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Full Length Research Paper

Performance analysis of modeling framework for wind speed prediction in wind farms

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This paper focuses on the analysis of prediction of wind speed in the wind farms. The performance of modeling can be analyzed by using the real time data with different heights of the wind mill. Artificial Neural Network is used here to develop models for predicting wind speed in wind farms. The models are mainly based on back propagation neural network and radial basis function neural network. The wind speed prediction is important because it is useful for assisting operational control of wind farms. The effectiveness of these models is demonstrated in this paper. It is found that the root mean square error can be reduced and the uncertainty of prediction and calculation time is also decreased in such a way that the efficiency of prediction is improved.

Key words: Arificial neural networks, prediction, models, back propagation network, radial basis function network, root mean square error.

INTRODUCTION

Nowadays energy crisis is the major problem in our country. The governments of most of the states have decided for few hours load shedding in every day. So we are thinking about other sources of electrical energy. Wind energy is one of the renewable, non- polluting sources of energy. The main problem of wind power generation of wind farm is the intermittent nature of wind power due to high correlation with stochastic non stationary wind speed. Wind speed prediction imposes many challenges to system operators which consists of maintaining system frequency, power balance and quality of power, planning which includes uncertainty in wind power to unit commitment, load scheduling etc. Prediction of wind speed is an important tool for ensuring the stability of power in the wind farms.

India has an installed wind power capacity of 14158 MW as on March 31, 2011 (Indian Wind Energy Association). India has 5th rank in the World for wind power installed capacity. Today India is a major player in the global wind energy market. India's first home grown wind technology company is Suzlon Energy Limited. The Suzlon Group is ranked as the world's fifth largest wind turbine supplier, in terms of cumulative installed capacity, at the end of 2011.

Wind speed prediction is necessary because of the intermittent, fluctuating and nonlinear nature of wind. Two main issues in the wind farm are how to make wind energy cost effective and how to integrate wind energy into the power grid. The wind speed prediction is an effective method to this problem. To obtain proper and efficient wind power utilization, the wind speed prediction plays an important role. Wind speed prediction has many applications such as Target tracking, Rocket launching, Ship Navigation, Missile guidance, Satellite launch and Electrical power demand forecasting etc (Sree and Ramakanth, 2008).

In the literature survey, several models are explained which are used for wind speed prediction. The models are mainly physical and statistical models (Gnana and Deepa, 2011). The physical model considers the physical reasoning to get the best results. The statistical model considers online measurements of data. The real time data is used here for the analysis of statistical model. Statistical models are more efficient than physical model. Artificial Neural network derives its computing power through its massively parallel distributed structure and its

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ability to learn and generalization for inputs. Neural network models have better performance than other models. Many approaches are used based on the neural network such as Multilayer perceptron (MLP), ADALINE, Back propagation network (BPN), Radial Basis Function network (RBFN), Recurrent neural network (RNN) and so on. Researchers have done some work related to these fields. In the literature review of wind forecasting proposed by Yuang and Jing-Shan (2007), the Statistical models are easy to model and cheaper to develop than other models. The disadvantage of this model is that as the prediction time increases, the prediction error also increased. Sree and Ramakanth (2008) proposed a model which uses BPN for wind speed prediction. Here the predicted wind speed differs from actual by a maximum of 5%. Akinci (2011) proposed a model, which uses Levenberg Marquardt for wind speed prediction. The main advantages in this model are the accurate and low mean square error. A new model was created by Han and Yang (2010) for prediction of wind speed. The key point here is to improve forecast accuracy. Ashraf et al. (2012) proposed a wind speed prediction model which used the parameter wind speed to get improved wind power. The test results obtained for 2, 3, 24 and 72 h in an advance. Liang (2010) implemented a model which uses RBFN. The main advantages for this model are the feasibility, high precision and high learning speed. The present model cannot meet the average error criteria which is about 25 to 40%. In the same year Ivan et al. (2006) proposed a new model which used RBF. The achievement in this model is more prediction time than previous one.

Jayaraj and Padmakumari (2003) implemented model which uses back propagation based on time series approach for wind speed prediction. The key point is to improve precision and slow convergence. Mohamed et al. (1998) proposed to predict wind speed based on BPN .The energy is saved by the reduction in operating cost by 2 to 5%.

Perez et al. (1998) implemented a model for the wind speed prediction using MLP with Levenberg Marquard and Polak Ribie algorithm. The advantage in this model is that the prediction of wind speed with accuracy more than 90%. In the same year Goncalo et al. (2006) proposed a model which uses radial basis function neural network for wind speed prediction and is found that it is more efficient than MLP. The achievements in this model are more efficient and feasible.

Fonte et al. (2005) implemented a model to predict average hourly wind speed based on BPN. The mean square error (MSE) in training set is 1.012 m/s. Jaya et al proposed the wind speed prediction is up to 1 h, 24 and 48 h based on back propagation time series. The achievements in this model are the reliability and flexible approximation. Mohandas et al (2006) introduced a neural network model which uses BP algorithm for prediction of wind speed and compared its performance with an Auto Regressive (AR) model. The root mean square error (RMSE) was used as performance indicator and the ANN technique performed better than the auto regressive model.

Perez et al. (1998) pointed out the use of stuggar NN simulator with back propagation for predicting wind speed may lead to rely on knowledge experience of the meteorologist. Here the key point is the feasibility with minimum possible errors. The advantage of this result is that the value of mean square error (MSE) is 0.00056 and predicted the wind speed for 20 min. Mithuharu and Bahman (1998) implemented a model for wind power generation which uses back propagation algorithm (BPA). The key point is to minimize the error and give more accurate wind speed forecasting. This improved wind forecast method provides accuracy of above 90%. The achievements of result are the improved accuracy and predicts up to 24 h ahead. Anurag and Deo (1995) implemented a model for forecasting wind speed with neural networks. This neural network model uses cascade correlation and back propagation algorithm for short-term wind speed prediction. The key points are more accuracy and the mean square error is 4.7%. The proposed models compared with the previous models and are more efficient than the other.

Artificial neural network (ANN) is an efficient and robust mathematical model of nonlinear regression, capable of dealing with great number of input variables. The goal of the algorithm is to find values of weight and biases that minimize the error between predicted and target measurements.

MATERIALS AND METHODS

Neural network model are successfully applying in variety of applications such as prediction, image processing and pattern classification. The appropriate Neural Network Models can be trained to predict future value of dependent variables. ANN is a computing technique which resembles as in the human brain. One of the basic ANN model is Multi layer perceptron (MLP). The back propagation (BP) algorithm is normally used for training MLP neural network. ANN is characterized between the neurons (Architecture), its method of determining weights of the connections (Training/Learning) and its activation function. In BPN, Levenberg Marquardt algorithm is used. In RBFN, Gaussian function is used. The activation is performed by the improvements of models. These are explained below.

Back propagation network

Back propagation network is feed forward network which is described in Chao and Wang (2007). In the architecture of back propagation network, we used 3 layer network models consisting of input, hidden and output layer. The input layer is set of numerical inputs. The inputs are then multiplied by weights and processed by individual processing units in second layer. The BP algorithm has two phases. In the first phase the inputs are given and propagated through to compute output. The output is compared with desired value, to obtain the error. The second phase involves backward pass through network during which error signal is passed to each unit in

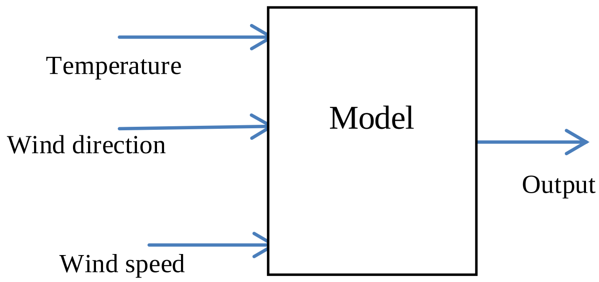

Figure 1. Architecture.

network and appropriate weight changes are calculated. The gradient descent method is adopted for updating the weights of neural network. In this paper, the BP method has been trained and tested on real time data.

The main advantage of the BPN is that, it can fairly approximate a large class of functions, relatively simple implementation and uses standard method. To be most effective, the momentum parameter and the learning rate coefficients are adjusted. Many optimization methods have been developed to improve the convergence speed of the conventional BP algorithm is described by Ying and Ching-Ping (2010).

Output, $Y_K(t) = f(net_k(t))$ (1)

where $net_k(t) = SUM(W_{ki} * X_i(t))$

W_{ki} is the weight and X is input

Activation function, $f(x) = 1/1+exp(-x)$ (2)

where X is input

The BP algorithm has some limitations such as low convergence and local minima. We are selecting proper momentum factor and learning rate for overcoming these limitations. The proper selection of these parameters is improved by the algorithm. The selection of learning rate and momentum factor is very important. We choose learning rate as small value and adding momentum for avoiding oscillation. When no momentum is used, it takes long time before the minimum has been reached with low learning rate. With high learning rate the minimum is reached because of the oscillation. Minimum error will be reached faster by adding the momentum factor.

Radial basis function network

Radial basis function network has been used for function approximation and recognizing applications. It mainly uses the Gaussian function. RBF networks consist of three layers as input, hidden and output layer. The hidden layer is a layer of RBF units. The output layer consists of a linear function. The interconnection between input and hidden layer form the hypothetical connection and between hidden and the output layer form weighted connections (Goncalo, 2006).

Each hidden layer unit represents a single radial basis function, with associated center position and width. Each neuron on the hidden layer employs a radial basis function as nonlinear transfer function to operate on the input data. The most often used RBF is Gaussian function that is characterized by a center ($\boldsymbol{c}_j$) and width (r_j). RBF functions by measuring the Euclidean distance between input vector ($\boldsymbol{x}$) and the radial basis function center ($\boldsymbol{c}_j$) and performs the nonlinear transformation with RBF in the hidden layer as given in below:

$H_j(x) = \exp(-(||\boldsymbol{x}-c_j||^2/r_j^2)$ (3)

In which, H_j is the notation for the output of the j^{th} RBF unit. For the jth RBF $\boldsymbol{c}_j$ and r_j are the center and width, respectively. The operation of the output layer is linear, which is given in Equation (4). The advantages of RBFN are more compact and it requires less time than BPN. And also eliminate local minima phenomena. The selection of centers of Gaussian function is important for nonlinear approximation. The weights between hidden and output layer can then be updated by using the gradient descent rule (Fonte et al., 2005).

The architecture of RBFN is 3 layer networks. The input layer is given the inputs. The hidden layers process the inputs. The output layer performs a simple weighted sum to get a linear output

Output, $Y = SUM(W_i * V_i(x)$ (4)

Where, W_{ki} is the weight and V is input

$Vi(x) = ø(|| X-X_i||)$

Activation function, $f(x) = \exp(-x^2)$ (5)

Where, X is input

Implementation

The model is constructed by combining artificial neurons. Initially, the inputs are selected. Secondly, the learning/training with the given inputs and then testing are done. The wind speed depends on temperature, past wind speed, wind direction and so on. The collected data are used as input to the model. Large number of input parameters can be used for the analysis of the new models. Here mainly used parameters are temperature, wind direction and past wind speed. The inputs are analyzed for two wind mills of different heights of 50 and 65 m. The real time data for the inputs to the new model are taken for every 10 s. Initially 500 data are used for the analysis of new model. Then 1000, 2000,5000,10000 etc. data are utilized for training and testing of the new model.

Architecture

For implementing the architecture, selection of inputs, hidden neuron and outputs are required. These selections depend upon nature of the problem. Here we are selecting temperature, wind direction and past wind speed as an inputs and predicted wind speed as an output. Neural network with one hidden layer with sufficient number of hidden neuron is capable of approximating any continuous function. The basic architecture is shown in Figure 1.

The selection of hidden neuron is very important. To fix hidden neuron based on trial and error method. Here we are using 7 hidden neurons with single hidden layer. Finally we are constructing model having single hidden layer with 7 hidden neurons, 3 inputs and 1 output.

For implementing the model, initialize the weights, epochs. The performance can change by increasing the epochs. The weights are calculated by using gradient descent rule. The error is the difference between actual and target value. The errors are minimized by

Table 1. Comparative Analysis.

Tower height (m)	Total data	Train data	Test data	Correlation Coeff (R)	Analysis of wind speed prediction			
					BPN		RBFN	
					MSE	Performance of error	MSE	Performance of error
65	500	350	150	0.995	0.2524	0.0023	0.253	4.08159E-05
50	500	350	150	0.995	0.2524	0.0023	0.0228	0.00007244
65	1000	700	300	0.9826	0.2572	0.00247	0.0211	1.75262E-05
50	1000	700	300	0.9975	0.4846	0.00062	0.0022	0.00001412
65	2000	1400	600	0.9929	0.1776	0.0029	0.0038	1.05433E-05
50	2000	1400	600	0.9934	0.0828	0.00172	0.005	0.0000392
65	5000	3500	1500	0.9953	0.1709	0.00119	0.0028	0.00003465
50	5000	3500	1500	0.9942	0.076	0.00109	0.0013	0.00001749
65	10000	7000	3000	0.947	0.0397	0.00163	0.0018	0.00001772
50	10000	7000	3000	0.9941	0.2144	0.00137	0.0228	0.0000284

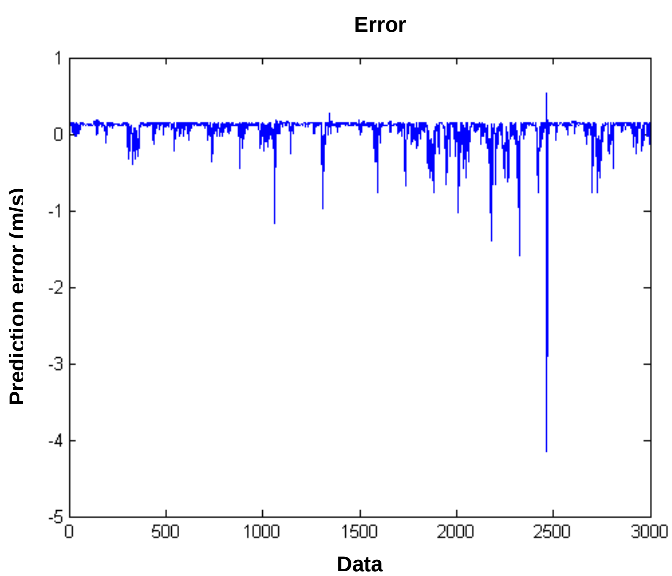

Figure 2. Prediction errror occur in BPN.

adjusting the weights.

Step 1

Data collection

The real time data is collected from Suzlon Energy Limited for one year. The inputs are temperature (degree Celsius), wind vane direction from true north (degree) and past wind speed (m/s). The data is collected in every 10 s for one year. And also we collected two different heights (65 and 50 m) of wind mill.

Step 2

Training of Network

For the purpose of developing models, it needs the training, testing and developing model at end stage for the past years in wind farms. The data required for input are daily wind speed, wind direction and temperature. Before training, Normalization is required. The data is normalized within (0 1). It scales number of data to improve the accuracy of subsequent numeric computations. Here 70% of total data is used for training.

Step 3

Testing of network

Evaluate the performance of network by testing models. Here 30% of total data is used for testing. Finally predicted wind speed is the output of the models.

RESULTS

The measured (collected) data were performed in Suzlon Energy Limited (50 and 65 m height) for one year. The 70% of data is used for training and 30% is used for testing the model. Using the set of collected data, new models for wind speed prediction based on ANN was developed and tested. The correlation coefficient (R) indicates the quality of the linear regression between measured and calculated value. Ideally, R=1.

The wind speed can predict by the available data. All simulations were done in MATLAB Version 7.11. Table 1 show comparative analysis of prediction errors in BPN and RBFN models. The correlation coefficient is also calculated with two different heights of wind mill. The performance of RBFN is better than BPN.

DISCUSSION

The Figures 4 and 7 shows the actual study of real time data of BPN and RBFN respectively. The prediction error is very much less than in Figure 5 than in Figure 2. The error suddenly decreases after 70% of testing is over

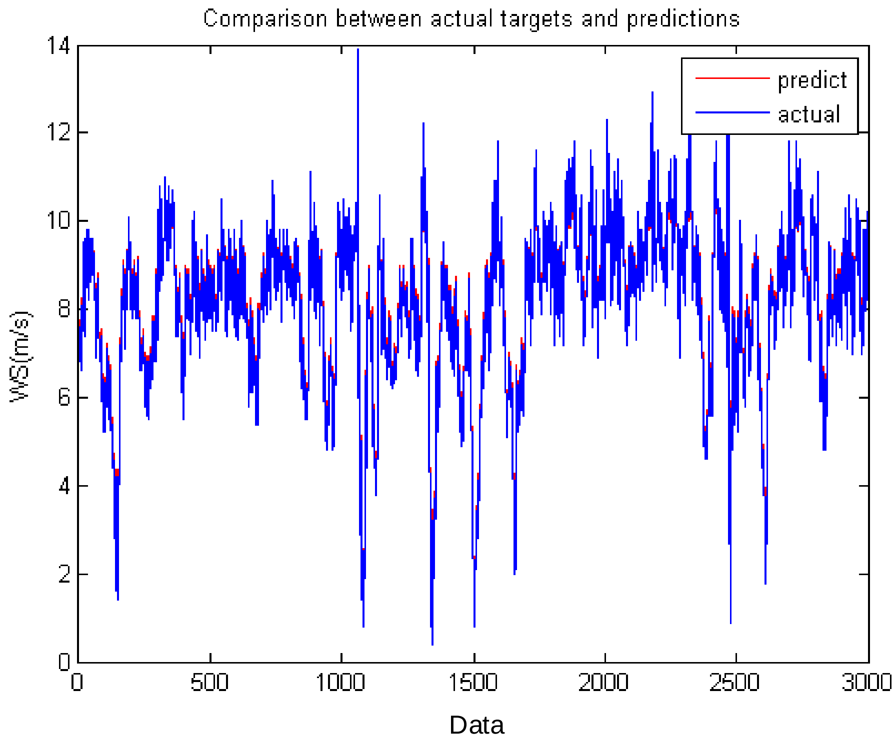

Figure 3. Actual and predict output wind speed using BPN.

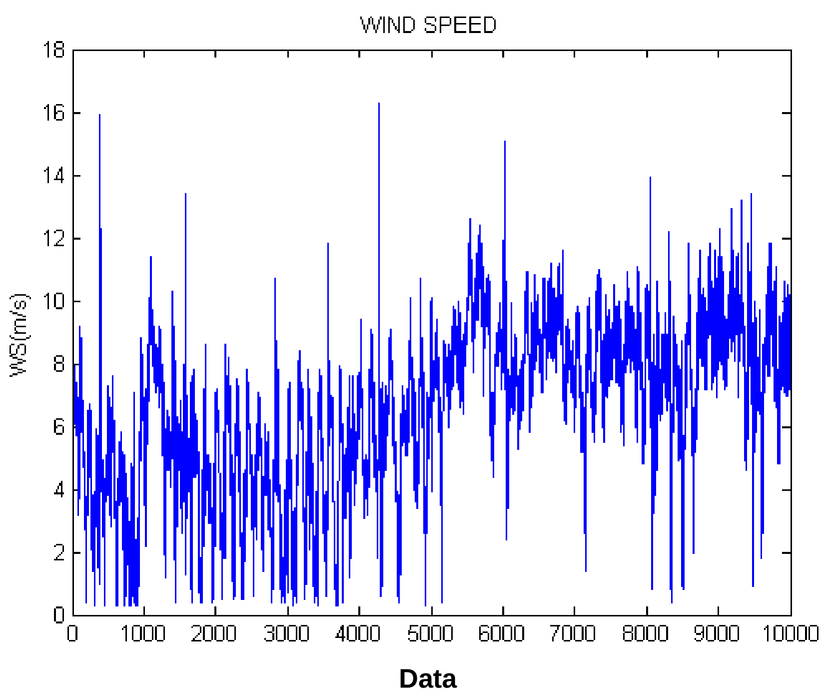

Figure 4. Actual wind speed data used in this study.

in the case of RBFN. The error suddenly decreases after 50% of testing is over in the case of BPN. The Figures 3 and 6 shows actual and predicted output of BPN and RBFN respectively. Table 2 shows the parameter

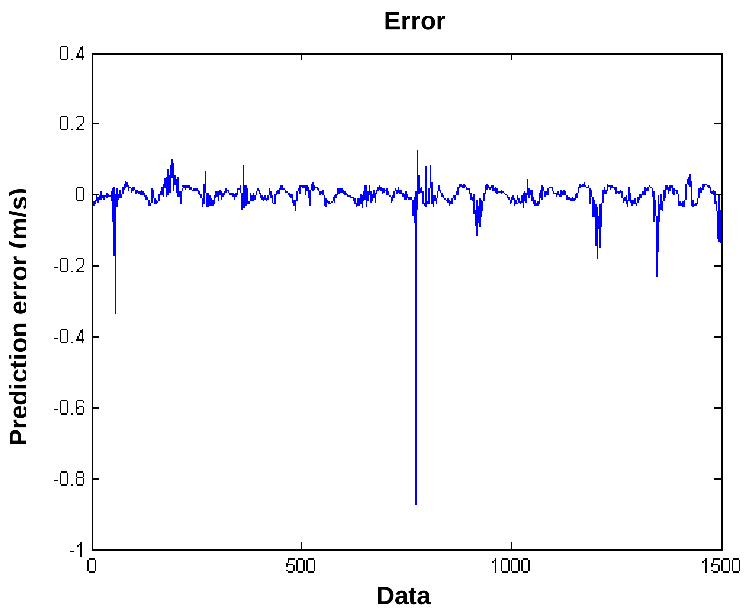

Figure 5. prediction error occurs in RBFN.

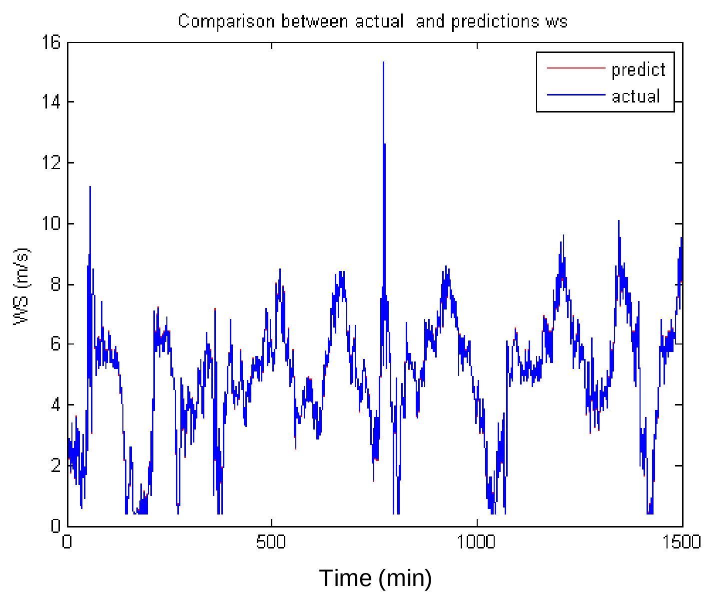

Figure 6. Actual and predict output wind speed using RBFN.

Table 2. Parameter selection.

BPN	RBFN
Learning rate = 0.25	Spread = 0.8
Momentum factor = 0.9	Max.no.of neuron = 12
No. of neuron in hidden layer = 7	Max.no.of neuron = 12
Inputs = 3	Inputs = 3
Epochs = 2000	Epochs = 2000
Trainfn = trainlm	Trainfn = newrb

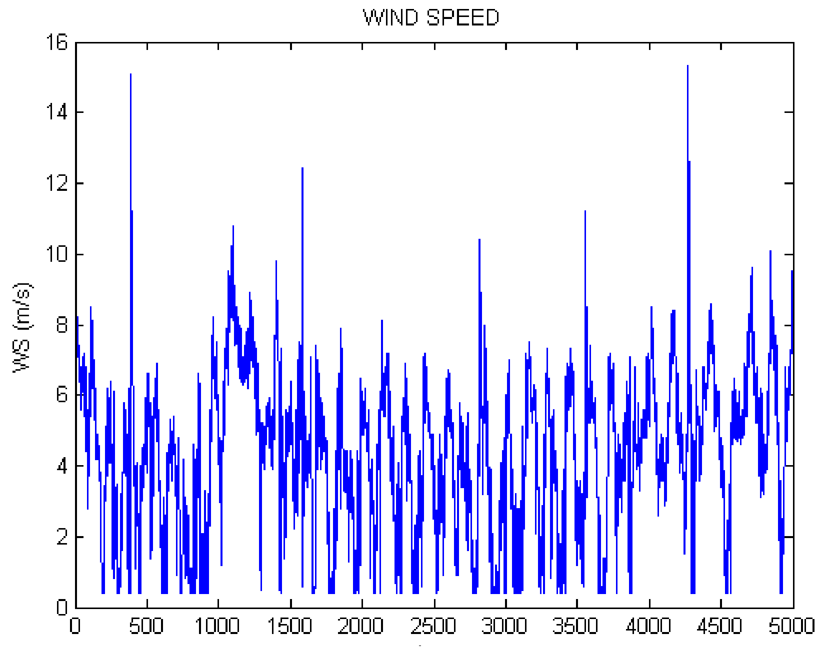

Figure 7. Actual wind speed data used in this study.

Table 3. Analysis.

Tower height (m)	Total data	Train data	Test data	Time	Analysis of wind speed prediction					
					BPN			RBF		
					m	b	r	m	b	r
65	500	350	150	0:00:16	0.8837	0.7801	0.9899	1.0077	0.0277	0.9984
50	500	350	150	0:00:01	0.8837	0.7801	0.9899	1.006	0.026	0.9974
65	1000	700	300	0:00:02	0.8521	0.3737	0.9835	0.9546	0.1263	0.999
50	1000	700	300	0:00:01	0.7651	0.4715	0.973	0.9544	0.1248	0.998
65	2000	1400	600	0:00:15	0.8768	0.7775	0.9981	0.9858	0.0866	0.9997
50	2000	1400	600	0:00:01	0.9224	0.3394	0.9917	0.9851	0.0649	0.995
65	5000	3500	1500	0:00:12	0.9427	0.1633	0.9815	0.9943	0.0342	0.9997
50	5000	3500	1500	0:00:12	0.9539	0.3469	0.9931	0.9964	0.0164	0.999
65	10000	7000	3000	0:00:05	0.947	0.4857	0.9955	0.9952	0.0131	0.9998
50	10000	7000	3000	0:00:11	0.9541	0.0616	0.9792	0.9572	0.216	9991

selection for the implementation of wind speed prediction in wind farms. The performance can be improved depends on the selection of parameters. Leven Marquand algorithm is used in the BPN. Table 3 shows comparison of regression analysis. The regression analysis performs linear regression between network response and target value. And it computes the correlation coefficient.

Conclusion

The proposed RBFN model is accurate than BPN model. Wind speed prediction model is a necessary tool in wind farms. The selection of parameter is important in the performance of models. The model which shows reduces RMSE, uncertainty of prediction and calculation time. And it is used for online applications. Evaluation of prediction model is carried out for one year. The graphs show the actual/predicted data and prediction errors. The RBFN model avoids local minima and reduces the calculation time.

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