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

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ABSTRACT

Accurate and stable wind speed forecasting is a crucial issue in the wind power industry, which has a significant effect on power system operation, power grid security and market economics. However, most prior articles only attach importance to improving the accuracy or stability, few of them focus on the accuracy and stability, simultaneously. Therefore, considering one criterion i.e. accuracy or stability is insufficient, in this study a novel powerful hybrid forecasting system is successfully developed, which contains four modules: data preprocessing module, optimization module, forecasting module and evaluation module. In this system, decomposing algorithm is applied to divide the original wind speed data into a finite set of components. Moreover, to achieve high accuracy and strong stability simultaneously, multi-objective ant lion optimization is employed to optimize the initial weights between layers and thresholds of the Elman neutral network in the optimization module, which overcomes the drawbacks of single-objective optimization algorithms. Finally, evaluation module including hypothesis testing and evaluation criteria is introduced to make a comprehensive evaluation for this system. The experimental results indicate that the average values of the mean absolute percent errors of the developed model utilizing 10-min, 30-min and 60-min interval data are 2.8220%, 5.0216% and 7.7205%, respectively, which are much lower than those of the comparison models.

1. Introduction

Recently, owing to the rapid growth of the enormous energy consumption, the present increasingly serious global energy crisis as well as the limited reserves of the conventional resources such as coal, natural gas, and oil etc. and their caused many adverse effects on the environment, the development and utilization of renewable energy resources have received considerable attention all over the world [1]. Therefore, under such background developing renewable energy sources and achieving the sustainable development of energy have become a major initiative of the world's energy development strategy [2].

Wind energy, regarded as one kind of the most significant and promising renewable energy resources such as wind, solar, geothermal, biomass, tidal, and hydropower etc., is clean, steady, abundantly available, reliable, inexhaustible, widespread, and economical [3], which has become the fastest growing renewable energy resource for electricity generation. Additionally, it can be effectively utilized to address the great majority of worldwide energy demands without producing sulfide, carbon dioxide or other harmful gases [4]. For example, by the end of 2015, the worldwide total cumulative installed wind capacity has reached about 432,680 MW. Moreover, in [5], it has been estimated that about 12% of the worldwide electricity will be supplied by wind energy in 2020. Meng et al. [6] also pointed that wind energy's contribution to the global electricity supply is expected to reach 22% by 2030. However, Azimi et al. [7] indicated that the intermittency and complex fluctuation of wind speed can cause reliability and stability problems for the power system operation, which have drawn increasing attention of many researchers all over the world [8]. These factors may also result in high cost and low efficiency, especially when wind power is integrated into power grid systems [9]. Moreover, the relevant research suggests that approximately 30% in the expectation of wind power generation can be promoted if the prediction accuracy of the wind speed increases 10% [10]. Thus, in an effort to enhance the utilization efficiency of wind power and reduce the integration cost of wind energy, the development of excellent forecasting techniques and obtained highly accurate and strongly stable wind speed forecasting have become imperative [11].

Over the past few decades, an increasing number of wind speed forecasting approaches have been developed in many relevant

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literatures. Generally, these methods can be broadly divided into four major categories: physical approaches, conventional (statistical) methods, artificial intelligent (AI) techniques and hybrid or combination models [12]. Physical models, also known as meteorological approaches, which are on account of numerical weather prediction (NWP) and mainly make use of physical data, such as temperature, density, speed, and topography information [13]. However, these approaches are not suitable for wind speed forecasting because of their complex calculation process and high costs. On the contrary, statistical models, also called stochastic time series models, such as the autoregressive (AR) methods, filtering methods, the autoregressive moving average (ARMA) methods, and widely utilized autoregressive integrated moving average (ARIMA) approaches et al., which are simple and easy to implement by utilizing numerous historical data for wind speed time series forecasting. For example, Poggi et al. [14] adopted AR model to forecast and simulate wind speed in Corsica and confirmed that AR model is able to reproduce correctly the mean statistical characteristics of the real wind speed data. Babu and Reddy [15] indicated that ARIMA models assume that the errors should follow the normal distribution, which also need the time series be made stationary before fitting a linear equation to the data. Moreover, Kavasseri and Seetharaman [16] utilized fractional ARIMA to forecast wind speed on the day-ahead and two-day-ahead horizons and finally the results showed that the developed model can perform better than the persistence model. However, these methods cannot deal with the non-linear features of wind speed time series because the major limitation is the pre-assumed linear form of these models [17].

Fortunately, with the rapid development of the soft-computing techniques during the past several years, an increasing number of different intelligence algorithms, such as artificial neural networks (ANNs), support vector machines (SVMs), and the expert system etc. have been successfully developed and widely applied in the field of wind speed forecasting [18]. However, among these models, ANNs, as a kind of the most booming branches, are different from the traditional statistical models or physical approaches, which have been widely accepted and popularly utilized to address complicated relationships, perform adaptive control and find prediction. Furthermore, it is very important for decision-makers to focus on alternative models, because they can learn from patterns and capture hidden non-linear relationships existing in given historical data, especially when the underlying relationships are unknown or difficult to determine [19]. For example, with the aim of improving prediction accuracy and developing a model for each month of the year, Cadenas and Rivera [20] applied ANNs to the hourly wind speed time series. Ren et al. [21] utilized ANNs to predict 6-hourly average wind speed time series and observed that the performances of ANNs are better than that of ARIMA. However, there are also many weaknesses with ANN models such as easily falling into local optimum, and over-fitting [22].

Due to the inherent shortcomings of each method and the intermittency, complex fluctuation of wind speed series, the above-mentioned forecasting techniques cannot always mine and capture the characteristics of wind speed, especially when faced with non-linear time series, which often result in poor forecasting results. Therefore, in order to obtain an advanced forecasting method for higher accuracy levels and wider forecast horizons, the methods called as hybrid models and combined models have emerged [23] and been widely applied in many applications, which mainly incorporate the individually superior features including various forecasting models, optimization algorithms and signal processing techniques. In recent years, with the purpose of developing hybrid models for wind speed forecasting, several optimization algorithms have been applied to optimize the initial weight and threshold values in ANNs to avoid the instability of the final results [24]. For instance, Meng et al. [6] developed a novel hybrid model integrated crisscross optimization algorithm, wavelet packet transform (WPT) and ANN for wind speed forecasting and experimental results demonstrated that their proposed hybrid model outperformed other benchmark models. Zhang et al. [25] developed a novel hybrid model including the complete ensemble empirical mode decomposition adaptive noise (CEEMDAN), flower pollination algorithm with chaotic local search (CLSFPA), five ANNs and no negative constraint theory (NNCT) [26] for short-term wind speed forecasting. The results showed that their developed hybrid model was superior to other single methods with regard to the accuracy and reliability of the forecasting results. In addition, in an effort to obtain excellent forecasting results with highly accuracy, in recent years a novel promising strategy of "decomposition and ensemble" or "divide and conquer" has been successfully proposed and widely utilized in many forecasting fields, which can really help to enhance the prediction performance [27]. For example, Tang et al. [28] applied ensemble empirical mode decomposition (EEMD) to decompose the historical data of nuclear energy consumption into a set of components from low-to-high frequency, and then employed least squares support vector regression (LSSVR) to predict all components. Finally, the experimental results indicated that the proposed approach was a promising model. Similarly, Wang et al. [29] applied the same strategy based on EEMD, genetic algorithm (GA) and ANNs to predict the short-term wind speed and obtained highly accuracy than before. Therefore, to achieve higher accuracy, the above-mentioned strategy of "decomposition and ensemble" will be also considered in this paper.

Moreover, most prior literatures only focus on improving prediction accuracy, which always neglect the importance of forecasting stability improvement, despite it is crucial to the effectiveness of forecasting models. However, both accuracy and stability are very vital when evaluating the performance of forecasting models. Therefore, considering the characteristics of wind speed data as well as one criterion i.e. accuracy or stability is insufficient, algorithms applied for optimizing the initial weight and threshold values of ANNs in hybrid forecasting methods should simultaneously pay more attention to accuracy and stability. Nevertheless, to obtain these two relatively independent objectives at the same time, high accuracy and strong stability, belongs to the multi-objective optimization problems (MOPs) rather than the single-objective optimization problems (SOPs). During the past several decades, an increasing number of multi-objective optimization algorithms such as the multi-objective flower pollination algorithm (MOFA), the binary coded elitist non-dominated sorting GA (NSGA-II) and the multi-objective dragonfly algorithm (MODA) etc. have been successfully proposed and popularly used to solve practical engineering problems. For instance, Chen et al. applied hybrid NSGA algorithm to make multi-objective optimal design of nuclear power plant [30]. Lu et al. developed multi-objective discrete virus optimization algorithm and then applied it for flexible job-shop scheduling problems with controllable processing times [31]. Unlike the single-objective optimization algorithms, which only have one global optimum, multi-objective optimization algorithms can search for and gather a series of optimal solutions for engineering problems with more than one objective at the same time.

The multi-objective ant lion optimization (MOALO) algorithm, as an extended version of ant lion optimization ALO algorithm, was first proposed by Mirjalili et al., which can not only benefit from high convergence and coverage, but also perform better than the NSGA-II and multi-objective particle swarm optimization (MOPSO) [32]. Moreover, up to now, there is no researches or applications of MOALO in terms of wind speed forecasting.

Therefore, with the hope of achieving more accurate and highly stable wind speed prediction at the same time, the promising principle