Hybrid Model for Short Term Wind Speed Forecasting Using Empirical Mode Decomposition and Artificial Neural Network

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Abstract

Wind speed modeling and prediction plays a critical role in wind related engineering studies. With the integration of wind energy into electricity grids, it is becoming increasingly important to obtain accurate wind speed forecasts. Accurate wind speed forecasts are necessary to schedule dispatchable generation and tariffs in the electricity market. In this paper a hybrid model named EMD-ANN for wind speed prediction is proposed based on the Empirical Mode Decomposition (EMD) and the Artificial Neural Networks (ANN) for renewable energy systems. All the models are analyzed with real data of wind speeds in Bilecik, Turkey using data measurement from the Turkish State Meteorological Service. Accuracy of the forecasting is evaluated in terms of MAE and MSE.

1. Introduction

Wind power is one of the cleanest renewable energy sources that produce no greenhouse gases, has no effect on climate change, and produces little environmental impacts. The energy generated from the wind has been well recognized as environmentally friendly, socially beneficial, and economically competitive for many applications.

In the last few decades wind power generation shows tremendous growth and is all set to increase in future. The integration of wind energy should have concern about the reliability of grid, since bulk integration may affect the reliability indices. Accurate wind speed information is of great importance for wind energy conversion system.

The wind speed forecast for the wind energy sector is essential due to the following reasons:

- Wind farms unit maintenance
- For electricity bidding
- To schedule the power generators
- To plan and schedule energy reserves and storages.

Short-term wind speed forecasting can be made in the order of several days and also from minutes to hours [1]. Usually, hourly forecasts of expected winds are helpful in dispatching decision making, daily forecasts of hourly winds are useful for the load scheduling strategy, and weekly forecasts of day-to-day winds greatly facilitate maintenance scheduling [2,3]. Several methods on the short-term wind speed forecasting have been developed over the past two decades. Statistical and artificial intelligence models used in the literature. Wind speed forecasting for three different regions of Mexico, hybrid models consisting of autoregressive integrated moving average models and artificial neural network models (ANN) were developed by Cadenes and Rivera [4]. Zhang et al., short-term wind speed forecasting was proposed by applying wavelet transform technique into hybrid model which hybrids the seasonal adjustment method and the radial basis feed forward neural network [5]. Kalogirou et al. investigated wind speed prediction using artificial neural networks [6]. In their study, a multilayered artificial neural network has been used for predicting the mean monthly wind speed in regions of Cyprus.

In this paper, EMD–ANN approach that hybridizes EMD and ANN is proposed to forecast wind speed. First, the original wind speed datasets are decomposed into a collection of intrinsic mode functions (IMF) and a residue by EMD, which are relatively stationary subseries and can be modeled. Second, both the IMF components and the residue are used to establish the corresponding ANN models. Finally, the prediction values of the original wind speed datasets are calculated by summing the forecasting values of every subseries.

2.Empirical Mode Decomposition (EMD)

The theory of intrinsic mode function (IMF) has been pioneered by Norden E. Huang et al when they did research on nonlinear problems and Hilbert Transform. At the same time, they proposed a method for signal decomposition, namely Empirical Mode Decomposition (EMD). It not only makes the signal decomposition unique but also has good local characteristics both in time domain and frequency domain. The EMD method gets extensive application in the power system [7,8].

Given an original wind speed series {Y(t)}, it can be described as the following equation (1) after the EMD calculation.

$$\mathrm{Y(t)} = \sum_{i=1}^{n} C_i(\mathrm{t}) + \mathrm{R}_n(\mathrm{t}) \tag{1}$$

Where {Ci(t)}, i=1,2,...n is the IMF in different decompositions and {Rn(t)} is the residue after n numbers of IMFs are derived.

An IMF satisfies the following two properties [9]:

(i) the number of extrema and the number of zero crossing in a whole sampled data set must either equal or differ at most by one;

(ii) At any point ,the mean value of the envelope defined by the local maxima and the envelop defined by the local minima is zero.

A sifting alterative process is employed to extract the separate components IMFs. The detailed steps of the sifting calculation can be demonstrated as follows [10-14]:

a) Identify all the local extrema of series {Y(t)}, including local maxima and local minima.

b) Connect all the local maxima by a cubic spline line to generate its upper envelop {$Y_{up}(t)$}. Similarly the lower envelop {$Y_{low}(t)$} is made with all the local minima.

c) Compute the mean envelop {M(t)} from the upper and lower envelops as follows (Equation 2):

$$M(t) = \frac{[Y_{up}(t) + Y_{low}(t)]}{2} \tag{2}$$

d) Extract the details as follows (Equation 3):

$$Z(t) = Y(t) - M(t) \tag{3}$$

e) Check whether {Z(t)} is an IMF: (i) if {Z(t)} is an IMF then set C(t)=Z(t) and meantime replace {Y(t)} with the residual R(t)=X(t)-C(t); (ii) if {Z(t)} is not an IMF, replace {Y(t)} with {Z(t)} then repeat Steps b-d until the termination criterion is satisfied. Equation 4 can be regarded as the termination condition of this iterative calculation:

$$\sum_{t=1}^{m} \frac{\left[Z_{j-1}(t) - Z_j(t)\right]^2}{\left[Z_{j-1}(t)\right]^2} \le \delta (j = 1, 2, \ldots; t = 1, 2, \ldots, m) \tag{4}$$

where m is the length of signal, δ is the terminated parameter which is usually set as 0.2-0.3, and j denotes the times of iterative calculation. The δ is usually determined by the requirements of application areas.

f) The procedure of steps a-e is repeated until all the IMFs are found.

3. Artificial Neural Networks (ANN)

Various types of artificial neural networks used for different forecasting have been developed. Nowadays, the artificial neural networks has been generally used in signal processing due to its nonlinear capacity and robust performance. In ANN theory, apart from the structure of network, the training data format also can affect the performance of network directly.

Basically, a neural network is a technique used to map a random input vector into a corresponding random output vector without assuming that there is any persistent relationship between the two sets. A typical neural network has three layers, the input layer, hidden layer and the output layer. The number of neurons corresponds to the size of the input and output layers, while the hidden layer can be manipulated to suit the level of the desired output. The mapping process is achieved by first assigning each individual input with connection weights, which transmit the information to the next neuron or junction. The weights vector is first assigned randomly and subsequently fixed by training the network.

A number of training algorithms are currently used in building various artificial intelligence systems, some of them are;, genetic algorithm, incremental and batch back propagation, quick propagation and Broydene Fletchere Goldfarbe Shanno Quasi-Newton Back Propagation which are the most common ones.

Levenberg-Marquardt training algorithms preferred to used in this study. Moreover, activation functions are chosen tansig in hidden layer and purelin in output layer.

4. Wind Speed Forecasting Model Based on EMD ANN

Every dataset is partitioned into a training data set ,validation data set and test data, to further evaluate the prediction accuracy. The training data set can be applied to establish the prediction model, and the validation dataset can be applied to validate the effectiveness of the established model. EMD-ANN model flow chart is shown in Figure1.

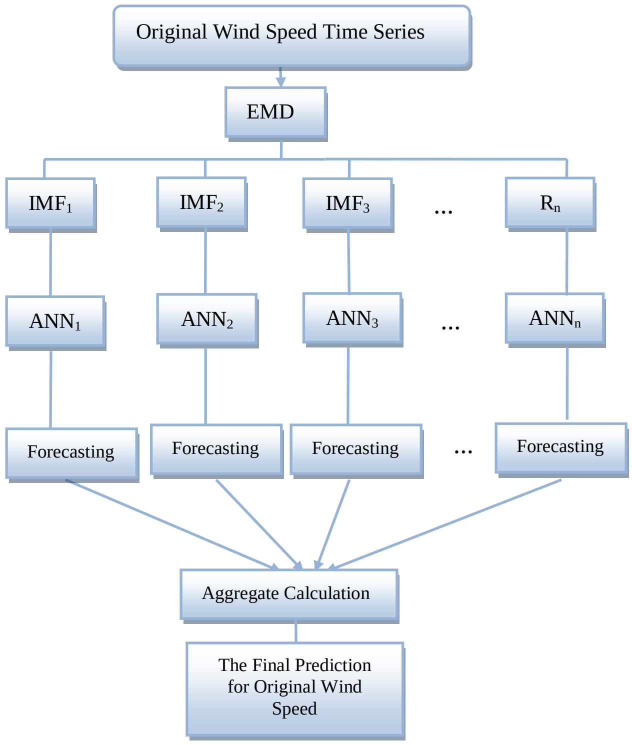

Fig. 1: EMD-ANN Model Flowchart

The wind speed data is real data taken at a height of 10 meters from the ground in Bilecik city, in Turkey. Figure 2 shows an hourly actual time series (including 744 samplings) of the wind speed in station. To verify the performance of the proposed hybrid EMD-ANN model in this study, the 1st 520th ones of this original series is utilized to establish models, the 521st 744th ones to check the validity and test of the established models. Figure 3 shows the calculation results of the descriptive EMD analysis for the data in Figure 2.

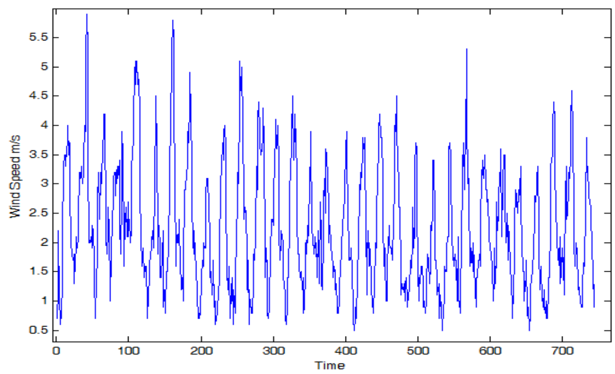

Fig. 2: Original Wind Speed Series

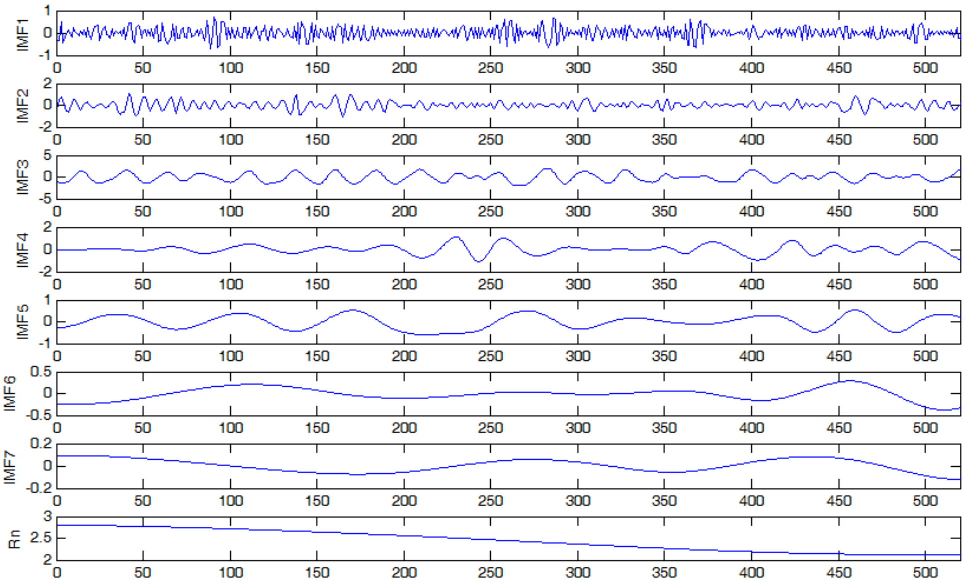

Fig 3: Decomposition Wind Speed Series by EMD

Data normalization is carried out to improve the accuracy of subsequent numerical computation and to obtain an infinitely better output of the model. The min/max technique is used for normalization of input data. The advantage is to preserve exactly all relationships in the data without introducing bias. The values used in the input and output layers are normalized using equation (5) in the range of [0-1].

$$X_{New} = [X - X_{min}]/ [X_{max} - X_{min}] \qquad (5)$$

Where X, X_{min}, X_{max} is the actual input data, minimum and maximum input data respectively.

To assess the forecast capacity of the EMD-ANN model, two indices for error forecast serve as the criteria to evaluate the forecasting performance; they are mean absolute error (MAE) and mean square error (MSE). The values of the indices are smaller and the forecast performance is better. The indices are defined as follows:

$$\mathrm{MSE}(x, y) = \frac{1}{N}\sum_{i=1}^{N}(x_i - y_i)^2 \qquad (6)$$

$$\mathrm{MAE}(x, y) = \frac{1}{N}\sum_{i=1}^{N}\left|x_i - y_i\right| \qquad (7)$$

Where N is the number of samples, X_i and Y_i are measured and predicted values, respectively.

Input values of neural network are designated lagged matrix data by sliding window technique in this study. All models architectures include, 3 hidden neurons, 1 output neuron. Other details of neural network models is given in section 2.

Figure 4 show the forecasting results at 111 samples of one-step ahead achieved by ANN and ANN-EMD models. The performance accuracy of these predictions are given in Table 1.

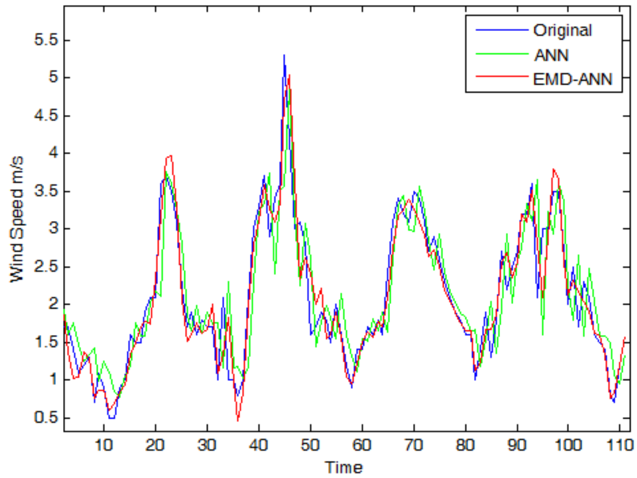

Fig. 4. Comparative Analysis of Forecasting Results

Each ANN is applied to forecast the corresponding subseries, and the final prediction of the original wind speed is obtained by aggregating the prediction results of each subseries. The one step ahead forecast is adopted in this study.

Figure 4 shows the forecasting series of wind speed data for Bilecik. EMD-ANN hybrid model provides better accuracy by comparison with ANN model.

Table 1 shows the performance metrics for all models.

Table 1: Perfomance test results of the models

Error	ANN	EMD-ANN
MAE	0.4037	0.2185
MSE	0.2871	0.0879

6. Conclusions

Wind speed high precision prediction is one of the most important technical aspects to protect the safety of wind power utilization.

In this paper a hybrid model named EMD-ANN for wind speed prediction is proposed based on the Empirical Mode Decomposition (EMD) and the Artificial Neural Networks (ANN) for renewable energy systems. First, the original wind speed data sets are decomposed into a collection of IMF's and a residue by EMD, which are relatively stationary subseries and can be readily modeled. Second, both the IMF components and the residue are used to establish the corresponding ANN models. Then, each subseries is predicted by the corresponding ANN. Finally, the prediction values of the original wind speed datasets are calculated by summing the forecasting values of every subseries.

The hybrid model (EMD-ANN) was concluded that provides better accuracy by comparison with ANN model. This neural network based proposed hybrid model is very much useful for predicting wind speed in renewable energy systems.

7.Acknowledgment

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8. References

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