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A novel bidirectional mechanism based on time series model for wind power forecasting

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HIGHLIGHTS

- Bidirectional mechanism with forward and backward models for wind power forecasting.
- The backward model based on extreme learning machine with backward optimization.
- Forecasts assessment using a comprehensive multiple-horizon error analysis.
- The novel mechanism outperforms other reference models for forecasting.
- The bidirectional mechanism can be implemented with other basic forecasting models.

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ABSTRACT

A novel bidirectional mechanism and a backward forecasting model based on extreme learning machine (ELM) are proposed to address the issue of ultra-short term wind power time series forecasting. The backward forecasting model consists of a backward ELM network and an optimization algorithm. The reverse time series is generated to train backward ELM, assuming that the value to be forecasted is already known whereas one of the previous measurements is treated as unknown. In the framework of bidirectional mechanism, the forward forecast of a standard ELM network is incorporated as the initial value of optimization algorithm, by which error between the backward ELM output and the previous measurement is minimized for backward forecasting. Then the difference between forward and backward forecasting results is used as a criterion to develop the methods to correct forward forecast. If the difference exceeds a predefined threshold, the final forecast equals to the average of forward forecast and latest measurement. Otherwise the forward forecast keeps as the final forecast. The proposed models are applied to forecast wind farm production in six time horizons: 1–6 h. A comprehensive error analysis is carried out to compare the performance with other approaches. Results show that forecast improvement is observed based on the proposed bidirectional model. Some further considerations on improving wind power short term forecasting accuracy by use of bidirectional mechanism are discussed as well.

1. Introduction

Wind energy is regarded as a good alternative to deal with environmental problems and energy crisis, which makes it the most rapidly growing renewable energy over the last decades. Many countries adopt various incentives and subsidy policies to develop domestic wind energy industry, such as EU countries, America and China. According to the report published by World Wind Energy Association [1], 63.7 GW of new wind power capacity was installed around the world in 2015. The total wind capacity of the world has reached 435 GW at the end of 2015, with cumulative growth of more than 17%.

Research works devoted to wind energy mainly focus on wind turbine condition monitoring [2] and power curve modeling [3,4], characterizations of wind power generation [5,6], wind resources assessment [7–9], impacts of wind power on power systems [10,11], wind farm control [12,13], wind speed and power forecasting, etc. Due to the intermittent and non-dispatchable features of wind power, the stability and reliability of conventional power system operation will be threatened with large-scale integration of wind power. Thus wind power forecasting as a sufficient

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tool has been widely utilized to alleviate various problems caused by wind power.

Wind power forecasting methods are generally classified into two groups [14–16]: physical and statistical ones. The physical models [17] take into consideration detailed physical description to model onsite conditions at the location of the wind farm, usually by refining coarse Numerical Weather Prediction (NWP) data. They are superior for short-term forecasting 6–72 h ahead. The statistical models can characterize the relationships between some explanatory variables and online measured power data, for which enough historical data is prerequisite. The statistical models can be further divided into two subclasses. The first class is the NWP based statistical models that intend for mapping the relationship between NWP data and measured wind power of wind farms [18–21]. They learn knowledge from historical data rather than consider the detailed physical processes. The forecasting time horizons are the same as that of physical models.

The other kind of statistical models are time series based models, which rely on historical wind speed or power measurements and take the predicted variable itself as explanatory variables. They are suitable for ultra-short term (typically minutes to hours) forecasting since they can capture the hidden stochastic characteristics of wind speed. This kind of models includes Box–Jenkins models [22], Kalman filters [23], grey models [24], Markov chain [25] and artificial neural networks (ANN) [26], etc.

The appeal of Box–Jenkins models lies in their simplicity and very low computation time. But they may have poor forecasting performance if the time series are nonstationary. Many improved models based on Box–Jenkins models are developed for wind speed and power forecasting. Duran et al. [27] proposed autoregressive with exogenous variable (ARX) models which incorporate wind speed time series to carry out the wind power prediction. Accuracy improvement due to the use of ARX models was found in comparison with persistence method and conventional autoregressive (AR) models. Riahy and Abedi [28] improved the wind speed forecasting performance of AR models by filtering out the less effective frequency components from the wind speed spectrum. Kavasseri and Seetharaman [29] used a fractional ARIMA model (*f*-ARIMA model) to forecast wind speed and wind power. Erdem and Shi [30] developed four ARMA based models to forecast wind speed and direction. Among them, two approaches feature the decomposition of wind data into different components or attributes. Each component or attribute is presented by a specified ARMA forecasting model. Other two models are based on vector autoregression (VAR) models.

Advanced machine learning approaches such as ANN and support vector machine (SVM) can also be applied to time series forecasting. Comprehensive comparison studies were carried out to examine the performances of different machine learning approaches for wind speed and power forecasting [26,31,32]. It is found that no single model outperforms others universally and model parameters and the dynamic characteristics of wind speed have impacts on the performance. Recently, extreme learning machine (ELM) has been used for wind energy forecasting [33,34] since it has good generalization performance and faster computation speed than networks trained using back-propagation algorithms.

Different hybrid prediction algorithms have been proposed in the literature in order to benefit from the unique capability of single models [35]. Liu et al. [36] compared hybrid ARIMA-ANN model and hybrid ARIMA-Kalman model. Case studies show both of them have good performances. Additionally, Zhang et al. [37] presented a fuzzy group forecasting model. Fuzzy aggregation and a defuzzification procedure are used to combine three different groups of LS-SVM forecasting models to get the final forecast. In [38] a two-step dynamic optimal combination model is proposed based on variable adaptive vector forgetting factor for ultra-short term wind power forecasting.

Apart from traditional weighting-based hybrid approaches, other hybrid forms are to combine forecasting models with data pre-processing techniques, error post-processing techniques and parameter selection and optimization techniques. Among the data preprocessing techniques, the wavelet decomposition [39–41] and empirical mode decomposition [42–44] are prevailing methods in terms of their easy implementation and adaptive ability of time–frequency analysis. The decomposition methods can decompose wind time series into low and high frequency components which describe the approximate and detail levels, respectively. The error post-processing techniques takes into account the residual error values obtained from a forecasting model and then use the estimated error to correct final forecasting results [45,46]. The parameter selection and optimization techniques allow improving the forecasting accuracy and avoiding the time consuming process of model optimization. Genetic algorithm [47], crisscross algorithm [48], particle swarm optimization [49], cuckoo search algorithm [50], etc. have been adopted to optimize the parameters of the wind speed and power forecasting models.

In the above mentioned models, various measures are taken to improve the forecasting accuracy of time series based models, such as incorporating exogenous variables, data preprocessing or error post-processing, parameter selection and optimization and combination of different methods. Unlike these approaches, a novel bidirectional mechanism and a backward forecasting model based on ELM for wind power time series forecasting are introduced in this paper. The backward forecasting model consists of a backward ELM network and an optimization algorithm. The reverse time series is generated to train backward ELM, assuming that the value to be forecasted is already known whereas one of the previous measurements is treated as unknown. In the framework of bidirectional mechanism, the forward forecast of a standard ELM network is incorporated as the initial value of optimization algorithm, by which error between the backward ELM output and the previous measurement is minimized for backward forecasting. Then the difference between forward and backward forecasting results is used as a criterion to determine the methods applied to correct forward forecast. If the difference exceeds a predefined threshold, the final forecast equals to the average of forward forecast and latest measurement. Otherwise the forward forecast keeps as the final forecast. The proposed models are used to forecast wind farm power production for six time horizons: 1–6 h. The experimental data used can be freely accessed online. A comprehensive error analysis is carried out to compare the performances of different models.

The structure of the paper is organized as follows: In Section 2, the bidirectional mechanism for wind power forecasting is described. Section 3 introduces detailed criteria for model evaluation. Section 4 is devoted to a case study based on bidirectional forecasting mechanism, including data description, models parameterization, forecasting performance evaluations and discussions. Conclusions and future works to be investigated are given in Section 5.

2. Methodology and models

2.1. Extreme learning machine for time series forecasting

The Extreme Learning Machine (ELM), developed by Huang et al. [51], is a feed-forward neural network for classification or regression with a single layer of hidden nodes, where the weights connecting inputs to hidden nodes are randomly assigned and not updated in the training procedure. ELM has been used in many fields such as face recognition, image classification, and wind