Energy Conversion and Management 112 (2016) 208–219

Contents lists available at ScienceDirect

Energy Conversion and Management

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

Deterministic and probabilistic interval prediction for short-term wind power generation based on variational mode decomposition and machine learning methods

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ARTICLE INFO

Article history:
Received 4 November 2015
Accepted 11 January 2016
Available online 23 January 2016

Keywords:
Wind power
Variational mode decomposition
Combined forecasting model
Self-adaptive multi-strategy differential evolution
Probabilistic interval prediction
Quantile regression averaging

ABSTRACT

Due to the increasingly significant energy crisis nowadays, the exploitation and utilization of new clean energy gains more and more attention. As an important category of renewable energy, wind power generation has become the most rapidly growing renewable energy in China. However, the intermittency and volatility of wind power has restricted the large-scale integration of wind turbines into power systems. High-precision wind power forecasting is an effective measure to alleviate the negative influence of wind power generation on the power systems. In this paper, a novel combined model is proposed to improve the prediction performance for the short-term wind power forecasting. Variational mode decomposition is firstly adopted to handle the instability of the raw wind power series, and the subseries can be reconstructed by measuring sample entropy of the decomposed modes. Then the base models can be established for each subseries respectively. On this basis, the combined model is developed based on the optimal virtual prediction scheme, the weight matrix of which is dynamically adjusted by a self-adaptive multi-strategy differential evolution algorithm. Besides, a probabilistic interval prediction model based on quantile regression averaging and variational mode decomposition-based hybrid models is presented to quantify the potential risks of the wind power series. The simulation results indicate that: (1) the normalized mean absolute errors of the proposed combined model from one-step to three-step forecasting are 4.34%, 6.49% and 7.76%, respectively, which are much lower than those of the base models and the hybrid models based on the signal decomposition techniques; (2) the interval forecasting model proposed can provide reliable and excellent prediction results for a certain expectation probability, which is an effective and reliable tool for the short-term wind power probabilistic interval prediction.

1. Introduction

With the rapid development of the global economy, the increasing demand for energy and the depletion of conventional resources (e.g., fossil fuel), the worldwide energy crisis has been gradually significant. Consequently, the exploitation and utilization of new clean energy gains much more attention from the society. As one of the most promising renewable energy, wind energy has experienced the most growth worldwide in the past several decades [1]. However, the intermittency and volatility of wind power generation has restricted the large-scale integration of wind turbines into power systems, which may lead to a seriously negative influence on the electrical energy quality and the security and stability of power systems. As a result, one of the most effective measures to mitigate the influence from the integration of wind turbines is to seek prediction accuracy as high as possible.

In recent years, a lot of research on the development of wind power forecasting modeling has been done. The models can be classified into three categories: the physical model, the statistical model and the combined model [2]. The first takes advantage of the meteorological and geographical information for modeling. The second develops the mathematical model representing the mapping relationship of the input variables into the output through history data, which includes the traditional statistical methods, artificial neural networks and machine learning models. The combined model can be established by the following three schemes [3]: (1) The weight-based combined model aggregates several individual models with weight coefficients determined by a certain weight scheme. The equal weight scheme is a simple method,

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http://dx.doi.org/10.1016/j.enconman.2016.01.023
0196-8904/

Nomenclature

EEMD	ensemble empirical mode decomposition
VMD	variational mode decomposition
GA–BP	genetic algorithm–back propagation
SVM	support vector machine
LSSVM	least squares support vector machine
ARIMA	autoregressive integrated moving average
GSA	gravitational search algorithm
PSO	particle swarm optimization
SE	sample entropy
PACF	partial autocorrelation function
ESN	echo state network
ELM	extreme learning machine
RELM	regularized extreme learning machine
QRA	quantile regression averaging
DE	differential evolution
SAMDE	self-adaptive multi-strategy differential evolution
ADMM	alternate direction method of multipliers
RBF	radial bias function
PSR	phase space reconstruction
ANN	artificial neural network
AOL	add-weighted one-rank local-region
GM	grey model
NGBM	nonlinear grey Bernoulli model
NMAE	normalized mean absolute error
NRMSE	normalized root mean square error
PICP	prediction interval coverage probability
PINAW	prediction interval normalized average width

which can enhance the forecasting robustness but cannot guarantee to perform better than all the individual models. The widely used weight scheme is to assign the weight coefficients for the individual models according to the prediction performance in the past. (2) The data pre-processing technique is adopted to decompose the original signal into a number of components in order to decrease the instability of the raw wind power series. In Ref. [4], the wavelet decomposition technique was used to tackle the nonstationarity of load series for the evolutionary extreme learning machine. The proposed method obtained better forecasting results compared with other well-established models on two publicly available datasets. Wang et al. [5] adopted the wavelet packet decomposition technique to process the original wind speed series to mine the traits more meticulously, and established the support vector machine (SVM) model combined with an artificial intelligence algorithm to enhance the forecasting capacity. In Ref. [6], the empirical mode decomposition algorithm was employed to decompose the raw wind power data into a set of subseries, and a hybrid prediction model based on chaos theory and grey theory was built. The results showed superior prediction accuracy. Wang et al. [7] presented a novel wind speed forecasting model based on ensemble empirical mode decomposition (EEMD) and genetic algorithm–back propagation (GA–BP) neural network. The simulation results showed that the proposed model was more accurate than the traditional GA–BP approach. (3) The parameter selection and optimization technique is implemented to choose the proper parameters for the forecasting models. Blonbou [8] established an artificial neural network in conjunction with an adaptive Bayesian learning procedure and Gaussian process approximation for very short-term wind power prediction. Since the predictor's parameters were adaptively optimized, the proposed prediction approach performed better than the reference model. In Ref. [9], the least squares support vector machine (LSSVM) model was presented for short-term wind power prediction, the parameters of which were optimized by the gravitational search algorithm (GSA). It demonstrated that the hybrid LSSVM–GSA model can improve the prediction accuracy prominently. Su [10] established a hybrid method based on the autoregressive integrated moving average (ARIMA) and Kalman filter to forecast the daily mean wind speed. And the particle swarm optimization (PSO) algorithm was employed to optimize the parameters of the ARIMA model to improve the prediction performance. In Ref. [11], a new hybrid evolutionary–adaptive methodology for short-term wind power forecasting was proposed and the results showed a significant improvement over previously reported methodologies.

In this paper, based on the three combination schemes above, a combined model is proposed for the purpose of improving the deterministic prediction accuracy for short-term wind power generation. Firstly, in order to handle the instability and randomness of the raw wind power series, the variational mode decomposition (VMD) [12] technique is used to decompose the original signal into a number of modes. Then the sample entropy (SE) [13] value for each mode is calculated to measure its complexity, by which the decomposed modes can be recombined to obtain a set of subseries. Secondly, for each subseries, the partial autocorrelation function (PACF) analysis is implemented to construct the training samples and different base models can be established. The base models in this study include least squares support vector machine, echo state network (ESN) and regularized extreme learning machine (RELM). Thirdly, the combined forecasting model based on optimal virtual prediction is developed, the weight matrix of which is determined by minimizing the forecasting error at the virtual prediction points prior to the actual prediction point. Hereby, an intelligent optimization algorithm is proposed to adjust the element values in the weight matrix. Finally, combined with the weight matrix above and the forecasting results for all the subseries by the base models at the actual prediction point, the deterministic prediction can be obtained.

Furthermore, since the probabilistic interval prediction contains more information compared to the deterministic prediction, high quality interval prediction is conductive to risk analysis and assessment of wind power series for the decision makers in power systems. A hybrid model constructed by the cuckoo search optimization-based back propagation neural network is developed to implement wind speed interval prediction by generating the lower and upper bounds [14], and the optimized relevance vector machine is proposed to provide the wind power fluctuation range at given confidence level [15]. Yet the studies above only provide the one-step interval prediction results corresponding to a certain expectation probability, the multistep interval prediction of the wind power series has not been taken into consideration.

In this study, a probabilistic interval prediction model based on quantile regression averaging (QRA) is presented for the wind power series. Based on the multistep deterministic forecasting results on the particular validation set and the corresponding testing point, the QRA method is implemented to generate a range of wind power fluctuation at different forecasting time steps corresponding to a certain expectation probability.

On the whole, the novelty of this study can be listed as follows: (1) It is the first time to adopt the VMD technique to handle the instability of the original wind power series, which is a newly developed multiresolution technique for adaptive and non-recursive signal decomposition. (2) The VMD technique and the combination of several base models are implemented simultaneously to develop a