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Multi-step wind speed forecasting based on a hybrid forecasting architecture and an improved bat algorithm

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ABSTRACT

As one of the most promising sustainable energy sources, wind energy plays an important role in energy development because of its cleanliness without causing pollution. Generally, wind speed forecasting, which has an essential influence on wind power systems, is regarded as a challenging task. Analyses based on single-step wind speed forecasting have been widely used, but their results are insufficient in ensuring the reliability and controllability of wind power systems. In this paper, a new forecasting architecture based on decomposing algorithms and modified neural networks is successfully developed for multi-step wind speed forecasting. Four different hybrid models are contained in this architecture, and to further improve the forecasting performance, a modified bat algorithm (BA) with the conjugate gradient (CG) method is developed to optimize the initial weights between layers and thresholds of the hidden layer of neural networks. To investigate the forecasting abilities of the four models, the wind speed data collected from four different wind power stations in Penglai, China, were used as a case study. The numerical experiments showed that the hybrid model including the singular spectrum analysis and general regression neural network with CG-BA (SSA-CG-BA-GRNN) achieved the most accurate forecasting results in one-step to three-step wind speed forecasting.

1. Introduction

As one of the most promising potential renewable energy sources [1], wind energy has attracted the focus of many researchers and scientists [2], and nearly every government across the world has introduced positive policies to support wind energy development [3,4]. In 2015, the global total capacity of wind farms is approximately 432,419 MW, with the 22% growth rate, as shown in Fig. 1 [5]. With the increased proportion of wind energy in whole energy networks, accurate wind speed forecasting results are becoming increasingly crucial for managers to schedule the daily power distribution and decrease the reserve capacity. To protect wind power from the breakdown and make sure the success of wind power conversation, accurate forecasting results of wind speed are also required [6]. However, due to the non-stationary and nonlinear fluctuations, wind speed is regarded as one of the hardest weather parameters to predict [7,8].

In recent decades, many methods have been presented for wind speed forecasting, and these methods can be divided into four categories [9]: (a) physical models; (b) statistical models; (c) spatial correlation models; and (d) artificial intelligence models. Physical models which are based on physical parameters, such as topography, temperature and pressure, are usually applied in long term wind speed forecasting [10–12]. Statistical models are built based on the mature statistical equations to get the potential change rule from history data sampling [13–17]. Spatial correlation models mainly consider the spatial relationship of wind speed at different sites. In some situations, it can obtain higher precision [18,19]. With the rapid development of artificial techniques, some artificial intelligence forecasting methods, including artificial neural networks (ANNs) [20–25], fuzzy logic methods [18,26] and support

Abbreviations: ANN, artificial neural network; ARIMA, autoregressive integrated moving average; BA, bat algorithm; CSA, cuckoo search algorithm; CG, conjugate gradient; EA, evolutionary algorithm; EEMD, ensemble empirical mode decomposition; EMD, empirical mode decomposition; FEEMD, fast ensemble empirical mode decomposition; FVD, forecasting validity degree; GA, genetic algorithm; GRNN, general regression neural network; MAE, mean absolute error; MAPE, mean absolute percentage error; MSE, mean square error; PSO, particle swarm optimization; RBFNN, radical basis function neural network; SDA, steepest descent algorithm; SSA, singular spectrum analysis; SVM, support vector machine; WD, wavelet decomposition; WPD, wavelet packet decomposition.

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Nomenclature

α	a random vector, with a value between 0 and 1	M	total number of CG iterations
β	a random vector, with a value between 0 and 1	N	number of generations P
$\boldsymbol{d}_i^k$	the search direction of $\boldsymbol{x}_i$ at iteration k	O	output of RBFNN
d_i	Euclidian distance	r	pulse rate of a bat
ε	a random vector, with a value between 0 and 1	R	spread parameter
$\phi(d_i)$	outputs from the hidden layer of RBFNN	$r_n(t)$	nth residue
F_i	the fitness function of $\boldsymbol{x}_i$	σ	spread parameter
$-\nabla f(\boldsymbol{x}^{iter})$	gradient of $\boldsymbol{x}^{iter}$	σ_j^i	marginal standard deviation
$\boldsymbol{g}_i^k$	gradient of $\boldsymbol{x}_i$ at iteration k	S_s	simple summation
h_j^i	correlation coefficient	S_w	weighted summation
I	input vector of RBFNN	t	current iteration number
$\mathbf{IMF}_j\,(t)$	intrinsic mode function	v_i^t	the velocity of $\boldsymbol{x}_i$ at iteration t
$iter$	current iteration number	w	interconnection weight
$Iter_{\mathbf{max}}$	maximum number of iterations	w_i	weight of the hidden layer of RBFNN
K	shape matrix	X	input vector of GRNN
k_j^i	(i, j)th element of the shape matrix K	$\boldsymbol{x}_b$	the value of $\boldsymbol{x}$ with the best fitness value in the population
L	the loudness of a bat	$\boldsymbol{x}_t$	training data
m_i	center vector	$\boldsymbol{x}_i^t$	position of $\boldsymbol{x}_i$ at iteration t
m_i^j	jth element of center vector	$\boldsymbol{x}^{iter}$	positions of bats
λ_j^{iter}	step length		
λ^k	step length of $\boldsymbol{x}_i$ at iteration k	Y	output vector of GRNN

vector machines (SVMs) [27], have been developed for wind speed forecasting.

Meanwhile, to decrease the negative influences that are intrinsic to individual models, many hybrid wind speed forecasting models have been proposed [28–36].

To achieve higher forecasting accuracy, some data-processing algorithms, such as wavelet decomposition (WD) [28], wavelet packet decomposition (WPD) [29], empirical mode decomposition (EMD) [30], the ensemble empirical mode decomposition (EEMD) algorithm [31] and the fast ensemble empirical mode decomposition (FEEMD) algorithm [32], have been employed in ANNs to build hybrid models. The data decomposition, which could reduce the non-stationary feature of the original data, promotes the forecasting performance indirectly.

Moreover, intelligent optimization algorithms including the genetic algorithm (GA) [33], particle swarm optimization (PSO) [34], the evolutionary algorithm (EA) [35], and the cuckoo search algorithm (CSA) [36], are utilized to determine the initial weights and thresholds of ANNs. In 2010, Yang proposed the bat algorithm (BA) [37], which is inspired by the echolocation characteristics of bats with varying pulse rates of emission and loudness. It has been applied to a wide range of optimization applications [38], including image processing [39], classifications [40], scheduling [41], the electricity market [42], energy systems [43] and various other problems. Experiments have shown its promising efficiency for global optimization.

Analyses based on single-step wind speed forecasting have been widely used, while their results are insufficient in ensuring the reliability and controllability of wind power systems. Thus, it is required to build a model to achieve accurate results for multi-step wind speed forecasting. Among various ANN models, the radical basis function neural network (RBFNN) and general regression neural network (GRNN) are good choices to achieve high convergence rates and accurate results. In this paper, a hybrid architecture, which contains four hybrid models, with two decomposing algorithms (i.e., FEEMD and singular spectrum analysis (SSA)) which are used to realize the non-stationary wind speed decomposition, and the modified RBFNN and GRNN is proposed for wind speed forecasting. In the modified RBFNN and GRNN, an improved BA, which is on the basis of conjugate gradient (CG) method to improve convergence performance over time and prevent individual bats from entrapment in local optima, is introduced to optimize the initial weights and thresholds of RBFNN and GRNN. The aim of this study is to investigate and enhance the forecasting performance of hybrid model based on signal processing algorithms, intelligent optimization algorithm and artificial neural networks for multi-step accurate wind speed forecasting. To investigate the forecasting abilities of the four models, the wind speed data collected from four different wind power stations in Penglai, China, were used as a case study. The main contributions in this paper are demonstrated as follows.

(1) ***The forecasting focus of the forecasting architecture is not only on the single-step forecasting but also on the multi-step forecasting***. Although the wind speed single-step predictions have been studied widely, to protect the wind power, wind speed single-step forecasting results alone are insufficient, and wind speed multi-step forecasting results are definitely expected, thus the forecasting architecture is aim to enhance the forecasting accuracy of multi-step wind speed forecasting.
(2) ***To globally investigate the forecasting performance of different combination of decomposing algorithms and neural networks, a forecasting architecture contains four hybrid models is proposed***. In the architecture, four different hybrid forecasting models based on the two most popular decomposing algorithms, an improved optimization algorithm and two neural networks, are investigated and compared (the performance of multi-step forecasting is given special attention in the investigation) with four different sites data for one-step to three-step forecasting to obtain the best one.
(3) ***The speed of local convergence and the accuracy of finding the optimal solution of BA are enhanced***. To improve both the exploration and exploitation capacities and avoid the weakness of the local optima searching ability, the improved BA based on CG is proposed, and to evaluate the improved algorithm, four testing functions are used.