising algorithms in the last years, for they have the strong performance of feature extraction and generalization [30]. Recently, the deep learning algorithms have been gradually used for building wind speed prediction models and they have been validated to be very practical for wind speed prediction. Chen et al. [31] designed the EnsemLSTM model for wind speed prediction, in which several LSTMs with different hyper-parameters were used as the predictors, and the SVM and EO (Extremal Optimization) were used to improve the prediction performance. Wang et al. [32] successfully introduced the DBN into their hybrid wind speed prediction model. Liu et al. [33] presented a wind speed prediction model, in which the LSTM was used to predict the low-frequency sub-layers. Hu et al. [34] developed a wind speed prediction model based on the DBN and transfer learning. For the short-term wind speed forecasting, the prediction accuracy, prediction robustness and computational cost are important. The multi-decomposition algorithms, ensemble algorithms and intelligent search algorithms can be very useful in improving the prediction accuracy and prediction robustness of the short-term wind speed, however, these algorithms often have some hyper-parameters and may significantly increase the computation, thus the models with these algorithms often use the simple predictors with low computation. To reduce the hyper-parameters of the model as well as obtain the good prediction performance, in this paper, a new short-term wind speed prediction model based on the strong predictor is proposed. Compared to the models using multi-decomposition algorithms, ensemble algorithms or intelligent search algorithms, the proposed model can have lower computational cost as well as the similar prediction accuracy and prediction robustness. The proposed model consists of three parts as the SSA, EMD and CNNSVM. The framework of the proposed model is described as follows: (a) The SSA, served as the preprocessing, is used to reduce the noise of the original wind speed data. (b) The EMD, served as the adaptive feature extraction algorithm, is used to decompose the nonlinear and non-stationary wind speed time series into a series of simple sub-layers with different frequency range. Compared to the complex wind speed time series, the simple sub-layers are easier to predict, thus EMD can be used to improve the prediction accuracy. (c) The CNNSVM, served as the prediction algorithm, is used to accomplish the prediction of each sub-layer.

The main contributions of this paper are explained as follows: (a) A new short-term wind speed prediction model is proposed based on the denoising algorithm, feature extraction algorithm, prediction algorithm and search algorithm. In the proposed model, the SSA can effectively reduce the noise and extract the trend information of the wind speed data; the EMD can automatically extract the fluctuation features of the wind speed data; the CNNSVM can well predict each of the wind speed sub-layers. Besides, to improve the generalization performance of the prediction algorithm, the grid search algorithm is used for tuning the parameters of the CNNSVM. (b) Due to introducing the EMD and grid search algorithm to the proposed model, the proposed model can automatically adjust some critical parameters according to the wind speed data. Therefore, compared to the models which need to set many parameters, the proposed model is more robust. (c) The CNNSVM algorithm, which has good generalization nonlinear mapping performance, is first designed for wind speed prediction. In the CNNSVM, the hyper-parameters of the convolutional layers are fixed, while the parameters of the SVM layer can be optimized through the grid search algorithm. Although the CNN and SVM have been used in wind speed prediction respectively, the CNNSVM used as a predictor for wind speed prediction has not been investigated before. (d) To investigate the

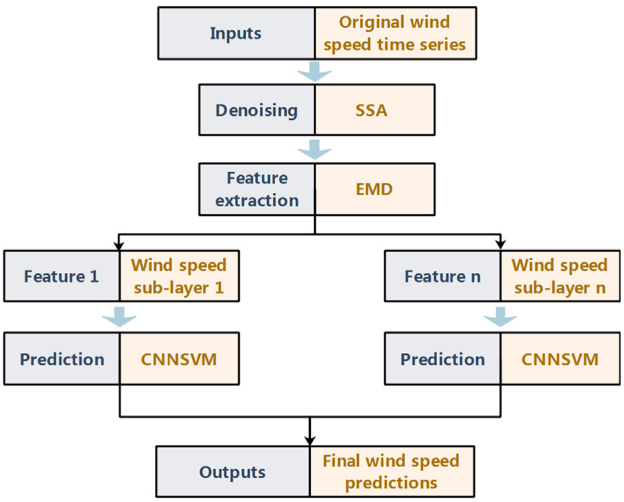

Fig. 1. The framework of the SSA-EMD-CNNSVM model.

prediction performance of the proposed model, four experimental tests are applied, besides, some models are adopted as the comparison models, including the SVM model, CNNSVM model, EMD-BP model, EMD-RBF model and EMD-Elman model.

The remainder of this paper is organized as follows: Section 2 presents the framework of the SSA-EMD-CNNSVM model and describes the related algorithms; Section 3 analyzes the prediction performance of the proposed model according to four experimental tests; Section 4 concludes this study.

2. The SSA-EMD-CNNSVM model

2.1. The framework of the SSA-EMD-CNNSVM model

The structure of the SSA-EMD-CNNSVM model is shown in Fig. 1, which can be summarized as follows:

(1) The SSA is adopted to reduce the noise of the original wind speed data. The details of the SSA are described in Section 2.2.

(2) The EMD is employed to decompose the wind speed time series into a series of sub-layers. The details of the EMD are described in Section 2.3.

(3) The CNNSVM is designed to predict each of the decomposed wind speed sub-layers. The details of the CNNSVM are described in Section 2.4.

(4) To evaluate the prediction performance of the proposed model, some models are used as the comparison models, including the SVM model, CNNSVM model, EMD-BP model, EMD-RBF model and EMD-Elman model. The details of the prediction performance metrics are provided in Section 2.5. The experiments and analysis are provided in Sections 3 and 4.

2.2. Singular spectrum analysis

SSA, a non-parametric algorithm, is widely used in time series analysis. SSA can extract the periodic or quasi-periodic components of the time series, thus it can reduce the noise of the original wind speed time series [35]. Generally, SSA includes four steps as embedding, SVD (Singular Value Decomposition), grouping and diagonal averaging. The embedding and SVD belong to data decomposition, while the grouping and diagonal averaging belong to data reconstruction [36]. The detailed steps of SSA are described as follows [37,38]:

(1) Embedding. In this step, the original wind speed data $X=(X_{1,\dots,}X_N)$ is shifted to a trajectory matrix $Y=(Y_{1,\dots,}Y_L)$ with L dimensions, where $2 \le L \le N$. Each element of the matrix Y is defined as $Y_i = (X_i,\dots X_{i+L-1})$, and the matrix Y is given as follows:

$$Y = \begin{pmatrix} X_1 & X_2 & \dots & X_K \\ X_2 & X_3 & \dots & X_{K+1} \\ \dots & \dots & \dots & \dots \\ X_L & X_{L+1} & \dots & X_N \end{pmatrix} \tag{1}$$

where $K = N - L + 1$.

(2) SVD. In this step, the matrix Y can be decomposed into d components, where $d = rank\ (Y)$. Through SVD, the eigentirples (λ_i, U_i, V_i) of the matrix YY^T can be obtained in descending order by λ_i, where λ_i denotes the singular value, U_i denotes the left eigenvector, and V_i denotes the right eigenvector. Therefore, the matrix Y can be further rewritten as follows:

$$Y = Y_1 + Y_2 + \dots Y_d \tag{2}$$

$$Y_i = \sqrt{\lambda_i}U_iV_i^T \tag{3}$$

(3) Grouping. In this step, m out of d components are selected as the trend components. Define $I = \{I_{1,\dots}I_m\}$ and $Y_I = Y_{I_1} + \dots + Y_{I_m}$, then Y_I can represent the trend component of the wind speed data, while the other $(d–m)$ components are regarded as the noise.

(4) Diagonal averaging. In this step, through the Hankelization procedure, the obtained group $\{Y_{I_1}, Y_{I_2}. \dots, Y_{I_m}\}$ are shifted to the time series group $\{X_{I_1}, X_{I_2}. \dots, X_{I_m}\}$. Then the original wind speed time series can be defined as follows:

$$X = X_{trend} + X_{noise} = X_{I_1} + X_{I_2} + \dots + X_{I_m} + X_{noise} \tag{4}$$

2.3. Empirical mode decomposition

EMD is an empirical signal processing algorithm used for extracting features of the nonlinear data. Since EMD does not need to set the parameters, it can automatically fit to the wind speed data. In order to reduce the parameters of the proposed model as well as improve the robust of the proposed model, in this paper, EMD is selected to decompose the wind speed data into several sub-layers. The computational steps of EMD can be described as follows [39]:

(1) Determine all the local extremes of the wind speed data $X(t)$.

(2) Connect all the local maxima to calculate the upper envelope $X_U(t)$ by using a cubic spline line. Similarly, connect all the local minima to calculate the lower envelope $X_L(t)$.

(3) Compute the mean envelope $M(t)$:

$$M(t) = [X_U(t) + X_L(t)]/2 \tag{5}$$

(4) Calculate the variable Y(t):

$$Y(t) = X(t) - M(t) \tag{6}$$

If $Y(t)$ is the IMF (*Intrinsic Mode Function*), set $c(t) = Y(t)$; otherwise, replace $X(t)$ by $Y(t)$, and repeat steps (1)–(4), until the termination condition is satisfied.

(5) Calculate the residual R(t):

$$R(t) = X(t) - C(t) \tag{7}$$

replace $X(t)$ with $R(t)$, and repeat steps (1)–(5), until all the IMFs are found.

2.4. Convolutional support vector machine

Compared to the original wind speed data, the wind speed sub-layers can be easier to predict. However, each wind speed sub-layer may still have some intrinsic features. To improve the feature extraction performance and generalization performance of the predictors, the CNNSVM is designed as the predictor for each wind speed sub-layer. The designed CNNSVM can combine the CNN method with the SVM method, and it has the merits of both methods.

CNN, acted as one of the most effective technologies in deep learning, is widely used in data processing, especially in vision domain [40]. Since CNN can automatically create the good filters and effectively extract the in-depth features of the data, CNN can have great potential in time series applications [41]. For each convolutional layer, the convolution operation can be formalized as follows [42]:

$$h_{ij}^k = f((W^k * x)_{ij} + b_k) \tag{8}$$

where f denotes the activation function, W^k denotes the weights of the kth feature map, and b_k denotes the bias of the kth feature map.

SVM is a powerful machine learning algorithm based on the structural risk minimization principle. SVM has good nonlinear mapping performance, and it can effectively map the data into the high dimensional feature space and perform the linear regression in the feature space [43]. The regression formula is expressed as follows [44]:

$$f(x) = w^T\varphi(x) + b \tag{9}$$

where φ is the nonlinear mapping function, w and b are the weight vector and bias. The optimization of SVM can be calculated as follows:

$$\min_{w,b,\xi,\xi^*} \frac{1}{2}w^T w + C\sum_{i=1}^{n}(\xi_i + \xi_i^*) \tag{10}$$

$$s.\ t. \begin{cases} y_i - (\langle w, x_i\rangle + b) \leqslant \varepsilon + \xi_i \\ (\langle w, x_i\rangle + b) - y_i \leqslant \varepsilon + \xi_i^* \ (i = 1, 2, \ldots l) \\ \xi_i, \xi_i^* \geqslant 0 \end{cases} \tag{11}$$

where l is the number of samples, x_i and y_i are the inputs and outputs of the training data, respectively; n is the number of the samples; ξ_i and ξ_i^* are the upper and lower training errors, respectively; ε and C are the insensitive loss factor and regularized constant, respectively.

By using the Lagrange multipliers a_i and a_i^*, the prediction function $f(\cdot,\cdot,\cdot)$ can be calculated as follows:

$$f(x, a_i, a_i^*) = \sum_{i=1}^{n}(a_i - a_i^*)K(x, x_i) + b \tag{12}$$

where $K(\cdot,\cdot)$ is the kernel function, and in this study, RBF is used as the kernel function.

The computational steps of the CNNSVM are shown in Fig. 2, which can be described as follows:

(1) Build and train the CNN model based on the training data of each wind speed sub-layer. Each CNN model includes three convolutional layers and two fully connected layers. In the convolutional layers, the channels are 4, 8 and 16, respectively. The activation function and optimization function are *ReLU* and *Adam algorithm*, respectively. In addition, to improve the generalization performance of the CNN model, the *dropout* [45] and *Lasso regularization* [46] are used in the multi-layer architecture. The dropout is used between convolutional layer 3 and fully connected layer 1, the ratio of the dropout is $p = 0.7$. The proportion of the Lasso regularization is 0.01, and the loss function is the sum of the mean squared error and Lasso regularization.

(2) Extract the fully connected layer 1 of the CNN model as the input features of the SVM, then build and train the SVM model. To improve the generalization and robustness of the SVM model, the grid search is used to search the ε and C.

(3) Save the CNN training model and SVM training model.

(4) Reload the training model and build the testing model. The testing model is built by connecting the fully connected layer 1 with the SVM layer directly. The parameters of the training model and testing model are shared. The multi-step predictions of the CNNSVM are shown in Fig. 3.

In the CNNSVM, the relationship among the activation function f, nonlinear mapping function φ, kernel function $K(\cdot,\cdot)$ and prediction function $f(\cdot,\cdot,\cdot)$ can be explained as follows:

(a) Six activation functions are used in the CNNSVM. f_1 can transfers the inputs to the convolutional layer 1, f_2 can transfers the convolutional layer 1 to the convolutional layer 2, f_3 can transfers the convolutional layer 2 to the convolutional layer 3, f_4 can transfers the convolutional layer 3 to the fully connected layer 1, f_5 can transfers the fully connected layer 1 to the fully connected layer 2, and f_6 can transfers the fully connected layer 2 to the outputs.

(b) The nonlinear mapping function φ can transfers the fully connected layer 1 to the SVM layer, and the kernel function $K(\cdot,\cdot)$ is the transformation of φ.

(c) The prediction function $f(\cdot,\cdot,\cdot)$ is used to obtain the prediction results of the CNNSVM.

2.5. Prediction performance metrics

To evaluate the prediction accuracy of the proposed model, in this paper, six prediction performance metrics are used, including MAPE

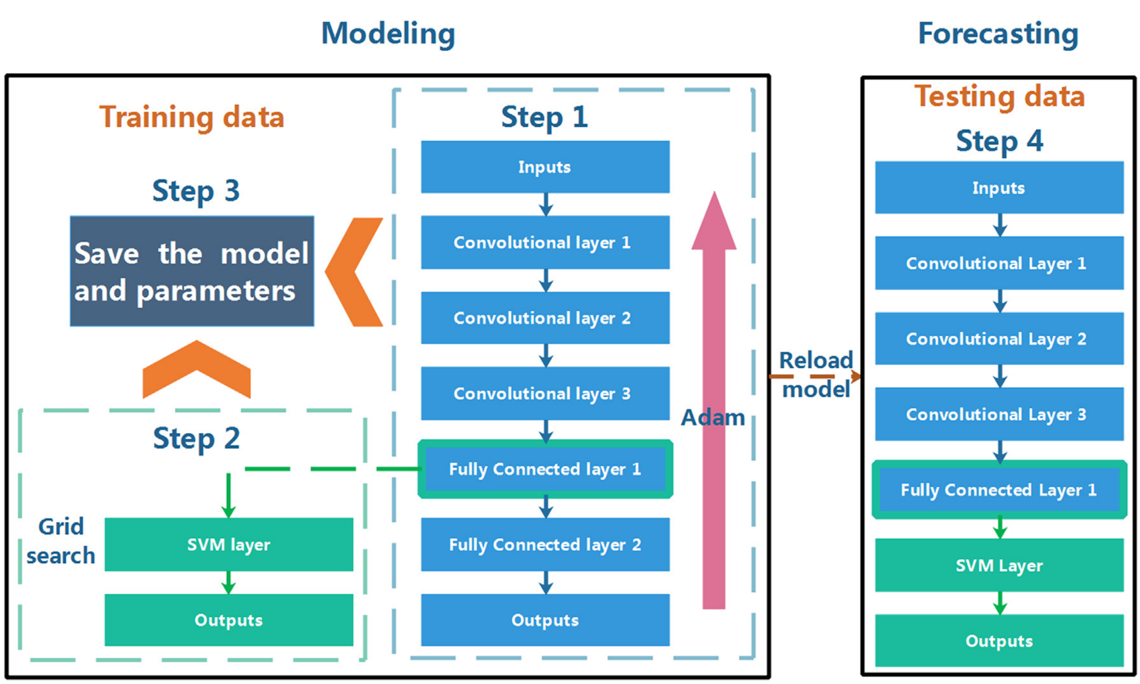

Fig. 2. Computational steps of CNNSVM.

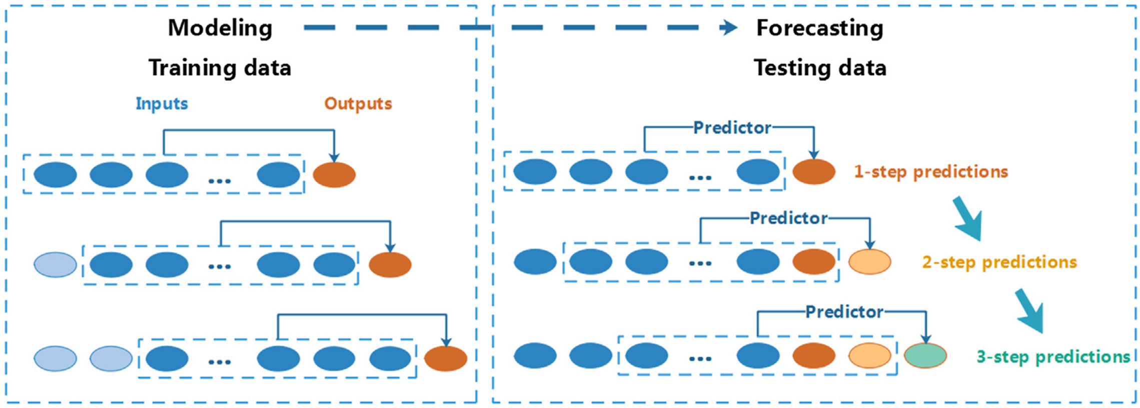

Fig. 3. Multi-step predictions of CNNSVM.

(Mean absolute percentage error), MAE (Mean absolute error), RMSE (Root mean square error), P_{MAPE} (Improvement percentage of mean absolute percentage error), P_{MAE} (Improvement percentage of mean absolute error) and P_{RMSE} (Improvement percentage of root mean square error) [22].

3. Case studies

3.1. Data description

In this paper, the wind speed data is gathered from a wind farm in Xinjiang, China. To verify the prediction performance of the proposed model, four sets of 10-min average wind speed time series, sampled from the wind speed data, are used as the experiment data. Each wind speed time series includes 700 samples, the 1st-600th samples are used for training and the 601st-700th samples are used for testing. The four wind speed time series are depicted in Fig. 4, and the statistical information of the four series are calculated and given in Table 1.

Table 1
Statistical information of the wind speed data.

Data	Min-Max values (m/s)	Mean (m/s)	Standard derivation	Skewness	Kurtosis
#1	0.00–9.30	4.53	1.97	−0.28	−0.33
#2	0.00–12.80	5.36	2.85	0.11	−0.69
#3	0.50–12.40	6.26	2.88	−0.23	−0.82
#4	1.00–13.90	6.86	2.87	0.17	−0.80

3.2. Experiments

In this paper, to investigate the generalization of the proposed model, four experiments are used. Besides, to validate the effectiveness of the SSA-EMD-CNNSVM model, some models are used as the comparison models, including the SVM model, CNNSVM model, EMD-BP model, EMD-RBF model and EMD-Elman model. The EMD-BP model, EMD-RBF model and EMD-Elman model are performed by using Matlab 2014b, while the SVM model, CNNSVM model and SSA-EMD-CNNSVM model are performed by using TensorFlow 1.6.0.

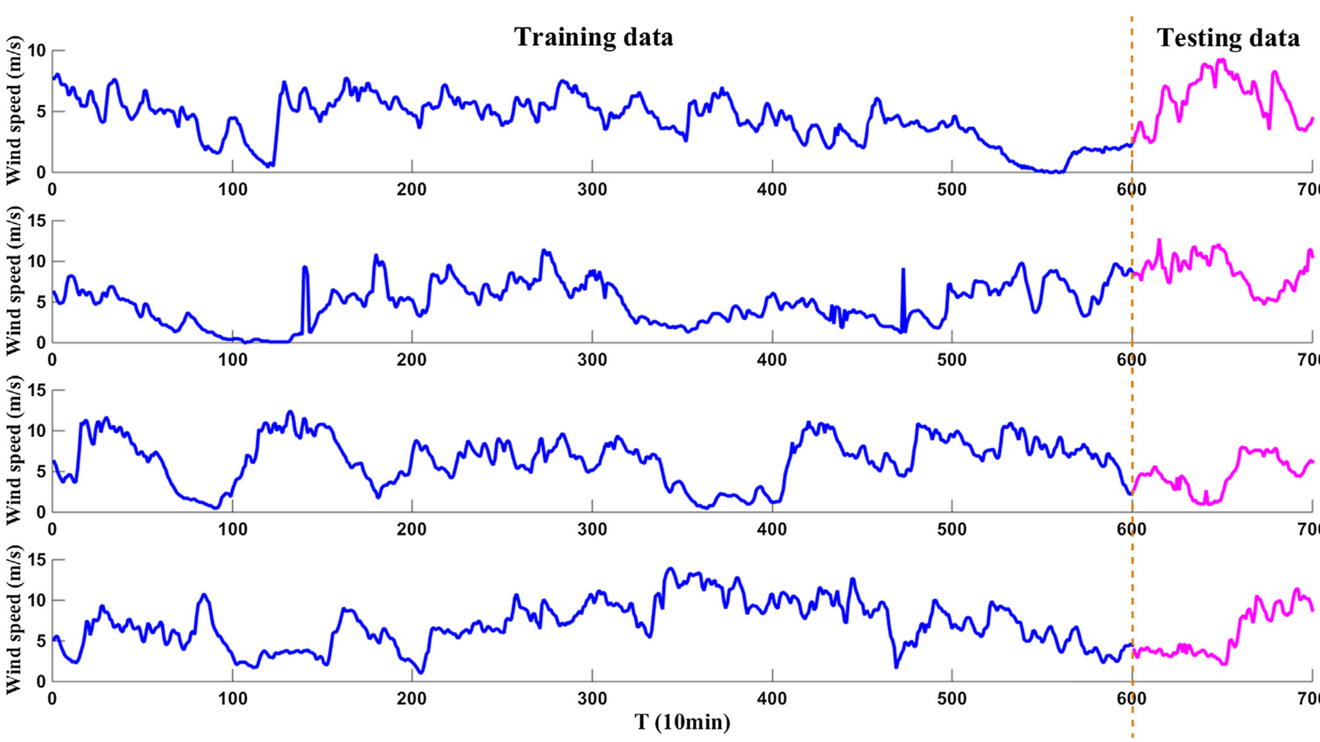

Fig. 4. Four sets of 10-min averaged wind speed data.

Table 2
Prediction results for experiment #1.

Indexes	1-step	2-step	3-step	1-step	2-step	3-step
	SVM			CNNSVM		
MAPE (%)	8.03	13.72	17.30	7.48	12.50	15.78
MAE (m/s)	0.48	0.83	1.07	0.43	0.73	0.95
RMSE (m/s)	0.67	1.13	1.38	0.61	1.03	1.27
	EMD-BP			EMD-RBF		
MAPE (%)	11.99	16.74	23.24	10.8	15.35	21.44
MAE (m/s)	0.68	0.90	1.27	0.63	0.88	1.28
RMSE (m/s)	0.85	1.07	1.61	0.88	1.24	1.74
	EMD-Elman			SSA-EMD-CNNSVM		
MAPE (%)	8.70	10.87	16.66	5.35	9.04	12.52
MAE (m/s)	0.49	0.62	0.95	0.31	0.52	0.74
RMSE (m/s)	0.65	0.84	1.27	0.40	0.70	0.98

Table 3
Prediction results for experiment #2.

Indexes	1-step	2-step	3-step	1-step	2-step	3-step
	SVM			CNNSVM		
MAPE (%)	8.55	12.96	16.62	6.41	9.74	12.20
MAE (m/s)	0.83	1.25	1.59	0.58	0.88	1.10
RMSE (m/s)	1.14	1.65	2.01	0.82	1.22	1.47
	EMD-BP			EMD-RBF		
MAPE (%)	10.64	13.24	14.76	18.8	22.00	21.70
MAE (m/s)	0.92	1.12	1.30	1.54	1.82	1.87
RMSE (m/s)	1.18	1.43	1.79	1.85	2.12	2.21
	EMD-Elman			SSA-EMD-CNNSVM		
MAPE (%)	11.31	13.68	14.09	5.19	7.41	8.39
MAE (m/s)	0.89	1.06	1.18	0.47	0.67	0.78
RMSE (m/s)	1.09	1.33	1.51	0.58	0.90	1.14

Table 4
Prediction results for experiment #3.

Indexes	1-step	2-step	3-step	1-step	2-step	3-step
	SVM			CNNSVM		
MAPE (%)	13.80	19.11	25.85	12.25	17.92	23.17
MAE (m/s)	0.40	0.62	0.85	0.37	0.60	0.80
RMSE (m/s)	0.64	0.87	1.14	0.59	0.80	1.05
	EMD-BP			EMD-RBF		
MAPE (%)	19.99	24.88	34.67	13.56	19.33	26.70
MAE (m/s)	0.64	0.77	1.04	0.32	0.55	0.78
RMSE (m/s)	0.87	1.05	1.38	0.42	0.75	1.02
	EMD-Elman			SSA-EMD-CNNSVM		
MAPE (%)	20.51	30.53	33.29	8.10	14.23	20.21
MAE (m/s)	0.52	0.77	0.80	0.28	0.50	0.73
RMSE (m/s)	0.67	0.93	1.00	0.38	0.69	0.91

Table 5
Prediction results for experiment #4.

Indexes	1-step	2-step	3-step	1-step	2-step	3-step
	SVM			CNNSVM		
MAPE (%)	9.07	13.18	15.89	8.93	13.61	16.02
MAE (m/s)	0.47	0.73	0.90	0.47	0.75	0.90
RMSE (m/s)	0.64	1.00	1.23	0.63	1.00	1.24
	EMD-BP			EMD-RBF		
MAPE (%)	14.33	17.39	23.25	20.92	22.14	24.20
MAE (m/s)	0.72	0.86	1.18	1.07	1.16	1.29
RMSE (m/s)	0.93	1.12	1.51	1.34	1.46	1.65
	EMD-Elman			SSA-EMD-CNNSVM		
MAPE (%)	15.42	19.97	29.67	4.84	8.07	10.31
MAE (m/s)	0.74	0.94	1.41	0.24	0.42	0.54
RMSE (m/s)	0.88	1.10	1.61	0.31	0.55	0.70

To analyze the multi-step prediction performance of the proposed model, the eight involved prediction models are targeted for 1-step, 2-step and 3-step forecasting. The prediction results including MAPE, MAE and RMSE of the eight involved models for four experiments are presented in Tables 2–5. The processed results of the SSA and EMD for experiment #1 are demonstrated in Fig. 5. The 1-step to 3-step prediction results of the involved models for experiment #1 are shown in Figs. 6–8.

3.3. Analysis

Based on Tables 2–5 and Figs. 6–8, it can be found that:

(1) The involved models have the similar prediction accuracy order in different experiments. This phenomenon indicates that: (a) the wind speed time series can be predicted; (b) the prediction results depend on the prediction models.
(2) The prediction accuracy of the decomposition based models is not always higher than that of the single models, while the proposed model can always outperform other comparison models. This phenomenon indicates that the denoising algorithm and parameters selection algorithm in the proposed model can contribute to improving the prediction performance.
(3) In different experiments, the ranges of prediction errors of the involved models are different. This phenomenon indicates that it must use the same data to complete the comparison between different models.
(4) The prediction accuracy of the CNNSVM model is slightly higher than that of the SVM model. This phenomenon indicates that the CNNSVM model is promising in wind speed forecasting.
(5) The MAPE, MAE and RMSE of all the involved models are increased with the steps. This phenomenon indicates that the prediction errors of each step would be added to those of the multi-step predictions.

To further exhibit the prediction performance of SSA-EMD-CNNSVM model, the P_{MAPE}, P_{MAE}, and P_{RMSE} are adopted for analysis. The improvement percentages of the comparison models by SSA-EMD-CNNSVM model for each experiment are given in Tables 6–9.

In accordance with Tables 6–9, it can be summarized that:

(1) The SSA-EMD-CNNSVM model has good generalization performance as it can have good prediction results in the four experiments.
(2) The SSA-EMD-CNNSVM model has satisfactory prediction accuracy as it can have better prediction accuracy than the comparison models in the four experiments.
(3) The prediction results of the SSA-EMD-CNNSVM model are better than those of the SVM model. For instance, in experiment #2, compared to the SVM model, the MAPE of the proposed model are reduced by 39.30%, 42.82% and 49.52%, respectively; the MAE of the proposed model are reduced by 43.37%, 46.40% and 50.94%, respectively; and the RMSE of the proposed model are reduced by 49.12%, 45.45% and 43.28%, respectively.
(4) The prediction results of the SSA-EMD-CNNSVM model are better than those of the CNNSVM model. This phenomenon indicates that the SSA-EMD components can improve the prediction performance of the proposed model. For instance, in experiment #2, compared to the CNNSVM model, the MAPE of the proposed model are reduced by 19.03%, 23.92% and 31.23%, respectively; the MAE of the proposed model are reduced by 18.97%, 23.86% and 29.09%, respectively; and the RMSE of the proposed model are reduced by 29.27%, 26.23% and 22.45%, respectively.
(5) The prediction results of the SSA-EMD-CNNSVM model are better than those of the EMD-BP model. For instance, in experiment #2, compared to the EMD-BP model, the MAPE of the proposed model are reduced by 51.22%, 44.03% and 43.16%, respectively; the MAE of the proposed model are reduced by 48.91%, 40.18% and 40.00%, respectively; and the RMSE of the proposed model are

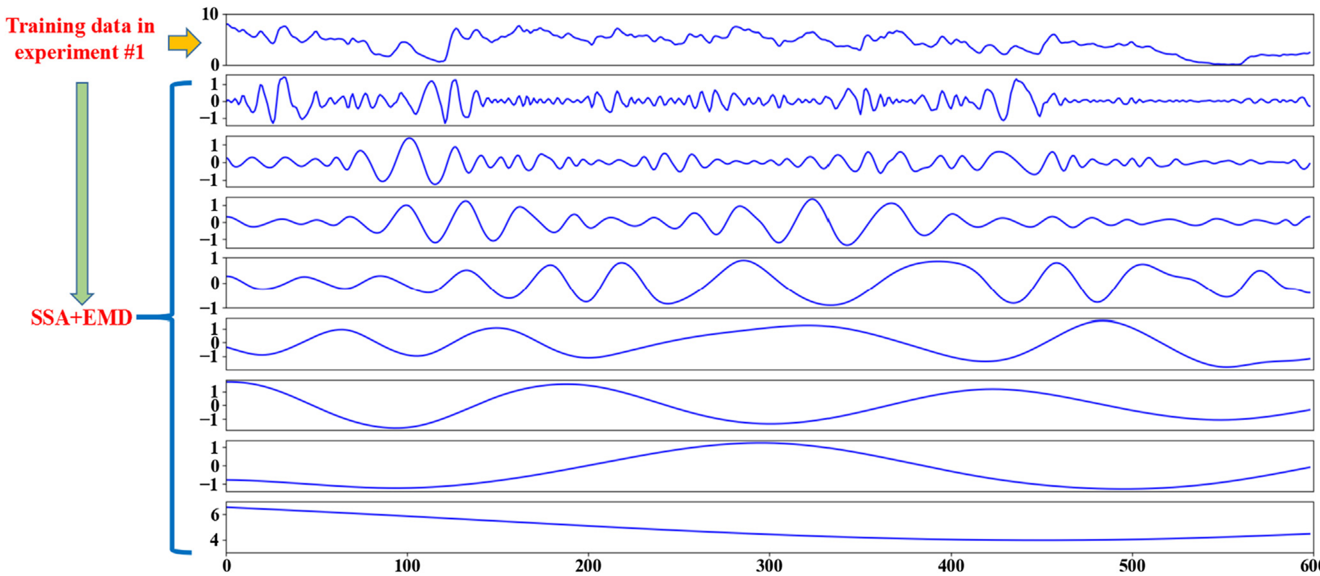

Fig. 5. The SSA and EMD results of experiment #1.

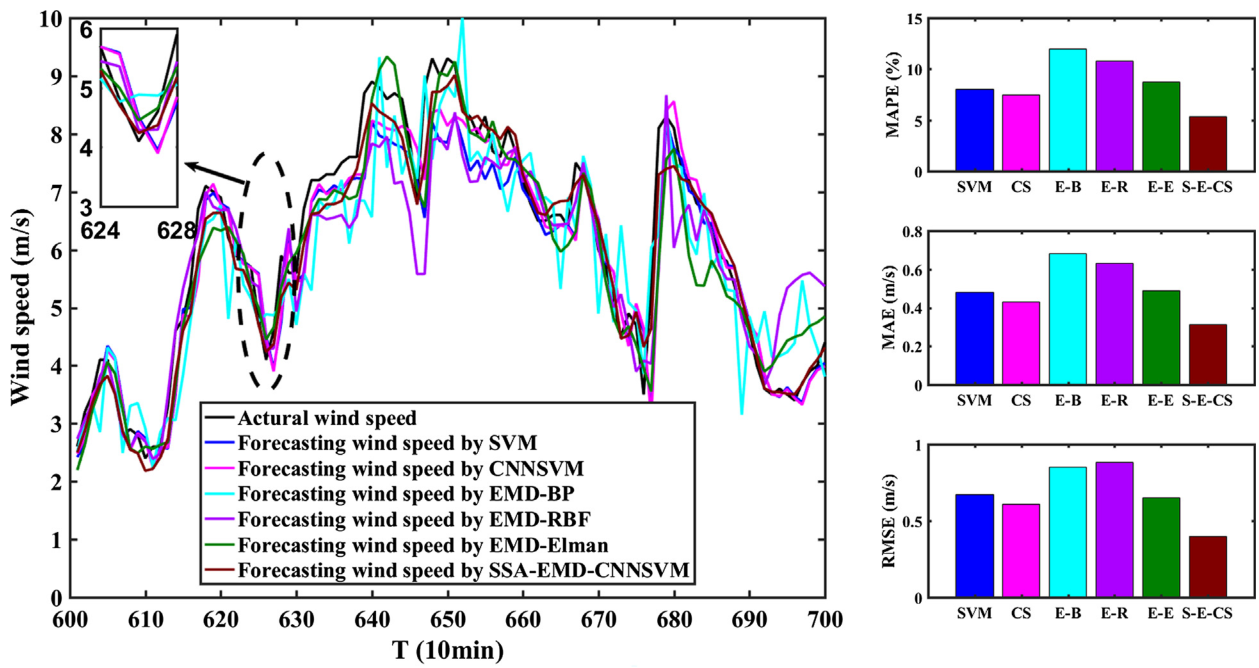

Fig. 6. The 1-step prediction results of experiment #1.

reduced by 50.85%, 37.06% and 36.31%, respectively.

(6) The prediction results of the SSA-EMD-CNNSVM model are better than those of the EMD-RBF model. For instance, in experiment #2, compared to the EMD-RBF model, the MAPE of the proposed model are reduced by 72.39%, 66.32% and 61.34%, respectively; the MAE of the proposed model are reduced by 69.48%, 63.19% and 58.29%, respectively; and the RMSE of the proposed model are reduced by 68.65%, 57.55% and 48.42%, respectively.

(7) The prediction results of the SSA-EMD-CNNSVM model are better than those of the EMD-Elman model. For instance, in experiment #2, compared to the EMD-Elman model, the MAPE of the proposed model are reduced by 54.11%, 45.83% and 40.45%, respectively; the MAE of the proposed model are reduced by 47.19%, 36.79% and 33.90%, respectively; and the RMSE of the proposed model are reduced by 46.79%, 32.33% and 24.50%, respectively.

4. Conclusions

In this paper, a new wind speed multi-step prediction model is designed based on the SSA, EMD and CNNSVM. In the SSA-EMD-CNNSVM model, the SSA is the denoising algorithm; the EMD is the feature extraction algorithm; and the CNNSVM is the prediction algorithm which includes the search algorithm. To investigate the prediction performance of the proposed model, some models are adopted as the comparison models, including the SVM model, CNNSVM model, EMD-BP model, EMD-RBF model and EMD-Elman model. According to the prediction results of the four experiments, it can be summarized that: (a) The proposed model has good prediction accuracy and generalization performance in short-term multi-step wind speed forecasting. (b) The proposed model can have significantly better performance than the seven comparison models from 1-step to 3-step wind speed predictions with the MAPE of 42.85% average performance promotion,

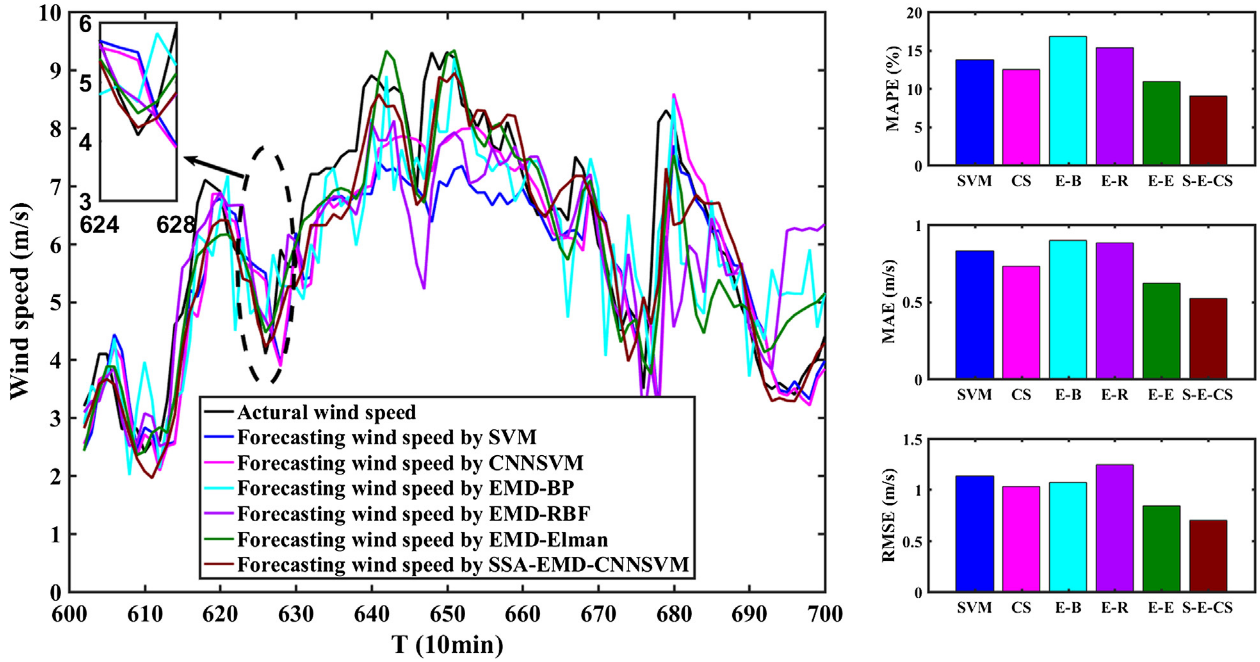

Fig. 7. The 2-step prediction results of experiment #1.

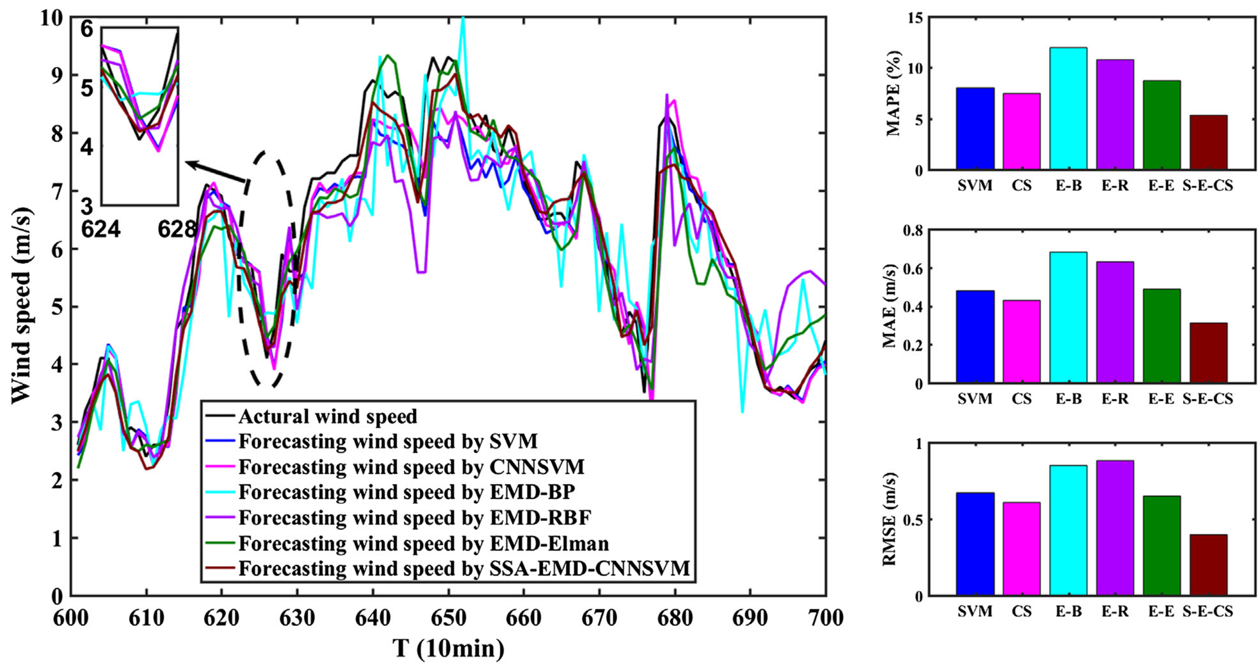

Fig. 8. The 3-step prediction results of experiment #1.

Table 6
Improvement percentages of the comparison models by SSA-EMD-CNNSVM model for experiment #1.

Comparison models	P_{MAPE} (%)			P_{MAE} (%)			P_{RMSE} (%)		
	1-step	2-step	3-step	1-step	2-step	3-step	1-step	2-step	3-step
SVM	33.37	34.11	27.63	35.42	37.35	30.84	40.30	38.05	28.99
CNNSVM	28.48	27.68	20.66	27.91	28.77	22.11	34.43	32.04	22.83
EMD-BP	55.38	46.00	46.13	54.41	42.22	41.73	52.94	34.58	39.13
EMD-RBF	50.46	41.11	41.60	50.79	40.91	42.19	54.55	43.56	43.68
EMD-Elman	38.51	16.84	24.85	36.73	16.13	22.11	38.46	16.67	22.83

Table 7
Improvement percentages of the comparison models by SSA-EMD-CNNSVM model for experiment #2.

Comparison models	P_{MAPE} (%)			P_{MAE} (%)			P_{RMSE} (%)		
	1-step	2-step	3-step	1-step	2-step	3-step	1-step	2-step	3-step
SVM	39.30	42.82	49.52	43.37	46.40	50.94	49.12	45.45	43.28
CNNSVM	19.03	23.92	31.23	18.97	23.86	29.09	29.27	26.23	22.45
EMD-BP	51.22	44.03	43.16	48.91	40.18	40.00	50.85	37.06	36.31
EMD-RBF	72.39	66.32	61.34	69.48	63.19	58.29	68.65	57.55	48.42
EMD-Elman	54.11	45.83	40.45	47.19	36.79	33.90	46.79	32.33	24.50

Table 8
Improvement percentages of the comparison models by SSA-EMD-CNNSVM model for experiment #3.

Comparison models	P_{MAPE} (%)			P_{MAE} (%)			P_{RMSE} (%)		
	1-step	2-step	3-step	1-step	2-step	3-step	1-step	2-step	3-step
SVM	41.30	25.54	21.82	30.00	19.35	14.12	40.63	20.69	20.18
CNNSVM	33.88	20.59	12.78	24.32	16.67	8.75	35.59	13.76	13.33
EMD-BP	59.48	42.81	41.71	56.25	35.06	29.81	56.32	34.29	34.06
EMD-RBF	40.27	26.38	24.31	12.50	9.09	6.41	9.52	8.00	10.78
EMD-Elman	60.51	53.39	39.29	46.15	35.06	8.75	43.28	25.81	9.00

Table 9
Improvement percentages of the comparison models by SSA-EMD-CNNSVM model for experiment #4.

Comparison models	P_{MAPE} (%)			P_{MAE} (%)			P_{RMSE} (%)		
	1-step	2-step	3-step	1-step	2-step	3-step	1-step	2-step	3-step
SVM	46.64	38.77	35.12	48.94	42.47	40.00	51.56	45.00	43.09
CNNSVM	45.80	40.71	35.64	48.94	44.00	40.00	50.79	45.00	43.55
EMD-BP	66.22	53.59	55.66	66.67	51.16	54.24	66.67	50.89	53.64
EMD-RBF	76.86	63.55	57.40	77.57	63.79	58.14	76.87	62.33	57.58
EMD-Elman	68.61	59.59	65.25	67.57	55.32	61.79	64.77	50.00	56.52

MAE of 39.21% average performance promotion, RMSE of 39.25% average performance promotion.

Although the proposed model can have good performance in short-term wind speed prediction, it still needs the high quality of historical wind speed data, for example the data should have the significant periodic or quasi-periodic components. Therefore, in some cases, the proposed model may not be as good as the models with the multiple data. Our future work will focus on the new models with the multiple data, we will improve the framework of the proposed model and combine the new models with the multiple data.

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References

[1] Wang Y, Wang J, Wei X. A hybrid wind speed forecasting model based on phase space reconstruction theory and Markov model: A case study of wind farms in northwest China. Energy 2015;91:556–72.

[2] Wan J, Ren G, Liu J, Hu Q, Yu D. Ultra-short-term wind speed prediction based on multi-scale predictability analysis. Cluster Comput 2016;19(2):741–55.

[3] Liu H, Duan Z, Li Y, Lu H. A novel ensemble model of different mother wavelets for wind speed multi-step forecasting. Appl Energy 2018;228:1783–800.

[4] Cadenas E, Rivera W, Campos-Amezcua R, Cadenas R. Wind speed forecasting using the NARX model, case: La Mata, Oaxaca, México. Neural Comput Appl 2016;27(8):2417–28.

[5] Allen DJ, Tomlin AS, Bale CSE, Skea A, Vosper S, Gallani ML. A boundary layer scaling technique for estimating near-surface wind energy using numerical weather prediction and wind map data. Appl Energy 2017;208(May):1246–57.

[6] Omer M, Lynch M, Yu F, Mcgann B, Jeanneret F, Sutton J. Environmental Modelling & Software Wind modelling, validation and sensitivity study using Weather Research and Forecasting model in complex terrain. Environ Modell Software 2017;90:107–25.

[7] Ulkat D, Günay ME. Prediction of mean monthly wind speed and optimization of wind power by artificial neural networks using geographical and atmospheric variables: case of Aegean Region of Turkey. Neural Comput Appl 2017.

[8] Hoolohan V, Tomlin AS, Cockerill T. Improved near surface wind speed predictions using Gaussian process regression combined with numerical weather predictions and observed meteorological data. Renew Energy 2018;126:1043–54.

[9] Zhao X, Liu J, Yu D, Chang J. One-day-ahead probabilistic wind speed forecast based on optimized numerical weather prediction data. Energy Convers Manage 2018;164:560–9.

[10] Wang Y, et al. Anew method for wind speed forecasting based on copula theory. Environ Res 2018;160:365–71.

[11] Dong Y, Wang J, Guo Z. Research and application of local perceptron neural network in highway rectifier for time series forecasting. Appl Soft Comput J 2018;64:656–73.

[12] Niu T, Wang J, Zhang K, Du P. Multi-step-ahead wind speed forecasting based on optimal feature selection and a modified bat algorithm with the cognition strategy. Renew Energy 2017;118:213–29.

[13] Zhao W, Wei YM, Su Z. One day ahead wind speed forecasting: A resampling-based approach. Appl Energy 2016;178:886–901.

[14] Liu H, Duan Z, Han F, Li Y. Bigmulti-step wind speed forecasting model based on secondary decomposition, ensemble method and error correction algorithm. Energy Convers Manage 2018;156:525–41.

[15] Sun S, Qiao H, Wei Y, Wang S. A new dynamic integrated approach for wind speed forecasting. Appl Energy 2017;197:151–62.

[16] Liu H, Wu H, Li Y. Smart wind speed forecasting using EWT decomposition, GWO evolutionary optimization, RELM learning and IEWT reconstruction. Energy Convers Manage 2018;161:266–83.

[17] Xu G, Xiu C, Wan Z. Hysteretic chaotic operator network and its application in wind speed series prediction. Neurocomputing 2015;165:384–8.

[18] Chen G, Yi X, Zhang Z, Wang H. Applications of multi-objective dimension-based firefly algorithm to optimize the power losses, emission, and cost in power systems. Appl Soft Comput J 2018;68:322–42.

[19] Wang L, Li X, Bai Y. Short-term wind speed prediction using an extreme learning machine model with error correction. Energy Convers Manage 2018;162:239–50.
[20] Santhosh M, Venkaiah C, Kumar DMV. Ensemble empirical mode decomposition based adaptive wavelet neural network method for wind speed prediction May Energy Convers Manage 2018;168:482–93.
[21] Khosravi A, Machado L, Nunes RO. Time-series prediction of wind speed using machine learning algorithms: A case study Osorio wind farm, Brazil. Appl Energy 2018;224:550–66.
[22] Mi X, Liu H, Li Y. Wind speed forecasting method using wavelet, extreme learning machine and outlier correction algorithm. Energy Convers Manage 2017;151:709–22.
[23] Wang Y, Xie Z, Hu Q, Xiong S. Correlation aware multi-step ahead wind speed forecasting with heteroscedastic multi-kernel learning. Energy Convers Manage 2018;163:384–406.
[24] Jiang Y, Huang G, Peng X, Li Y, Yang Q. A novel wind speed prediction method: Hybrid of correlation-aided DWT, LSSVM and GARCH. J Wind Eng Ind Aerodyn 2018;174:28–38.
[25] Li Y, Wu H, Liu H. Multi-step wind speed forecasting using EWT decomposition, LSTM principal computing, RELM subordinate computing and IEWT reconstruction. Energy Convers Manage 2018;167:203–19.
[26] Song J, Wang J, Lu H. A novel combined model based on advanced optimization algorithm for short-term wind speed forecasting. Appl Energy 2018;215:643–58.
[27] Li C, Xiao Z, Xia X, Zou W, Zhang C. A hybrid model based on synchronous optimisation for multi-step short-term wind speed forecasting. Appl Energy 2018;215:131–44.
[28] Rodrigues Moreno S, Coelho S. Wind speed forecasting approach based on singular spectrum analysis and adaptive neuro fuzzy inference system. Renew Energy 2018;126:736–54.
[29] Qureshi AS, Khan A, Zameer A, Usman A. Wind power prediction using deep neural network based meta regression and transfer learning. Appl Soft Comput J 2017;58:742–55.
[30] Liu H, Mi X, Li Y. Smart deep learning based wind speed prediction model using wavelet packet decomposition, convolutional neural network and convolutional long short term memory network. Energy Convers Manage 2018;166:120–31.
[31] Chen J, Zeng G, Zhou W, Du W, Lu K. Wind speed forecasting using nonlinear-learning ensemble of deep learning time series prediction and extremal optimization. Energy Convers Manage 2018;165:681–95.
[32] Wang HZ, Wang GB, Li GQ, Peng JC, Liu YT. Deep belief network based deterministic and probabilistic wind speed forecasting approach. Appl Energy 2016;182:80–93.
[33] Liu H, Mi X, Li Y. Smart multi-step deep learning model for wind speed forecasting based on variational mode decomposition, singular spectrum analysis, LSTM network and ELM. Energy Convers Manage 2018;159:54–64.
[34] Hu Q, Zhang R, Zhou Y. Transfer learning for short-term wind speed prediction with deep neural networks. Renew Energy 2016;85:83–95.
[35] Dong Q, Sun Y, Li P. A novel forecasting model based on a hybrid processing strategy and an optimized local linear fuzzy neural network to make wind power forecasting: A case study of wind farms in China. Renew Energy 2017;102:241–57.
[36] Xiao L, Qian F, Shao W. Multi-step wind speed forecasting based on a hybrid forecasting architecture and an improved bat algorithm. Energy Convers Manage 2017;143:410–30.
[37] Yu C, Li Y, Zhang M. An improved wavelet transform using singular spectrum analysis for wind speed forecasting based on Elman neural network. Energy Convers Manage 2017;148:895–904.
[38] Ma X, Jin Y, Dong Q. A generalized dynamic fuzzy neural network based on singular spectrum analysis optimized by brain storm optimization for short-term wind speed forecasting. Appl Soft Comput J 2017;54:296–312.
[39] Liu H, Mi X, Li Y. An experimental investigation of three new hybrid wind speed forecasting models using multi-decomposing strategy and ELM algorithm. Renew Energy 2018;123:694–705.
[40] Tsironi E, Barros P, Weber C, Wermter S. An analysis of convolutional long short-term memory recurrent neural networks for gesture recognition. Neurocomputing 2017;268:76–86.
[41] Oehmcke S, Zielinski O, Kramer O. Input quality aware convolutional LSTM networks for virtual marine sensors. Neurocomputing 2018;275:2603–15.
[42] Ding L, Fang W, Luo H, Love PED, Zhong B, Ouyang X. A deep hybrid learning model to detect unsafe behavior: Integrating convolution neural networks and long short-term memory. Automation Construction 2018;86:118–24. March 2017.
[43] Wang J, Hu J. A robust combination approach for short-term wind speed forecasting and analysis-combination of the ARIMA (autoregressive integrated moving average), ELM (extreme learning machine), SVM (support vector machine) and LSSVM (least square SVM) forecasts using a GPR (gaussian process regression) model. Energy 2015;93:41–56.
[44] Zhang C, Wei H, Zhao J, Liu T, Zhu T, Zhang K. Short-term wind speed forecasting using empirical mode decomposition and feature selection. Renew Energy 2016;96:727–37.
[45] Cai M, Liu J. Maxout neurons for deep convolutional and LSTM neural networks in speech recognition. Speech Commun 2016;77:53–64.
[46] Ambach D, Schmid W. A new high-dimensional time series approach for wind speed, wind direction and air pressure forecasting. Energy 2017;135:833–50.