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Big multi-step wind speed forecasting model based on secondary decomposition, ensemble method and error correction algorithm

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ABSTRACT

Wind power is one of the most promising powers. Wind speed forecasting can eliminate the harmful effect caused by the intermittent and fluctuation of wind power, and big multi-step forecasting can provide more time for the power grid to be adjusted. To achieve the high-precision big multi-step forecasting, a novel hybrid model named as the WD-SampEn-VMD-MadaBoost-BFGS-WF is proposed in the study, which consisting of three main modeling steps including the secondary decomposition, the ensemble method and the error correction. The detail of the proposed model is given as follows: (a) wind speed series are decomposed by the WD (*Wavelet Decomposition*) to obtain wind speed subseries. The SampEn (*Sample Entropy*) algorithm is used to estimate the unpredictability of these wind speed subseries. The most unpredictable subseries will be decomposed secondarily by the VMD (*Variational Mode Decomposition*); (b) the subseries are proceeded by the MAdaBoost (*Modified AdaBoost.RT*) with the BFGS (*Broyden–Fletcher–Goldfarb–Shanno Quasi-Newton Back Propagation*) neuron network to obtain forecasting subseries; (c) all of the forecasting subseries will be combined with the original subseries to form the combined wind speed series, which will be further proceeded by the WF (*Wavelet Filter*) to obtain the corrected forecasting series from the point of the frequency domain; (d) the corrected forecasting series are reconstructed to get the final forecasting series. To validate the effectiveness of the proposed model, several forecasting cases are provided in the study. The result indicates that the proposed model has satisfactory forecasting performance in the big multi-step extremely strong simulating wind speed forecasting.

1. Introduction

Energy storage and pollution has hindered the usage of petroleum, natural gas, etc. Comparing to those conventional energy, the wind power is renewable, which catches the world's attention. Recently, the wind power increases rapidly [1]. The worldwide wind power reached 486.661 MW at the end of 2016, with 54.846 MW added in 2016, which represents a growth rate of 11.8%. The electricity, which is generated by the wind turbines installed worldwide by the end of 2016, is around 5% of the world's electricity demand [2].

In the process of using the wind power, accurate and stable forecasting of wind speed is expected, which can achieve the timely and effective management of the power grid and help eliminate the adverse impact in the growing wind energy scenario as well as increasing the revenues from the power market with bidding strategies optimized [3]. However, because of the inherent randomness and volatility of wind speed, it is a big challenge to propose an effective and practical method to forecasting the wind speed accurately in the big multiple steps. The proposed wind speed forecasting methods can be classified as four main types as: (a) statistical methods, (b) physical methods, (c) intelligent methods and (d) hybrid methods [4]. The physical methods include the forecasting models as spatial correlation, NWP (*Numerical Weather*

Abbreviations: NWP, numerical weather prediction; CS, Cuckoo search; FS, fuzzy system; WRF, weather research and forecasting; KF, Kalman filter; ARIMA, auto-regressive integrated moving average; ARCH, autoregressive conditional heteroskedasticity; ANN, artificial neural networks; SVM, support vector machine; CRO, Coral Reefs optimization algorithm; ELM, extreme learning machine; MFNN, multi-layer feed-forward neural network; SPSA, simultaneous perturbation stochastic approximation; HM, Hammerstein Model; AR, auto-regressive; AdaBoost, adaptive boosting; MLP, multilayer perceptron; DNN-MRT, deep neural network based meta regression and transfer learning; WD, wavelet decomposition; FEEMD, fast ensemble empirical mode decomposition; EMD, empirical mode decomposition; WPD, wavelet packet decomposition; SSA, singular spectrum analysis; BFGS, Broyden–Fletcher–Goldfarb–Shanno Quasi-Newton Back Propagation; LSSVM, least square support vector machine; PSOGSA, partial swarm optimization combined with gravitational search algorithm; FCM, fuzzy C-means; EEMD, ensemble empirical mode decomposition; SampEn, sample entropy; VMD, variational mode decomposition; MAdaBoost, Modified AdaBoost.RT; WF, wavelet filter; MAE, mean absolute error; MAPE, mean absolute percentage error; RMSE, root mean squared error; CWT, continuous wavelet transform; DWT, discrete wavelet transform; LMD, local mean decomposition; ADMM, alternate direction method of multipliers

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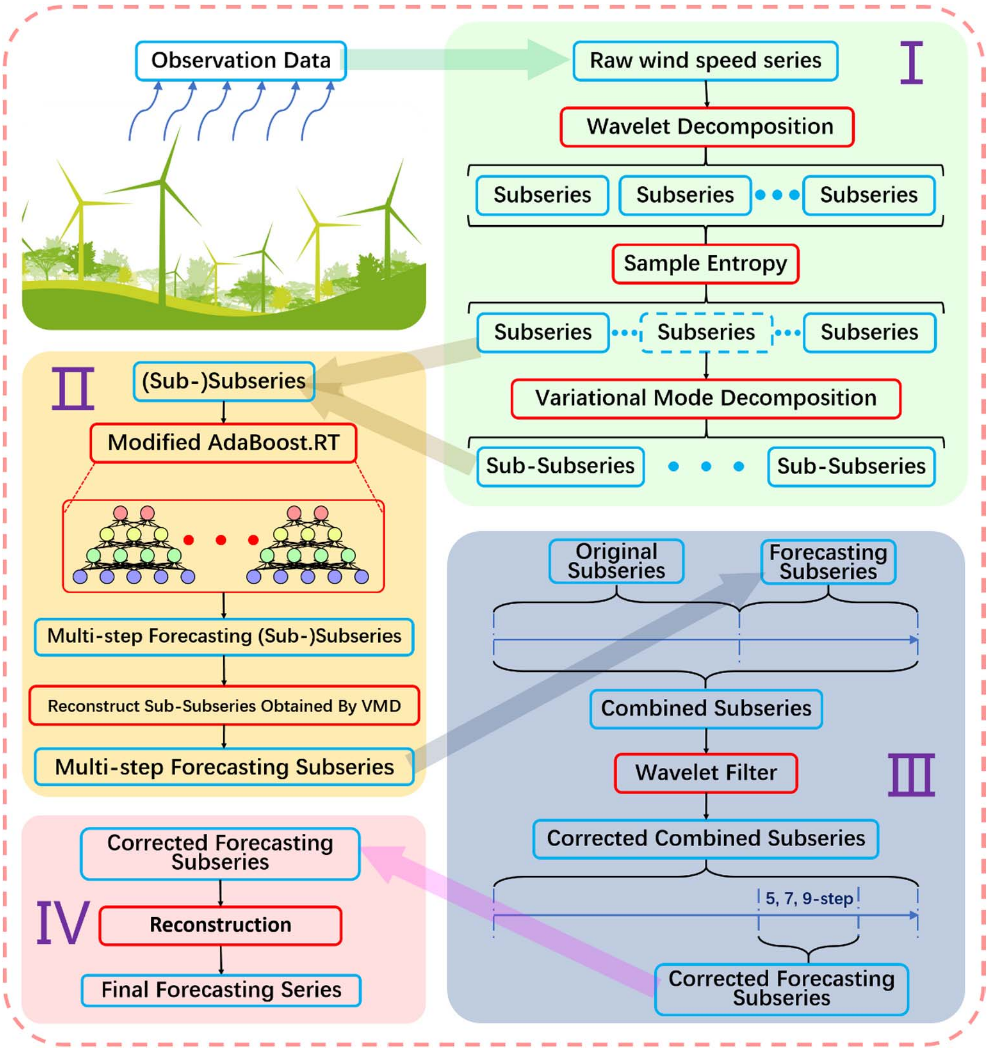

Fig. 1. The framework of the proposed forecasting model.

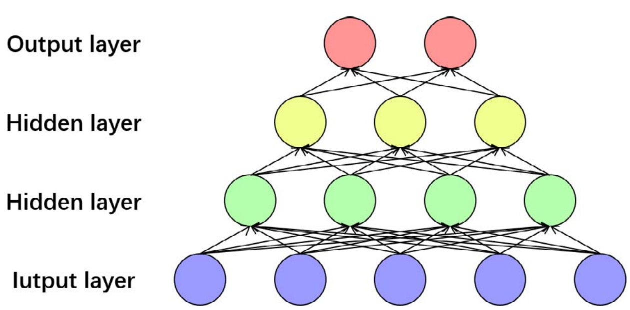

Fig. 2. The structure of the adopted BFGS neural network.

Prediction), etc [5]. Zhao et al. [6] put forward a CS-FS-WRF-E model consisting of the CS (*Cuckoo Search*) algorithm, the FS (*Fuzzy System*) and the WRF (*Weather Research and Forecasting*). Cassola and Burlando [7] proposed a new wind speed and wind power forecasting approach using the KF (*Kalman Filter*) to process the generations of a NWP model. The KF is aimed to minimize the predicting errors. In general, the physical forecasting models always have worse accuracy in the short-term forecasting than the statistical methods [4]. Besides, the real-time performance of the physical forecasting models is also an important point for them to be applied in the real-time forecasting systems [8]. In terms of the statistical methods, the most widely used model is ARIMA (*Auto-Regressive Integrated Moving Average*) model, Masseran [9] introduced a forecasting model composed of the ARIMA and the ARCH (*Autoregressive Conditional Heteroskedasticity*), which is proved that the proposed model had better performance than single ARIMA model. In addition, the statistical methods also can be used to improve the accuracy performance of other forecasting models. Wang et al. [10] proposed residual modification models to improve the precision of seasonal ARIMA, and the performance of the modification models appeared to be more workable than that of the single seasonal ARIMA. *Liu* et al. [11] used ARIMA model to discover the statistical rule of wind speed series. At the same time, the built ARIMA model was also adopted to determine the initial parameter of the Kalman filtering and the numbers of inputting neurons of the ANN (*Artificial Neural Networks*) forecasting models. Although the statistical methods are simple and effective, they have potential to be further promoted in the future. Because the intelligent methods are smart and robust, they are widely adopted as one of the basic foresting frameworks to forecast the non-stationary wind speed. There are numerous algorithms in the wind speed intelligent modeling and forecasting, such as ANN, SVM (*Support Vector Machine*), etc. Li and Shi [12] investigated three types of typical neural networks, namely, the adaptive linear element, the back propagation and the radial basis function, to investigate the wind speed forecasting performance based on the neural networks. Salcedo-Sanz et al. [13] presented a novel approach for the short-term wind speed prediction based on a CRO (*Coral Reefs Optimization Algorithm*) and an ELM (*Extreme Learning Machine*). Hong et al. [14] proposed a new method of wind power and speed forecasting using a MFNN (*Multi-layer Feed-forward Neural Network*) trained by the SPSA (*Simultaneous*