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Comparative study on three new hybrid models using Elman Neural Network and Empirical Mode Decomposition based technologies improved by Singular Spectrum Analysis for hour-ahead wind speed forecasting

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ABSTRACT

High precision forecasting of wind speed is urgently needed for wind power utilization. In this paper, Empirical Mode Decomposition (EMD) based technologies, including EMD and its advanced versions ensemble EMD (EEMD) and complete EEMD with adaptive noise (CEEMDN) are applied for improving wind speed prediction accuracy. Three new hybrid models (EMD-SSA-ENN, EEMD-SSA-ENN and CEEMDN-SSA-ENN) are proposed in which EMD, EEMD and CEEMDN are combined with Singular Spectrum Analysis (SSA) and Elman neural network (ENN) respectively. SSA is exploited to re-handle components with the highest frequency disaggregated from the decomposition technologies, of which the procedure is systematically studied herein. The experimental prediction results show that: 1. through the retreatment of SSA, the performances of the new proposed hybrid models improve significantly; 2. compared to the persistence method, single ENN model, ARIMA, EMD-RARIMA and some methods in the references, all the proposed methods can give a much more accurate forecast; 3. among all the proposed methods, the performance of the hybrid model CEEMDN-SSA-ENN are the best.

1. Introduction

As one of the clean and renewable energies, wind power has becoming increasingly competitive and widely used around the world. With the wind nature characteristics of intermittence and fluctuation, to protect the safety of the power utilization and integration, high precision forecasting of wind speed is demanding and critical [1,2].

There are four main methods for wind speed forecasting: statistical methods, physical methods, intelligent methods and hybrid models. Since each single model has its own nature deficiencies (e.g.: statistical methods cannot handle non-linear problem well [3], some key parameters in intelligent methods are not easily chosen [4,5] and physical methods consume much computing resources [6]), hybrid models absorbing essences of single models are becoming the mainstream approaches [7]. Due to the inherent features of non-stationary, high fluctuations and irregularity, many hybrid models are in collaboration with decomposition technology, including the Wavelet Transform (WT) [8,9] and Empirical Mode Decomposition (EMD). They are aimed to disaggregate an original wind speed into a sequence of more stationary sub series before further forecasting to improve prediction precision.

Without too much priori knowledge, EMD is relatively easy to be understood and employed. Liu et al. [10] used EMD to decompose the original data into several Intrinsic Mode Functions (IMFs) and a residue, which were modeled and forecasted by Autoregressive Moving Average (ARMA) respectively and then summarized as the final prediction. Ren et al. [11,12] reported hybrid models employing the k Nearest Neighbor algorithm (KNN) and Support Vector Regression (SVR) as regression models collaborated with EMD respectively for wind speed forecasting. Liu [13] combined the artificial neural network (ANN) and EMD to make wind speed prediction. The training algorithms of ANN were discussed. He also came up a method combined EMD and the recursive autoregressive integrated moving average model (RARIMA) for wind speed forecasting [14]. Ren et al. [12] and Hong et al. [15] used the back propagation neural network (BPNN) and EMD to make one-hour ahead wind speed forecasting, while Wang et al. [16] utilized Elman Neural Network (ENN) with EMD. Sun and Liu [17] proposed a hybrid model in which the fast EEMD (FEEMD) and the regular-

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ized extreme learning machine (RELM) were applied. Wang et al. [18] employed the EEMD and BPNN improved by the genetic algorithm technique (GA) to make short term wind speed forecasting. Fei [19] presented a hybrid model combined with EMD and the multiple-kernel relevance vector regression algorithm for wind speed prediction.

There is no further treatment on the components decomposed by the EMD in the above works. In order to reinforce the prediction accuracy, by defining the overall energy of a time series, Ghelardoni [20] classified the decomposition components by EMD into two sets, respectively describing the trend and the local oscillations, which were modeled and forecasted by SVR. There is usually little regularity in the decomposed component with the highest frequency band called IMF1 [21]. Liu [22] made re-decomposition on IMF1 by WT, then the least square support vector machine (LSSVM) models were built for all the new decomposition components and the others without further retreatment. Guo [21] discarded IMF1 and all the rest decomposed components were modeled by BPNN, whose performance was little worse than that of ENN as Ref. [16] indicated. The performance of all the three hybrid models were greater than those without deeply managing the decomposition components by the EMD.

Therefore, it is essential to make further process on the decomposition components by the EMD to enhance the hybrid prediction model. But about the clustering process of the decomposition components in Ref. [20], it may be subjective, since the energy threshold distinguishing the two kind series is not easily determined. As for the re-decomposing IMF1 by WT in Ref. [22], too many models are adopted with too much computation cost. Different from the method in Ref. [21], it is believed that there are still potential and useful information involved in IMF1. So IMF1 will be further processed by Singular Spectrum Analysis (SSA), which is introduced for the first time. Another is worth mention that EMD usually falls into in a trouble called "mode mixing" [23,24]. Hence, its advanced version the ensemble empirical mode decomposition (EEMD) and the complete ensemble empirical mode decomposition with adaptive noise (CEEMDN) are proposed to overcome the weakness. So three new hybrid models are proposed, including EMD-SSA-EEN, EEMD-SSA-EEN and CEEMDN-SSA-EEN. The original wind speed series is firstly decomposed into a sequence of sub series by EMD, EEMD and CEEMDN respectively, then the series IMF1 with the highest frequency band will be re-handled by SSA, finally the processed IMF1 and all the rest components will be modeled by ENN to get the final wind speed forecasts. The retreatment procedure of SSA on the decomposition component IMF1 will be systematically investigated. The performances of these three new hybrid models will be also talked in details.

The rest of paper is organized as follows: Sections 2 reviews methodology in detailed; Section 3 introduces the proposed method; Section 4 gives some predictions and makes comparative studies.

2. Methodology

2.1. EMD and its improved versions

2.1.1. EMD

EMD [25] is widely used technique dealing with non-linear and non-stationary time series. Through the EMD process, the original time series $X(t)$ can be disaggregated into n IMFs and a residue as follows:

$$X(t) = \sum_{i=1}^{n} c_i + r_n \tag{1}$$

2.1.2. EEMD

Since EMD is usually trapped in a trouble called "mode mixing", which means that there are oscillations of very disparate amplitude in a mode or very similar oscillations in different modes [23,24], EEMD is proposed [23]. With the help of addition of white Gaussian white noise, the mode mixing problem can be alleviated. The key process of EEMD can be described as follows.

Step a. For a signal $X(t)$, create a new noise-added signal : $x^i(t) = X(t) + \varepsilon^i(t)$

where $\varepsilon^i(t)$ is a Gaussian white noise.

Step b. Decompose $x^i(t)$ into several IMFs and a residue by EMD. That is designated as:

$$x^i(t) = \sum_{j=1}^{n} c_j^i + r_n^i \tag{2}$$

Step c. Repeat step a and step b with different Gaussian white noise each time.

Step d. Average on all the corresponding IMFs as the final results.

2.1.3. CEEMDAN

In EEMD, each EMD decomposition process of a noise-added signal may produce different number of modes. Then CEEMDAN is proposed to round the trouble with a lower computational cost [24]. The calculation steps of CEEMDAN are as follows.

Step a. Generate a number of noise-added series: $x^i(t) = X(t) + \omega_0\varepsilon^i(t), i \in \{1, \ldots, I\}$, where $\varepsilon^i(t)$ are different Gaussian white noise with a unit and ω_0 is a noise coefficient.

Step b. Apply EMD to each $x^i(t)$ to extract the first decomposed IMF $c_1{}^i(t)$. Make average of the whole IMF1: $c_1(t) = \frac{1}{I}\left(\sum_{i=1}^{I} c_1^i(t)\right)$, to get the first residue: $r_1(t) = x(t) - c_1(t)$

Step c. In the second process, continue to disaggregate the noise-added residue $r_1(t) + \omega_1 E_1(\varepsilon^i(t))$ to obtain the second IMFs:

$$c_2(t) = \frac{1}{I}\sum_{j=1}^{I} E_1(r_1 + w_1 E_1(\varepsilon^i(t))) \tag{3}$$

where $E_1(.)$ is a function to extract the first IMF decomposed by EMD.

Step d. Repeat for another IMF until the residue is no longer feasible to be decomposed (it does not have at least two extrema).

2.2. SSA

SSA is a widely used approach for time series analysis, including trend of quasi-periodic component detection and extraction and denoising [26,27]. The core idea of SSA is to decompose a raw original time series into a sum of sub series, identified as either a trend, periodic or quasi-periodic component, or noise. Then it is followed by the reconstruction of the original series. Therefore, there are two stages decomposition and reconstruction in the process of SSA as follows:

Stage I. Decomposition

Step a. Embedding

For a signal $X(t) = (X_1, \ldots, X_N)$, generate $Y_i(t) = (X_i, \ldots, X_{i+k-1})$ for L dimensions to construct a trajectory matrix Y: