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New wind speed forecasting approaches using fast ensemble empirical model decomposition, genetic algorithm, Mind Evolutionary Algorithm and Artificial Neural Networks

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A B S T R A C T

Wind speed high-precision prediction is one of the most important technical aspects to protect the safety of wind power utilization. In this study, two new hybrid methods [*FEEMD-MEA-MLP/FEEMD-GA-MLP*] are proposed for the wind speed accurate multi-step predictions by combining FEEMD (*Fast Ensemble Empirical Mode Decomposition*), MEA (*Mind Evolutionary Algorithm*), GA (*Genetic Algorithm*) and MLP (*Multi Layer Perceptron*) neural networks. In these two hybrid methods, the FEEMD algorithm is adopted to decompose the original wind speed series into a number of sub-layers and the MLP neural networks optimized by the MEA algorithm and the GA algorithm are built to predict the decomposed wind speed sub-layers, respectively. The innovation of the study is to investigate the promoted percentages of the MLP neural networks by the FEEMD decomposition and the MEA/GA optimization, respectively. The involved forecasting models in the performance comparison in the study include the hybrid FEEMD-MEA-MLP, the hybrid FEEMD -GA-MLP, the hybrid FEEMD-MLP, the hybrid MEA-MLP, the hybrid GA-MLP and the single MLP. Two experimental results show that: (a) among all the involved methods, the hybrid FEEMD-MEA-MLP model has the best forecasting performance; (b) the FEEMD algorithm promotes the performance of the MLP neural networks significantly while the MEA/GA algorithms do not improve the performance of the MLP neural networks significantly; and (c) the hybrid FEEMD-MEA-MLP method and the hybrid FEEMD-GA-MLP method are both effective in the wind speed high-precision predictions.

1. Introduction

In recent years, the wind speed prediction becomes more and more important for the wind energy applications. The accurate wind speed forecasting results can decrease the possibilities of the wind power breakdown and protect the security of the wind power conversion [1].

Scientists have presented some important results in the wind speed prediction. Shukur et al. [2] proposed a new hybrid method to predict the wind speed by combining the ARIMA (*Auto Regressive Integrated Moving Average*) and the KF (*Kalman Filter*). In the proposed method, the ARIMA was adopted to determine the inputting structure of the KF, and the optimized KF was employed to realize the wind speed forecasting computation with the ANN (*Artificial Neural Networks*). The performance of the proposed method was validated by using daily wind speed data from Iraq to Malaysia. Haque et al. [3] presented a new hybrid wind speed forecasting method by based on the WT (*Wavelet Transform*) and the FART (*Fuzzy Adaptive Resonance Theory*). The WT was exploited to decompose the raw wind speed data, the FART was built to do the real forecasting computation. The presented hybrid method had been validated by using some real data measured from North Cape wind farm in Canada. Liu et al. [4] designed a new hybrid wind speed predicting approach by combining the EMD (*Empirical Mode Decomposition*) and the ANN. The EMD was utilized to decompose

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Abbreviations

ARIMA	Auto Regressive Integrated Moving Average
ANN	Artificial Neural Networks
BP	Back Propagation
BM	Bayesian Model
CRO	Coral Reefs Optimization
EMD	Empirical Mode Decomposition
ERNN	Elman Recurrent Neural Networks
ELM	Extreme Learning Machine
FART	Fuzzy Adaptive Resonance Theory
GA	Genetic Algorithm
HSA	Harmony Search Algorithm
KF	Kalman Filter
MLP	Multi Layer Perceptron
MLR	Multiple Linear Regression
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
NARX	Nonlinear Autoregressive Model with Exogenous Inputs
OFM	Organizing Feature Maps
PA	Polynomial Algorithm
PSO	Particle Swarm Optimization
PM	Persistent Model
RBF	Radial Basis Functions
RT	Regression Tress
SVR	Support Vector Regression
SIA	Seasonal Index Adjustment
WT	Wavelet Transform
WDF	Weibull Distribution Function

the original non-stationary wind speed data into a series of sub-layers and the ANN was used to build the best forecasting models for all the sub-layers. The results showed that the proposed method forecasted the extremely jumping samplings successfully. Petković et al. [5] provided a comparison of the wind speed distribution prediction using various soft computing methodologies. The PA (*Polynomial Algorithm*) and RBF (*Radial Basis Functions*) neural network were applied as the kernel function to optimize the SVR (*Support Vector Regression*) to estimate the parameters of the WDF (*Weibull Distribution Function*). Liu et al. [6] investigated an experiment comparing the Wavelet-GA (*Genetic Algorithm*)-MLP (*Multi Layer Perceptron*) with the Wavelet-PSO (*Particle Swarm Optimization*)-MLP for realizing the wind speed high-precision multi-step predictions. Troncoso et al. [7] evaluated the forecasting performance of different RT (*Regression Tress*) in the short-term wind speed prediction. Their experimental results showed that the RT based forecasting methods were able to obtain very satisfactory results. Palomares-Salas et al. [8] compared eight models for the wind speed one-hour ahead forecasting. In the study, the PM (*Persistent Model*), the ARIMA model, the MLR (*Multiple Linear Regression*) and five different types of neural networks were estimated. The comparing results indicated that the BP (*Back Propagation*) neural network had the best performance. Su et al. [9] presented a hybrid wind speed predicting framework by adopting the PSO, the ARIMA and the KF. In the hybrid framework, the PSO was employed to optimize the parameters of the ARIMA model, and then the optimized ARIMA model was utilized to build the initial equations for the KF predictor. Actually the ARIMA-KF algorithm in the proposed PSO-ARIMA-KF format had been published before in Ref. [10]. Baran et al. [11] put forward a BM (*Bayesian Model*) based statistical wind speed forecasting approach. The results provided in the paper showed that the BM was suitable for the wind speed high-precision predictions. Gnana Sheela et al. [12] studied the ANN based computing models for the wind speed predictions. The OFM (*Organizing Feature Maps*) and the MLP were adopted in the proposed models. Their results validated that the hybrid OFM-MLP model had higher accuracy than the single MLP, BP and RBF. Wang et al. [13] designed a new wind speed forecasting strategy. In the strategy, the SVR was employed to detect and preprocess the outliers of the raw wind speed data and the ERNN (*Elman Recurrent Neural Networks*) optimized by the SIA (*Seasonal Index Adjustment*) was built to perform the wind speed prediction. It had been proved in the paper that the proposed strategy was good at the medium-term wind speed forecasting situation. Salcedo-Sanz et al. [14] adopted a new hybrid bio-inspired solver to select the best parameters of meteorological variables for the ELM (Extreme Learning Machine) based wind speed predictor. The bio-inspired solved was generated by the recently proposed CRO (*Coral Reefs Optimization*) and the HSA (*Harmony Search Algorithm*). Two experiments indicated that the optimized ELM obtained satisfactory wind speed forecasting performance. Azad et al. [15] investigated the performance of the long-term wind speed forecasting by the NARX (*Nonlinear Autoregressive Model with Exogenous Inputs*) neural networks. Two groups of real wind speed samples from two meteorological stations in Malaysia were adopted to validate the built NARX forecasting models. The results proved that the built models were satisfactory. From the upper reviewed literature, it can be seen that: (a) the hybrid forecasting methods always can have better performance than the single ones in the wind speed predictions; (b) in the proposed hybrid methods, the signal processing algorithms (e.g., wavelet decomposition [3,6], empirical mode decomposition [4], etc) are adopted to decrease the instability of the raw wind speed data to decrease the high-precision forecasting difficulty and the intelligent optimizing algorithms (e.g., genetic algorithm [6], particle swarm optimization [9], coral reefs optimization [14], etc) are utilized to promote the computational capacity of the built forecasting models for the accurate results; and (c) the neural networks have been generally applied in the wind speed predictions.

In this study, two new hybrid forecasting methods [*i.e., the hybrid FEEMD-MEA -MLP method and the hybrid FEEMD-GA-MLP method*] are proposed by combining the FEEMD (*Fast Ensemble Empirical Mode Decomposition*), the MEA (*Mind Evolutionary Algorithm*), the GA (*Genetic Algorithm*) and the MLP (*Multi Layer Perceptron*) neural networks. The originality of the proposed hybrid methods is explained as follows: (a) the processing of the raw wind speed data and the optimization of the forecasting models are both adopted in this study. In the proposed hybrid forecasting framework, the FEEMD algorithm is used to decompose the raw wind speed signals to decrease the non-stationarity of the original data, the MLP neural networks are established to predict various decomposed wind speed sub-layers, and the MEA/GA algorithms are employed to select the optimized initial parameters for the built MLP models. It can be imagined that by the utilization of the FEEMD decomposition and the MEA/GA optimization, the forecasting performance of the MLP neural network can be promoted considerably; (b) the contribution percentages of various components (*i.e., the FEEMD, the MEA and the GA*) to promote the MLP based wind speed predictors will be fully investigated. Since the formats of the hybrid FEEMD-MEA-MLP and FEEMD-GA-MLP methods have not