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Short Term Wind Speed Forecasting using Hybrid ELM Approach

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Abstract

Objectives: To enrich the accuracy of the wind speed forecasting to calculate wind power generation connecting to grid with the help of machine learning algorithms. **Methods/Statistical Analysis:** A novel hybrid method, Persistence - Extreme Learning Machine (P-ELM) algorithm is proposed. It uses the features of both Persistent and Extreme Learning Machine algorithms. The historical data of meteorological parameters viz. pressure, temperature and past wind speeds are considered as input parameters and wind speed for the next instant as the output, measured at one hour interval for a period of a month are used for the study. **Findings:** The forecasting is carried out for three areas Guntur, Vijayawada and Ongole of Andhra Pradesh state, India for winter, summer and rainy seasons. The performance of the P-ELM is evaluated in terms of Mean Absolute Error (MAE) and Root Mean Square Error (RMSE). From the results obtained it can be concluded that the P-ELM algorithm leaves behind the fundamental Persistent and Extreme Learning Machine algorithm not only in terms of error metrics but also in simulation time. The entire simulation is carried out with the help of MATLAB 2013a software. **Application/Improvements:** This technique is very much helpful in real time forecasting of wind speed to avoid the high level of uncertainty involved in wind generation, there by increases the power system security and stability.

Keywords: Extreme Learning Machine (ELM), Forecasting, Machine Learning Algorithms, Persistent Extreme Learning Machine (P-ELM), Wind Speed

1. Introduction

Wind energy is a clean energy, which is in-exhaustive and infinite in nature. The total global wind power at the end of 2015 was reached to 432.9 GW, reported by GWEC. It is a sound alternative to the traditional power generation resources. During the last few decades there was an accelerated shoot-up in the penetration of wind power in to the electrical power system. However the turbulent nature of wind generation necessitates the power system operators to adopt highly sophisticated forecasting methods to anticipate the wind speed accurately. In spite of all these many researchers has been focused to develop a solid methodology to envision the wind speed variations. In[1] Boot strap based ELM approach (BELM) was proposed to overcome some of drawbacks of NN forecasting techniques, like local minima, over training and high computational cost and the same was tested on Australian wind farm. A hybrid intelligent algorithm[2] was proposed to predict intervals of wind power generation based on ELM and Particle swarm optimization approach and evaluated the performance of proposed approach by considering two wind farms in Australia. In[3] Proposes a probabilistic wind power forecasting method using Quantile regression method with the help of Wavelets, Firefly algorithm, Fuzzy ARTMAP and Support vector machine for wind power forecast. The efficiency of proposed hybrid approach is tested on data of wind power from the Kent Hill wind farm in New Brunswick, Canada. In[4], the authors put forward the Levy α-stable distribution, to describe the heavy-tailed characteristics of the wind power forecast error (WPFE) data. It develops statistical, distribution-based description of the WPFE. The performance was tested on historical WPFE on the wind farms in the Belgian power system. In[5] Focuses on probabilistic wind power forecasting with consideration of geographically distributed information. In this First, the original single-valued predictions are corrected by

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integrating off-site information, later these are upgraded to full probabilistic forecasts. The performance of this approach was checked with wind farm in Denmark. In[6], the authors enroot a mixed ARMA model. In this paper wind direction is added in to wind speed and wind power forecast. Using K-means algorithm wind directions are classified, the dummy variables related to wind speed are wind directions are used in mixed ARMA model. The projected methodology was tested with the data retrieved from Denmark off shore site. In[7] recommended a nonlinear least square piecewise model to figure out the wind power correctly and the performance was tested on a small Canadian wind farm. In[8], a hybrid approach based on neuro – fuzzy wind power prediction system was constructed. A wireless sensor network also used to measure and transmit the parameters air temperature, wind speed, air density and air pressure. In[9], the short term wind power was forecasted using a new Imperialistic Competitive Algorithm- Neural Network (ICA-NN) with the help of data retrieved from SCADA and NWP approaches. The schemed technique was tested on a model built for summer side wind farm in Prince Edward, Canada. The authors[10] projects a hybrid strategy consisting of nonlinearity dimensionality reduction component by auto-encoder network and wind power was forecasted with the help of Sparse Bayesian Regression optimized by Artificial Bee Colony Optimization. This was tested on real data obtained from wind farm in western china. In[11], a very short term wind power was forecasted with the help of Auto Regressive model (AR), Kalman Filter (KF) and Neural Network (NN), the results are compared. With the help of historical data, forecasting was done for a very short period in terms of seconds.

In[12], the authors recommended an enhanced particle swarm optimization based hybrid approach for wind power prediction in short time. They combine Persistence method, back propagation neural network and the radial basis function neural network. The performance was tested on the real data obtained from wind energy conversion system located in Taichung coat of Taiwan. In[13] Realizes a new probabilistic approach for probabilistic wind power forecasting based on artificial intelligence. The uncertainties due to inaccuracies of the numerical weather predictions, the weather stability and the deterministic forecasting model. This approach was implemented on the two wind farms located in Lasithi wind farm and the Klim wind farms. The authors of[14] envisioned the short term wind power by combining empirical mode decomposition(EMD) and radial basis function neural networks (RBFNN). EMD decomposes wind power to reduce nonlinear and non-stationary characteristics of wind power, and then RBFNN was used to predict the wind power. This procedure was tested on the data obtained from Zhejiang Provincial Electric Power Test Research Institute. In[15] Suggests a hybrid intelligent approach by combining wavelet transform (WT), particle swarm optimization (PSO) and adaptive-network-based fuzzy inference system (ANFIS) to forecast wind power and as well as electricity prices in short term. The effectiveness was tested for fore sighting of wind power in Portugal. In[16], different forecasting models and the current use of wind power forecasting in US electricity markets are discussed and suggested to revise the market design to better use of advanced wind forecasting techniques. In[17], the authors have reviewed different statistical methods for Wind power forecasting and have given a small brief about the Physical methods, Statistical methods and Hybrid methods for forecasting of wind. In[18], analyses the impact of integrating wind power generation on the amount of regulation and load following requirements needed for California independent system operator. The authors have claimed that, the methodology proposed can have application in balancing authorities, project developments and government organizations to access the wind integration to the grid.

In[19] reviewed, how the energy balancing with wind energy is done in short term. The advancement to traditional scheduling methodology used in industries was also discussed. However the experience of system operator will be critical to future developments. In[20], with the aid of artificial neural networks and new back propagation algorithm wind power was predicted. The effectiveness of the algorithm was simulated by collecting the data from Tamil Nadu state Electricity board. In[21], reviewed volumes of papers and presented an overview on current advancements in wind power forecasting on different time scales. Based on wind speed and wind power future development in forecasting was proposed. In[22], several soft computing techniques for wind power prediction have been spoken of. The performance of two methods BPNN and RBFNN are accessed by calculating mean average percentage error. The real time data was collected from a weather station of Ontario, Canada. In[23], Focuses on long term wind power and wind speeds. The GRPE Drpe algorithm was introduced to train the recurrent forecast models. The performance was tested

with the test data obtained from Roka's wind park on the Greek island of Crete. In[24], a short wind power forecasting was done by considering meteorological data viz. wind speed, wind direction, temperature, relative humidity and pressure of atmosphere. The back propagation neural network was trained with NWP data and future 24hrs of wind power was forecasted using the BPNN. The work was sponsored by Yike solar energy generation limited corporation of Ningxia power generation group, the National Natural Science Foundation of China (NSFC). With the help of accurate prediction of wind speed and direction[25] optimal sitting of wind turbine was done. Under the variable conditions of wind speed and load, dynamic analysis of PMSG was done efficiently[26].

2. Mathematical Model of ELM

Extreme Learning Machine algorithm is developed over Neural Network to trim down the shortcomings of NN such as overtraining and local minima. It built with only one hidden layer and it is a feed forward neural network. It involves randomly initialization of the input weights and bias factors[27]. The calculations are very easy as it involves only matrix computations[28]. Let S be the number of input samples fed as the inputs to ELM structure. The input samples are organized as $(x_p, y_p)^S{}_{p=1}$ where $x_p = [x_{p1}, x_{p2}, x_{p3,}, ..., x_{ps}]^T$ and $y_p \in R^t$ with $y_p = [y_{p1}, y_{p2}, y_{p3}, ..., y_{pt}]^T$. The mathematical model of ELM with h number of hidden nodes and A (.) activation function, is given as:

$$F(x_q) = \sum_{P=1}^{h} \beta_p A(\alpha_p \cdot x_q + \gamma_p), \quad q = 1,2,....., S \tag{1}$$

Where $\alpha_p = [\alpha_{p1}, \alpha_{p2}, \alpha_{p3}, ..., \alpha_{ps}]^T$ is the weight vector connecting p^{th} hidden node and the input nodes, $\beta_p = [\beta_{p1}, \beta_{p2}, \beta_{p3}, ..., \beta_{pt}]^T$ is the vector of weights connecting p^{th} hidden node and the output nodes. γ_p Is biasing factor of p^{th} hidden node and $A(\alpha_p \cdot x_q + \gamma_p)$ is the output of p^{th} hidden node corresponding to input neuron x_q. The Equation (1) can be modelled as

$$A\beta = Y \tag{2}$$

Where A is the matrix of outputs of hidden layer. A matrix can be expressed as

$$A = \begin{bmatrix} A(\alpha_1 x_1 + \gamma_1) & A(\alpha_2 x_1 + \gamma_2) & . & . & A(\alpha_h x_1 + \gamma_h) \\ . & . & . & . & \\ . & . & . & . & \\ . & . & . & . & \\ A(\alpha_1 x_S + \gamma_1) & A(\alpha_2 x_S + \gamma_2) & . & . & A(\alpha_h x_S + \gamma_h) \end{bmatrix}_{SXh} \tag{3}$$

Y is target matrix given as: $Y = [y_1, y_2, y_3, ..., y_t]^T$.

In ELM algorithm firstly the input weights α and biases γ are randomly initialized and Output matrix of hidden layer, A is computed. Finally $\bar{\bar{\alpha}}$, $\bar{\bar{\gamma}}$ and $\bar{\bar{\beta}}$ are can be obtained as

$$\left\| A(\bar{\bar{\alpha}}, \bar{\bar{\gamma}})\bar{\bar{\beta}} - Y \right\| = \min_{\beta} \left\| A(\alpha, \gamma)\beta - Y \right\| \tag{4}$$

This is reflecting to minimizing the cost function in the conventional gradient based back – propagation learning algorithm.

$$F_{BP} = \sum_{q=1}^{S} \left[\sum_{p=1}^{h} \beta_p A(\alpha_p \cdot x_q + \gamma_p) - y_q \right]^2 \tag{5}$$

For a randomly assigned input weights and biases, training an SLFN costs analogues to finding the smallest norm least square solution of the above system in (1)and can be stated as

$$\bar{\bar{\beta}} = A^{+} Y \tag{6}$$

Where A^{+} is the Moore – Penrose generalized inverse of the matrix A and is evaluated from Singular value decomposition (SVD) method[29-31]. The ELM is a best answer for shortcomings of traditional NN such as over training, local minima and difficulty computational procedures. It converges to best results with less computations as it involves only simple matrix calculations.

3. Modelling of proposed P-ELM

Many a literature has been thrown light on Persistent model of forecasting of wind power or wind speed. It assumes that the forecasted value at $(t+1)^{th}$ instant is same as it was at t^{th} instant[32].

$$Wsp(t+1) = Wsp(t) \tag{7}$$

Where $Wsp(t+1)$ is the wind speed at $(t+1)^{th}$ instant

and $Wsp(t)$ is the wind speed at t[th] instant. It is very simple way of forecasting and is used as a comparison tool over NWP methods. This naive approach is very much suitable for very short term and short term time horizon forecasts. But it shoots down the accuracy as forecasting time horizon increases.

The hitch in the Persistent method is overcome by combining ELM with Persistent approach, combinely termed as Persistent-Extreme Learning Machine (P-ELM) algorithm. This method uses the fast convergence and efficient training process of ELM and easy prediction nature of Persistent method. The sound features of above two methods facilitates the forecasting of wind speed in short term very precisely. The mathematical modelling of P-ELM is given below.

In P-ELM, let the input samples patterns be $(x_p, x_{p+1})_{p=1}^{S-1}$ Where $x_p \in R^S$, $x_p = [x_{p1}, x_{p2,} x_{p3}, ..., x_{p(S-1)}]^T$ and $x_{p+1} = [x_{(p+1)1}, x_{(p+1)2}, x_{(p+1)3}, ..., x_{(p+1)S}]^T$.

The mathematical model of P-ELM with h number of hidden nodes and A (.) activation function, is given as:

$$F(x_q) = \sum_{P=1}^{h} \beta_p A(\alpha_p \cdot x_q + \gamma_p), \quad q = 1,..., S \tag{8}$$

The equation(1) can be modelled as

$$A\beta = X^{\otimes} \tag{9}$$

The matrix A is modified as

$$A = \begin{bmatrix} A(\alpha_1 x_1 + \gamma_1) & A(\alpha_2 x_1 + \gamma_2) & . \; . & A(\alpha_h x_1 + \gamma_h) \\ . & . & . \; . \; . & \\ . & . & . \; . \; . & \\ . & . & . \; . \; . & \\ A(\alpha_1 x_{S-1} + \gamma_1) & A(\alpha_2 x_{S-1} + \gamma_2) & . \; . & A(\alpha_h x_{S-1} + \gamma_h) \end{bmatrix}_{(S-1)Xh} \tag{10}$$

$X^{\otimes}$ is target matrix given as: $X^{\otimes} = [x_2, x_3, x_4, ..., x_s]^T$.

After randomly initialization of α and γ, the hidden layer output is calculated. $\overline{\overline{\alpha}}, \overline{\overline{\gamma}}$ and $\overline{\overline{\beta}}$ are obtained with the help of following equation.

$$\left\| A(\overline{\overline{\alpha}}, \overline{\overline{\gamma}})\overline{\overline{\beta}} - X^{\otimes} \right\| = \min_{\beta} \left\| A(\alpha, \gamma)\beta - X^{\otimes} \right\| \tag{11}$$

The cost function to be minimized is

$$F^{\otimes}{}_{BP} = \sum_{q=1}^{S} \left[\sum_{p=1}^{h} \beta_p A(\alpha_p \cdot x_q + \gamma_p) - x_q \right]^2 \tag{12}$$

Finally $\overline{\overline{\beta}}$ is calculated with the help of Moore – Penrose method

$$\overline{\overline{\beta}} = A^{+} X^{\otimes} \tag{13}$$

4. Performance Evaluation

The performance of projected methodology is evaluated by forecasting wind speeds for short term periods, up to 24 hours. The metrics calculated were Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) to measure the accuracy.

$$MAE = \frac{1}{S} \sum_{p=1}^{S} (Wsp_p{}^{forecasted} - Wsp_p{}^{actual}) \tag{14}$$

$$RMSE = \sqrt{\frac{1}{S} \sum_{p=1}^{S} (Wsp_p{}^{actual} - Wsp_p{}^{forecasted})^2} \tag{15}$$

Where $Wsp_p{}^{actual}$ is the actual wind speed, $Wsp_p{}^{forecasted}$ is the wind speed forecasted for the p^{th} pattern, and S is the number of samples.

5. Results

The input parameters to the P-ELM structure is considered as temperature in °C, Pressure in mbar and wind speed in m/s as the speed of wind is strongly dependent on temperature and pressure. The output parameters are temperature, pressure and wind speed for the next instant. The real time data was taken from the Indian Solar Resource Data website. The sites under case study are Guntur, Vijayawada and Ongole cities, which are located in the state of Andhra Pradesh, India. For the short term wind speed prediction the data considered during the month of 1st January, 2011 to 31st January, 2011 for the winter season. The data set contains 24 hours samples per day, for 31 days. The total number of patterns are 744, in which 521 samples are taken to train the P-ELM structure and remaining 223 samples are used for testing purpose. For the season of summer from 1st May, 2011 to 31st May, 2011 data was considered. Similarly for rainy season, 1st September, 2011 to 30th September, 2011totally 720 input patterns, where in which 504 input patterns are for training and 216 are used for testing. For the selected three locations, in each location the wind speed was forecasted for three seasons for the next 24 hours.

The results of proposed approach are shown from Figure 1 to Figure 9. For the three areas Guntur, Vijayawada and Ongole, three seasons, winter, summer and spring are obtained. The graph is drawn for the wind speed predicted values with respect to time up to 223 hours. Table 1 summarizes comparison of proposed approach with already existing Persistence and ELM methods. The proposed hybrid approach proved as the best forecasting techniques over the other two. The MAE and RMSE for the Guntur area, for the season of January is 2.0091 and 2.0828 respectively, whereas ELM results in 2.4857 and 2.3522 respectively. Similarly for the remaining two areas Vijayawada and Ongole, MAE and RMSE are calculated for three different seasons.

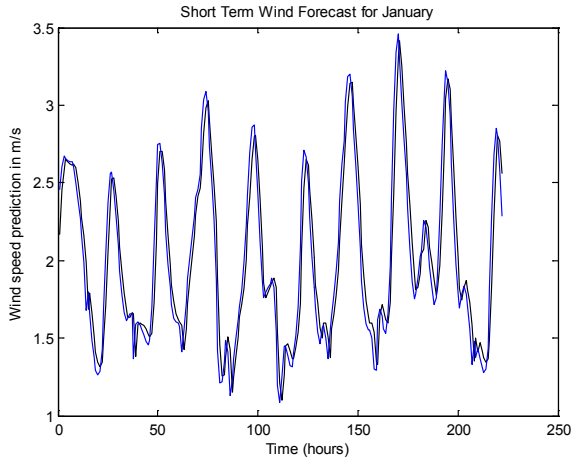

Figure 1. Winter Season: Actual wind speed (blue line), Forecasted (Black line) vs. Time (hours) for Guntur region.

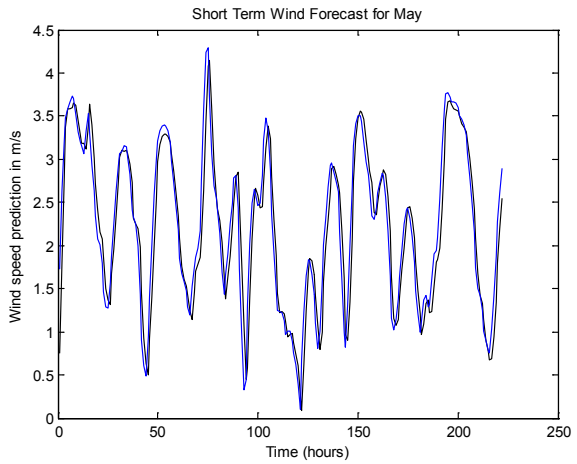

Figure 2. Summer Season: Actual wind speed (blue line), Forecasted (Black line) vs. Time (hours) for Guntur region.

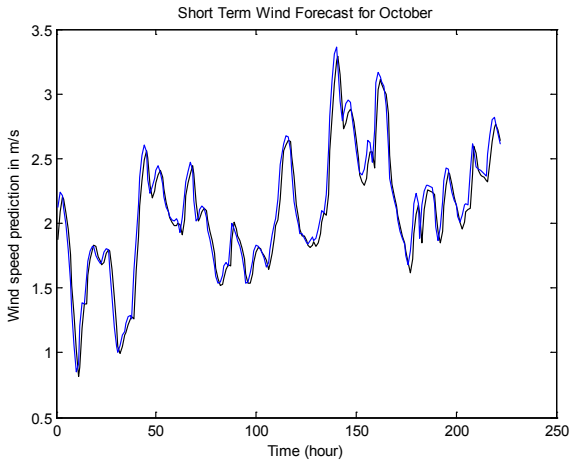

Figure 3. Rainy Season: Actual wind speed (blue line), Forecasted (Black line) vs. Time (hours) for Guntur region.

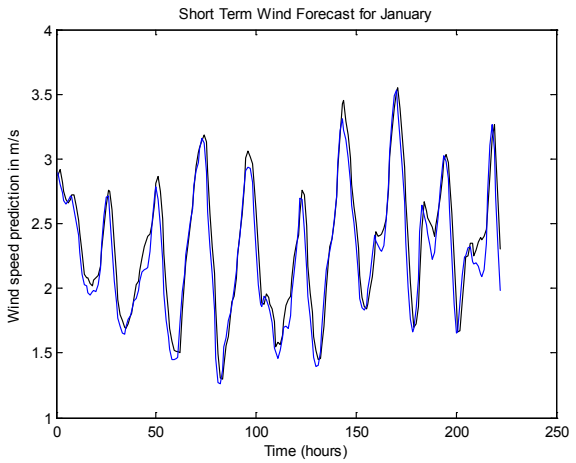

Figure 4. Winter Season: Actual wind speed (blue line), Forecasted (Black line) vs. Time (hours) for Ongole region.

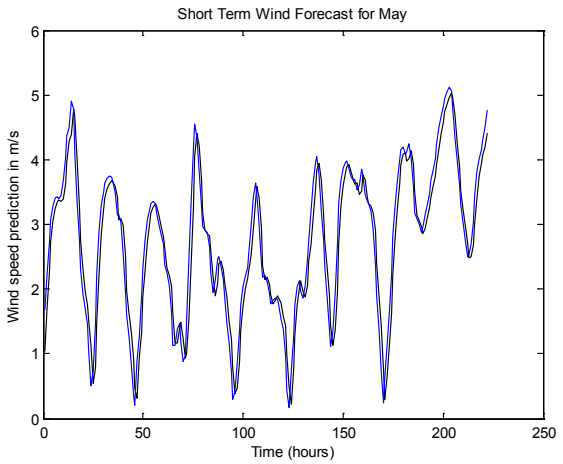

Figure 5. Summer Season: Actual wind speed (blue line), Forecasted (Black line) vs. Time (hours) for Ongole region.

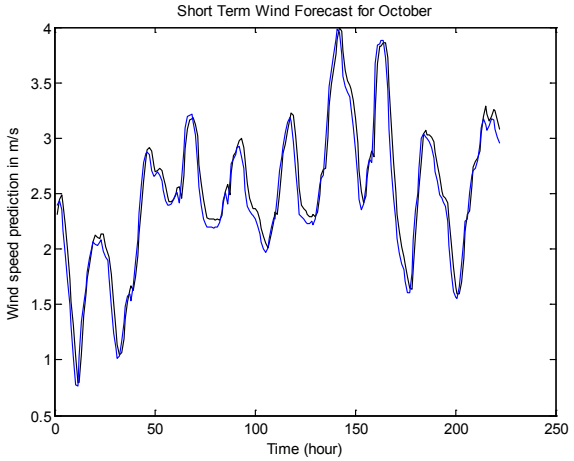

Figure 6. Rainy Season: Actual wind speed (blue line), Forecasted (Black line) vs. Time (hours) for Ongole region.

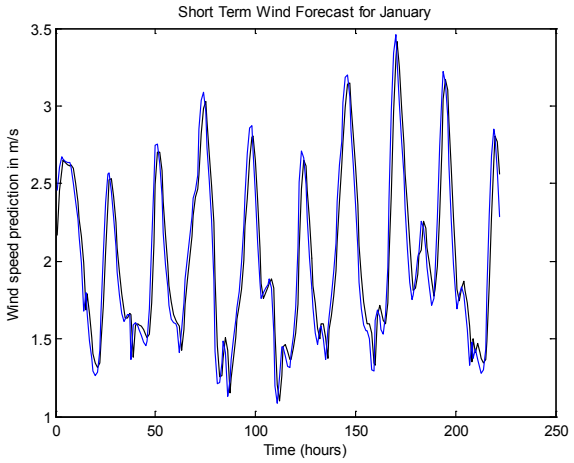

Figure 7. Winter Season: Actual wind speed (blue line), Forecasted (Black line) vs. Time (hours) for Vijayawada region.

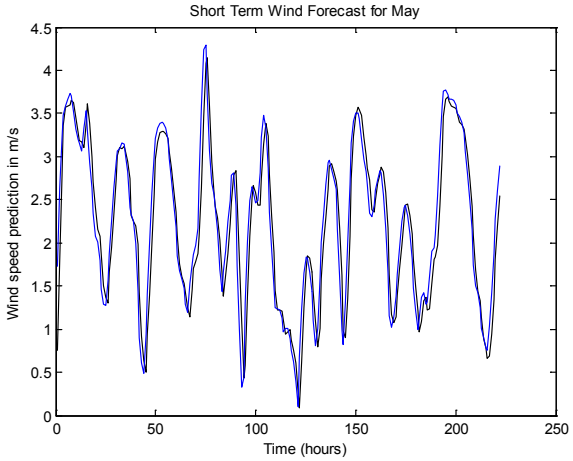

Figure 8. Summer Season: Actual wind speed (blue line), Forecasted (Black line) vs. Time (hours) for Vijayawada region.

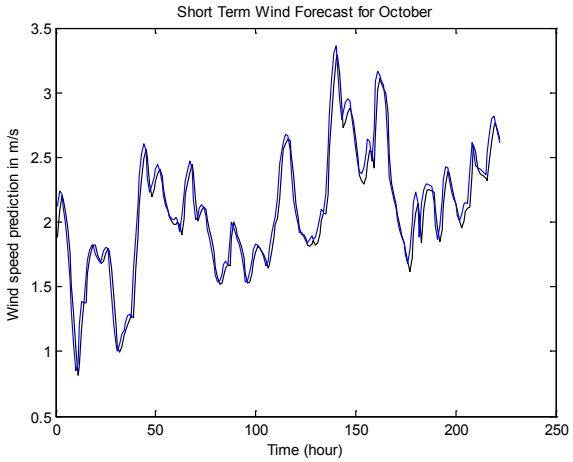

Figure 9. Rainy Season: Actual wind speed (blue line), Forecasted (Black line) vs. Time (hours) for Vijayawada region.

Table 1. Comparison of Results

	ELM		PERSISTANCE		P-ELM	
	Winter		Winter		Winter	
	MAE	RMSE	MAE	RMSE	MAE	RMSE
Guntur	2.4857	2.3522	2.9712	2.205	2.0091	2.0828
Vijayawada	2.4412	2.1249	2.9666	2.1921	2.2035	2.0654
Ongole	2.8754	2.711	2.4794	2.7735	2.2575	2.388
	Summer		Summer		Summer	
Guntur	2.6248	2.514	2.6855	2.9434	2.2388	2.3877
Vijayawada	2.7114	2.897	2.8717	2.8847	2.2165	2.4121
Ongole	3.012	3.475	2.7501	2.923	2.2394	2.4666
	Rainy		Rainy		Rainy	
Guntur	2.8501	2.3547	2.3541	2.4264	2.1061	2.123
Vijayawada	2.9742	2.4721	2.3224	2.4565	2.1194	2.1212
Ongole	2.9754	2.9881	2.4701	2.5942	2.2022	2.2742

The time taken for the computation process is around 16.0190 seconds with MATLAB 2013a version and PC of 2GB RAM. Hence the proposed approach accuracy is very high with less computational time. This approach is very much suitable for real time forecasting.

6. Conclusion

In the present work, a novel hybrid forecasting approach was proposed for short term forecasting of wind speed in Guntur, Vijayawada and Ongole cities in three different seasons. The proposed method is based on the combination of Persistence and Extreme Learning Machine algorithm. The values of MAE and RMSE results show that P-ELM outperforms over the other two algorithms, with the acceptable computational time. Hence the proposed approach can be used for real time applications also.

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