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Research and application of ensemble forecasting based on a novel multi-objective optimization algorithm for wind-speed forecasting

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ABSTRACT

Wind energy is rapidly emerging as an appealing energy option because it is both abundant and environmentally friendly. Because of the stochastic nature and intrinsic complexity of wind speed, precise and reliable wind-speed prediction is vital for wind-farm planning and the operational planning of power grids. To improve wind-speed forecasting accuracy or stability, many forecasting approaches have been proposed. However, these models usually only consider one criterion (accuracy or stability) and have limitations associated with using individual models. In this paper, an ensemble method optimized by a novel multi-objective optimization algorithm is introduced. With respect to ensemble weight coefficients, a bias-variance framework, which is formulated by a multi-objective optimization problem, is used to assess model accuracy and stability. A novel hybrid flower pollination with bat search algorithm is proposed to search for the optimal weight coefficients based on the previous step, while Pareto optimality theory provides the necessary conditions to identify an optimal solution. In addition, data decomposition and de-noising are also incorporated into the data pre-processing stage. To evaluate the forecasting ability of the proposed model, a case study of 12 wind-speed datasets from two wind farms in the eastern coastal areas of China was completed. The experimental results of this study indicate that the developed ensemble model is superior to other comparison models in terms of the high precision and stability of wind-speed prediction.

1. Introduction

The current fossil fuels in the world will dry up before long, mainly due to high demand and, in some situations, extravagant consumption [1]. Meanwhile, fossil fuels, including petroleum, natural gas and coal sources, are harmful to the environment and their future depletion is inevitable [2]. Thus, it is vital to search for alternative and renewable energy sources to replace traditional fossil fuels as soon as possible [3]. Wind energy is regarded as an appealing energy option because it is abundant, environmentally friendly, and will be able to satisfy the growing demand for electricity. Thus, analysis and assessment of wind energy are meaningful but markedly difficult tasks for research. In the exploitation of wind power, several challenges are still faced, including its temporal and spatial variability and unsteady provision of electricity to the power system [4]. The planning, scheduling, maintenance and control of wind-energy systems depend on reliable wind-speed prediction, so obtaining accurate wind speeds is important [5].

Numerous methods have been proposed to improve wind-speed forecasting in recent decades. These methods can be categorized into three types: physical approaches, statistical approaches and artificial-intelligence models [6]. Physical methods, such as numerical weather-prediction (NWP) models, are based on physical processes in the atmosphere for forecasting but perform poorly for short-term wind-speed simulation. Conventional statistical methods draw on vast historical data and try to find relationships among a wealth of explanatory variables; such methods usually involve the auto-regressive integrated moving-average model (ARIMA), quantile-regression model (QR), and Kalman-filter (KF) model and achieve more accurate short-term wind-speed predictions than physical models. Shukur et al. [7] utilized the ARIMA models to determine the inputs structure of the KF and Artificial Neural Network (ANN). In the presented method, the ANN and the KF model optimized by the ARIMA models were used to handle the

Abbreviations: BSFPA, flower pollination algorithm with bat search algorithm; MOBSFPA, multi-objective BSFPA; PSO, particle swarm optimization; NWP, numerical weather-prediction; ARIMA, auto regressive integrated moving average model; QR, quantile-regression model; ANN, artificial neural network; SVM, support vector machine; CPSO, chaotic particle swarm optimization; MOO, multi-objective optimization; BPNN, back propagation neural network; RBFNN, radial basis function neural network; GRNN, general regression neural network; WNN, wavelet neural network; SVD, Singular Value Decomposition; SSE, square sum of the error; MAE, mean absolute error; RMSE, root mean square error; MAPE, average of absolute error; DM test, Diebolde-Mariano test

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nonlinearity and the stochastic uncertainty of the raw wind speed data, respectively. Lv et al. [8] built a forecasting model based on wavelet analysis and quantile regression to realize the wind speed prediction. The simulated results provided in the paper showed that the proposed model had satisfactory forecasting performance. However, the fluctuating and intermittent characteristics of wind-speed sequences require more complicated functions to capture the non-linear relationships rather than assuming a linear correlation structure [9]. With the development of artificial intelligence techniques, artificial neural networks (ANNs), fuzzy logic systems, support vector machines (SVMs) and other mixed methods have been proposed and are widely used in wind-speed forecasting. A large number of forecasting approaches have been proposed for wind-speed prediction, and all of these methods have improved the precision of wind-speed predictions to some extent. Moghram and Rahman [10] concluded that there is no single best approach. Model performance under specific conditions should be analyzed and understood, with incremental improvements made based on the knowledge gained. Instead of focusing on the selection of the best forecasting model, Bates and Granger [11] have suggested using an ensemble of different forecasts. However, the best choice of weights is still unknown. Because ensemble forecasting is attracting much attention, many researchers have discussed the selection of the weight coefficients of ensemble models. In previous studies, the ensemble forecasting models are focused on accuracy or stability improvement when the weights for all single models are optimized. For instance, Yang et al. [12] used differential evolution (DE) to optimize the weight coefficients of several single models to improve forecasting accuracy. Xiao et al. [13] proposed a combined model based on chaotic particle-swarm optimization (CPSO) to optimize the weight coefficients for wind-speed forecasting accuracy. Xiao et al. [14] applied the cuckoo search algorithm (CSO) to determine the optimal weights of a combined model. And the results indicated that the combined model can improve the prediction performance to some extent. The aforementioned ensemble forecasting models only employ a single-objective optimization algorithm to optimize one criterion (accuracy or stability). However, both accuracy and stability should be regarded as equally vital in the forecasting field. To further optimize performance, this paper considers the optimization of *Bias* and *Variance* as different performance indices to achieve both accuracy and stability of the ensemble model simultaneously. The coefficients of each ensemble are the solution of a multi-objective optimization (MOO) problem [15] whose objective functions are the elements of different performance indices. To find an optimal combination of these forecasting paradigms, a novel multi-objective bat-search flower-pollination algorithm (MOBSFPA) is proposed for optimizing the weight coefficients of an ensemble model in this paper. The flower pollination algorithm (FPA), proposed by Yang in 2012 [16], is a novel bionic evolutionary algorithm that imitates flower pollination behavior in nature. However, when addressing more complex problems, the FPA suffers from the tendency to fall into locally optimal solutions and slow convergence rates. To improve the performance of the FPA with respect to optimization problems, the novel hybrid optimization algorithm called BSFPA is proposed, which combines the flower-pollination algorithm [16] and the bat search algorithm [17]. The bat search algorithm is used to enrich the searching behavior and accelerate the local convergence of the FPA; its optimization capacity is validated using five popular benchmark functions. To improve the accuracy and stability of a forecasting model simultaneously, the new evolutionary BSFPA is incorporated into a multi-objective optimization algorithm (MOBSFPA) to obtain the weights of an ensemble forecasting model. The forecasting performance of the novel BSMOFPA-based ensemble approach is investigated based on actual wind-speed data from Shandong Province. The original wind-speed data, which were collected at a 70-m hub height of the wind turbines from the wind farms in Weihai and Shagou, were employed to test whether the proposed models can be applied under different conditions. However, original wind-speed time series are highly noisy and unstable; using the primary wind-speed series to directly establish prediction models will introduce large errors [18,19]. To overcome this problem, singular-spectrum analysis (SSA) [20] is used for data pre-processing to remove the noise of the original wind-speed data for easy forecasting. The main contributions in this paper are as follows:

(1) The forecasting focus of the ensemble forecasting architecture outperforms other individual models. In the architecture, an ensemble forecasting model that combines four neural network models is optimized by a multi-objective optimization algorithm to obtain better performance than single forecasting models.
(2) The speed of local convergence and the accuracy in finding the optimal solution of FPA are enhanced. To improve both the exploration and exploitation capacities and avoid the weakness of the local optimum searching ability, the hybrid FPA with Bat search is proposed, and to evaluate the improved algorithm, five benchmark functions are used.
(3) The forecasting accuracy and stability of the ensemble model are enhanced. The multi-objective bat-search flower-pollination algorithm (MOBSFPA) is employed to select the weight coefficients of the ensemble model. According to the experimental results, the forecasting performance of multi-objective bat-search flower-pollination algorithm is better than those of single-objective optimization algorithms.
(4) More accurate metrics are applied to evaluate the forecasting performance of the proposed model. In addition to the traditional criteria including sum of square error (SSE), mean absolute error (MAE), root mean square error (RMSE) and mean absolute percentage error (MAPE), to assess the performance of the proposed ensemble model, this paper introduces the Diebold-Mariano (DM) test to further evaluate the model. This test provides a reliable assessment of the forecasting performance of the model.

The remainder of the article is organized as follows. Section 2 describes the whole ensemble forecasting strategy. Section 3 presents several forecasting performance metrics. Section 4 presents the forecasting results of the models and a discussion of the forecasting performance of the proposed model. Finally, Section 5 concludes the study.

2. Proposed ensemble forecasting method

In this section, a hybrid model based on the MOBSFPA is developed for wind-speed forecasting. To simultaneously obtain accurate and stable forecast results, the ensemble model consists of three stages, namely, data pre-processing, individual forecasting algorithms, and ensemble forecasting optimized by multi-objective optimization (MOBSFPA). A schematic overview of the proposed ensemble model is shown in Fig. 1.

2.1. Data pre-processing - singular spectrum analysis

SSA (singular spectrum analysis) performs four steps: embedding, singular value decomposition, grouping and diagonal averaging. The time series is usually decomposed in the first two steps and reconstructed in the third and fourth steps. The procedure of SSA is briefly described as follows.

Step 1: Embedding. The embedding step transforms the original time series into a sequence of multidimensional vectors. For a one-dimensional time series $\mathbf{X} = (x_1,\cdots,x_N)$ with length N, given a window length L $(1 < \mathrm{L} < \mathrm{N})$, the original series is mapped into K $(K = N - L + 1)$ lagged vectors. The K lagged vectors, called the trajectory matrix, can be written as