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A novel combined model based on advanced optimization algorithm for short-term wind speed forecasting

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HIGHLIGHTS

- A combined model based on advanced optimization algorithm is successfully proposed.
- Design three experiments from the real wind farm to verify the effectiveness.
- The proposed combined model can enhance the forecasting accuracy significantly.
- Experiments demonstrate the availability and reliability of the developed model.

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ABSTRACT

Short-term wind speed forecasting has a significant influence on enhancing the operation efficiency and increasing the economic benefits of wind power generation systems. A substantial number of wind speed forecasting models, which are aimed at improving the forecasting performance, have been proposed. However, some conventional forecasting models do not consider the necessity and importance of data preprocessing. Moreover, they neglect the limitations of individual forecasting models, leading to poor forecasting accuracy. In this study, a novel model combining a data preprocessing technique, forecasting algorithms, an advanced optimization algorithm, and no negative constraint theory is developed. This combined model successfully overcomes some limitations of the individual forecasting models and effectively improves the forecasting accuracy. To estimate the effectiveness of the proposed combined model, 10-min wind speed data from the wind farm in Peng Lai, China are used as case studies. The experiment results demonstrate that the developed combined model is definitely superior compared to all other conventional models. Furthermore, it can be used as an effective technique for smart grid planning.

1. Introduction

Owing to the deterioration of the environment and the depletion of conventional energy resources, renewable energy has aroused widespread interest and research enthusiasm [1]. Wind energy is of crucial importance among the low-carbon energy technologies. It has the potential to achieve sustainable energy supply and occupies an indispensable position in the global new energy market [2]. Moreover, it has experienced an unexpectedly high growth recently and has received increasing attention globally [3]. In 2016, its annual market was 54.6 GW of wind capacity worldwide with a total installed capacity of almost 487 GW according to the Global Wind Energy Council [4].

However, many problems related to wind power generation that seriously restrict its development have arisen. More specifically, the stochasticity and intermittency of wind power could decrease system forecast reliability and wind power quality [5]. Furthermore, the continuous fluctuation of wind speed makes it difficult to predict how much power will be injected into the distribution network, which may cause energy transportation issues. Generally, wind speed forecasting can effectively reduce the risks associated with wind power generation arising from wind-related uncertainty [6,7]. Therefore, many researchers have given much attention to research methods of wind speed prediction. These methods are categorized into the following four types [8]: (i) physical arithmetic, (ii) conventional statistical arithmetic, (iii) spatial correlation arithmetic, and (iv) artificial intelligence arithmetic.

Physical arithmetic mainly utilizes physical data such as temperature, speed, density, and topography information[9], which are based on numerical weather prediction (NWP) model [10,11], to forecast

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wind speed in the succeeding periods. Cheng et al. [12] assimilated measured wind speed values from wind turbines into a NWP system, which enhanced the prediction accuracy of wind speed and wind power. Cassola et al. [13] improved the forecasting performance of wind speed by using the Kalman filtering technique in correcting the NWP model output. However, physical methods are not capable of dealing with short-term horizons and cost a lot of computing time and resources [14]. Statistical arithmetic, which is more appropriate for short-term wind speed forecasting, merely utilizes historical data to predict wind speed and employs the differences between the actual and forecasted wind speed to adjust the model parameters [15,16]. Examples are the auto-regressive moving average (ARMA) [17], auto-regressive integrated moving average (ARIMA) [18], and fractional ARIMA models [19]. Han et al. [20] proposed two hybrid models based on ARMA model and the non-parametric model. Results showed that non-parametric based hybrid models generally outperformed other models. Maatallah et al. [21] developed a novel wind speed prediction model by combining the Hammerstein model and an autoregressive model, which ultimately obtained a higher forecasting accuracy. However, according to the assumption that there are linear patterns among the time series, nonlinear structures cannot be effectively captured by statistical methods [22]. Moreover, spatial correlation arithmetic considers the spatial relationship of wind speed from different sites. For example, Tascikaraoglu et al. [23] proposed a novel wind speed prediction model using a wavelet transform and a spatio-temporal method, which improved the short-term wind speed forecasting relative to other benchmark models. Nevertheless, this model requires wind speed measurements from multiple spatial correlated sites; thus, it is difficult to implement owing to the stringent measurement requirements and their time delays [24].

In addition, as artificial intelligence arithmetic has rapidly developed and has been widely used, many researchers have effectively utilized artificial intelligence methods to predict wind speed. These methods include artificial neural networks (ANNs) [25,26,27], support vector machines (SVMs) [28,29], and fuzzy logic (FL)methods [30,31]. In the literature, some applications of artificial intelligence methods are as follows. Guo et al. [32] presented a novel hybrid approach based on back propagation neural network (BPNN) and seasonal exponential adjustment, which effectively enhanced the prediction accuracy of wind speed. Liu et al. [33] developed a new forecasting approach using Elman neural network (ENN) and a secondary decomposition algorithm, which exhibited satisfactory performance in multi-step wind speed forecasting. Zhang et al. [34] employed a radial basis function (RBF) neural network and a multi-objective optimization method to perform interval forecasting of wind speed and ultimately achieved a higher forecasting precision. Xiao et al. [35] developed a hybrid wavelet neural network (WNN) model with an improved cuckoo search algorithm. Experiment results demonstrated that the hybrid model significantly reduced the prediction error relative to other comparative models in electrical power system forecasting. Zhou et al. [36] successfully proposed a systematic method to adjust the parameters of SVM for short-term wind speed forecasting resulting in a better precision performance. Owing to the stronger nonlinear forecasting capacity of the model, artificial intelligence arithmetic is generally superior compared to the time-series models [37].

Over the past few decades, numerous wind speed forecasting approaches, which have enhanced the forecasting accuracy of wind speed series to a certain extent, have been presented. However, considering the relatively noisy and unstable characteristics of wind speed data, wind speed prediction by directly using the original data would lead to substantial forecasting errors and poor performance [38]. Therefore, with the aim of decreasing the stochastic disturbance of data sequence and achieving a higher forecasting accuracy, data preprocessing techniques, such as the empirical mode decomposition (EMD) [39] and the ensemble empirical mode decomposition (EEMD), have been considered and applied for wind speed forecasting [40]. Although these two techniques have improved the forecasting performance to a certain extent, they still have some disadvantages, such as the mode mixing problem in EMD and the residual noise in EEMD. Considering the defects of the aforementioned data preprocessing methods, a novel technique called improved complete ensemble empirical mode decomposition adaptive noise (ICEEMDAN), proposed by Marcelo et al. [41], is employed for reducing the noise and uncertainty of wind speed series in this study.

Review of previously literature shows that the forecasting approaches discussed above have some inherent drawbacks. The disadvantages of such methods are summarized as follows:

(1) Physical arithmetic is extremely weak in coping with short-term horizons; therefore, these methods do not have accurate and effective results in short-term forecasting. Moreover, they are fairly sensitive to market information and require a large amount of operation time and computational resources. (2) Conventional statistical arithmetic cannot address forecasting with high noise and fluctuation, irregular and nonlinear trends, or features of wind speed series data, which are mainly limited by the prior assumption of a linear form among time series. Furthermore, in realistic cases, these approaches require numerous historical data for wind speed prediction and have a high dependence on data; thus, once the original data change abruptly due to environmental or social factors, prediction errors will suddenly increase much [42]. (3) Spatial correlation arithmetic makes it relatively difficult to implement perfect wind speed forecasting owing to the vast quantities of information such as wind speed values of many spatially correlated sites that need to be considered and collected [43]. (4) Distinct from the other approaches, artificial intelligence arithmetic, which could successfully capture hidden non-linear relationships among given historical data, has been widely researched and applied to address complicated relationships and effectively perform forecasting [44]. However, there are still many disadvantages and defects with artificial intelligence methods, for example, easily getting into a local optimum, over-fitting, and exhibiting a relatively low convergence rate [45]. (5) The individual forecasting models do not pay attention to the necessity and importance of data preprocessing, and hence, cannot always achieve a high forecasting accuracy and satisfy the requirements of time series forecasting. Therefore, owing to the unavoidable drawbacks of the individual models, the abovementioned forecasting methods cannot always capture the wind speed trend and cannot be applied in all situations. Consequently, a combined model, which is deemed as an excellent method that utilizes the advantages of individual approaches to obtain a higher forecasting accuracy, has often been taken into consideration [46].

Based on the analysis above, a novel combined model is developed in this study. It combines a data preprocessing technique, an advanced optimization algorithm, no negative constraint theory (NNCT) [47], and several forecasting algorithms, namely BPNN [48], ENN [49], WNN [50], and generalized regression neural network (GRNN) [51]. It successfully capitalizes on the merits of the individual forecasting models, resulting in further improvements. More specifically, based on the decomposition and ensemble strategy, the original wind speed series are decomposed and reconstructed into a filtered time series, which ensures that the high frequency noise signal is eliminated effectively. Then, several individual algorithms are used for forecasting the processed wind speed data. Next, a novel deciding weight method based on a swarm intelligence-based evolutionary computation technique and the leave-one-out strategy is successfully developed to integrate the individual models and obtain the final forecasting result. As far as we know, this advanced computation technique has been effectively employed in some hybrid models to enhance the forecasting accuracy, being initially performed to optimize the weight of each model and employed in the combined forecasting model. The primary contributions and novelties of this study are described below:

(1) ***Based on the decomposition and ensemble strategy, a data***