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Research paper

Wind Speed Forecasting in Different Seasons Using ELM Batch Learning Algorithm in Indian Context

[1]Rashmi. P. Shetty, [2]A. Sathyabhama, [3]Srinivasa. Pai. P, [4]Ranjith Shetty K

[1,2]Department of Mechanical Engineering NITK, Surathkal, India
[3,4]Department of Mechanical engineering NMAMIT, Nitte, India
**Corresponding author Email: [1]iprashmi@nitte.edu.in*

Abstract

Efficient wind speed forecasting is important for wind energy sector for better wind power integration. This paper focuses on developing seasonal wind speed forecasting models in Indian context. Wavelet transform (WT) technique has been used for denoising the data obtained from supervisory control and data acquisition (SCADA) of a 1.5 MW wind turbine located in central dry zone of Karnataka, to reduce the unnecessary fluctuations in the wind speed time series. Partial auto correlation function (PACF) has been used for selection of input parameters, which greatly influences the forecasting accuracy. Forecasting models have been developed using a fast and efficient extreme learning machine (ELM) algorithm. The results have been compared with conventional back propagation (BP) algorithm. The results show that the seasonal models developed using ELM have better forecasting performance compared to BP.

Keywords: *Wind speed forecasting, Seasonal model, Wavelet denoising, PACF, ELM*

1. Introduction

Global warming and climate change due to rising pollution are posing great environmental challenge. To counter these problems and to fulfil the steadily increasing energy demand, the energy sector is focusing more towards renewable energy sources. Wind energy being more competitive out of all the other sources, is expected to supply 12% of the world electricity demand by 2020 [1]. India is ranked fifth leading wind generation market in the world having wind energy proportion of 66.7% of its total renewable energy capacity [2]. India provides policy support for renewable energy at both state and central level and has an ambitious renewable energy target of 60 GW generation by wind in 2022, thus reduce the dependence on fossil fuel in its energy portfolio [3].

Wind energy sector is in strong need of accurate wind speed prediction and forecasting models, due to the stochastic nature of the wind. Such predictions provide effective approach for wind farm maintenance, power system scheduling, optimal operation, storage planning and electricity marketing [4-6]. The methods for wind speed forecasting models are classified as physical, statistical, artificial intelligence and hybrid models. The physical models are based on numerical weather prediction, which uses topological data such as temperature, altitude, pressure and humidity. They are complex and time consuming, thus are ideal for medium and long term forecasting [7]. Statistical or time series models use online measurement data for training these models, hence are easier to implement. The Auto Regressive (AR), Auto Regressive Moving Average (ARMA) and Auto Regressive Integrated Moving Average (ARIMA) are the most widely used statistical models [8-10]. Though these models are easy to implement, as they use only historical data, the nonlinear and non-stationary variation of wind speed, limits the performance of these statistical models.

To accurately map the nonlinear relationships and to provide better predictive performance, the Artificial Neural Network (ANN) and machine learning techniques have been widely used for wind speed forecasting applications. Zhen-hai Guo et al [11] proposed an ANN model for forecasting the wind speed based on BP algorithm and proved that the method is better than forecasting without seasonal exponential adjustment. Gong and Jing shi [12] compared three types of neural network (NN) for forecasting the wind speed and found that the accuracy depends on the type of NN and model inputs. Thanasis G. et al [13] used different types of local recurrent NN for wind speed and power forecasting. The results demonstrated the recurrent models trained by online learning schemes outperformed the static models. To overcome the drawbacks of a single model, use of hybrid models are becoming increasingly popular. The forecasting accuracy of these models are enhanced by integrating the advantages of two or more models. Jianming Hu et al [14] developed a hybrid wind speed forecasting approach by combining support vector machine (SVM) with ensemble empirical mode decomposition (EEMD). It was found that this model outperformed ARIMA, Seasonal ARIMA and SVM methods. Hui Liu et al [15] used hybrid empirical mode decomposition (EMD) and ANN for wind speed prediction. The model showed higher accuracy in comparison to ANN and ARIMA and hence greater suitability for jumping wind samplings. Hongmin Li et al [16] developed three hybrid models based on optimization algorithms and decomposition methods and proved that these models perform better than other models such as ARIMA, EMD-ARIMA, EMD-BP.

Traditional ANN models use gradient descent learning process, which is generally slow and needs iterative tuning of the network parameters. These models also have the tendency to converge to local minima. Extreme Learning Machine (ELM) algorithm proposed by G.B Haung [17] is a fast learning algorithm with better generalization performance, less simulation parameters and avoids the difficulties of local minima problem. Hence finds application in numerous areas of research including wind speed forecasting. Hui Liu et al [18] proposed four hybrid wind forecasting models by using different signal decomposing algorithms and ELM. It was found that ELM is suitable for wind speed forecasting and the utilization of decomposition algorithm resulted in better performance. Xin Wang et al [19] used a wavelet decomposition based ELM model for short term wind power prediction and found the method to be more precise compared to others. The performance of the neural network models depends highly on selection of input parameters. Chu Zhang et al [20] proposed a compound structure ELM with hybrid backtracking search algorithm (HBSA) for feature selection and binary valued BSA for optimal combination of weights and bias. The hybrid model provided satisfactory forecasting accuracy by effectively capturing the nonlinear characteristics of wind speed.

The performance of ANN is mainly dependent on the number of input variables. Zenhai Guo et al [21] proposed EMD based feed forward neural network (FNN) by selecting the input variables using PACF. In comparison to the basic FNN, the developed model showed good performance. Cong Feng et al [22] used deep feature selection framework for selection of suitable inputs for two layer ensemble machine learning model to forecast wind speed. The multi model framework resulted in 30% increase in the accuracy in comparison to the single model approach.

In this paper, an ANN model using ELM algorithm has been used for forecasting the wind speed for three different seasons namely winter, summer and monsoon in the Indian context. WT is used for denoising the original wind speed data. PACF has been used for selecting the suitable input variables to the forecasting model. The results have been compared with conventional BP models.

2. Wavelet based Denoising

Noise in wind speed data is introduced due to various reasons like anemometer error depending on the angle of attack [24], non-linearity of rotation of anemometer, over estimation at turbulent gusty wind condition etc. [25]. Such noise in wind speed affects the performance of the forecasting model in a great manner. Thus, denoising is the essential part of wind speed data pre-processing.

Various researchers have used traditional filtering such as Butterworth filter [26] and wavelet techniques for denoising. The wavelet theory which was proposed in 1980 by Morlet is more effective than conventional Fourier transform and hence finds applications in many fields such as signal processing, optics, speech discrimination etc. Due to this, it is a most effective method of signal processing technique used to process the wind speed series in order to improve the forecasting performance of the neural network model [21].

The three main steps followed in wavelet denoising are:

1) Wavelet decomposition: In this step the wavelet function and number of decomposition layers are selected.

2) Threshold processing: In this step either hard or soft thresholding is used to derive the coefficients.

3) Wavelet reconstruction: In this step the processed coefficients are used to get the denoised signal [23].

3. Extreme Learning Machine Algorithm

ELM is a fast and efficient learning algorithm introduced by G.B Haung in 2002 [17]. Conventional gradient learning algorithm is iterative in nature and hence leads to slow learning. In addition, it also suffers from easy convergence to local minima and demands tuning of many simulation parameters. In addition to overcoming all these difficulties, ELM also gives better generalization performance. In ELM, the output weights are analytically determined by using a simple generalized inverse operation called Moorse Penrose inverse operation.

ELM algorithm is as follows:

Suppose there are N distinct samples $\{x_i, y_i\}$ where x_i and y_i are input and target vectors respectively. The network output of a single layer FFN can be given as

$$O_j = \sum_{i=1}^{Q} \beta_i g_i(w_i x_j + b_i) \tag{1}$$

where, $g(x)$ is the hidden node activation function, w_i and β_i are the network weights between input- hidden and hidden- output layers respectively, b_i is the bias of the hidden layer selected randomly.

The above equation can also be written as Hβ=T (2)

where H is the hidden layer output matrix as given in Eq. 3 , β is the weight matrix between hidden and output layer as given in Eq. 4 and T is the target vector as given in Eq.5

$$H = \begin{bmatrix} g(w_1x_1+b_1) & \dots & g(w_Qx_1+b_Q) \\ . & & . \\ . & \dots & . \\ . & & . \\ g(w_1x_N+b_1) & \dots & g(w_Qx_N+b_Q) \end{bmatrix}_{NXQ} \tag{3}$$

$$\beta = \begin{bmatrix} \beta_1^T \\ . \\ . \\ . \\ \beta_Q^T \end{bmatrix}_{QXm} \quad (4) \qquad \text{and } T = \begin{bmatrix} t_1^T \\ . \\ . \\ . \\ t_N^T \end{bmatrix}_{NXm} \quad (5)$$

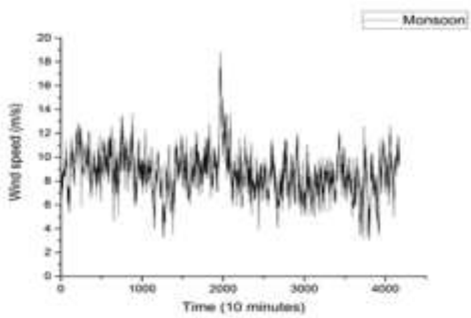
The output weight matrix can be found by

$$\beta = H^{\dagger} T \tag{6}$$

where $H^{\dagger}$ is the Moorse- Penrose generalized inverse of matrix H [24].

4. Model Development

Wind speed variation is strongly affected by the season. In India, there are three climatic seasons namely winter, summer and monsoon which is common over the entire geography. Accordingly three models have been developed by considering the one month representative data (January, April, July) from each of the season. Historical wind speed data of 10 min resolution collected in the year 2015 from SCADA of a large wind farm in the central dry zone of Karnataka state has been used in this study. The variation of wind in three representative months are shown in Fig. 1. The total data points in three months considered for study are 4400, 4299 and 4301. The wind data statistics for different seasons are given in Table 1. From the figures and the table, it can be observed that, monsoon season has a steady wind and higher mean wind speed value. Hence it is the ideal season for wind power generation compared to others.



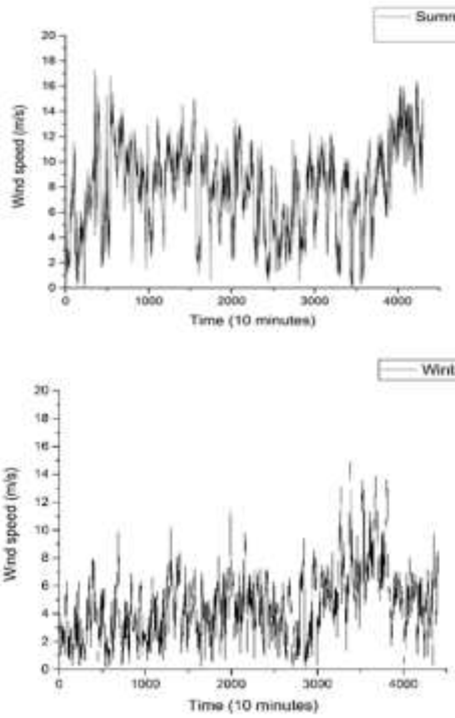


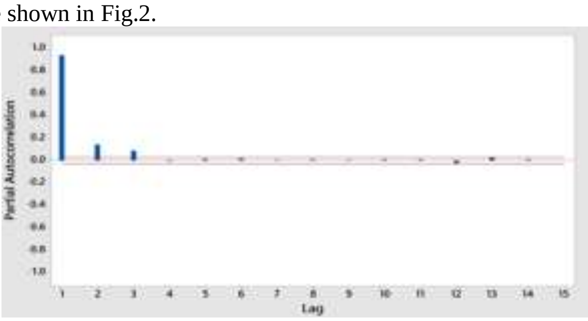
Fig.1: Original wind speed time series for different seasons

Table 1: Statistics of wind speed

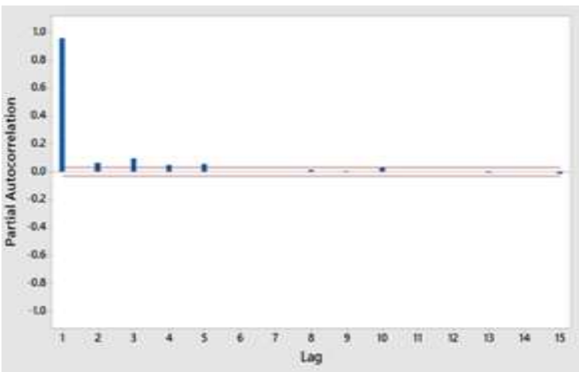
	Max	Min	Mean	Median
Winter	14.9	0.2	4.59	4.1
Summer	17.3	0.1	7.91	8.3
Monsoon	18.8	3	8.66	8.6

4.1 Selection of Inputs

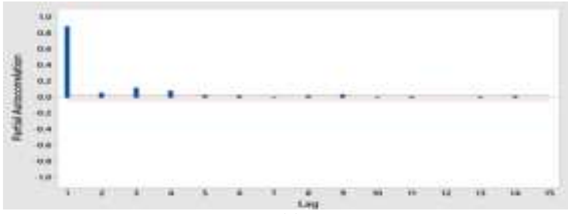
The performance of the ANN depends mainly on the input parameters selected for model development. Hence PACF has been used to select the number of previous wind speeds that have highest correlation to the wind speed in the next instance using MINITAB-17. The PACF plots for winter, summer and monsoon are shown in Fig.2.



(a) Winter



(b) Summer



(c) Monsoon

Fig. 2: PACF plots for wind speed

From the plots it can be seen that first three, five and six lags respectively show high correlation with significance level of more than 0.005 for winter, summer and monsoon respectively. Based on this analysis the data sets are prepared and accordingly there are three, five and six input neurons for winter, summer and monsoon models respectively. 85% of the data set has been considered as training data and the remaining for test data. Accordingly, 3737 and 659 are the training and test data size of winter and the corresponding values of summer and monsoon are 3651, 644 and 3540, 625 respectively.

4.2 Wavelet Denoising of Wind Speed Series Data

In this study, denoising of the original wind
Speed series has been done using three different wavelet functions namely symlet (sym), daubechies (db) and coiflet (coif) using sqtwlog soft thresholding method.
Three evaluation metrics namely mean absolute percentage error (MAPE), mean absolute error (MAE) and root mean square error (RMSE) have been used for comparing the performance of use of different wavelet functions for denoising and are given as follows:

$$MAPE = \frac{1}{N}\sum_{i=1}^{N}\frac{|X_n - \widetilde{X_n}|}{X_n} \times 100 \tag{7}$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|X_n - \tilde{X}_n| \tag{8}$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(X_n - \widetilde{X_n})^2} \tag{9}$$

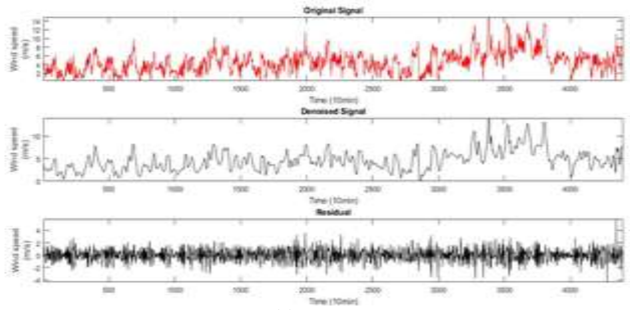
Where X_n and $\widetilde{X_n}$ are the actual and predicted values respectively. To select the best wavelet function for denoising, ELM model has been used by considering the data of monsoon season with fourth level decomposition. Table 2 gives the sample results for different functions. The performance of db4 wavelet is found to be better compared to others and hence is chosen for further study. The corresponding denoising results for different seasons are shown in Fig 3. From the figure it can be noted that the wind speed variation pattern of denoised signal is exactly same as that of original signal and the value of the residual is negligible. Hence it is clear that minor unwanted fluctuations have been filtered out by the denoising technique retaining the characteristics of the original signal. Further model development has been done using denoised wind data.

Table 2: Performance of ELM model for different wavelet functions

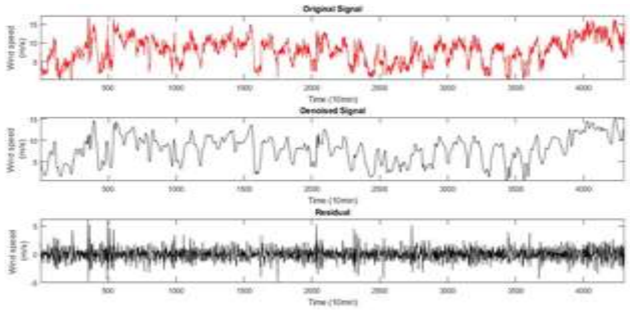
	MAPE (%)	MAE	RMSE
db4	1.6362	0.0975	0.0690
sym4	1.6853	0.1094	0.0773
coif4	1.6732	0.1103	0.0780

4.3 ELM Model Development

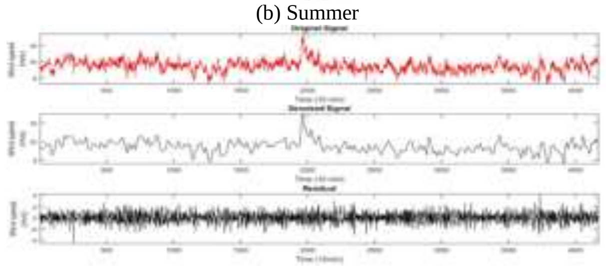
Three seasonal models have been developed using the wavelet denoised signal. In developing the three seasonal models, the number of hidden neurons have been selected on trial and error basis to achieve minimum error. The optimal number of hidden neurons for winter, summer and monsoon models are found to be 50, 50 and 60 respectively.



(a) Winter



(b) Summer



© Monsoon

Fig. 3: Denoising results

5. Results and Discussion

The central dry zone of Karnataka has good wind potential. Seasonal wind forecasting models have been developed in the present work by considering data from three representative months of three seasons.

Comparison of forecasting errors for different seasons is presented in Table 3. From the table, it can be observed that monsoon season has resulted in comparatively lower values of MAPE (%), MAE and RMSE. This is because in monsoon season, high speed and steady winds with less fluctuations is received as observed from Fig.1. On the other hand the wind speed in winter season is highly fluctuating and has thus resulted in higher error values.

The results of ELM have been compared with conventional BP models using the wavelet denoised data. The comparison of actual and forecasted wind speed by BP and ELM models for 100 sample data points in monsoon season has been plotted in Fig.4. From the table it is clear that ELM models have lower error values and forecasted values are closer to the actual. Thus proving the superiority of ELM algorithm in developing wind speed forecasting model.

Table 3: Comparison of errors for different ELM models

Dataset	Models	MAPE (%)	MAE (m/s)	RMSE (m/s)
Winter				
	ELM	2.3304	0.1190	0.0841
	BP	3.4882	0.1261	0.1965
Summer				
	ELM	1.2497	0.1500	0.1061
	BP	2.6896	0.1827	0.4251
Monsoon				
	ELM	1.3782	0.0929	0.0657
	BP	2.3233	0.2075	0.3155

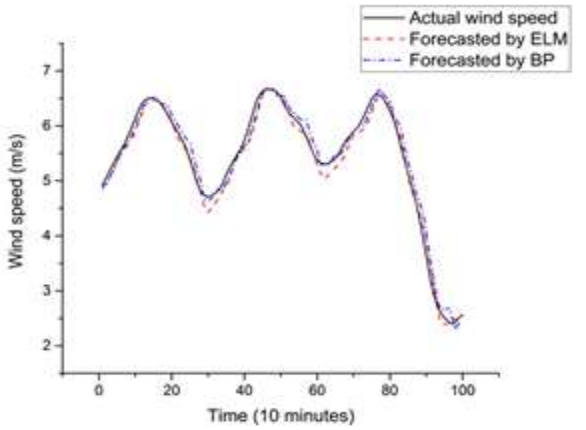


Fig. 4: Comparison of forecasting models for monsoon season

To prove the reliability of the model developed, the results obtained have been compared with that of the results available in the literature in Table 4. It can be observed that ELM model developed in this work by considering the monsoon data has resulted in lower error in comparison to other works.

Table 4: Comparison of results with literature

	Model	**MAPE (%)**	**MAE(m/s)**	**RMSE (m/s)**
Da Liu et al [27]	W-SVM-GA	14.79	0.7843	1.2125
Hongmin Li et al [16]	NCFM	5.7528	0.2565	0.1088
Present work model	ELM	1.3782	0.0929	0.0657

Wavelet- Support vector machine-Genetic algorithm (W-SVM-GA)

Novel combined forecasting model (NCFM)

5.1 Validation

For validation purpose, ELM model has been considered taking into account monsoon data. The model is validated considering 5% of the data that is 209 samples from the month of August which is not a part of training or test data. The validation results are presented in Table 5. The actual and predicted values has been plotted in Fig.5. From the figure and the table it is clear that the model performance is satisfactory for the validation set with MAPE (%) of 2.7406.

Table 5: Validation Results

Dataset	**Models**	**MAPE (%)**	**MAE (m/s)**	**RMSE (m/s)**
Monsoon	ELM	2.7406	0.2687	0.1900

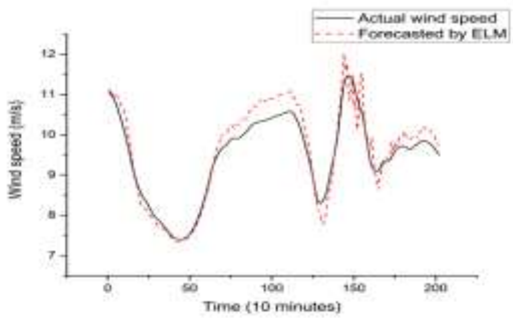


Fig. 5: Validation results for ELM model considering monsoon data

6. Conclusions

Due to the stochastic nature of wind, reliable and accurate forecasting of its speed plays an important role in the wind farm development. Seasonal wind forecasting models namely winter, summer and monsoon have been developed by using ELM algorithm in Indian context. From the present study it is observed that the monsoon season gets high speed and steady wind which lead to better performance of this model compared to others. Also it is important to note that seasonal trend of wind speed variation greatly influences the accuracy of the forecasting model.

Use of wavelet based denoising of data and PACF for selection of input parameters has a definite contribution in forecasting performance of the models. ELM is an efficient algorithm for wind speed forecasting applications as it has resulted in better performance in comparison to BP. There is a 33.19%, 53.53 %, 40.62% reduction in MAPE for prediction considering winter, summer and monsoon seasons respectively for ELM in comparison to BP, proving the superiority of the algorithm.

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