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Wind speed forecasting method using wavelet, extreme learning machine and outlier correction algorithm

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ABSTRACT

The wind speed forecasting is important for the security of the wind power systems. This paper proposes a new hybrid method for the multi-step wind speed forecasting based on Wavelet Domain Denoising, Wavelet Packet Decomposition, Empirical Mode Decomposition, Auto Regressive Moving Average, Extreme Learning Machine and Outlier Correction Method. In the proposed hybrid architecture, the Wavelet Domain Denoising is adopted to reduce the noise of the original wind speed series and a secondary decomposing algorithm is presented to reduce the intermittent of the original wind speed series. In the proposed secondary decomposing algorithm, the Wavelet Packet Decomposition is utilized to decompose the wind speed series into a number of non-stationary sub-layers and stationary sub-layers, and the Empirical Mode Decomposition is used to further decompose the obtained non-stationary data into a series of intrinsic mode functions. Finally, the Auto Regressive Moving Average and Extreme Learning Machine models are employed to complete the multi-step forecasting computation for the decomposed stationary sub-layers and intrinsic mode functions, respectively. In addition, the new Outlier Correction Method is proposed to guarantee the robustness of the built Auto Regressive Moving Average and Extreme Learning Machine models during their forecasting computation. To estimate the performance of the proposed new hybrid forecasting method, a series of performance comparing experiments is provided in the study. The involved comparing forecasting models consist of the Auto Regressive Moving Average model, the BP model, the Elman model, the Extreme Learning Machine and the proposed different hybrid models. The experimental results indicate that: in the comparisons of all the involved mainstream wind speed forecasting models, the proposed hybrid model has the best forecasting performance.

1. Introduction

Due to the increasing energy demand and environmental concerns [1], wind power, as an environmentally friendly source of renewable energy, has attracted global attention. Besides, the power management is very important [2]. However, since the wind speed is intermittent, it is difficult to obtain their high precision and robust forecasting results [3].

In recent years, a number of new wind speed forecasting methods have been proposed, which can be classified into five types as: the physical models, the conventional statistical models, the spatial correlation models, the artificial intelligence models and the hybrid models [4]. The physical models are usually based on the NWP (*Numerical Weather Prediction*) models, which provide the wind speed forecasting by using the mathematical models of the weather and topological data like pressure, humidity, temperature and altitude [5]. These models often include many complex variables, therefore they are very effective for medium-term and long-term wind speed predicting cases. The conventional statistical models can describe the changing rules of the wind speed time series based on their relating historical data, which mainly include the persistence models, AR (*Auto Regressive*) models, ARMA (*Auto Regressive Moving Average*) models, ARIMA (*Auto Regressive Integrated Moving Average*) models and f-ARIMA (*fractional-Auto Regressive Integrated Moving Average*) [6]. In the past few years, numerous autoregressive methods have been investigated. Lydia et al. [7] made a comparison of some linear and non-linear autoregressive models in wind speed forecasting. Erdem et al. [8] built the traditional-linked ARMA models and vector ARMA models for wind speed forecasting. Cadenas et al. [9] presented the wind speed prediction models based on the ARIMA and artificial neural network methods. Kavasseri et al. [10] designed the f-ARIMA models for day-ahead wind speed forecasting. These conventional statistical models can obtain the wind speed forecasting by the linear or non-linear functions. Since they are simple and fast, they are widely used in practice. The spatial correlation models

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take the spatial interaction of different sites into account for the wind speed forecasting, which can obtain the interact information of different sites through the correlation analysis, and further select the wind speed data of the sites with high correlation in different period [11]. These models always have high forecasting accuracy and can significantly promoted the accuracy of the temporal based models, thus a lot of recent researches have focused on the temporal-spatial models. The artificial intelligence models can implement the wind speed high-precision prediction adopting some new intelligent modeling algorithms, such as the SVM (*Support Vector Machine*), the various network models in the ANN (*Artificial Neural Network*) [12], etc. These models can structure the relationship between the input data and output data, and they have good data error tolerance [13]. They are widely used in the physical methods, temporal methods and spatial methods because of their good performance in processing the complex and nonlinear signals [14]. The hybrid models are proposed based on the combinations of the upper mentioned different models [15]. These models are flexible, they can be the combination of different models in different methods like physical methods, temporal methods and spatial methods, they can also be the combination of different models in one kind of the methods like the temporal methods [16]. However, only the optimal combinations of different models can obtain the good hybrid models, the simple combinations may obtain the bad hybrid models, so the frameworks of the hybrid models are important [17]. The experimental results from some wind speed forecasting cases show the good hybrid forecasting models always have satisfactory forecasting performance [18].

Some important hybrid wind speed forecasting methods have been proposed. Meng et al. [19] designed a hybrid forecasting method by combining the wavelet packet decomposition, the crisscross algorithm and the artificial neural networks. Their results showed that the crisscross algorithm was better than the traditional BP (*Back-propagation*) and PSO (*Particle Swarm Optimization*) algorithms in training the selected neural networks. By including the crisscross algorithm, the hybrid neural networks improved the forecasting accuracy of the traditional networks significantly. Wang et al. [20] proposed a hybrid model using the GPR (*Gaussian Process Regression*), the ARIMA, ELM (*Extreme Learning Machine*), SVM and LSSVM (*Least Square Support Vector Machine*). The proposed hybrid model predicted the wind speed satisfactorily. Shukur et al. [21] used the recognized ARIMA to select the initial parameters of the KF (*Kalman filter*) and the ANN models. Their simulated results validated that the hybrid KF-ANN model was effective in the jumping wind speed forecasting. Liu et al. [22] presented a hybrid model based on the SDA (*Secondary Decomposition Algorithm*) and the Elman neural networks. In the proposed combination, the WPD (*Wavelet Packet Decomposition*) was adopted to decompose the original wind speed series, and the FEEMD (*Fast Ensemble Empirical Mode Decomposition*) was utilized to decompose the detailed components generated by the WPD procedure. The experimental results showed that the hybrid model had satisfactory accuracy. Cadenas et al. [23] proposed an ARIMA-ANN forecasting model. The ARIMA models were firstly built to predict the wind speed and obtain the errors then the ANN models were used to forecast the errors. The results reflected that the hybrid model had a higher accuracy than both the independent ARIMA and ANN models. Chitsaz et al. [24] proposed a hybrid forecasting approach using the WNN (*Wavelet Neural Network*) and the improved Clonal selection algorithm. The results confirmed that the built model obtained the high-accuracy forecasting results. Su et al. [25] provided a hybrid wind speed forecasting approach using the PSO, the ARIMA and the Kalman filter. The PSO was employed to optimize the parameters of the ARIMA model, and the ARIMA model was used to obtain the parameters of the Kalman filter. The results showed that the performance of the hybrid model was better than that of the ARIMA and PSO-optimized ARIMA models. Pousinho et al. [26] presented a hybrid wind power forecasting approach adopting the PSO and the ANFIS (*Adaptive-network-based Fuzzy Inference System*). The PSO was utilized to optimize the membership functions of the chosen ANFIS. The proposed hybrid approach had the accurate wind speed forecasting results.

In this paper, a new hybrid wind speed forecasting method is proposed. The contents of the proposed method are provided as follows: (a) the WDD (*Wavelet Domain Denoising*) is adopted to reduce the noisy characters of the original wind speed series; (b) a secondary decomposing algorithm is presented to reduce the non-stationarity of the original wind speed series. In the proposed secondary decomposing algorithm, the WPD (*Wavelet Packet Decomposition*) is utilized to decompose the wind speed series into a number of NS (*Non-stationary Sub-layers*) and SS (*Stationary Sub-layers*) wind speed data, and the EMD (*Empirical Mode Decomposition*) is used to further decompose the obtained NS data into a series of IMFs. To check whether a WPD decomposed wind speed sub-layer is stationary, the ADF (*Augmented Dickey-fuller Test*) is utilized in the study; (c) the ARMA (*Auto Regressive Moving Average*) and ELM (*Extreme Learning Machine*) forecasting models are built to complete the multi-step forecasting computation for the decomposed SS and IMFs, respectively; (d) the new OCM (*Outlier Correction Method*) algorithm is proposed to guarantee the robustness of the built ARMA and ELM models during their forecasting computation; and (e) in order to verify the forecasting performance of the proposed hybrid model, a number of forecasting experiments are provided in this study. The included forecasting models are comprised of the ARIMA model, the BP model, the Elman model, the ELM model, the hybrid WPD-ELM model and the proposed hybrid WDD-WPD-ARMA (SS)-EMD-ELM (NS)-OCM model.

The innovations of the proposed hybrid forecasting method are explained as follows: (a) a secondary signal adaptive decomposing algorithm is proposed by combining the WPD, ADF and EMD theories. In the proposed secondary decomposing algorithm, the WPD is utilized to decompose the wind speed series into a number of sub-layers, then the ADF is utilized to check whether a sub-layer is NS or SS wind speed data, and finally the EMD is used to further decompose the obtained NS data into a series of IMFs. Although there have been some secondary decomposing algorithms, the secondary decomposition for the non-stationary signals obtained by the first decomposition has not been investigated and the combination of the WPD, ADF and EMD in the secondary wind speed decomposition has not been investigated. The purpose of the secondary decomposition is to decrease the non-stationarity of the original wind speed data as much as possible; (b) in the study, the wavelet algorithm is not used to decompose the original wind speed data into a number of wind speed sub-layers directly but to remove the noise of the original wind speed data. The wind speed decomposing tasks are distributed to the hybrid secondary WPD-EMD combination; (c) the ARMA models are effective to predict the stationary time series, while the ELM models have the fast learning speed and good generalization performance, to balance the computing real-time performance and the forecasting accuracy, the ARMA models and the ELM models are built to forecast the SS and IMFs, respectively; and (d) to correct the unexpected forecasting values for each SS and IMFs, and further guarantee the robustness of the forecasting results from the built ELM/ARMA models, a new OCM model is presented in the last computing step of the proposed WDD-WPD-ARMA(SS)-EMD-ELM(NS)-OCM model.

This paper is organized as follows: (a) the framework of the hybrid prediction model in this study is provided in Section 2; (b) the algorithms involved in the hybrid WDD-WPD-ARMA(SS)-EMD-ELM(NS)-OCM model are explained in Section 3; (c) five wind speed forecasting experiments are presented in Section 4; and (d) the results in this study are concluded in Section 5.

2. Framework of the proposed hybrid model

The framework of the proposed hybrid model in the study is demonstrated in Fig. 1. As shown in Fig. 1, the proposed hybrid model can be explained in details as follows: