Energy Conversion and Management 163 (2018) 134–150

Contents lists available at ScienceDirect

Energy Conversion and Management

journal homepage: www.elsevier.com/locate/enconman

A novel hybrid forecasting system of wind speed based on a newly developed multi-objective sine cosine algorithm

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ARTICLE INFO

Keywords:
Wind speed forecasting
Hybrid forecasting system
Modified data decomposition approach
Multi-objective sine cosine algorithm
Forecasting accuracy and stability

ABSTRACT

Wind speed forecasting plays a crucial role in power system operations, power grid security management, and in the electricity market. This is of great significance for society and is still a challenging task. However, most previous studies were based on simple data preprocessing and they only focused on improving either the forecasting accuracy or stability while ignoring the significance of improving these two aspects simultaneously, which will lead to poor forecasting performance. Therefore, a hybrid forecasting system based on a newly developed algorithm proposed herein—referred to as the multi-objective sine cosine algorithm (MOSCA)—is developed, which includes four modules, specifically, data preprocessing, optimization, forecasting, and evaluation module. For this system, a modified data decomposition approach is successfully developed to further improve its forecasting performance. In addition, a hybrid wavelet neutral network (WNN) based on MOSCA is developed to obtain high accuracy and strong stability simultaneously. Case studies utilizing eight wind speed datasets collected from two wind farms are performed as examples to analyze the performance of the developed forecasting system. The results clearly reveal that the developed forecasting system is superior to all the considered models herein in terms of both accuracy and stability. As a result, it is concluded that the proposed approach can be an efficient and effective technique for wind speed forecasting.

1. Introduction

Wind energy, which is regarded as one of the most promising and economical sustainable energy, is of great importance in energy development due to its advantages in regards to pollution, safety, renewability, environmental protection, and ecological friendliness [1,2]. Recently, it has been drawing greater attention from many researchers and scientists [3] and has been becoming the fastest-growing clean energy for electricity generation [4]. The detailed information about the global top 10 wind energy installation capacities from January to December in 2016 is shown in Fig. 1. Furthermore, the global cumulative installed capacity of wind farms has increased to about 486,749 MW at the end of 2016 [5]. However, because of the randomness and non-linearity aspects associated with wind speed data, wind power utilization is not only a challenging task but also a significant issue in terms of economic development and social progress [6,7]. Moreover, accurate wind speed forecasting strongly influences the safe usage of wind energy resources [8], which plays a significant part in the protection of wind power systems in operation [9]. Therefore, enhancing wind speed forecasting performance has become highly desirable and should not be delayed [10].

Over the past few decades, many wind speed forecasting approaches have been developed, which can be divided into four types [11]: physical methods, statistical methods, spatial correlation methods, and artificial intelligence methods. Physical methods employ meteorological and geographical information as well as historical data to perform wind speed forecasting, but they are poor in short-term wind speed forecasting [7,12]. In contrast, statistical methods, such as auto-

Abbreviations: AR, auto-regressive; ARMA, auto-regressive moving average; ARIMA, autoregressive integrated moving average; ES, exponential smoothing (ES); ANNs, artificial neural networks; SVM, support vector machine; WNN, wavelet neural network; GRNN, general regression neural network; SSA, singular spectral analysis; WT, wavelet transform; WPT, wavelet packet transform; EMD, empirical mode decomposition; EEMD, ensemble empirical mode decomposition; CEEMD, complementary ensemble empirical mode decomposition; VMD, variational mode decomposition; MCEEMD, modified complementary ensemble empirical mode decomposition; PSO, particle swarm optimization; FA, firefly algorithm; CSA, cuckoo search algorithm; EA, evolutionary algorithm; GA, genetic algorithm; SCA, sine cosine algorithm; NSGA-II, non-dominated sorting genetic algorithm version 2; MOEA/D, multi-objective evolutionary algorithm based on decomposition; MODA, multi-objective dragonfly algorithm; MOALO, multi-objective ant lion optimization; MOSCA, multi-objective sine cosine algorithm; NFL, no free lunch; GRA, grey relational analysis; FE, forecasting effectiveness; IGD, inverted generational distance; AE, average error; MAE, mean absolute error; RMSE, root mean square error; MAPE, mean absolute percentage error; IA, index of agreement; FB, fractional bias; U1, Theil U statistic 1; U2, Theil U statistic 2; DA, direction accuracy; GRD, grey relation degree; VR, variance ratio; DM test, Diebold-Mariano test

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https://doi.org/10.1016/j.enconman.2018.02.012
Received 2 December 2017; Received in revised form 27 January 2018; Accepted 3 February 2018
0196-8904/

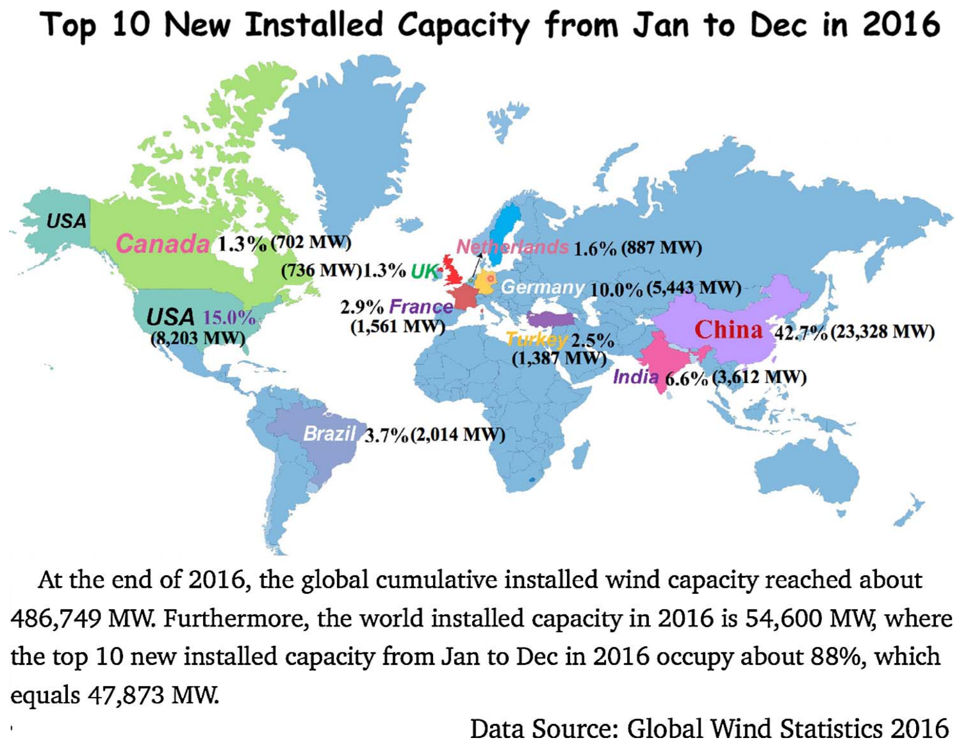

Fig. 1. The top 10 wind energy installation capacities from Jan to Dec in 2016.

regressive (AR) [13], auto-regressive moving average (ARMA) [14] and exponential smoothing (ES) [15], are built based on the relationship between each variable for wind speed forecasting. These models are more accurate than physical models in short-term wind speed forecasting, but they cannot solve special and nonlinear events due to inherent weaknesses [16]. Spatial correlation methods mainly consider wind speed spatial relationships, which can achieve greater forecasting accuracy in some conditions [17,18]. Developments in artificial intelligence have led to methods that employ, for example, artificial neural networks (ANNs) [19–22], support vector machine (SVM), [23] and fuzzy logic approach [24] to be developed and widely employed in wind speed forecasting.

All these individual models have their own advantages and disadvantages, and they cannot always obtain the desired forecasting results. In order to eliminate the negative aspects that are intrinsic to the individual methods, many hybrid forecasting models have been developed that are able to obtain promising performances in wind speed forecasting and, as a result, are now used in mainstream application [1,25]. More specifically, these hybrid models are always proposed based on the individual strengths of multifarious algorithms, mainly including data preprocessing approaches (i.e., singular spectral analysis (SSA) [9], wavelet transform (WT) [26], wavelet packet transform (WPT) [27], empirical mode decomposition (EMD) [28], ensemble empirical mode decomposition (EEMD) [29], complementary ensemble empirical mode decomposition (CEEMD) [30], and variational mode decomposition (VMD) [31], among others) as well as artificial intelligence optimization algorithms (i.e., genetic algorithm (GA) [4], particle swarm optimization (PSO) [32], cuckoo search algorithm (CSA) [33], evolutionary algorithm (EA) [34] and firefly algorithm (FA) [35], among others). For example, Wang et al. [4] proposed a hybrid forecasting model based on EEMD and GA for wind speed forecasting. The case studies reveal that the developed model can improve forecasting accuracy and computational efficiency, which is suitable for on-line ultra-short-term and short-term wind speed forecasting. Similarly, Zhang et al. [28] developed two novel hybrid wind speed forecasting models that integrated feature selection, EMD, ANN and SVM. The results from those studies indicate that these two developed forecasting models have satisfactory performance. Jiang et al. [33] proposed a hybrid model for short-term wind speed forecasting that takes advantage of the fluctuations in the data from adjacent wind turbine generators. This method can effectively improve forecasting accuracy for individual wind turbine generators.

However, to the best of our knowledge, most previous research were based on simple data preprocessing, which can improve forecasting performance to some extent. However, and importantly, they ignore the potential improvements that can be gained as a result of the effectiveness of data preprocessing as well as the significance of further mining the of the characteristics of wind speed, despite the wind speed being crucial to the forecasting performance of one model. More importantly, simple data preprocessing cannot completely capture the main features of wind speed time series, which leads to a poor forecasting performance. It is noteworthy that data preprocessing plays an indispensable role in wind speed forecasting because it makes a significant contribution to the effectiveness of the final forecast. Because of its significance, relevant works on improving the effectiveness of data preprocessing method are particularly needed. Therefore, to overcome the deficiencies of simple data preprocessing, a modified complementary ensemble empirical mode decomposition (MCEEMD) approach is developed, which employs variational mode decomposition to solve the challenging task. This approach can further improve the effectiveness of data preprocessing and enhance forecasting effectiveness in wind speed forecasting.

Moreover, most previous research only focused on improving forecasting accuracy by incorporating traditional single-objective optimization algorithms, which usually ignores the significance of forecasting effectiveness determined by forecasting stability [36]. Therefore, single-objective optimization algorithms can improve forecasting accuracy but cannot enhance forecasting stability. As a result, these algorithms can overcome the drawback of individual models to some extent. More importantly, only enhancing either forecasting accuracy or stability is insufficient. Therefore, the research and application of multi-objective optimization algorithms for wind speed forecasting is not only novel but also worth giving attention.

Fortunately, some multi-objective optimization algorithms have been developed to solve the multi-objective optimization problems,