Applied Energy 99 (2012) 324–333

Contents lists available at SciVerse ScienceDirect

Applied Energy

journal homepage: www.elsevier.com/locate/apenergy

Performance analysis of four modified approaches for wind speed forecasting

Wenyu Zhang [a,b], Jie Wu [c,*], Jianzhou Wang [c], Weigang Zhao [c], Lin Shen [c]

[a] Key Laboratory for Semi-Arid Climate Change of the Ministry of Education, College of Atmospheric Sciences, Lanzhou University, Lanzhou 730000, China
[b] Key Laboratory of Arid Climatic Change and Reducing Disaster of Gansu Province, Lanzhou 730000, China
[c] School of Mathematics & Statistics, Lanzhou University, Lanzhou 730000, China

HIGHLIGHTS

- ▶ Seasonal compact to wind speed forecasting is taken into account.
- ▶ Multiple criterions are used as measures for evaluating forecasting quality.
- ▶ We examine superiority of the modified models in different wind observation sites.
- ▶ All of the modified models are more accurate than the original methods.

ARTICLE INFO

Article history:
Received 25 October 2011
Received in revised form 24 May 2012
Accepted 25 May 2012
Available online 23 June 2012

Keywords:
Wind speed forecasting
Parameter selection
Data decomposition
Evaluation criterion

ABSTRACT

Providing accurate wind speed prediction algorithms has become increasingly significant because of the important technological and economic impacts of wind speed on wind power generation. In this study, two combined strategies for wind speed forecasting are proposed and followed. Four approaches derived from these strategies are employed. The first two approaches employ Particle Swarm Optimization (PSO) to optimize the parameters in the first-order and second-order adaptive coefficient (FAC and SAC) methods. The remaining two approaches employ the decomposition of wind speed data into seasonal and trend components. The seasonal component is represented by the seasonal exponential adjustment, and the trend component is predicted by the hybrid models of PSO and FAC or SAC. By employing these four approaches, the daily mean wind speed is forecasted for four observation sites in Gansu, China. Multiple evaluation methods are used to assess forecasting quality: the mean square error, the mean absolute percentage error and the relative error. It is found that all four approaches better predict wind speed than the original FAC and SAC models.

1. Introduction

Because of increasing energy consumption, the limited reserves of fossil fuels and conventional fuels will no longer meet the growing demand. Meanwhile, more attention has being drawn to the adverse environmental effects caused by traditional fossil fuels. As a consequence, it is imperative and advisable to seek sustainable, clean and environmentally friendly alternative energy resources. Because wind power is a pollution-free and sustainable energy that does not contribute to global warming, it is often regarded as a potential replacement for fossil fuels. The implementation of wind power in electric power systems is growing rapidly. As indicated in [1], wind power systems have been playing a vital role in everyday life for people in developing countries who live without electricity and who account for one-third of the world's total population. For developed countries, as one source of renewable energy, wind energy will greatly support them to fulfill the plan of meeting the energy consumption demand during the 21st century. A conservative estimate indicates that the global wind power potential is approximately 20,000 TW h/year [2]; once this potential can be fully utilized, wind power will make an enormous contribution to the balance of the world's energy.

However, in the practical application of wind power, a problem is that electricity from wind energy cannot be as steadily generated as electricity from other sources due to the uncertainty in the generated amount and intermittency of wind power. Factors such as wind speed, air density and turbine characteristics will all cause variations of the wind energy produced. Specifically, the amount of wind energy produced varies with the cube of the wind speed. Therefore, it is imperative that the accuracy of wind speed prediction be improved to attain more accurate predictions of wind power generation.

Recently, many models have been suggested to improve the accuracy of wind speed prediction, such as conventional statistical models [3,4], neural networks [5], fuzzy logic [6], support vector

* Corresponding author. Tel.: +86 931 8914050; fax: +86 931 8912481.
E-mail address: wuj19870903@126.com (J. Wu).

0306-2619/$ - see front matter © 2012 Elsevier Ltd. All rights reserved.
http://dx.doi.org/10.1016/j.apenergy.2012.05.029

machine [7] and spatial–temporal models [8]. In addition, applying hybrid models based on these approaches to modeling wind speed are frequently used. For instance, Monfared et al. [9] designed a strategy which uses hybrid methods of neural networks and fuzzy logic. With actual wind speed time series sampled in Rostamabad from 2002 to 2005, these authors showed that this approach both requires less computational time and provides better prediction performance. A hybrid method which consists of artificial neural networks and Bayesian methods was proposed by Li et al. [10]. The results indicated that, in contrast to artificial neural networks, whose performance is not consistent when the site or evaluation criterion changes, prediction errors presented by the Bayesian combination approach always become smaller. Cadenas and Rivera [11] developed hybrid methods which consist of Artificial Neural Network (ANN) and Autoregressive Integrated Moving Average (ARIMA). The authors concluded that the combined models outperform the individual ANN and ARIMA approaches. To predict wind speed in the short-term, Sancho et al. [12] developed the hybridization of artificial neural networks with the mesoscale model. They found that this combination strategy was successful and was superior in its forecasting results.

Parameter and input data selection also have a great impact on the wind speed forecasting accuracy of models; thus, work has been performed related to the strategy thereof. ARIMA models are frequently employed to predict wind speed where the differencing parameter '*d*' is always set to an integer. Uniquely, Rajesh and Krithika [13] studied an ARIMA model named fractional-ARIMA where the differencing parameter '*d*' was assumed to be a fractional number. It was found that the proposed models give better forecasting results compared with the persistence method. Fan and Liu [14] made a revised parameter based on the weighted forecasting method of Gray related degree. The effectiveness of the proposed model was demonstrated using a test in a certain area. In addition to the Evolutionary Programming method, Particle Swarm Optimization was also used to estimate the hyper-parameters in Support Vector Machines regressions by Sancho et al. [15]. The complete evolutionary approach was then adopted for wind speed forecasting at a wind farm in Spain and experiment showed that this algorithm was superior to a previous model which used a multi-layer perceptron in the regression process. Colorado et al. [16] developed a methodology according to the laws of thermodynamics and inverse neural networks with the purpose of reducing the irreversibility of the heat transformer. This modified methodology was quite useful for calculating the most suitable input parameters to ensure lower irreversibilities in the heat transformer operation. Additionally, Louka et al. [17] published an application of using filtered data as the input for wind energy forecasting. The results showed that this idea really supplied valid forecasting for long horizons. For neural networks, Sancho et al. [18] exploited diversity in the input data to prove that this method obtained preferable results to those from a single artificial neural network.

The above models all reconstructed the wind speed time series from previous data. Some techniques have also been designed to include other geographical and atmospheric variables such as altitude, wind direction, local temperature, radiation or pressure at the measuring point. For example, latitude, longitude, altitude and month were adopted by Fadare [19] as elements in the input layer of the ANN network, while the data in the output layer was set as the monthly average wind speed. An acceptable accuracy was obtained in this study.

These and other studies all come to a similar conclusion that accurate wind speed forecasting is particularly important. To reduce the forecasting error, more modified forecasting models need to be developed. Taking into account the fact that hybrid algorithms combined with other algorithms and parameter selection can always improve the forecasting accuracy, this paper concentrates on obtaining satisfactory forecasting results using both of these ideas. PSO is a useful tool in selecting the most suitable parameter; therefore, it is applied in this study to improve the forecasting accuracy. In addition, the seasonal and trend components coexist in wind speed data in general. Thus, the seasonal exponential adjustment technique is first employed to guarantee that the primary data series is free from the influence of the seasonal trend, and then the trend component is forecasted separately. Based on these ideas, two combined strategies and four modified forecasting models based on first-order adaptive coefficient (FAC) and second-order adaptive coefficient (SAC) methods are proposed. Then, the performances of these models are evaluated using the actual wind speed data sampled from four observation sites in Gansu and three error evaluation criteria, namely the mean square error, the mean absolute percentage error and the relative error.

The remainder of this paper is organized as follows. Related methodologies are briefly described in Section 2. In Section 3, two combined strategies and four modified models based on FAC and SAC are proposed. Simulation and model evaluation results are reported in the fourth section. Finally, Section 4 presents conclusions from the study.

2. Related algorithms

In this section, the conventional FAC and SAC models are introduced first. We then furnish a brief introduction of the seasonal exponential adjustment (SEA) technique. Lastly, the parameter selection approach—PSO—is described.

2.1. Conventional FAC and SAC approach

FAC and SAC are two adaptive forecasting models in which their parameters are updated continuously so that the models are more flexible.

2.1.1. FAC method

As a common prediction strategy, employing the weighted average of the latest data x_t ($t \leqslant T$) and the historical forecasted value $\hat{x}_t$ to obtain the value of the next moment $\widehat{x}_{t+1}$ is frequently applied. That is,

$$\hat{x}_{t+1} = \alpha x_t + (1-\alpha)\hat{x}_t. \tag{1}$$

However, in general, one fixed α is not suitable for every occasion. Therefore, by replacing α with α_t, which varies with t, we write formula (1) as

$$\hat{x}_{t+1} = \alpha_t x_t + (1-\alpha_t)\hat{x}_t \tag{2}$$

or

$$\hat{x}_{t+1} = \hat{x}_t + \alpha_t(x_t - \hat{x}_t) = \hat{x}_t + \alpha_t e_t, \tag{3}$$

where $e_t = x_t - \widehat{x}_t$ is the residual error.

The FAC method is proposed based on this idea, where α_t is determined through a novel approach. In this method, determination strategies of α_t are different depending on the sign of e_t. Generally, the situation is divided into two categories:

a. A systematic error exists; therefore, all values of e_t are either positive or negative. In this case, α_t should be adjusted according to the rules shown in Fig. 1.
b. No systematic error exists. In this situation, values of e_t appear alternately positive and negative, and $|e_t|$ is not too large, so α_t can remain unchanged.