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A combination forecasting approach applied in multistep wind speed forecasting based on a data processing strategy and an optimized artificial intelligence algorithm

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HIGHLIGHTS

- A combined model is proposed for multi-step ahead wind speed forecasting.
- Data preprocessing technology is introduced to improve the forecasting performance.
- Quasi-Newton algorithm is used to increase the particle diversity of water cycle algorithm.
- The accuracy and stability of wind speed forecasting are improved simultaneously.
- The simulation results are validated well in China.

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ABSTRACT

Owing to the complexity and uncertainty of wind speed, accurate wind speed prediction has become a highly anticipated and challenging problem in recent years. Researchers have conducted numerous studies on wind speed prediction theory and practice; however, research on multi-step wind speed prediction remains scarce, which hinders further development in this area. To improve upon the accuracy and stability of multi-step wind speed prediction, this paper proposes a combination model based on a data preprocessing strategy, an improved optimization model, a no negative constraint theory, and several single prediction models. To improve upon forecasting performance, an improved water cycle algorithm based on a quasi-Newton algorithm is proposed to optimize the weight coefficients of the single models. In the empirical research, 10-min and 30-min wind speed data from Shandong Province in China, collected for case studies, were used to assess the comprehensive performance of the proposed combination model. Finally, we used 10-fold cross-validation and multiple error criteria to evaluate the comprehensive performance of the proposed combination model. The simulation results indicate that (a) the quasi-Newton algorithm can effectively increase the diversity of the water cycle algorithm particles, resulting in improved water cycle algorithm optimization performance; (b) the combination model exhibits superior predictive performance to a single model by taking advantage of each single model; and (c) the proposed combination model can effectively improve multi-step wind speed prediction results.

1. Introduction

Energy is an important material basis for human social progress and economic development; however, heavy use of traditional energy results in environmental pollution. In recent years, increasing attention has been paid to the development of renewable energy. With the

Abbreviations: WRF, weather research and forecast; HRM, high resolution model; COSMO, consortium for small scale modeling; MM5, mesoscale model 5; NWP, numerical weather prediction; ARIMA, autoregressive integrated moving average; S-T Model, spatio-temporal model; FIS, fuzzy inference system; LRA, linear regression approach; ANN, artificial neural network; KF, Kalman filter; BP, back propagation neural network; BP_2, back propagation neural network with 2 hidden layer; ENN, Elman neural network; RBF, radical basis function; SVM, support vector machine; PSO, particle swarm optimization; FNN, fuzzy neural network; WT, wavelet transform; SSA, singular spectrum analysis; EMD, empirical mode decomposition; EEMD, ensemble empirical mode decomposition; CEEMD, complementary ensemble empirical mode decomposition; IMFs, intrinsic mode functions; WCA, water cycle algorithm; FE, forecasting effectiveness; DM, Diebold-Mariano value; DE, differential evolution; WNN, wavelet neural network

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development and utilization of renewable energy, wind power technology and costs are second only to those of hydro-power, which is the most valuable renewable energy source for the future. China is one of the major energy-consuming countries, therefore paying particular attention to the development of renewable energy sources. During the first half of 2017, China's wind power generation capacity was 149 billion kWh, an increase of 21%. According to the 13th five-year plan for wind power development, China's grid-connected wind power will reach over 210 million kW, with an annual wind power generation capacity of more than 420 billion kWh, by 2020 [1]. Unlike traditional power generation, wind power exhibits the characteristics of complexity and instability, which leads to lower power system security and stability. To optimize the grid dispatch and improve wind farm efficiency, accurate wind speed prediction is becoming increasingly necessary [2].

Numerous scholars have proposed various forecasting models to improve the accuracy and stability of wind speed forecasting. Different classification methods are available for wind speed prediction models, according to different classification criteria. Depending on the required application, these models can be divided into long-term, medium-term, short-term, and ultra-short-term forecasting models [3]. Long-term forecasting models are mainly applied to feasibility studies of wind farm design, and estimate the annual power generation of wind farms. Medium-term forecasting models provide a basis for the operation and maintenance planning of wind farms and the load dispatch planning of power plants. Short-term forecasting models can be used for reasonable dispatching of the power grid to ensure the power supply quality. Ultra-short-term forecasting models can be used for wind turbine control and improved power quality [4]. According to the structure of forecasting models, they are classified as single, hybrid, and combined models [5]. A hybrid model is defined as a forecasting model that integrates several single models to achieve increased predictive accuracy and stability [6]. A combined model combines several forecasting models and assigns a weighting coefficient to each method according to its forecasting performance [7]. Based on the forecasting process, these forecasting models can be divided into two categories: physical and statistical methods.

The physical method is based on the forecast results of the numerical weather prediction (NWP), to obtain weather data such as wind speed, wind direction, air pressure, and air temperature [6]. Thereafter, the wind speed and wind direction of the wind turbine set are calculated according to information such as the contour line, roughness, obstacles, and temperature stratification around the wind farm. The most commonly used physical models are weather research and forecast, the high-resolution model, the consortium for small scale modeling, and the mesoscale model 5 (MM5) [8]. The physical model has become relatively mature, and is applied to long-term wind speed forecasting and the assessment of wind energy resources. Maria [9] proposed a wind power forecasting system, integrating NWPs with an artificial neural network (ANN), and the simulation results demonstrated that this system achieved an interesting improvement in the forecasting performance, particularly with longer time horizons. The drawbacks of the physical method are also obvious: it requires additional background information, the calculations are complex, and it is unsuitable for short-term and ultra-short-term wind speed forecasting [10]. Statistical methods are easy to use and offer time savings compared to physical methods. Statistical methods are aimed at mining the relationships among historical data and establishing forecasting models, including traditional statistical and machine learning models [11]. Commonly used traditional statistical models include the autoregressive integrated moving average model (ARIMA), Kalman filter (KF), and spatial correlation method [12]. Erdem [13] employed several approaches based on autoregressive moving average method (ARMA) to forecast wind speed and direction, and the simulation results indicated that these approaches are superior to the traditional linked ARMA model. Cassola [14] analyzed the KF to determine the optimal configuration for wind speed and power forecasting. The simulation results demonstrated that tuning the time step and forecast horizon of the filter can provide significant forecast improvements with respect to the wind speed model direct output, particularly when used for very short-term forecasting. Frequently used machine learning models include the back propagation neural networks (BPNN), radial basis function networks, Elman neural network (ENN), wavelet neural network (WNN), fuzzy neural network, etc. For example, Li [15] compared three different ANNs in terms of wind speed and found that the selection of the neural network type and parameters significantly affects the wind speed forecasting performance. Sideratos [16] described a novel methodology for wind power forecasting based on the RBF, which focuses on the uncertainty information regarding future wind power production by predicting a set of quantiles with predefined nominal probabilities. Liu [17] proposed a new hybrid approach based on the secondary decomposition algorithm and ENNs in order to improve the wind speed forecasting accuracy, and the results indicated that the proposed model considerably improved the forecasting performance of standard ENNs considerably. Compared to these single models, hybrid and combined models are the mainstream for wind speed and power forecasting.

Over the past several years, numerous researchers have devoted their efforts to proposing more accurate and stable wind speed forecasting models for wind power forecasting systems [18,19]. The commonly used hybrid model structure involves the integration of data preprocessing, parameter optimization model, and forecasting model. Wavelet transform (WT), singular system analysis (SSA) and empirical mode decomposition (EMD) are used in many hybrid models for preprocessing original data, and these de-noising technologies are highly effective in improving forecasting accuracy and stability. For example, Tan [20] and Tascikaraoglu [21] incorporated their forecasting model based on WT to improve the forecasting accuracy of the electrical price and wind speed, respectively. An [22] introduced an EMD-based signal filtering method that is fully data driven in order to reduce the noise signals of electricity demand series, and this method could noticeably improve the forecasting accuracy. Meta-heuristic algorithms are effective methods for optimizing the forecasting model weights and thresholds [23]. Jiang and Ma [24] proposed a novel hybrid model integrating fast empirical ensemble mode decomposition, improved simulated annealing, modified particle swarm optimization (PSO) and a BPNN, to improve wind speed forecasting accuracy of wind speed. The simulation results indicated that the proposed model was more effective. The combined model has also been the focus of research in recent years [6]. Xiao [2] discussed a new combined model and proposed an optimization algorithm for its weight coefficients based on the non-positive constraint combination theory. The simulation results indicated that this combined model could effectively improve the prediction accuracy compared to other benchmark models.

The purpose of this paper is to improve the accuracy and stability of ultra-short-term wind speed forecasting. Over the past several years, numerous prediction models have been proposed for this purpose. A summary of the reviewed forecasting models is listed in Table 1. The combination model can incorporate the advantages of each model and effectively avoid the shortcomings in order to improve the accuracy stability of wind speed forecasting [6]. A novel combined model, integrating data preprocessing, a weight optimization algorithm, non-positive constraint theory, and several single forecasting models, is proposed in this paper. Complete ensemble EMD (CEEMD) was used to remove the original data noise in order to obtain a more representative trend. Several single models, including the BPNN, BPNN with double hidden layers, RBFNN, ENN, and WNN were used as forecasting models. An improved optimization algorithm combining the water cycle algorithm (WCA) and Broyden family algorithm was proposed to optimize the weights of the corresponding forecasting models. To verify the forecasting performance of this proposed combined model, 10-min and 30-min wind speed data from Yantai, Shandong Province, China were used for simulation.