Energy Conversion and Management 155 (2018) 188–200

Contents lists available at ScienceDirect

Energy Conversion and Management

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

Comparison of two new intelligent wind speed forecasting approaches based on Wavelet Packet Decomposition, Complete Ensemble Empirical Mode Decomposition with Adaptive Noise and Artificial Neural Networks

Hui Liu, Xiwei Mi, Yanfei Li*

Key Laboratory of Traffic Safety on Track of Ministry of Education, School of Traffic and Transportation Engineering, Central South University, Changsha 410075, Hunan, China

ARTICLE INFO

Keywords:
Wind speed forecasting
Wavelet packet decomposition
Complete Ensemble Empirical Mode Decomposition with Adaptive Noise
Artificial Neural Network

ABSTRACT

The wind speed forecasting is an important technology for the management of the wind energy. In this study, a new hybrid framework using the WPD (*Wavelet Packet Decomposition*), the CEEMDAN (*Complete Ensemble Empirical Mode Decomposition*) and the ANN (*Artificial Neural Network*) is proposed for wind speed multi-step forecasting. In the proposed framework, the WPD is employed to decompose the original wind speed series into a series of sub-layers, while the CEEMDAN is adopted to further decompose all the obtained sub-layers into a number of IMFs (*Intrinsic Mode Functions*). Finally, three types of ANN models, including the BP (*Back-propagation Neural Network*) models, the RBF (*Radial Basis Function Neural Network*) models and the GRNN (*General Regression Neural Network*) models, are utilized to complete the predicting computation for the decomposed wind speed series, respectively. To investigate the prediction performance of the presented framework, nine models are included in the comparisons as: the BP model, the WPD-BP model, the WPD-CEEMDAN-BP model, the RBF model, the WPD-RBF model, the WPD-CEEMDAN-RBF model, the GRNN model, the WPD-GRNN model and the WPD-CEEMDAN-GRNN model. Two experimental results indicate that: the proposed WPD-CEEMDAN-ANN models have better performance than the involved corresponding ANN models and WPD-ANN models in three-step predictions.

1. Introduction

With the increasing demand for electricity, wind energy, which is clean and abundant, has drawn widespread attention [1]. In the past years, wind energy has rapidly developed. However, since the wind power is intermittent and non-stationary, it is difficult to enable reliable guidance for the wind energy management [2]. To overcome this problem, many technologies are used. One of the main technologies is wind forecasting [3].

Over the past few decades, numerous research studies on wind predictions have been presented by using the physical methods [4]. Howard et al. [5] presented the physical model based on the correction and down-scaling method. Pelikan et al. [6] designed the empirical model by using the physical parameters. Kavasseri et al. [7] built the wind speed forecasting models based on the f-ARIMA methods. Erdem et al. [8] investigated the wind speed and direction prediction performance of some ARMA based approaches. Zhou et al. [9] proposed the improved SVM (*Support Vector Machine*) models for short-term wind speed forecasting. Shrivastava et al. [10] adopted the SVM models for interval forecasts. Sun et al. [11] established the hybrid model based on the FEEMD (*Fast Ensemble Empirical Mode Decomposition*) and RELM (*Regularized Extreme Learning Machine*). Among these models, the

Abbreviations: ANN, Artificial Neural Network; AR, Auto Regressive; ARIMA, Auto Regressive Integrated Moving Average; BA, Bat Algorithm; BP, Back-propagation Neural Network; CEEMDAN, Complete Ensemble Empirical Mode Decomposition; CG, Conjugate Gradient; CLSFPA, Flower Pollination Algorithm with Chaotic Local Search; CNN, Convolutional Neural Network; CS, Compressive Sensing; CSA, Cuckoo Search Algorithm; EEMD, Ensemble Empirical Mode Decomposition; ESM, Exponential Smoothing Method; FA, Firefly Algorithm; FAC, First-order Adaptive Coefficient; GA, Genetic Algorithm; GRNN, General Regression Neural Network; HBSA, Hybrid Backtracking Search Algorithm; HWM, Holt-Winters Model; IMFs, Intrinsic Mode Functions; IS, Input parameter Selection; KF, Kalman filter; LSSVM, Least Square Support Vector Machine; MAE, Mean Absolute Error; MAPE, Mean Absolute Percentage Error; MLP, Multilayer Perceptron Neural Network; MOBA, Multi Objective Bat Algorithm; NNCT, No Negative Constraint Theory; NSGA, Non-dominated Sorting Genetic Algorithm; OVMD, Optimized Variational Mode Decomposition; PSO, Particle Swam Optimization; PSOSA, Particle Swarm Optimization based on Simulated Annealing; PSR, Phase Space Reconstruction; RBF, Radial Basis Function Neural Network; RMSE, Root Mean Square Error; SAC, Second-order Adaptive Coefficient; SAM, Seasonal Adjustment Method; SDA, Secondary Decomposition Algorithm; SEA, Seasonal Exponential Adjustment; SOM, Self-Organizing feature Maps; SSA, Singular Spectrum Analysis; SVR, Support Vector Regression; VMD, Variational Mode Decomposition; v-SVM, v-Support Vector Machine; WD, Wavelet Decomposition; WPD, Wavelet Packet Decomposition

* Corresponding author.
E-mail address: yanfeili@csu.edu.cn (Y. Li).

http://dx.doi.org/10.1016/j.enconman.2017.10.085
Received 17 July 2017; Received in revised form 7 October 2017; Accepted 28 October 2017

Table 1
Summary of the previous research on the wind speed decomposition algorithms.

Decomposition algorithms	Researchers
WD	Qin et al. [16], Kiplangat et al. [17], Wang et al. [19], Tascikaraoglu et al. [21]
WPD	Wang et al. [20], Meng et al. [22]
EEMD	Wang et al. [15]
FEEMD	Sun et al. [11]
CEEMDAN	Zhang et al. [18],
OVMD	Zhang et al. [23]
SSA	Xiao et al. [24], Wang et al. [25]
WPD-FEEMD	Liu et al. [26]
FEEMD-VMD	Wang et al. [27]

hybrid methods often have better prediction performance than the single models [12], therefore they have attracted increasing attention [13]. Generally, the hybrid methods contain decomposition algorithms and prediction algorithms [14].

Since the decomposition algorithms can reduce the non-stationary characteristics of the time series, they are widely adopted in the hybrid methods for the wind predictions. Wang et al. [15] investigated a novel wind speed forecasting method using the EEMD (*Ensemble Empirical Mode Decomposition*), the GA (*Genetic Algorithm*) and the BP. The cases study validated that the proposed model was more accurate than the GA-BP model. Qin et al. [16] established a hybrid wind speed interval forecasts approach based on the WD (*Wavelet Decomposition*), the CSA (*Cuckoo Search Algorithm*) and the BP. The WD was applied to reduce the high-frequency components, the CSA was incorporated into BP for parameters optimization and the BP was used to forecast the lower and upper bounds. The results demonstrated that the established approach could obtain high quality interval forecasts. Kiplangat et al. [17] demonstrated a hybrid method based on the WD and the simple linear models. The numerical results confirmed that the WD-AR model had higher prediction accuracy than the AR model. Zhang et al. [18]

Table 2
Summary of the previous research on the wind speed prediction algorithms.

Prediction algorithms	Researchers
NWP	Howard et al. [5], Pelikan et al. [6]
AR/ARMA/AMIMA/f-ARIMA	Kavasseri et al. [7], Erdem et al. [8], Kiplangat et al. [17], Maatallah et al. [36]
BP/RBF/GRNN/CNN/ELM/RELM/Elman/ANFIS/ESN/Adaboost	Salcedo-sanz et al. [1], Wu et al. [2], Liu et al. [3], Zhang et al. [4], Sun et al. [11], Liu et al. [12], Liu et al. [14], Wang et al. [15], Qin et al. [16], Zhang et al. [18], Wang et al. [19], Meng et al. [22], Zhang et al. [23], Xiao et al. [24], Wang et al. [25], Liu et al. [26], Wang et al. [27], Ren et al. [29], Sheela et al. [34], Feng et al. [35]
SVM/v-SVM/LSSVM	Zhang et al. [4], Zhou et al. [9], Shrivastava et al. [10], Liang et al. [13], Wang et al. [20], Santamaría-Bonfil et al. [30], Jiang et al. [31], Zhang et al. [33], Feng et al. [35]
KF	Shukur et al. [38]
Chaotic time series model	Tascikaraoglu et al. [21], Guo et al. [32]
SAM/ESM/SEA/SAC	Wang et al. [28], Zhang et al. [37]

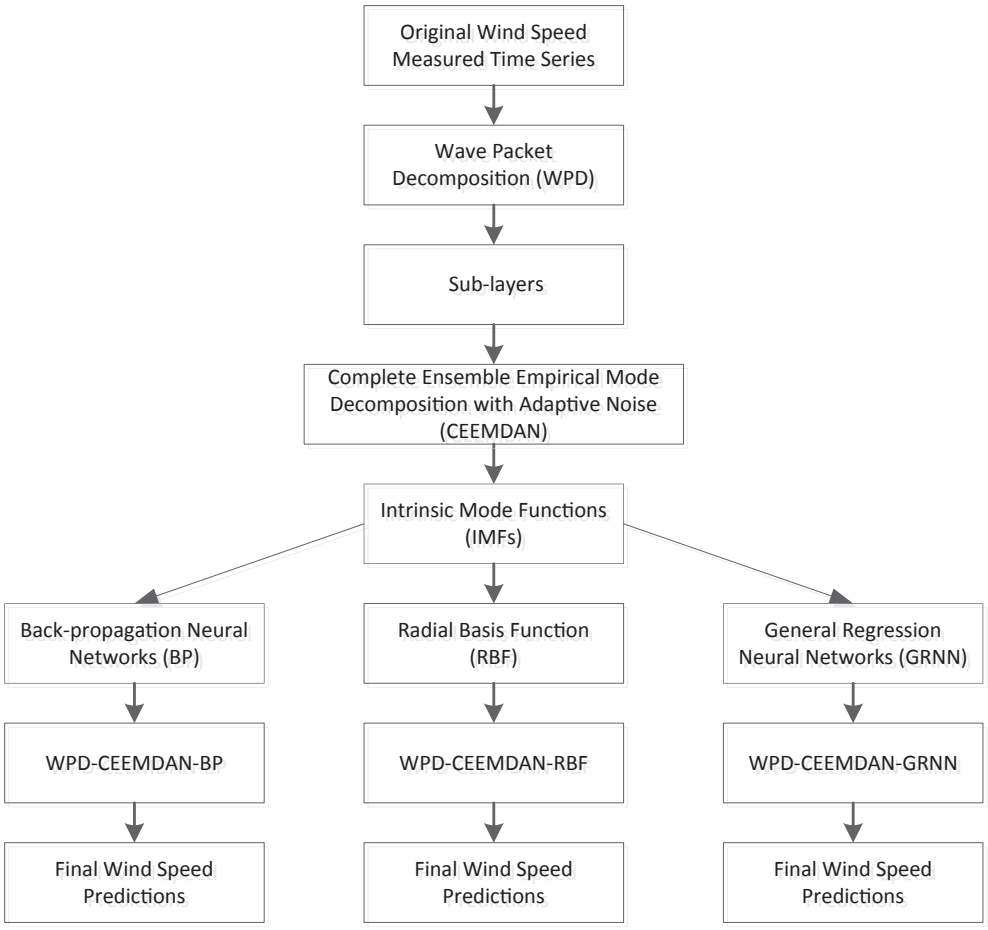

Fig. 1. The proposed hybrid prediction framework.