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An effective secondary decomposition approach for wind power forecasting using extreme learning machine trained by crisscross optimization

Hao Yin[a], Zhen Dong[a], Yunlong Chen[a], Jiafei Ge[a], Loi Lei Lai[a], Alfredo Vaccaro[b], Anbo Meng[a,*]

[a] School of Automation, Guangdong University of Technology, Guangzhou 510006, Guangdong, China
[b] Engineering Department, University of Sannio, Benevento 82100, Italy

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ABSTRACT

Large-scale integration of wind energy into electric grid is restricted by its inherent intermittence and volatility. So the increased utilization of wind power necessitates its accurate prediction. The contribution of this study is to develop a new hybrid forecasting model for the short-term wind power prediction by using a secondary hybrid decomposition approach. In the data pre-processing phase, the empirical mode decomposition is used to decompose the original time series into several intrinsic mode functions (IMFs). A unique feature is that the generated IMF1 continues to be decomposed into appropriate and detailed components by applying wavelet packet decomposition. In the training phase, all the transformed sub-series are forecasted with extreme learning machine trained by our recently developed crisscross optimization algorithm (CSO). The final predicted values are obtained from aggregation. The results show that: (a) The performance of empirical mode decomposition can be significantly improved with its IMF1 decomposed by wavelet packet decomposition. (b) The CSO algorithm has satisfactory performance in addressing the premature convergence problem when applied to optimize extreme learning machine. (c) The proposed approach has great advantage over other previous hybrid models in terms of prediction accuracy.

1. Introduction

Different from the conventional power that is dispatchable and easy to predict, the wind power has its inherent nature of volatility and intermittence. Due to the uncertainty of wind power generation, the large-scale integration of wind turbines into power system is restricted [1]. Therefore, accurate wind power prediction is of great significance for power system operation in terms of unit commitment, energy market efficiency as well as lowering the cost by reducing the power reserves [2].

In the past few decades, several wind power forecasting approaches have been proposed, which usually fall into physical, empirical and artificial intelligence (AI) methods. The physical method predicts wind power by utilizing the numerical weather prediction (NWP) data into the manufacturer power curves [3]. However, the physical method is very complicated and is not reliable for short-term prediction. So it is usually used as an input for empirical models [4]. The empirical methods aim to describe the relation between historical time series of wind power at the location of interest by generally recursive techniques [5]. Most of the empirical models, such as autoregressive moving average model (ARMA) [6], autoregressive integrated moving average model (ARIMA) [7], assume that the wind speed data is normally distributed. However, it is a well known characteristic of general wind speed series that its variation at a given site can be modeled using the Weibull distribution, which is not a normally distributed function and as a result, a transformation of the original wind speed data is required making the time series unstable and difficult to predict [8]. In addition, the volatility of wind power time series requires more complex function for capturing the stochastic relations, but these models are based on the assumption that a linear correlation structure exists among time series values [9].

In recent years, many machine learning forecasting techniques have been developed to address the nonlinear time series-based wind power forecasting problem. Among them, the artificial neural network (ANN) has become a popular method for wind energy forecasting due to its ability to capture the nonlinear relationship among the historical data. The applications of different ANNs in the wind power prediction field can be found in [10–13]. Compared with traditional algorithms such as the BP (back-propagation), the extreme learning machine (ELM) is a powerful algorithm with faster learning speed and better performance [14]. ELM tries to get the smallest training error and norm of weights. More examples of applying ELM to wind power prediction can be found

* Corresponding author.
E-mail address: menganbo@vip.sina.com (A. Meng).

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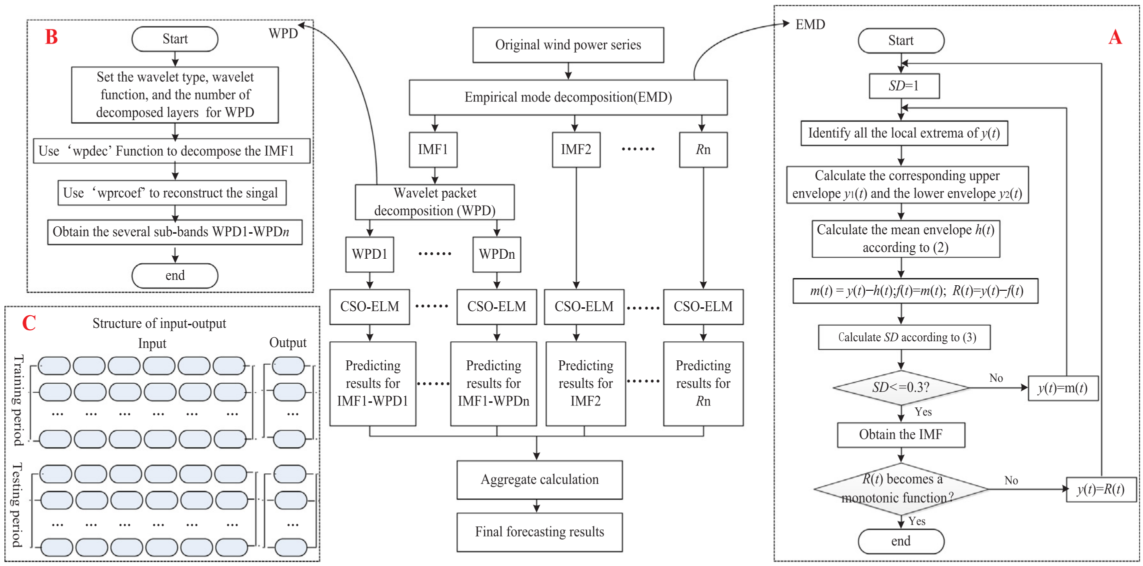

Fig. 1. Framework of the SHD-CSO-ELM model.

in [15,16]. Since the output weights in ELM are computed based on the random input weights and hidden layer biases, there may exist a set of non-optimal or unnecessary input weights and hidden layer biases. In view of the significant impact of the input weights and hidden layer biases on ELM predictive performance, some optimization techniques such as genetic algorithms (GA), simulated annealing and differential evolution (DE) have been used to optimize the input weights and hidden layer biases of ELM in [17].

As pointed in [9], the direct utilization of original wind power data in a single forecasting model usually leads to a large error. Previous research has shown that the multi-scale decomposition techniques, such as wavelet decomposition (WD), wavelet packet decomposition (WPD), empirical mode decomposition (EMD), ensemble empirical mode decomposition (EEMD) and variational mode decomposition (VMD) can greatly reduce the forecasting difficulty and improve the forecasting accuracy. For example, Liu et al. [18] presented a hybrid model by combining wavelet, wavelet packet and artificial neural network (ANN). Their experimental results show that the WPD-ANN model has advantage over other single and hybrid models. Liu et al. [19] presented a hybrid forecasting framework using wavelet decomposition and support vector machines (SVM) optimized by genetic algorithm (GA). Their studies show that the WD-GA-SVM model is more efficient than a persistent model and a GA-SVM model without WD. Wang et al. [20] presented a hybrid forecasting method based on EEMD and GA (Genetic Algorithm)-BP (Back Propagation). Their simulation shows that the forecasting accuracy of EEMD-GA-BP method is much better than the traditional GA-BP forecasting method and the method based on EMD and GA-BP algorithm. Liu et al. [21] presented two hybrid forecasting frameworks based on WD and GA-multilayer perceptron (MLP) and WD-particle swarm optimization (PSO)-MLP to predict non-stationary wind speeds. Their simulation results show that the contribution of the GA and the PSO components in improving the MLP are not statistically significant while that of the Wavelet component is statistically significant. Guo et al. [22] presented a modified EMD-based feed-forward neural network for wind speed forecasting. Their studies show that EMD is a promising alternative decomposition method for dealing with the non-stationary original time series. More decomposition-based hybrid forecasting models can be found in [23–28].

In this study, a novel secondary hybrid decomposition (SHD) model is developed for short-term wind power forecasting. The SHD approach involves two different decomposition techniques, namely EMD and WPD. In particular, EMD is selected as the main decomposition method because of its powerful ability of decomposing a non-stationary signal into several completely adaptive basic functions called intrinsic mode functions (IMFs). However, that IMF1 generated by EMD is unsystematic and irregular. According to [29], the more non-linear the original series is, the more irregular IMF1 will be, leading to a significant increase in the difficulty of prediction. So far, there are no effective methods of handling IMF1 reported in the literature. In [22], an interesting finding is that the forecasting accuracy can be slightly improved when IMF1 is removed from the set of IMFs. It is obvious that such practice of evading IMF1 is not unfounded. One important contribution of this paper is that we manage to address the IMF1 problem by applying WPD to further decompose the generated IMF1 into appropriate and detailed components. The experimental results demonstrate that such secondary hybrid decomposition approach can significantly improve the prediction accuracy as compared with separate EMD or WPD.

After secondary hybrid decomposition, ELM is considered as the forecasting method for every decomposed subseries generated by the proposed SHD. Another contribution in this work is that all the ELMs are optimized by our recently developed crisscross optimization (CSO) algorithm. It has been proved that CSO has obvious advantage over other heuristic algorithm in terms of reducing the search blind spots and enhancing the global search ability especially when addressing the complex non-convex optimization problems [30]. By combining the advantages of SHD, ELM and CSO, a novel hybrid approach called SHD-CSO-ELM is developed and validated by multi-step ahead prediction of a wind farm located in Spain.

The remainder of the paper is organized as follows: Section 2 states the framework of this study. Section 3 provides the original wind power time series and presents the proposed SHD-CSO-ELM model. Section 4 provides the parameters selection of proposed model. Section 5 gives the experimental results, and the conclusions are made in Section 6.

2. Framework of modeling

The proposed hybrid approach for wind power forecasting has two primary stages. Firstly, the proposed SHD is applied to decompose the wind power time series. Subsequently, all sub-series generated by SHD are forecasted by ELMs, which are optimized by CSO. Finally all the forecasting results of every sub-series are aggregated to reconstruct the wind power signal. Fig. 1 illustrates the proposed approach. The detailed implementation of SHD and CSO-based ELM is presented in Section 3.2 and 3.3, respectively. The modeling steps are described as follows.