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A new hybrid model optimized by an intelligent optimization algorithm for wind speed forecasting

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ABSTRACT

Forecasting the wind speed is indispensable in wind-related engineering studies and is important in the management of wind farms. As a technique essential for the future of clean energy systems, reducing the forecasting errors related to wind speed has always been an important research subject. In this paper, an optimized hybrid method based on the Autoregressive Integrated Moving Average (ARIMA) and Kalman filter is proposed to forecast the daily mean wind speed in western China. This approach employs Particle Swarm Optimization (PSO) as an intelligent optimization algorithm to optimize the parameters of the ARIMA model, which develops a hybrid model that is best adapted to the data set, increasing the fitting accuracy and avoiding over-fitting. The proposed method is subsequently examined on the wind farms of western China, where the proposed hybrid model is shown to perform effectively and steadily.

1. Introduction

Considering the world energy crisis, the use of renewable energy is becoming an increasingly essential approach to reduce the influence of higher oil prices in many countries [1]. In this regard, wind power has been increasingly recognized as a significant source of renewable energy that is clean and pollution-free [2]. Currently, wind power represents approximately 10% of the energy consumption in Europe and over 15% in Germany, Spain and the USA [3]. In China, abundant wind energy resources exist, especially in the Gansu Corridor, which annually produces over 1.5×10^{15} kW h/m^2 of power over a 70-m area near the ground [4]. Thus, the analysis and estimation of wind energy in this area is a meaningful but notably difficult task for research. As is well-known, one of the primary reasons for the low utilization rate of wind power is the volatility of the wind speed. This volatility makes it hard to predict when wind power will be brought into the grid, and energy transportation becomes difficult, as well [1]. An effective way to resolve this problem is wind speed forecasting, which can improve the power grid efficiency. Therefore, wind speed forecasting is a key issue in achieving the management of wind farms.

In recent studies, there have been two primary methods of wind speed prediction, which are based upon the weather forecasting and the time series. The former uses hydrodynamic atmospheric methods and contains physical phenomena, including thermal, frictional and convection effects. Several of these approaches are good for long-term wind speed forecasting but perform poorly in the short-term, such as Mesoscale Model 5 (MM5), Consortium for Small Scale Modeling (COSMO), Weather Research Forecast (WRF) and High Resolution Model (HRM). The time series-based model (which is the subject of this paper) uses only historical wind data to build statistical models and provides a suitable short-term forecasting result for wind farms [5]. Among the statistical approaches, many models have been used to advance the accuracy of prediction. The regression method, least-squares method, time series analysis, wavelet analysis and other algorithms have been widely applied [6]. The above models are all time series-based. Pousinho et al. [7] published a forecasting model using particle swarm optimization and adaptive-network-based fuzzy inference system, as the use of a single statistical method cannot always satisfy forecasting accuracy due to the complex nonlinearity and seasonality of wind speed. Both theoretical and empirical research projects have suggested that different prediction models can supplement the capturing properties of data sets; thus, a combination method may perform much better than any individual forecasting model [8–10]. In this paper, a hybrid forecasting model is built for daily wind speed forecasting in the Gansu Corridor, employing both statistical and artificial intelligence methods.

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Considering that the Autoregressive Integrated Moving Average (ARIMA) model is suitable for capturing short-range correlations and has been used widely in a variety of forecasting applications [5], the ARIMA model is taken as a basic model in this study. Ergin Erdem published a technique based on ARIMA in wind speed forecasting [9]. The ARIMA model was initially presented by Box–Jenkins [10] and was successfully used in such applications as forecasting economic, marketing and social problems. However, the main disadvantage of the ARIMA method is that it has low accuracy in forecasting non-stationary or fluctuating time series. Based on a PSO algorithm proposed by Eberhart and Kennedy [11], an optimized ARIMA model has been developed by us after the basic model. The advantage of this optimized model is that few assumptions are needed, and no a priori postulation of the models is required. Furthermore, with the constant adjustment of the ARIMA parameters in the modeling process, the features of the data can be better explored.

Although the basic and the PSO-optimized ARIMA models are well-suited to capture short range correlations [5], another limitation of the ARIMA model is the difficulty of adjusting the model's parameters when the time series contains new information. To solve this problem, it was proposed to test the ARIMA model in combination with a Kalman filter; this testing constitutes the main objective of this paper. The Kalman filter, which is proposed by Kalman [12], is a sequential algorithm for minimizing state error variance. Along with an extended version, the Kalman filter has been used successfully by several researchers [13]. The primary advantage of the Kalman filter is that the method can be applied in both linear and nonlinear systems [14] and thus is able to overcome the shortcomings of the ARIMA model.

Recently, considerable research has focused on wind speed forecasting, and several hybrid methods have a good performance in this area. In the hybridization of artificial neural networks achieved by Sancho et al. [15,16], the superiority of the hybrid model is demonstrated and found to be successful and feasible. In this paper, the ideas of parameter optimization and information mining have been manifested. Combining the Kalman filter with the ARIMA model, the basic steps taken were as follows. First, the basic ARIMA model was established based on historical data; as a standard time-series method, the ARIMA model has good properties for forecasting. Second, the ARIMA model's parameters were optimized by the PSO algorithm. PSO is a useful method in selecting a model's parameters and improving its forecasting accuracy. As used by Marcela et al. [16] on the reactive power dispatch of wind farms, this algorithm has been tested to be effective and optimal. Finally, a model combining the Kalman filter with the PSO-optimized ARIMA method was established for wind speed forecasting. As time goes on, more wind speed information obtained, more accurate wind speed characteristic will be derived by forecasting models, the new information on the wind speed is absorbed by this hybrid optimized model. Therefore, the performance of this hybrid, optimized model will be stable and accurate.

The remaining sections are arranged as follows. The preparation methods and main modeling process are described in Section 2. Section 3 predicts the wind speed of the Gansu Corridor using three different methods and provides the forecasting results and analyses. Finally, the conclusion is presented in Section 4.

2. Preparation methods for forecasting and modeling process

2.1. ARIMA model

The ARIMA model, which is among the most popular approaches, was introduced for use in forecasting by Box and Jenkins [10]. Hybrid forecasting method, which generally employs an ARIMA model as a linear model to predict the linear component and employs nonlinear model to predict the other component in time series. It is always valid to improve the forecasting performance of wind speed [1]. The applications of ARIMA model [17–19] also demonstrate its superiority in many areas.

A general ARIMA (p,d,q) model describing the time series is written as follows:

$$\phi(B)\nabla^d x_t = \theta(B)e_t, \tag{1}$$

where x_t and e_t represent wind speed and random error at time t, correspondingly. B is a backward shift operator defined by $Bx_t = x_{t-1}$, and related to ∇; d is the order of differencing; $\nabla = 1 - B$, $\nabla^d = (1 - B)^d$. $\phi(B)$ and $\theta(B)$ are autoregressive (AR) and moving averages (MA) operators of orders p and q, separately, that are defined as follows:

$$\phi(B) = 1 - \phi_1 B - \phi_2 B^2 - \cdots - \phi_p B^p, \tag{2}$$

$$\theta(B) = 1 - \theta_1 B - \theta_2 B^2 - \cdots - \theta_q B^q, \tag{3}$$

where $\phi_1, \phi_2, \ldots, \phi_p$ are the autoregressive coefficients and $\theta_1, \theta_2, \ldots, \theta_q$ are the moving average coefficients.

The time series x_t can also be represented as a linear transfer function of the noise series:

$$x_t = \mu + \varphi(B)e_t, \tag{4}$$

where

$$\varphi(B) = 1 + \varphi_1 B + \varphi_2 B^2 + \cdots. \tag{5}$$

$\phi(B)$ can be computed as $\varphi(B) = \theta(B)/\phi(B)$.

2.2. PSO algorithm

Particle Swarm Optimization (PSO) is a society-based swarm algorithm that was initially developed by Kennedy and Eberhart [11]. Bonabeau et al. [20] gave a detailed description and analysis of swarm intelligence in 2000. At the same time, some PSO models have also been applied in forecasting. Zhao and Yang [21] proposed a PSO-based single multiplicative neuron model in the forecasting field. Hong Kuo et al. [22] discussed an improved method based on fuzzy time series and PSO for forecasting enrollments. Hong [23] researched chaotic PSO algorithms using support vector regression in electric load forecasting.

The procedure is defined by a population of random solutions that then searches for an optimal state through renovating generations. However, compared to genetic algorithms, the advantages of PSO are easier to actualize and possess fewer parameters to regulate [24]. At the same time, PSO, compared to differential evolution, is an important characteristic from an end-user attitude, according to which a clustering algorithm must not only be exact but also must propose reproducible and reliable results [25].

In this paper, the particle of PSO is autoregressive coefficients and moving average coefficients in ARIMA model. Let m represents the number of particles and n is the number of optimized parameters. Thus, the ith particle $x_i(t)$ is $x_i(t) = (x_{i1}, x_{i2}, \ldots, x_{in})$ $(i = 1, 2, \ldots, m)$ in the search space. The ith particle's velocity is also a n-dimensional vector that is represented as $v_i(t) = (v_{i1}, v_{i2}, \ldots, v_{in})$ $(i = 1, 2, \ldots, m)$. There are two best values during the optimization process, called *Pbest* and *Gbest*, respectively, which are the best value obtained by each single particle or by all particles in the population. The sensitivity analysis experiment was carried out by changing the number of particles and the number of iterations in order to assure the convergence to a minimum of the PSO swarm.

The PSO algorithm can be displayed by the following equations:

$$v_i(t+1) = w \cdot v_i(t) + c_1 rand_1(Pbest_i - x_i) + c_2 rand_2(Gbest - x_{id}) \tag{6}$$