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A self-adaptive hybrid approach for wind speed forecasting

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ABSTRACT

Wind power, as a promising renewable energy source, has environmental benefits, as well as economic and social ones. To evaluate wind energy properly and efficiently, this study proposes a hybrid forecasting approach that combines the Extreme Learning Machine (ELM), which rarely presents in literature on wind speed forecasting, the Ljung-Box Q-test (LBQ) and the Seasonal Auto-Regressive Integrated Moving Average (SARIMA) to enhance the accuracy of wind speed forecasting. The proposed hybrid method is examined by forecasting the mean daily and mean monthly wind speed of four wind speed observation sites located in northwestern China. The results confirm that, compared with other popular models (ARIMA , SARIMA , Back-Propagation neural network (BP) and ELM), the hybrid forecasting method improves the predictions of daily and monthly wind speed, which indicates that the developed hybrid method exhibits stronger forecasting ability. The forecasting results also suggest the hybrid approach has better generality and practicability in different wind farms.

1. Introduction

With global economic development, global energy demand is growing drastically, particularly in developing countries. Wind energy, as one of the most popular renewable energies, has attracted great concern and is being developed around the world. At the end of June 2013, the installed wind power capacity has amounted to 296,255 MW globally, and the installed wind turbine generators globally can generate approximately 3.5% of the global electricity demand [1]. In China , the wind energy industry has been booming over the past decade. In 2012, the newly installed wind power capacity reached 12.96 GW [2]. In the initial six months of 2013, the installed capacity increased 5.5 GW, which accounted for 39% of the world market for new wind turbines. By June 2013, China has been the largest single wind market with an installed capacity of 80.8 GW [1].

It is generally acknowledged that forecasting plays an essential role in wind power generation in order to utilize this natural resource better. Some studies have demonstrated that there is a strong nonlinear relation (i.e., roughly cubic) between wind power and its speed, causing the extraordinary necessity of high accuracy prediction of wind speed in production. The difficulty lies in the fact that the system of wind speed, impacted by a series of complicated factors, including pressure and temperature differences, etc. is not easy to forecast [3].

To deal with wind speed forecasting, various methods and models have been proposed such as physical modeling methods, statistical models and soft computing methods in the last decades. Physical models forecast the wind speed by utilizing weather data. The Numerical Weather Prediction (NWP) [4–6] models produce the wind forecasting for large-scale area. However, they possess an essential difficulty in collecting the topography information. Several advanced tools, such as mesoscale meteorological model (MM5) and Computational Fluid Dynamics (CFD), are developed to better model the wind flow, particularly in complex terrain, but they lack further validation work.

Statistical models primarily forecast wind speed through analyzing historical data. The time series techniques can perform well and obtain good forecasts when the data show linearity and stationarity. The widely used time series models are the Auto-Regressive Moving Average (ARMA), the Auto-Regressive Integrated Moving Average (ARIMA), the Fractional Auto-Regressive Integrated Moving Average (FARIMA), the Seasonal Auto-Regressive Integrated Moving Average (SARIMA), exponential smoothing techniques and grey predictors [7–11].

Soft computing methods such as neural networks and fuzzy regression possess good generalization capabilities, especially in tackling nonlinear problems. And they have been extensively used

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to forecast wind speed. Among the soft computing methods, Artificial Neural Networks (ANNs) are some of the most extensively used approaches for the prediction of wind speed. Numerous types of artificial neural networks [12–17] have been proposed, such as the Back-Propagation neural network (BP), the Radial Basis Function neural network (RBF), the Multi-Layer Perceptron network (MLP) , and the Support Vector Machine (SVM). Fuzzy theory has also been employed for the wind speed forecasting [18,19]. Although soft computing methods are capable of handling wind speed sequence with nonlinearity, generalization ability is not guaranteed; therefore, a well-trained model may lead to poor prediction performance for new observations. In addition, neural networks occasionally have a problem with local minima or overfitting. Neural networks are also sensitive to parameter selection and are time-consuming.

When employing these soft methods, various methods for data preprocessing are taken to decompose the wind speed series or eliminate the stochastic volatility. Guo et al. [20] proposed a Seasonal Exponential Adjustment (SEA)-based BP neural network for the wind speed prediction. The SEA method was designed as a preprocessor to eradicate the seasonal effects from the observed wind speed datasets. In the literature [21], a type of modified Empirical Mode Decomposition (EMD)-based, feed-forward neural network was proposed for wind speed forecasting, with EMD removing the stochastic volatility. Liu et al. [22] put forward an EMD-based BP neural network for hourly wind speed prediction, in which EMD was adopted to decompose the wind speed series into a series of Intrinsic Mode Functions (IMF) for establishing BP model. Hu et al. [23] suggested a forecasting approach associated with the Ensemble Empirical Mode Decomposition (EEMD) and the SVM, as data preprocessor and predictor, respectively, to enhance the prediction precision of wind speed. Liu et al. [24] presented two wind speed forecasting models (Fast Ensemble Empirical Mode Decomposition (FEEMD)-MLP and FEEMD- Adaptive Neuro Fuzzy Inference System (ANFIS)) with the FEEMD to preprocess the wind speed series. Liu et al. [25] proposed a hybrid model for short-term wind speed prediction consisting of Wavelet Transform (WT), Genetic Algorithm (GA) and SVM, in which WT decomposes the wind speed series into two components for wind speed forecasting. Wang et al. [26] put forward an EMD–Elman Neural Network (ENN) approach for the wind speed forecast, with the FEEMD used to decompose the wind speed series for the ENN.

In recent years, there has been a trend in hybrid approaches suggested for wind speed or power forecasting. These hybrid approaches primarily comprise two types of forecasting methodologies. The first forecasting methodology is to make use of several independent forecasting techniques and develop a hybrid model in which the single models are connected through weight. In this type of hybrid models, a special case is to select the best model from the several single independent forecasting models. Li et al. [27] proposed a combinational methodology for the mean hourly wind speed forecasting. The developed approach combined three types of artificial neural network models through weights determined by a Bayesian model averaging (BMA) algorithm [28]. The BMA weighed individual forecasts based on their posterior model probabilities, and thus generated an averaged model, with the better performing forecasts receiving higher weights than the worse performing ones. Sánchez [29] proposed a type of adaptive forecast combinational model named adaptive exponential combination (AEC) to integrate a set of alternative predictions for the final forecast of wind energy. The AEC was intended to adjust the combination coefficients to the evolution of the observations by dynamically adapting the influence of prediction errors in the weighting combination coefficients. The suggested approach was prone to select the best available predictor according to the changes over time. Nan et al. [30] suggested a combinational forecasting model which was composed of a statistical time series model and a BP neural network for the short-term prediction of wind speed, in which the weight of each individual model was determined by the proportion of the each model's fitting errors in the total fitting errors of all. Combinational forecast models have also been applied in other energy fields. Azadeh et al. [31] proposed an integrated algorithm for forecasting monthly electrical energy consumption based on ANN, a computer simulation and a suite of experiments using stochastic procedures, in which the method of Analysis of Variance (ANOVA) [32] was utilized to test the null hypothesis of the above alternatives being statistically equal and select either ANN, simulated-base ANN or a conventional time series for the future demand estimation based on the test data. Azadeh et al. [33] put forward a forecasting framework which combined fuzzy regression and statistical model to predict electricity demand. The suggested approach was prone to select the best available predictor according to the changes over time by the method of Granger-Newbold [34]. The Granger-Newbold method was used to compare the two models and determine the preferred model.

The other forecasting methodology is based on the concept that wind speed time series can be decomposed into linear and nonlinear components. It can take advantage of available models for the prediction of the two components. Guo et al. [35] put forward a hybrid methodology formed by SARIMA with a least square SVM (LSSVM) model to make use of the unique strengths of SARIMA and LSSVM in linear and nonlinear modeling. The result demonstrated that the proposed hybrid technique outperformed the individual SARIMA and LSSVM models. Cadenas and Rivera [36] hybridized an ARIMA model with an ANN method to forecast the wind speed in three observation sites of Mexico. The former captured the linear components from the original wind time series while the latter extracted nonlinear component from the residuals obtained by the established ARIMA. The proposed hybrid method led to reduction in prediction errors compared with the single ARIMA or ANN methods. Shi [9] integrated the ARIMA with ANN and SVM into ARIMA-ANN and ARIMA-SVM model for the forecasting of short-term wind speed. The comparison with the single forecasting models revealed that the proposed hybrid method had better prediction performance and boosted the forecasting accuracy. Liu et al. [37] came up with ARIMA-ANN and ARIMA-Kalman. The ARIMA model determined the input of the ANN model and initialized the measurement and state equations of the Kalman model. Liu et al. [38] utilized a hybrid approach (Auto-Regressive and Moving Average(ARMA)–Generalized Auto-Regressive Conditional Heteroskedasticity(GARCH)) to evaluate the mean and volatility of wind speed, in which ARMA was used to govern the mean wind speed and the ARMA–GARCH was used to model the mean and volatility of wind speed.

The hybrid approaches can generate more accurate and reliable wind speed predictions to some extent. However, the models derived from the first forecasting methodology are the combinations of several independent forecasting techniques that are connected through weight, thus, the combinational models can be regarded as extensions of single models and subject to their own drawbacks. The models derived from the other forecasting methodology decompose wind speed time series into linear and nonlinear components and take advantage of available models for the prediction of these two components. However, in the literature, the analysis of the residual series is rarely made, impeding the proper usage of the model. Hence, it is necessary to check the correlation of the residuals before residual prediction when adopting the aforementioned methodology.

Moreover, these above-mentioned models cannot be adaptively selected for forecasting models according to the time-varying