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Multi-step ahead wind speed prediction based on optimal feature extraction, long short term memory neural network and error correction strategy

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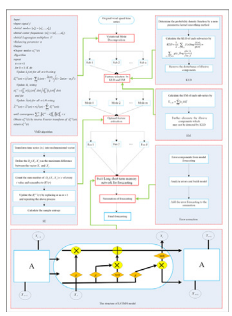
HIGHLIGHTS

- Develop an optimal feature extraction algorithm to capture the optimal features of wind speed fluctuations.
- Introduce an error correction strategy to improve the prediction precision of wind speed.
- A innovate hybrid model is successfully proposed for multi-step ahead wind speed prediction.
- Design three experiments from the real wind farms to validate the availability and reliability of the developed model.

GRAPHICAL ABSTRACT



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ABSTRACT

Forecasting wind speed accurately is a key task in the planning and operation of wind energy generation in power systems, and its importance increases with the high integration of wind power into the electricity market. This research proposes an innovative hybrid model based on optimal feature extraction, deep learning algorithm and error correction strategy for multi-step wind speed prediction. The optimal feature extraction including variational mode decomposition, Kullback-Leibler divergence, energy measure and sample entropy is utilized to catch the optimal features of wind speed fluctuations for balancing the calculation efficiency and prediction accuracy. The deep learning algorithm based on long short term memory network, is utilized to detect the long-term and short-term memory characteristics and build the suitable prediction model for each feature sub-signal. The error correction strategy based on a Generalized auto-regressive conditionally heteroscedastic model is developed to modify the above prediction errors when its inherent correlation and heteroscedasticity cannot be ignored. Three real forecasting cases are applied to test the performance and effectiveness of the developed model. The simulation results indicate that the developed model consistently has the smallest statistical errors, and outperforms other benchmark methods. It can be concluded that the developed approach is conductive to strengthening the prediction precision of wind speed.

1. Introduction

Wind power being one of the most promising renewable energy sources, has a rapid development throughout the world recently. The total installed capacity of wind power has been doubled in the past 3 years, and it is estimated that in 2020, approximately 12% of total

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world electricity demands will be supplied from wind power [1]. With the high integration of wind power into electric power, the power system is becoming more unreliable because of the intermittent and stochastic natures of wind speed fluctuations [2]. To guarantee a reliable system operation, the power system operator has to schedule sufficient spinning reserve for wind power, which will increase the operating cost of wind power and limit the large-scale exploitation and utilization of wind energy [3]. Thus, forecasting wind speed accurately is indispensable for reducing the operating cost of wind power and enhancing the efficiency of wind power utilization [4].

In the past few decades, lots of methods have been developed for wind speed forecasting, which are usually classified into two categories including physical methods and statistical methods [5]. Physical methods employ the meteorological parameters and physical laws to establish the mathematical models for wind speed forecasting, which usually require substantial computational time and are not good at short-term prediction [6]. Statistical methods intend to use the historical samples to simulate the wind speed fluctuations, which have advantages for short-term prediction. These statistical methods are usually divided into three groups including time series models, machine learning models and hybrid models [7]. These time series models include auto-regressive (AR) model, moving average model (MA) and auto-regressive moving average model (ARMA). Erdem and Shi [8] adopted four ARMA models to predict the vector of wind speed and direction, and the simulate results validated the effectiveness of these models. Lydia et al. [9] used several AR models to enhance the prediction performance of wind velocity. Cadenas and Rivera [10] predict the wind speed by an improved ARMA model, and the results showed that the prediction precision of the proposed model was higher than the persistence model. Although these time series models have satisfactory forecasting performance when wind speed signal shows linearity and stationarity, but they suffer from the disadvantages of nonlinear fitting capability weakness because of their linear assumption among time series. To capture these nonlinear characteristics of wind speed change, lots of machine learning models have been proposed to perform wind speed prediction. For instance, Ren et al. [11] introduced a particle swarm optimization (PSO) to improve the prediction performance of a back propagation (BP) neural network, and the simulate results demonstrated the effectiveness of the proposed model. Zhang et al. [12] presented a radial basis function (RBF) neural network for improving the prediction performance of wind speed. Santamaría-Bonfil et al. [13] employed a support vector regression (SVR) to conduct the wind speed prediction, and the simulate results indicated that the SVR model outperformed these benchmark models. In addition, numerous hybrid models have been developed for wind speed forecasting. For instance, Salcedo-Sanz et al. [14] presented a hybrid model based on fifth generation mesoscale model and artificial neural networks (ANNs) for wind speed forecasting. Song et al. [15] developed a novel hybrid model based on advanced optimization algorithm to improve the forecasting performance of wind speed. Wang et al. [16] proposed a hybrid system based on multi-objective whale optimization algorithm for wind speed prediction. Zhao et al. [17] developed a novel hybrid model based on a weather research and forecasting (WRF) model and an optimized association approach for multi-step ahead wind speed and power prediction. Salcedo-Sanz et al. [18] exploited the input data diversity and developed a novel hybrid model based on physical models and ANNs to improve the forecasting performance of wind speed.

Recently, numerous feature selection methods have been introduced to enhance the forecasting ability of the mainstream prediction models. These methods are usually classified into two categories including wrapper methods and filter methods [19]. Wrapper methods may require large amount of computing time and are usually combined with fast machine learning prediction models, whereas filter methods are performed based on the data and are usually faster than wrapper methods [20]. Thus, the filter methods mainly including wavelet decomposition (WD) and empirical mode decomposition (EMD), have been widely applied in wind speed prediction issues in recent years. For instance, Kiplangat et al. [21] utilized the WD to select the features from original wind speed signal and build the ARMA model for prediction. The results showed the advantages of feature selection method based on WD. Zhang et al. [22] developed two feature selection-based hybrid models which combined EMD with machine learning models (ANN and SVR) for wind speed forecasting, and the simulate results validated the effectiveness of the proposed models. In general, the WD technique has advantages for time-frequency analysis [23], while the EMD has better self-adaptability in handling the chaotic nature and inherent complexity of original signal [22]. Nevertheless, there are some drawbacks: (a) the performance of the WD relies on the choice of wavelet basis and decomposition levels highly; (b) the EMD lacks the clear physical meaning and strict mathematical theory; (c) these common WD (or EMD)-based hybrid models may be unreasonable and cause a big disturbance on the final forecasting because not all sub-signals obtained by WD (or EMD) are beneficial in wind speed prediction. To overcome these disadvantages, it is necessary to develop an effective feature selection algorithm for extraction meaningful features and removing the irrelevant features from original wind speed signal.

The prediction models are the core part of these feature selection-based hybrid models. Different from the shallow learning models, the deep learning models, such as deep belief network (DBN), convolutional neural network (CNN) and recurrent neural network (RNN), can capture the deep inherent features from original data and have been developed rapidly in recent years [24]. Kuremoto et al. [25] designed a DBN with restricted Boltzmann machines for time series prediction and the simulate results validated the effectiveness of the proposed model. Wang et al. [26] presented a CNN model for probabilistic wind power prediction and concluded that the proposed model was superior to the benchmark models. However, these deep learning models are not widely used for wind speed prediction. Taking into account the long-term and short-term dependency of wind speed change, a special kind of RNN called as long short term memory network (LSTMN), is utilized to detect the long-term and short-term memory natures of wind speed change in this study.

Additionally, recent studies show that the error correction strategy (ECS) is also one of the most effective ways to improve the prediction accuracy of wind speed [27]. In Ref. [28], a Markov model was used to correct the prediction errors of the SVR and the results verified the effectiveness of the ECS. Shi et al. [29] employed ANN and SVR to correct the forecasting errors of the ARMA and the simulate results validated the contribution of the ECS. However, most of these filter-based methods neglect the errors of the prediction models because of the hypothesis of white noise. It is obviously not true.

In this study, a novel filter-based hybrid model is developed for multi-step ahead wind speed prediction, which combines deep learning algorithm (DLA) with optimal feature extraction (OFE) and ECS. The OFE includes variational mode decomposition (VMD), Kullback-Leibler divergence (KLD), energy measure (EM) and sample entropy (SE). The proposed model is composed of five steps as follows: (a) the VMD is utilized to resolve a non-stationary wind speed signal into several more stationary sub-signals; (b) two feature selection algorithms including KLD and EM are applied to capture meaningful features from original wind speed signal and remove the disturbance of illusive components introduced by filter algorithm itself; (c) the SE is adopted to recombine the features obtained from two feature selection algorithms for balancing the calculation efficiency and prediction accuracy; (d) the LSTMN is employed to establish the prediction model for each feature sub-signal; (e) the hybrid of LSTMN and Generalized auto-regressive conditionally heteroscedastic (GARCH) is adopted to correct the above prediction errors when its inherent correlation and heteroscedasticity cannot be neglected. Three real forecasting cases are applied to verify the performance and effectiveness of the proposed model. The simulation results show that the proposed model consistently has the minimum statistical errors, and outperforms other benchmark methods.