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A hybrid model based on synchronous optimisation for multi-step short-term wind speed forecasting

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HIGHLIGHTS

- A new synchronous optimisation method is proposed to optimize models of FS, TSD and BM.
- A hybrid model of VMD-GSO-ELM in a GSA-based synchronous framework is designed.
- The impacts of FS and TSD have been evaluated by comparative study.
- The proposed model has dramatically improved the forecasting accuracy.

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ABSTRACT

Wind speed forecasting plays an important role in estimating the power produced from wind farms. However, because of the non-linear and non-stationary characteristics of the wind speed time series, it is difficult to model and predict such series precisely by traditional wind speed forecasting models. In this paper, a novel hybrid modelling method is proposed, in which time series decomposition, feature selection, and basic forecasting model are combined in a synchronous optimisation framework. In this method, the above-mentioned modelling factors, which affect model performance, could make a concerted effort to improve the model. Specifically, variational mode decomposition, the Gram–Schmidt orthogonal, and extreme learning machine, are optimized synchronously by gravitational search algorithm in the proposed hybrid short-term wind speed forecasting model. First, variational mode decomposition is employed to decompose the original wind speed time series into a set of modes and into one bias series. Subsequently, the Gram–Schmidt orthogonal is used to select the important features. Next, the set of modes are forecasted using the ELM. Finally, the key parameters of the models in three stages are optimized synchronously by gravitational search algorithm. Seven data sets from the Sotavento Galicia wind farm and two wind farms in China have been adopted to evaluate the proposed method. The results show that the proposed method achieves significantly better performance than the traditional signal forecasting models both on one-step and multi-step wind speed forecasting with at least 40% average performance promotion over all the seven competitors.

1. Introduction

As a burgeoning renewable energy, wind energy has been developing fast in the recent decade. Owing to the intermittency and stochastic fluctuation of wind, the utilization and operation of wind power would be challenging. Accurate short-term wind speed forecasting plays a significant role in meeting the challenges. More precise wind speed forecasting can effectively decrease the risk of wind power breakdown in hybrid power systems. However, the non-linear and non-stationary characteristics of the wind speed render it difficult to model and predict precisely. Significant efforts have been made from different aspects, which are primarily concentrated on the basic models (BMs), preprocessing methods, and hybrid and optimisation strategies, to improve forecasting performance.

For the development of the basic forecasting model, a variety of approaches, which could be categorized into three classes, have been proposed: physical models, statistical models, and machine learning models. Physical models can employ the physical parameters such as temperature, pressure, and topography, to establish multi-variable wind speed prediction models [1,2]. A large number of statistical methods have also been proposed to predict the wind, such as the autoregressive moving average models [3,4], statistical regression [5],

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Markov model [6], and Bayesian method [7]. Another category for this task is the machine learning techniques, for instance, the deep Boltzmann machine [8], deep belief network [9], Kalman filtering [10,11], artificial neural network (ANN) [12,13], support vector machine (SVM) [14], and extreme learning machine (ELM) [15].

Apart from these basic categories, preprocessing methods such as time-series decomposition (TSD) and feature selection (FS), also play important roles in wind speed forecasting. Because of the non-stationary and non-linearity of wind speed time series, the TSD methods, such as the empirical mode decomposition (EMD) [16,13], wavelet transform (WT) [17,18], and variational mode decomposition (VMD) [19,20], have been widely applied for the purpose of decomposing the original complex time series into several simple-structured series, before the data sets are constructed and input into the basic predicting model. The FS methods are manifested to help in selecting the best inputs of the basic predicting model, which would affect the model accuracy greatly. Some FS methods are attractive in applications such as principal component analysis (PCA) [21], partial autocorrelation function (PACF) and singular value decomposition (SVD) [22], the Gram–Schmidt orthogonal (GSO) [19], and deep feature selection [23].

To attain better performance, researchers have concentrated on hybrid and optimisation strategies. In terms of hybrid strategies, combinations of TSD and BM, FS and BM, or complicated combinations of TSD, FS, and BM are the main formats. In [13], a hybrid model consisting of an EMD and an ANN (EMD–ANN) for wind speed prediction is proposed, in which an EMD is used to decompose the original time series into intrinsic mode functions (IMFs) and every IMF is then predicted by a subordinate ANN before those predicted sub-series are being composed as the final wind speed prediction values. Similar combinations have come forth in recent years, such as VMD-ELM [19], VMD-SVM [20], FEEMD-MLP [24], EMD-PACF-SVM [16], VMD-PACF-ELM [15]. In these hybrid models, the integration of TSD could improve the forecasting performance by overcoming the barriers of non-linearity and non-stationary of wind speed, and the FS methods help to eliminate redundant information in feature sets and to improve the efficiency and accuracy of modelling.

Model optimisation has been proven to improve the performance of wind speed forecasting models. Meta-heuristic optimisation algorithms have been integrated in hybrid wind speed forecasting models for model improvement [15,17,25–27]. Many good examples can be found on this method. For instance, SVM-based hybrid models were optimized by genetic algorithm (GA) [17] and binary gravitational search algorithm (GSA) [28]; Particle swarm optimisation (PSO) has been used to optimize an ANN model [25]. In [17], a combined model of WT-SVM was optimized by GA, in which the SVM parameters were the optimisation variables. Although the main purpose of the integrated optimisation algorithm is the parameter tuning of the BM, the optimisation algorithm may also be applicable for other tasks, such as the optimisation for FS or the optimisation for both BM and FS. The synchronous optimisations of hybrid and of the combination of FS and BM have become prevalent, and the performance of synchronous optimisation has also been confirmed. In [26], the coral reefs optimisation algorithm (CRO) has been used in the optimisation of the FS and ELM parameters. In [29], a hybrid GSA was designed for the FS and BM synchronous optimisation, whereas the binary GSA was used for FS and the real-value GSA was used for SVM optimisation in an integral optimisation frame.

From the review of related works, we found that complicated hybrid model such as TSD-FS-BM have been studied, and meta-heuristic optimisation strategies for single BM, FS or even FS-BM have also been addressed. However, problems that trigger our interest still remain. Models of TSD, FS, and BM are all affected by control parameters of their own; hence, separate optimisations of these models will most likely cause conflicts and render the model out of tune, thus hindering a robust optimisation performance. For example, the number of modes K and the iterative factor τ determine the performance of the VMD [30], and in a VMD-based hybrid model, such as the VMD-ELM, VMD parameters are typically tuned separately with ELM parameters optimized by meta-heuristics [15]. For FS methods such as GSO, there are also control parameters that require optimisation. Separate optimisations and tuning for different models in a hybrid forecasting system seem to restrict the overall performance. Will a synchronous optimisation be more effective in enhancing the performance of a hybrid model? To the best of our knowledge, none have reported the synchronous optimisation for the TSD-FS-BM models.

Inspired by this idea, this paper presents a novel optimisation strategy for hybrid models combining BM, TSD, and FS, while a meta-heuristic optimisation algorithm is used for the synchronous optimisation of all the essential parameters of those sub-models. Typically, gravitational search algorithm (GSA) is applied to optimize a hybrid model consisting of the VMD, GSO, and ELM. Sufficient comparative experiments have been conducted to verify the proposed approach in applications of different wind farms.

The main contributions and novelty of this paper are reflected in the following: (1) a new synchronous optimisation method is proposed for a hybrid wind speed forecasting model of TSD-FS-BM for the first time; (2) a hybrid model of VMD-GSO-ELM in a GSA-based synchronous framework is designed; (3) the impact of different factors that contributes to the improvement of the hybrid model have been evaluated quantitatively.

The remainder of this paper is presented as follows: Section 2 introduces the theoretical backgrounds of the VMD, GSO, ELM, and the GSA. Section 3 describes the proposed approach for the short-term wind speed forecasting method. Section 4 presents the details of the experiment arrangement and results. Finally, Section 5 summarizes our conclusions.

2. Theoretical backgrounds

2.1. VMD

The VMD is a common signal processing method designed to analyse non-steady signals [30]. By applying VMD, the time series $x(t)$ could be decomposed into K subseries or variational modes $\underline{u}_k$ ($k = 1, \ldots, K$), with limited bandwidth in the spectral domain. It is assumed that each variational mode u_k has a centre pulsation (frequency) ω_k, which is determined during the decomposition process. To obtain u_k and ω_k, VMD is required to solve a constrained optimisation problem, which is described by the following equation:

$$\min_{\{u_k\},\{\omega_k\}} \left\{ \sum_{k=1}^{K} \left\| \partial_t \left[\left(\delta(t) + \frac{j}{\pi t} \right) * u_k(t) \right] e^{-j\omega_k t} \right\|_2^2 \right\} \tag{1}$$

subject to

$$\sum_{k=1}^{K} u_k(t) = x(t) \tag{2}$$

where δ is the Dirac distribution and $*$ denotes convolution.

A quadratic penalty term and the Lagrangian multiplier are used to handle the optimisation problem. The augmented Lagrangian, L is given by

$$\begin{aligned} L(\{u_k\},\{\omega_k\},\lambda) = {} & \alpha \sum_{k=1}^{K} \left\| \partial_t [(\delta(t) + \frac{j}{\pi t}) * u_k(t)] e^{-j\omega_k t} \right\|_2^2 \\ & + \left\| x(t) - \sum_{k=1}^{K} u_k(t) \right\|_2^2 + \langle \lambda(t), x(t) - \sum_{k=1}^{K} u_k(t) \rangle \end{aligned} \tag{3}$$

where α denotes the balancing parameter of the data fidelity constraint.

The variational problem in (3) can be solved by the alternate direction method of multipliers (ADMM) approach while different decomposed modes and the centre frequency during each shifting