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Short-term wind speed prediction: Hybrid of ensemble empirical mode decomposition, feature selection and error correction

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ABSTRACT

Accurately forecasting wind speed is a critical mission for the exploitation and utilization of wind power. To improve the prediction accuracy, the nonlinearity and nonstationarity embedded in wind speed time series should be reduced. Because the subseries has less nonlinearity and nonstationarity after decomposition, the decomposition-based forecasting methods are widely adopted to provide the higher predictive accuracy. However, latest studies showed the real time decomposition-based forecasting methods could be worse than the single forecasting models. The aim of this study is to improve the performance of the real time decomposition-based forecasting method after the factors attributed to its unsatisfactory performance are uncovered. In this paper, the feature selection and error correction are adopted in the real time decomposition-based forecasting method to enhance the prediction accuracy. In the proposed method, the raw wind speed time series is decomposed into a number of different subseries by ensemble empirical mode decomposition; then two feature selection methods including kernel density estimation-based Kullback-Leibler divergence and energy measure are used to reduce the disturbance of illusive components; further the least squares support vector machine is adopted to establish the one-step ahead forecasting models for the remaining subseries; finally, the hybrid of least squares support vector machine and generalized auto-regressive conditionally heteroscedastic model is introduced to correct resulting error component if its inherent correlation and heteroscedasticity cannot be neglected. Based on two sets of measured data, the results of this study show that: (1) the real time decomposition-based method may be ineffective in practice; (2) both the feature selection and error correction can improve forecasting performance in comparison with the real time decomposition-based method; (3) compared with other involved methods, the proposed hybrid method has the satisfactory performance in both accuracy and stability.
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1. Introduction

As a renewable and environmentally friendly energy resource, wind energy is of vital importance among the low-carbon energy technologies and has attracted the global attention. According to the World Wind Energy Report [1], the total installed wind power capacity has reached to 160,000 MW in 2009, and it is expected to double every 3 years. Along with the rapid development and utilization of wind energy, the green gas emission and the traditional fossil fuels utilization are drastically reduced. However, due to the stochastic and intermittent characteristics of the wind source [2], the integration efficiency of wind power into a multisource energy network poses many challenges on a series of tasks, such as the energy generation planning and turbine maintenance scheduling [3]. These challenges have severely hindered the exploitation of wind energy. One of the methods to mitigate these challenges is the improvement of short-term wind speed forecasting accuracy and the reduction of its uncertainty [4].

Abbreviations: ARMA, Auto-Regressive Moving Average; ARIMA, Auto-Regressive Integrated Moving Average; FARIMA, Fractional Auto-Regressive Integrated Moving Average; MTK, Modified Taylor Kriging; ANN, Artificial Neural Networks; SVM, Support Vector Machine; MLP, Multi Layer Perceptron; LSSVM, Least Squares Support Vector Machine; SSA, Singular Spectrum Analysis; RBFNN, Radial Basis Function Neural Network; GSA, Gravitational Search Algorithm; ANFIS, Adaptive Network-based Fuzzy Inference System; PSO, Particle Swarm Optimization; GARCH, Generalized Autoregressive Conditionally Heteroscedastic; ELM, Extreme Learning Machine; EMD, Empirical Mode Decomposition; EEMD, Ensemble Empirical Mode Decomposition; FEEMD, Fast Ensemble Empirical Mode Decomposition; WD, Wavelet Decomposition; WPD, Wavelet Packet Decomposition; GA-BP, Genetic Algorithm-Back Propagation; IMF, Intrinsic Mode Function; KDE, Kernel Density Estimation; KLD, Kullback-Leibler Divergence; MEMD, Multivariate Empirical Mode Decomposition; PDF, Probability Density Function; ACF, Autocorrelation Function; PACF, Partial Autocorrelation Function; MAE, Mean Absolute Error; MRPE, Mean Relative Percentage Error; RMSE, Root Mean Square Error; RMSRE, Root Mean Square Relative Error; KS, Kolmogorov-Smirnov; CDF, Cumulative Distribution Function.

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In the past few decades, numerous methods have been proposed to enhance the prediction accuracy including physical approaches and statistical models. Every kind of methods has their own advantages and disadvantages. The physical approaches take into account the meteorological factors and are generally used for long-term wind speed prediction [5]. On the other hand, the statistical models are usually suitable for short-term wind speed prediction based on the historical data. These statistical models mainly include linear time series and nonlinear intelligent models, which will be reviewed below.

Time series models, such as auto-regressive moving average (ARMA) and auto-regressive integrated moving average (ARIMA), have been widely applied in short-term wind speed prediction. In Ref. [6], ARMA model was adopted to forecast the tuple of wind speed and direction, and the forecasting results validated the effectiveness of this method. Cadenas and Rivera [7] proposed an ARIMA model to forecast the wind speed and the forecasting results were better than the persistence model. In recent years, a number of new time series models have been developed. In Ref. [8], a fractional-ARIMA (FARIMA) was used to forecast wind speed on the 24 h and 48 h horizons and showed significant improvements compared to ARIMA model. Liu et al. [9] proposed a modified Taylor Kriging model for wind speed prediction and the forecasting precision was found to be higher than ARIMA model. These models can explicitly reveal the linear relationship in the time series. However, they usually have unsatisfactory forecasting performance for the wind speed data with strong nonlinear features.

Different from the time series models, the nonlinear intelligent models can explain the nonlinear relationship between the input and output. Thus, they can provide better prediction results if the nonlinear characteristics of wind speed time series are prominent. For example, Cadenas and Rivera [10] proposed an artificial neural networks (ANN) for wind speed prediction and the forecasting results showed the proposed method could improve the prediction accuracy effectively; Mohandes et al. [11] introduced a support vector machine (SVM) to conduct the wind speed prediction and the prediction results were better than the multilayer perceptron (MLP); Zhou et al. [12] presented an optimal least squares SVM (LSSVM) based on better tuning LSSVM model parameters for wind speed forecasting and the prediction results were satisfactory. Every coin has two sides. Compared with the linear time series model, these nonlinear models may suffer from inefficient or over-fitted training and need more manual intervention for model parameters tuning [13].

Recently, the uncertainty of wind power prediction has been incorporated. For example, Qadrdan et al. [14] proposed an efficient method to generate probabilistic wind power forecast scenarios using singular spectrum analysis (SSA), Monte Carlo simulation and a scenario reduction algorithm. The final results validated the effectiveness of the approach. Bramati et al. [15] developed a new method for wind power prediction using the dynamic system of equations, which considered the uncertainty from the climate and the functioning of turbines. The prediction results showed the proposed method outperformed the benchmark model.

To further enhance the accuracy of the wind speed or power prediction, various hybrid approaches have been developed. For example, Liu et al. [16] proposed four different hybrid methods for high-precision multi-step wind speed predictions based on the adaptive boosting algorithm and MLP neural networks and the results showed these hybrid methods were effective. Meng et al. [17] adopted a new hybrid model for wind speed prediction based on wavelet packet decomposition (WPD), crisscross optimization algorithm and ANN, and the results showed the proposed method had significant advantage over the other reference models. These hybrid models mainly include weighting-based approaches, parameter optimization-based approaches, error correction-based approaches and decomposition-based approaches and could generally utilize the strengths of individual methods [5]. For instance, Han and Liu [18] proposed a weighting-based forecasting method where the maximum entropy principle was utilized to obtain the weight coefficient of persistence, ARIMA and four ANN-based models. The forecasting results showed that this hybrid method outperformed those single models. Shi et al. [19] proposed another weight-based hybrid model combining LSSVM and radial basis function neural network (RBFNN) based on grey relational analysis and wind speed distribution features. The results showed that the proposed model had significantly improved the forecasting accuracy. Ref. [2] addressed a parameter optimization-based forecasting method where the parameters of LSSVM model were optimized by gravitational search algorithm (GSA) and the results validated the effectiveness of the approach. Pousinho et al. [20] presented another parameter optimization-based forecasting method based on adaptive network-based fuzzy inference system (ANFIS). The forecasting results showed that particle swarm optimization (PSO)-based hybrid model could improve the prediction accuracy by comprehensive parameter selection. Liu et al. [21] presented an error correction-based forecasting method which used generalized auto-regressive conditionally heteroscedastic (GARCH) model to modify the ARMA model forecasting results. The results showed the performance of the ARMA-GARCH was satisfactory. Liang et al. [4] proposed another error correction-based method for multi-step ahead wind speed prediction where SVM or extreme learning machine (ELM) was established to forecast the error component and the simulation results demonstrated the effectiveness of the proposed model. Liu et al. [22] applied decomposition-based forecasting method which used the recursive ARIMA model to forecast individual subseries of wind speed time series based on empirical mode decomposition (EMD). The forecasting results showed the hybrid model had superior performance over the single ARIMA model. Hu et al. [23] investigated the possibility of improving the quality of wind speed forecasting by combining ensemble EMD (EEMD) and SVM. This model showed the better prediction capacity compared with other models. Sun and Liu [24] developed a hybrid model which combines fast EEMD (FEEMD) with regularized ELM for wind speed forecasting and the simulation results showed that the built model was effective and practicable. Liu et al. [25] had developed another four different hybrid models by combining four mainstream signal decomposing algorithm [e.g., wavelet decomposition (WD), WPD, EMD and FEEMD] and ELM for multi-step wind speed forecasting. This hybrid method integrated the advantages of individual models and improved the forecasting accuracy. Clearly, although the hybrid methods may increase the prediction accuracy, they introduce the complexity of the algorithm. Hence, it is necessary to balance the prediction accuracy and the complexity before the hybrid methods are used.

Focusing on the decomposition-based forecasting methods, Wang and Wu [13] pointed out that many of these methods based on the pre-processing scheme that all data, including the known data (the training data) and the unknown data (the forecasting data), were decomposed only once before prediction. This pre-processing scheme was unreasonable and violated the purpose of the wind speed prediction. In order to address this problem, they used another pre-processing scheme that the original data should be divided into training and forecasting parts, and the decomposition for training part should be real time. With newly obtained data, the training data should be updated and re-decomposed. However, the results showed that this real time decomposition-based forecasting methods may be ineffective in comparison with

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