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Short-term wind speed forecasting using a hybrid model

Ping Jiang [a], Yun Wang [b, *], Jianzhou Wang [a]

[a] *School of Statistics, Dongbei University of Finance and Economics, Dalian, China*
[b] *School of Computer Science and Technology, Tianjin University, Tianjin, China*

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ABSTRACT

Wind speed forecasting is a crucial issue in the wind power industry. However, the disadvantage of the existing wind speed forecasting models is that they often ignore similar fluctuation information between the adjacent WTGs (wind turbine generators), which leads to poor forecasting accuracy. This paper proposes a hybrid wind speed forecasting model to overcome this disadvantage. Specifically, grey correlation analysis is applied to select useful fluctuation information from the adjacent and observed WTGs, and the chosen fluctuation information is fed into the v-SVM (v-support vector machine), which offers good capability in nonlinear fitting, to perform wind speed forecasting of the observed WTGs. Meanwhile, to reduce the impacts of the model parameters on the final forecasting performance, CS (cuckoo search) is used to tune the parameters in the v-SVM. The results from two case studies show that the proposed model, which considers the fluctuation information of the adjacent WTG, offers greater accuracy than the other compared models. As concluded from the results of three accuracy tests, the performances of v-SVM and ε-SVM (ε-support vector machine) show no significant difference, and the CS algorithm is more efficient than the PSO (particle swarm optimization) for tuning of the parameters in the v-SVM.

1. Introduction

Currently, environmental pollution is a global issue that is receiving significant attention, and the development of new forms of renewable resources to reduce pollution is a problem that must be solved. As a renewable resource, wind power has attracted broad attention, both at home and abroad, and a large number of wind farms have been built. Currently, wind power represents approximately 10% of the energy consumption in Europe, and this value is greater than 15% in countries such as Spain and Germany [1,2]. The integration of wind power indeed brings many benefits, but the fluctuations of voltage and frequency lead to many challenges in power generation scheduling plans and power quality. It is known that, the power supply must be equal to the power demand at all times. However, it is difficult to maintain this balance due to the uncertain and intermittent nature of the wind power output.

Wind power is directly related to wind speed in wind farms. Therefore, more accurate wind speed forecasting can more efficiently utilize wind energy and also offer a possible solution to the balance problem. However, the irregular changes in wind speed increase the difficulty in accurate wind speed forecasting. Moreover, the accuracy of wind speed forecasting is not only dependent on the forecasting method but also on the forecasting cycle and the wind speed traits of the forecasting site. In general, the shorter the forecast period, the smaller the error will be and vice versa. Based on the forecasting horizon, wind speed forecasts can be grouped into three categories, namely, short-term forecast, medium-term forecast and long-term forecast [3]. Short-term forecasts can be used in turbine control and preload sharing. Medium-term forecasts can be applied in reasonable power system management and for energy trading. Long-term forecasts can help to achieve a low spinning reserve and optimal operating costs by maintaining the scheduling of the wind turbines [4].

Many researchers have focused on development of effective and reliable wind speed and wind power forecasting models, and a number of different models have been proposed recently. The mainstream models used by these researchers can be divided into several categories, namely, physical forecasting models, conventional statistical forecasting models, artificial intelligence forecasting models, statistical machine learning methods, fuzzy logic-based models, spatial correlation models and hybrid models [4,5], among others.

* Corresponding author.
E-mail address: wangyun15@tju.edu.cn (Y. Wang).

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List of abbreviations

AR	autoregressive model
ARMA	autoregressive moving average model
ARIMA	autoregressive integrated moving average model
HAR	Hammerstein autoregressive
ANNs	artificial neural networks
BP	back propagation
RBF	radial basis function
RNN	recurrent neural networks
BNs	Bayesian Networks
ELM	extreme learning machine
SVM	support vector machine
LSSVM	least squares support vector machine
GP	Gaussian process
MLP	multilayer perceptron
ANFIS	adaptive neuro-fuzzy inference system
WT	wavelet transform
WPT	wavelet packet transform
C, γ, ν-CS	the C, γ, ν parameters in ν-SVM model optimized by CS algorithm
G-ν-SVM-PSO	ν-SVM optimized by PSO algorithm with input determined by grey correlation analysis
EMD	empirical model decomposition
EEMD	ensemble empirical mode decomposition
FEEMD	fast ensemble empirical mode decomposition
GAs	genetic algorithms
PSOs	practical swarm algorithms
ACO	ant colony optimization
CS	cuckoo search algorithm
ν-SVM	ν-support vector machine
ε-SVM	ε-support vector machine
I-V-T	initial value transform
A-V-T	average value transform
P-D-F	polar difference transform
MAE	mean absolute error
MAPE	mean absolute percentage error
RMSE	root mean square error
WTGs	wind turbine generators
ν-SVM-CS	ν-SVM optimized by CS algorithm
G-ε-SVM-CS	ε-SVM optimized by CS algorithm with input determined by grey correlation analysis
G-ν-SVM-CS	ν-SVM optimized by CS algorithm with input determined by grey correlation analysis

The physical forecasting models use historical wind speed, terrain feature data, and many meteorological data (atmospheric pressure, temperature and humidity) to forecast the wind speed of the considered site [4,6]. Many physical models have been recently introduced, and the most popular four are Prediktor [7], Previento [8], LocalPred [9] and eWind [10]. Additionally, the MOS (model output statistics) module can also be embedded into the physical models [11]. In the ultra-short-term and short-term horizons, the changes in wind speed are greatly influenced by atmospheric dynamics. Therefore, it becomes essential to use physical forecasting models in these cases.

Another approach for wind speed or wind power forecasting is the conventional statistical forecasting models, which are built based on statistical modelling and only use historical wind speed series. The typical statistical model is AR (autoregressive model), which has been widely applied for short-term wind speed forecasting. For instance, AR was applied to a wind speed forecasting task at an airport in Ref. [12], and the results showed that the width of intervals produced by AR were narrower than the intervals generated by the persistence model. In Ref. [13], when the diurnal pattern was removed, AR was used to fit the centre parameter of a truncated wind speed distribution, and a 16% error reduction was obtained compared with the persistence model. AR is a well-known special form of ARMA (autoregressive moving average) model, and ARMA was also applied to forecast the future wind speed. In Ref. [14], after transformation and standardization of the original wind speed series, ARMA also performed better than the persistence model, especially in longer-term forecasts. For the sake of straightforward implementation, ARIMA (autoregressive integrated moving average) was used directly on a non-stationary wind speed time series to conduct hour-ahead wind speed forecasts in Ref. [15]. Moreover, the effectiveness of the fractional-ARIMA model was proven for day-ahead and two-day-ahead wind speed forecasting in North Dakota in Ref. [16]. Additionally, the HAR (Hammerstein Auto-Regressive) model, which adapts the Hammerstein model to an AR approach, was proposed for wind speed forecasting in Ref. [17], the results showed that the HAR can better capture various wind speed characteristics, including asymmetric wind speed distribution and non-stationary time series profile, etc. [17].

The conventional statistical models assume that the future wind speed is a linear combination of current and past wind speed, and thus they cannot capture the nonlinear patterns hidden in the wind speed time series. Currently, together with the rapid development of computer technology, many nonlinear forecasting models, e.g., ANNs (artificial neural networks) including BP (back propagation) [18] and RBF (radial basis function) [19], RNNs (recurrent neural networks) [20], BNs (Bayesian Networks) [21], ELM (extreme learning machine) [22], the statistical machine learning methods and others have been developed to conduct wind speed forecasting. The results in Refs. [23,24] show that the different structures of the networks lead to different wind speed forecasting performances. ELM, which is faster than the conventional ANNs, was not only used to forecast future wind speed [22] and also applied to realize wind energy estimation [25,26]. However, the main drawback of ANNs is that they often suffer from local minima and over-fitting [27]. The statistical machine learning methods, which contain SVM (support vector machine) [28,29], LSSVM (least squares support vector machine) [30,31] and GP (Gaussian process) [32], are used to overcome the above shortcomings. The results in Ref. [28] tell us that SVM outperforms multilayer perceptron (MLP) neural networks in wind speed forecasting in terms of the root mean square errors. Additionally, the LSSVM model was proven superior to the persistence model in the majority of wind speed forecasting tasks [30]. In Ref. [32], GP produced more accurate deterministic wind speed forecasts than MLP and RBF and was also useful for estimating the upper and the lower bounds of the wind speed. The main disadvantage of the statistical machine learning methods is that they are highly sensitive to the parameters in the models [29,31].

Fuzzy logic-based models are also widely used in many fields, such as wind speed forecasting [33,34], wind speed distribution estimation [35–39] and tourism demand forecasting [40]. The genetic algorithm optimized fuzzy model was applied to produce 30-min, one-hour and two-hour ahead wind speed predictions, and

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