A Compound Wind Speed Model Based on Signal Decomposition and LSSVM Optimized by QPSO

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Abstract. A new compound model based on wavelet packet decomposition (WPD) and quantum particle swarm optimization algorithm (QPSO) tuning least squares support vector machine (LSSVM), namely WPD-QPSO-LSSVM, is developed in this study for forecasting short-term wind speed. In the developed model, WPD is firstly applied to preprocess the raw volatile wind speed data test samples to obtain relatively stable different components. Then, LSSVMs are utilized to predict short-term wind speed by these stable subseries components after the input variables are reconstructed by partial autocorrelation function (PACF), and the final short term wind speed forecasting results can be obtained by aggregation of each prediction of different components. In the end, the actual historical wind speed data are applied to evaluate the forecasting performance of the proposed WPD-QPSO-LSSVM model. Compared with the recent developed methods, the proposed compound WPD-QPSO-LSSVM approach can effectively improve the forecasting accuracy.

Keywords: Wavelet packet decomposition · Quantum particle swarm optimization algorithm · Least squares support vector machine · Wind speed forecasting

1 Introduction

With the development of industrial technology and computing technology, wind power has experienced rapid development over the past few decades. The global new installed wind turbine capacity reaches 60.4 GW and the overall installed wind power capacity approaches to approximately 651 GW in 2019, which can effectively reduce greenhouse gas emissions [1]. However, this rapidly growing wind power has yielded great negative effects on the operation dispatching, economic analysis and power system stability for complex nonlinear characteristics of wind speed. Wind power forecasting modeling is one of the simplest methods to overcome these problems [2].

During last few decades, numerous reliable models have been made for improving wind speed or wind power forecasting accuracy, which mainly includes physical methods, time series forecasting approaches, artificial intelligent methods and compound

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models [1, 3, 4]. Physical methods make wind power prediction using massive physical data of wind farm and numerical weather prediction model. High computational cost and low accuracy hinder physical methods in the practical real-time application. Statistical methods are skilled in capturing linear information within wind speed data.

To overcome the limitations of physical methods and statistical approaches, artificial intelligent based models and Extreme Learning Machine (ELM) [11], Echo state network (ESN) [5, 8], artificial neural networks (ANN) [2], wavelet neural network (WNN) [10], back-propagation neural network (BPNN) [9] and LSSVM [13], have been developed for their potential capacity in extracting nonlinear feature in the testing samples [5, 6]. For single individual model always suffer from over-fitting or under-fitting, high sensitivity to inappropriate initial parameters, and instability, compound models based on signal preprocess, parameter optimization and artificial intelligent approach have been developed to enhance the wind speed forecasting performance. Reference [5] proposed a novel hybrid wind speed prediction model, in which ESN is employed to make forecasting of each decomposed subseries after three important parameters of ESN are tuned by differential evolution (DE). In Ref. [9], fast ensemble empirical mode decomposition (FEEMD) was developed for preprocessing the empirical wind speed samples to obtain more reliable subseries, and improved BPNN was utilized to make forecasting of each decomposed subseries. Reference [2] developed a novel compound wind speed forecasting model combining ANN optimized by crisscross optimization algorithm with wavelet packet decomposition (WPD). Liu et al. [17] developed a compound model combining support vector machine (SVM) model tuned by genetic algorithm (GA) with WT to make short-term wind speed prediction. SVM is one of widely used machine learning methods which realizes its function based on structure risk minimization theory and it can do well in processing small sample and non-linearity signal with high dimension. However, SVM method is often time-consuming for its complex computation. To overcome this shortage, LSSVM is developed by solving linear equations substituting for a quadratic programming problem, thus, improving the computing performance.

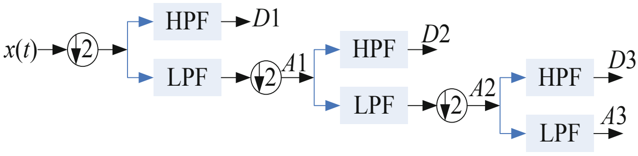
Inspired by above literatures, a compound short-term wind speed forecasting model WPD-QPSO-LSSVM is proposed in this study. In the developed model, LSSVM method is adopted as the core forecasting engine to construct wind speed forecasting model. To improve the regression performance of LSSVM, WPD is utilized to decompose the empirical wind speed time series into relatively stable components, and quantum particle swarm optimization algorithm (QPSO) is employed to optimize the parameters in LSSVM for avoiding falling into local optimum.

The remains of this study are arranged as follows. Wind speed forecasting modeling is described in Sect. 2. Case study is presented in Sect. 3. Finally, the conclusions are obtained in Sect. 4.

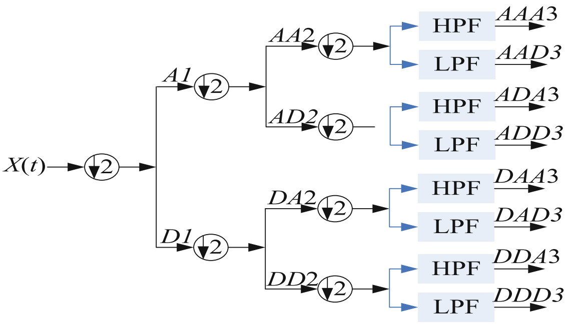
2 Wind Speed Forecasting Modeling

2.1 Wind Speed Preprocess Method

WPD, well-known signal processing method, is developed by improvement of wavelet translate (WT). Compared with WT method, WPD breaks down not only the approximation coefficient components but also the detail coefficient components, therefore, WPD approach can obtain more stable subseries for forecasting engine, the process of signal decomposition at three level is displayed as follows (Fig. 1).



(a) Signal process by WT at three level



(b) Signal process by WPD at three level

Fig. 1. Signal decomposition by WT and WPD at three level

2.2 LSSVM Optimized by QPSO

LSSVM model is skilled in solving small sample and nonlinear signal with high dimension, however, the regression performance of LSSVM is affected by kernel function and kernel parameters. As radial basis function (RBF), express as Eq. (1), with less parameters has good local exploitation capacity in signal process at fast speed, it is adopted as kernel function for LSSVM.

$$f_{RBF}(x_i, x_j) = \exp(-\frac{||x_i - x_j||}{2\delta^2}). \tag{1}$$

Penalty factor γ and kernel parameter δ are two important parameters in LSSVM model that influence the wind speed forecasting results, thus, they are tuned by artificial intelligent method QPSO to obtain optimal parameter combination for LSSVM. Mean absolute percent error (MAPE), expressed as Eq. (2), is used as the fitness function to evaluate the forecasting results.

$$MAPE = \frac{1}{N}\sum_{i=1}^{N}\frac{|s(i) - \hat{s}(i)|}{s(i)} \times 100\%. \tag{2}$$

Where $s(i)$ and $\hat{s}(i)$ mean are actual wind speed data and forecasting wind speed value, respectively.

2.3 The Working Mechanism of the Proposed WPD-QPSO-LSSVM Model

a. The Proposed WPD-QPSO-LSSVM Model

The historical wind speed data from a wind farm located in East of Anhui province are used to evaluate the proposed compound WPD-QPSO-LSSVM model, shown in Fig. 2, where P_m, P_g and S denote personal optimum, global optimum and mean optimal location center of population, respectively. The wind speed forecasting modeling process can be divided into following stage.

Stage I: Wind speed preprocessing. Apply WPD method to decompose the training wind speed data into a few components with different frequency. Prior to wind speed forecasting obtained by QPSO-LSSVM method, PACF is utilized to calculate time lag of each subseries for construction of the input candidate matrix. To lower learning difficulty of LSSVM, each decomposed component is translated linearly into [0, 1].

Stage II: LSSVM tuned by QPSO. Inappropriate parameters may cause LSSVM into over-fitting or under-fitting state when applied into wind speed prediction. This study utilizes QPSO algorithm to optimize the model parameters for improving generation ability.

Stage III: Train LSSVM tuned by QPSO with every decomposed component, the 1^{st}–576^{th} wind speed time series are employed as the training samples, the subsequent 576^{st}–672^{th} wind speed time series are utilized as the testing samples to evaluate the forecasting results.

Stage IV: Apply the well-trained QPSO-LSSVM model to carry out wind speed forecasting and utilize the statistical index RMSE, MAPE and MAE to analyze the forecasting results.

b. Evaluation Index for Wind Speed Forecasting

To evaluate the forecasting performance of the proposed WPD-QPSO-LSSVM model, three statistical indices, expressed as Eq. (3) and (4), are used to analyze the forecasting results.

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}|s(i) - \hat{s}(i)|^2}. \tag{3}$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|s(i) - \hat{s}(i)|. \tag{4}$$

Where RMSE and MAE denote root mean square error, mean absolute error and, respectively. $s(i)$ and $\hat{s}(i)$ mean are actual wind speed data and forecasting wind speed value, respectively.

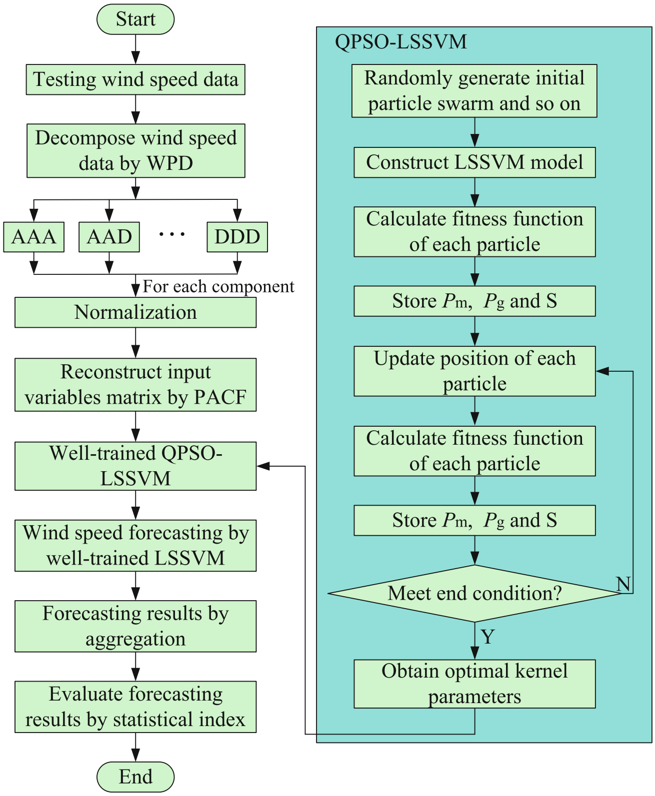


Fig. 2. Working flow of the proposed wind speed forecasting model

3 Case Study

3.1 Testing Wind Speed Time Series

In this study, 15-min interval wind speed time series collected from a wind farm of East Anhui are utilized to test the proposed WPD-QPSO-LSSVM model. The wind speed time series are shown as Fig. 3, and its statistical properties are listed in Table 1. From the figure and table, wind speed time series fluctuate highly.

3.2 Wind Speed Preprocessing

In the study, WPD approach is applied to decompose the training samples to eliminate the high volatility and obtain relatively stable subseries. The Daubechies of order4 (db4) is adopted as the mother wavelet function for WPD. The decomposed results obtained by WT and WPD are shown in Fig. 4 and Fig. 5, respectively.

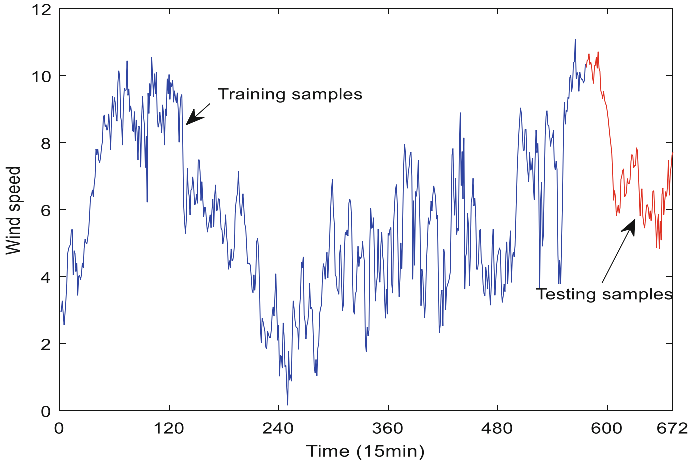


Fig. 3. Training and testing wind speed time series

Table 1. Statistical index of training and testing wind speed (m/s)

Data set	Max.	Min.	Median	Mean	St. dev.
Total samples	11.09	0.17	5.93	6.01	2.33
Training samples	11.09	0.17	5.47	5.76	2.34
Testing samples	10.72	4.85	6.92	7.44	1.66

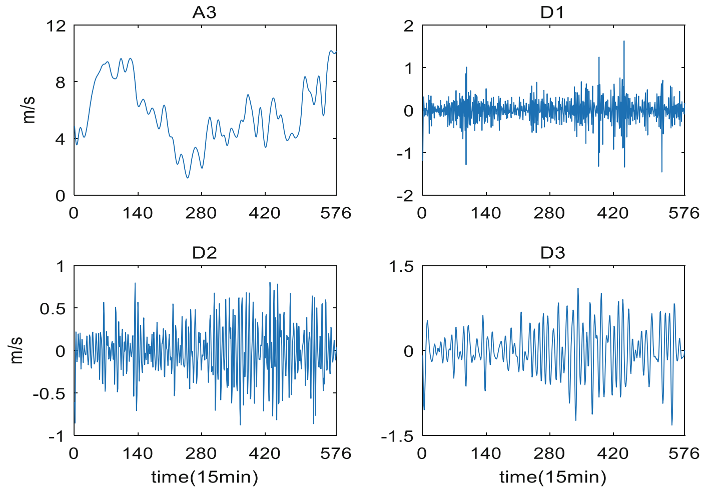


Fig. 4. The decomposed results of the training samples by WT at three level

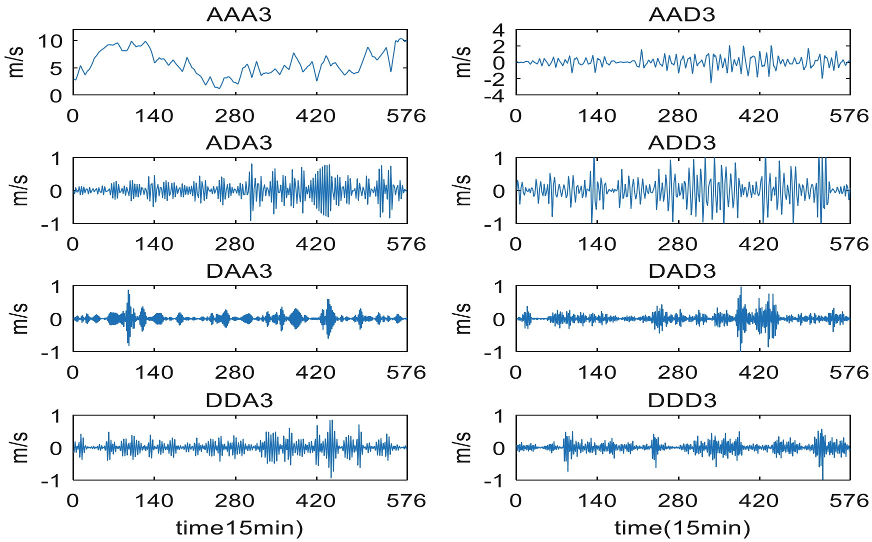


Fig. 5. The decomposed results of the training samples by WPD at three level

After decomposition, each subseries is linearly normalized into interval [0, 1] to reduce the forecasting difficulties. Prior to wind speed forecasting by LSSVM, the input variables matrixes are reconstructed according to the lag values of each decomposed variables determined by PACF, if lag value is 8, the reconstruction of input matrix for LSSVM by PACF is shown in Fig. 6.

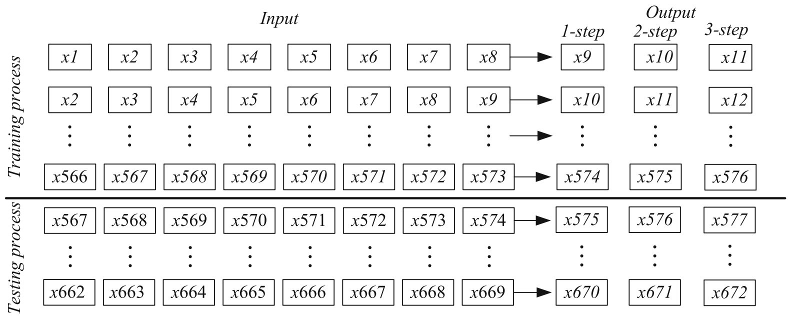


Fig. 6. Reconstruction of input matrix for LSSVM by PACF

3.3 Numerical Results

The first 1^{st}–576^{th} wind speed time series are used to train the QPSO-LSSVM model and the subsequent 577^{th}–672^{th} wind speed time series are applied to test the QPSO-LSSVM model. The testing process are divided into two parts: Experiment I and Experiment II. In

Experiment I, compare the developed WPD-QPSO-LSSVM model with single forecasting models including Persistence, ARMA, BPNN, WNN, and LSSVM. In Experiment II, compare the developed WPD-QPSO-LSSVM model with other hybrid forecasting models including QPSO-LSSVM, WT-GA-SVM [17], and EMD-ANN [18].

Statistical indices of the proposed and single forecasting models are shown in Table 2. Persistence is always used as benchmark model to evaluate the new developed forecasting approach. In the same way, Persistence is applied to compare with the new developed WPD-QPSO-LSSVM model. From Table 2, the one-step MAPE values of Persistence, ARMA, BPNN, WNN, LSSVM and the proposal are 13.13%, 11.03%, 9.03%, 8.46%, 7.88% and 4.75%, respectively. Compared with Persistence model, the forecasting performance of the proposal improves obviously. The proposal also outperforms single model ARMA, BPNN, WNN and LSSVM in not only one-step forecasting, but also two-step and three-step forecasting. The reasons of this comparisons are: single forecasting models utilize the original wind speed time series to make prediction, which shows highly nonlinear characteristics and improve forecasting difficulties. In addition, QPSO algorithm is applied to tune LSSVM which avoid over-fitting or under-fitting.

Table 2. Statistical indices of the proposed and single forecasting models

Horizon	Index	Persistence	ARMA	BPNN	WNN	LSSVM	Proposal
1-step	MAE (m/s)	0.99	0.84	0.67	0.65	0.61	0.35
	MAPE (%)	13.13	11.03	9.03	8.46	7.88	4.75
	RMSE (m/s)	0.99	0.92	0.82	0.80	0.78	0.59
2-step	MAE (m/s)	1.13	0.93	0.79	0.7	0.68	0.41
	MAPE (%)	15.09	12.82	10.46	9.69	9.11	5.56
	RMSE (m/s)	1.06	0.96	0.89	0.84	0.82	0.64
3-step	MAE (m/s)	1.35	1.05	0.92	0.89	0.85	0.5
	MAPE (%)	18.23	14.24	12.31	11.82	11.11	6.79
	RMSE (m/s)	1.16	1.03	0.96	0.94	0.92	0.71

Statistical indices of the proposed and other hybrid forecasting models are shown in Table 3. WT-GA-SVM [17] and EMD-ANN [18] are recently developed hybrid wind speed forecasting models, which are employed to further evaluate the developed WPD-QPSO-LSSVM method. The parameters in WT-GA-SVM and EMD-ANN models are set according to Refs. [17] and [18], respectively. Compared with WT-GA-SVM and EMD-ANN models, the fitness function MAPE values of the proposal are cut by 0.63% and 0.88% in on-step forecasting, respectively. Compared with QPSO-LSSVM, the MAPE values are cut by 2.17% in one-step forecasting. From statistical indices in the tables, it can be obviously seen that the new developed WPD-QPSO-LSSVM model obtains smaller forecasting errors than WT-GA-SVM, EMD-ANN, the reasons are that WPD can yield more stable decomposed subseries than WT and EMD, and the regression performance of LSSVM outperforms SVM and ANN. Thus, the comparisons substantiate the developed WPD-QPSO-LSSVM model can carry out wind speed prediction effectively.

Table 3. Statistical indices of the proposed and other hybrid forecasting models

Horizon	Index	QPSO-LSSVM	WT-GA-SVM	EMD-ANN	Proposal
1-step	MAE	0.52	0.41	0.42	0.35
	MAPE	6.92	5.38	5.63	4.75
	RMSE	0.72	0.64	0.65	0.59
2-step	MAE	0.61	0.47	0.51	0.41
	MAPE	8.15	6.39	6.71	5.56
	RMSE	0.78	0.69	0.71	0.64
3-step	MAE	0.71	0.55	0.59	0.5
	MAPE	9.58	7.41	7.86	6.79
	RMSE	0.85	0.74	0.77	0.71

4 Conclusion

A new hybrid WPD-QPSO-LSSVM model is developed for multi-step ahead wind speed forecasting in this study. Some conclusions can be drawn from above analysis and comparisons: (1) the single forecasting models BPNN, WNN and LSSVM obtain higher forecasting accuracy than Persistence and ARMA for the intelligent methods can better deal with the nonlinear time series than the statistical approaches. (2) The compound models WT-GA-SVM, EMD-ANN and the proposal model can obtain higher prediction accuracy than the single forecasting methods Persistence, ARMA, BPNN, WNN and LSSVM because original wind speed time series exhibit high nonlinearity and volatility that require preprocessing. (3) The proposed WPD-QPSO-LSSVM mothed outperforms the recently developed EMD-ANN and WT-GA-SVM models in that WPD method can obtain more stable and smaller subseries than WT and EMD approaches, and the regression performance of LSSVM also outperforms SVM and ANN. Thus, the new developed WPD-QPSO-LSSVM model is an effective wind speed approach.

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