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Performance Investigation of Six Artificial Neural Networks for Different Time Scale Wind Speed Forecasting in Three Wind Farms of Coimbatore Region

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ABSTRACT: Accurate wind speed forecasting is a challenging, crucial and important task because it highly impacts on the power system and wind farm planning, scheduling and control operation. This article presents comparative performance analysis on the wind speed forecasting application based on the six artificial neural network namely, back propagation network (BPN), multi-layer perceptron network (MLPN), radial basis function network (RBFN), ELMAN network (EN), improved back propagation network (IBPN), and recursive radial basis function network (RRBFN). The real-time acquisitions utilized to forecast wind speed by means of six artificial neural networks are the 10 minutes mean wind farm data's acquired at three acquisition location in Coimbatore region. Wind speed, wind direction, air pressure, temperature, relative humidity and dew point are taken as inputs for the six artificial neural network bases forecasting model to forecast different time scale wind speed forecasting. The effectiveness is validated by means of the five evolution error metrics such as mean absolute percentage error (MAPE), mean relative error (MRE), mean absolute error (MAE), root mean square error (RMSE), and mean square error (MSE). Simulation results revealed that even for the similar data sets, recursive radial basis function network based forecasting model outperform among the six artificial neural networks with the best forecasting accuracy and the lowest statistical errors.

KEYWORDS: Back Propagation Network; Multi-layer Perceptron Network; Radial Basis Function Network; ELMAN Network; Improved Back Propagation Network; Recursive Radial Basis Function Network; Wind Speed; Forecasting.

1 INTRODUCTION

Our society is becoming increasingly dependent on reliable electric power supply. Energy crisis is one of the major issues in recent year. Conventional energy source namely fuel, natural gas and coal are exhaustible and also damaging economic progress, human life and environment. Hence, Renewable portfolio standard and Kyoto protocol insist on renewable energy in order to prevent the dangerous anthropogenic interference with climate system. Among various renewable energy resources, wind energy receive great attention due to the special features such as clean, pollution free, avoid fuel provision and transport, moderate start up cost, renewable and availability.

In India, development of wind energy begins in the 1980's and significantly increased in the recent years. As of 31 January 2016 installed wind energy capacity in India was 25, 188 MW [1], when compared to worldwide installed wind energy capacity India ranked in forth position. In India, Tamil Nadu is leading with installed wind energy capacity. India first home growth Wind Turbine Technology Company is Suzlon Energy Limited. Wind energy is the one of the center of attractive renewable energy power production method; wind speed is the most important explanatory variable for wind power production, but wind speed is having stochastic in nature. Therefore, wind speed forecasting is necessitated because of the smart grid technology, economical load and power dispatching, balancing energy system and enhancing power system reliability. The wind speed forecasting can be classified as long-term, medium-term, short-term, and very short-term based on the time scale and it's applications as shown in Table 1.

Table 1. Classification of wind speed forecasting based on time scale

Range	Applications	Time Horizon
1 day to 1 weak (or) more ahead.	1) Planning the Maintenance, Scheduling of Wind Farms to achieve the Optimal operating cost. 2) Planning for Unit Commitment. 3) Operation Management of Wind Energy Market. 4) Planning for Reserve Requirements.	Long-Term Wind forecasting.
6 hours to ahead.	1) Electricity Market. 2) Power system Management (or) Energy Trading. 3) Generation Online / Offline Control.	Medium-Term Wind forecasting.
30 minutes to 6 hours ahead.	1) Onsite Management of wind Farm. 2) Load Decrements / Increments Decision Making. 3) Economical Load dispatch.	Short-Term Wind forecasting.
Few seconds to 30 minutes ahead.	1) Frequency Control. 2) Regulation Action. 3) Electricity Market Clearing. 4) Turbine Action Control.	Very Short-Term Wind forecasting.

An exact forecasting of wind speed is one of the important issues in renewable energy systems because of dilute and fluctuating nature of wind. The wind has the uncertain irregularity characteristic. In order to meet the better generalization capabilities for the wind speed forecasting the network inputs and output are properly modeled and the hidden neuron number should be appropriately selected for the neural network design. In the current scenario a lot of forecasting research fields has been heuristic in nature. Previous work related to different time scale wind speed forecasting using various forecasting methods are illustrated as follows:

Anurag More et al. 1995 [2] proposed a neural network uses cascade correlation and back propagation algorithms for short-term wind speed prediction. Damousis IG et al. 2004 [3] developed wind speed prediction model by means of the Takagi, Sugeno, Kang (TSK) fuzzy model. Fonte et al. 2005 [4] pointed out average hourly based wind speed prediction using back propagation network without the knowledge of metro logical data. Limitation: accuracy is very poor. Torres J et al. 2005 [5] suggested ARMA based hourly average wind speed forecasting model. Cameron W Potter and Michael Negnevitsky 2006 [6] carried out work on adaptive neuro fuzzy inference system for very short-term wind speed forecasting. Thanasis G et al. 2006 [7] presented local recurrent neural network based long-term wind speed forecasting. Erasmo Cadenas and Wilfrido Rivera 2007 [8] implemented integrated moving average (ARIMA) and artificial neural network (MLP) based wind speed forecasting. Mohammad Monfared et al. 2009 [9] pointed out fuzzy logic and artificial neural network based wind speed forecasting model in order to reduce the learning time and neuron numbers. Junfang Li et al. 2010 [10] suggested ELMAN neural network based one step ahead wind speed prediction. Nan Xiaoqiang et al. 2010 [11] implemented time series and back propagation neural network based combinational forecasting model for short-term wind speed forecasting. Ying-Yi Hong and Ching-Ping Wu 2010 [12] performed market basket analysis (MBA) and radial basis function network based short-term wind speed and wind power forecasting.

Upadhyay KG et al. 2011 [13] suggested multilayer feed-forward neural network with resilient back propagation based short-term wind speed forecasting. Pourmousavi Kani SA and Ardehali MM 2011 [14] performed Markov chain integrated artificial neural network based prediction model for very short-term wind speed prediction. Pedro Gomes and Rui Castro 2012 [15] presented ARMA and multilayer perceptron network based short-term wind speed forecasting. TarekAboueldahab 2012 [16] established hybrid model (GA/PSO-NN) with passive congregation for short-term wind speed prediction. Ramesh Babu N and Arulmozhivarman P 2013 [17] performed a hybrid method composed of Wavelet Transform and Neural Network (WTNN) for wind speed forecasting. Ying-Yi Hong et al. 2013 [18] developed artificial neural network with integration of empirical mode decomposition (EMD) based forecasting model for short-term wind speed and wind power forecasting. Hanieh Borhan Azad et al. 2014 [19] performed hybrid method for long-term forecasting. Cao Gao-cheng and Huang Dao-huo 2015 [20] presented radial basis function neural network based ultra-short-term wind speed prediction. Jianzhou Wang et al.

2015 [21] pointed out hybrid models based medium-term wind speed forecasting. Osamah Basheer Shukur and Muhammad Hisyam Leea 2015 [22] proposed hybrid auto regressive (AR)-ANN and AR-KF(Kalman Filter) based daily wind speed forecasting, compared to ARIMA and AR-ANN based model AR-KF based forecasting model outperform in terms of better forecasting accuracy. Erdong Zhao et al. 2016 [23] carried out work on wind speed prediction using hybrid self-adaptive ARIMAX model with an Exogenous WRF simulation.

The greatest aim of the analysis is to identify the best artificial neural network based forecasting model in order to improve the forecasting accuracy with the least statistical errors.

2 COMMON TYPES OF WIND SPEED FORECASTING

The most common types of wind speed forecasting are classified as four types namely persistence method, physical method, statistical method (time series and ANN), and hybrid method.

2.1 PERSISTENCE METHOD (OR) NAÏVE PREDICTOR

A Persistence method is the simplest and most economical method to forecast the wind speed. This method is based on the assumptions of high correlation between the present and future wind speed values. If the measured wind speed at time (t) is V (t) and P (t), then the forecast wind speed at t+Δt can be formulated as linear equation as follows:

$$V(t+\Delta t)=V(t) \tag{1}$$

$$P(t+\Delta t)=P(t) \tag{2}$$

The above linear equation shows that it is assumed that wind speed at time t+Δt will be same as it was at time t. This method is more accurate than most of the physical and statistical methods for very short-term wind speed forecasting. Hence, for any new forecasting techniques should be tested against persistence method in order to validate how much it will improve over this technique.

Limitation of the persistence method is if the forecasting lead time is increases the accuracy of this method is decreases and this method is based on assumption.

2.2 PHYSICAL METHOD

Physical method, model the dynamics of the atmosphere by parameterization of the Planetary Boundary Layer (PBL) concept also known as the Atmospheric Boundary Layer (ABL). ABL is the lowest part of the atmosphere that is in continuous contact with the surface of earth. Here, the physical quantities such as velocity, temperature and moisture of the wind / air are turbulent and vertical mixing is stronger. The physical methods consist of some physical of some based equations to convert meteorological data from a certain time, to the forecasts wind speed at a site considered. This method is more effective and accurate for long-term forecasting.

2.2.1 NUMERICAL WEATHER PREDICTION METHOD (NWP)

Numerical weather prediction method simulates the atmosphere by numerically integrating the equations of motion starting from the current atmospheric states. This is performed by mapping the real world on to a discrete 3 – D computational grid that divides the globe in to numerous polygonal patterns of certain dimensions. Numerical weather prediction (NWP) is based on kinematic physical equation that utilized various weather data such as (temperature, relative humidity, light intensity, dew point, and atmospheric pressure) and operates by solving complex mathematical equation. Some of the models of NWP are Fifth generation Mesoscale mode (MM5), Weather Research and Forecasting (WRF) model, Regional Spectra Model (RSM), Prediktor, HIRLAM, etc.

Limitation of NWP: 1) Complex, 2) Expensive, 3) Limited observation set for calibration, 4) high computational time is needed.

2.3 STATISTICAL METHOD

Statistical method is implemented based on training of the model with a sample of real data specific to that location, taken over a number of discrete periodic cycles. The statistical method is based on training with measurement data and uses difference between the forecasts wind speed and the actual wind speed in immediate past to tune the model parameters in order to minimize the forecasting error. This method is effective and most accurate for short and medium term wind speed forecasting.

Limitation of the statistical method is forecasting time increases forecasting error also increases. In spite of this limitation this method is very simple, low cost and any stage of modeling is possible. This method is based on patterns rather than predefined mathematical model.

Statistical method is further divided in to two sub divisions: 1) Time Series, 2) Artificial Neural Network.

2.3.1 TIME SERIES METHOD

Time Series method aims at modeling the stochastic process that yields the structure of an observed series of an event that is observed in certain intervals, and making future forecasts through the observation values belonging to the past interval. Time Series method does not require any records beyond historical wind data. This method is very accurately provides the timely forecasting and it is easy to model. Some models of Time Series method are Auto Regressive (AR), Auto Regressive Moving Average (ARMA), Auto – Regressive Integrated Moving Average (ARIMA), ARMA with Exogenous inputs (ARMAX), Auto Regressive Exogenous (ARX), Grey Predictor, Linear Predictor, Exponential Smoothing, Bayesian Model Averaging (BMA), Algebraic Curve Fitting (ACF), etc.

Limitation of the time series method is cannot forecast more than a day ahead.

2.3.2 ARTIFICIAL NEURAL NETWORK (ANN)

Artificial Neural Network is an analysis paradigm that is roughly modeled after the massively parallel structure of the brain. Artificial Neural Network (ANN) deals with nonlinear and complex problem in terms of classification (or) prediction. ANN has ability of performing nonlinear and complex modeling without a prior knowledge about the relationship between input and variables. ANN are trained based on the past wind speed measurement data taken over a long time to learn the relationship between input data and output wind speed. In general ANN is had three layers 1) Input layer, 2) Hidden Layer, 3) Output Layer. Input layer: Measured and collected historical wind data is fed for learning. This layer does not perform any computation. Hidden and output layers are responsible for providing the wind speed forecasting result.

ANN is having good self learning ability (so learn the relationship between inputs and output any mathematical formulation), adaptability, real-time operation, fault tolerance ability, and cost effective. Few types of ANN methods are feed-forward (BPN, MLP, RBFN), Feedback (ELMAN, Recurrent), Support Vector Machine (SVM), ADALINE, Probability Neural Network (PNN), etc.

Limitation of ANN method: falling into local minimum, slow convergence, difficult to confirm the structure of network (or) system. In spite of this limitation ANN method outperform than time series method for all time scale.

2.4 HYBRID METHOD

Hybrid method is generally combinations of different methods were utilized to forecast the accurate wind speed for different time scale. The objective of hybrid method is to benefit from the merits of each method and obtain a globally optimal forecasting performance. Types of combinations are as follows:

1) Combination of physical and statistical (time series) method.
2) Combination of physical and statistical (ANN) method.
3) Combination of statistical method and novel method.
4) Combination of physical and novel method.
5) Combination of statistical (time series) and statistical (ANN) method.

Some of the hybrid methods are Evolutionary computation (EC) + Fuzzy, Wavelet transform + Fuzzy, EC+ANN, Fuzzy + time series, ANN+NWP, NWP + time series, ANN + Fuzzy, ANN + time series, etc.

Hybrid methods advantages are avoided over training and high computation cost, achieve the optimal forecasting accuracy by reduce the forecasting error, avoid local minimum problem, reduce the convergence time, etc.

Limitation hybrid method is in some case the single method is out performs than hybrid method.

This article implements six ANN based forecasting models such as back propagation network (BPN), multi-layer perceptron network (MLPN), radial basis function network (RBFN), ELMAN network, Improved back propagation network (IBPN) and Recursive Radial Basis Function Network (RRBFN) and applied for different time scale wind speed forecasting.

3 DIFFERENT ARTIFICIAL NEURAL NETWORKS BASED WIND SPEED FORECASTING MODELS

Artificial neural network based six wind speed forecasting models namely BPN, MLPN, RBFN, EN, IBPN and RRBFN network input and output variables depicted in Table 2.

Table 2. Input and output variables of proposed neural network model

Input Variables	Description	Output Variable	Description
U_1	Wind Speed (N)	Y	Forecast wind speed (N_{fw})
U_2	Wind Direction (WD)		
U_3	Air Pressure (AP)		
U_4	Temperature (TD)		
U_5	Relative Humidity (RH)		
U_6	Dew Point (DP)		

Input vector, $U = [N, WD, AP, TD, RH, DP]$ (3)

Output vector, $Y = [N_{fw}]$ (4)

3.1 BACK PROPAGATION NETWORK BASED FORECASTING MODEL

In fields of artificial neural network back propagation network is one of the famous network. The input layer neurons are interlinked to the hidden layer by means of the sigmoidal activation function. Hidden layer neurons are interlinked to the output layer by means of the sigmoidal activation function. Gradient descent algorithm is used for weight modification. The architecture of the proposed back propagation networks model for wind speed forecasting shown in Fig. 1.

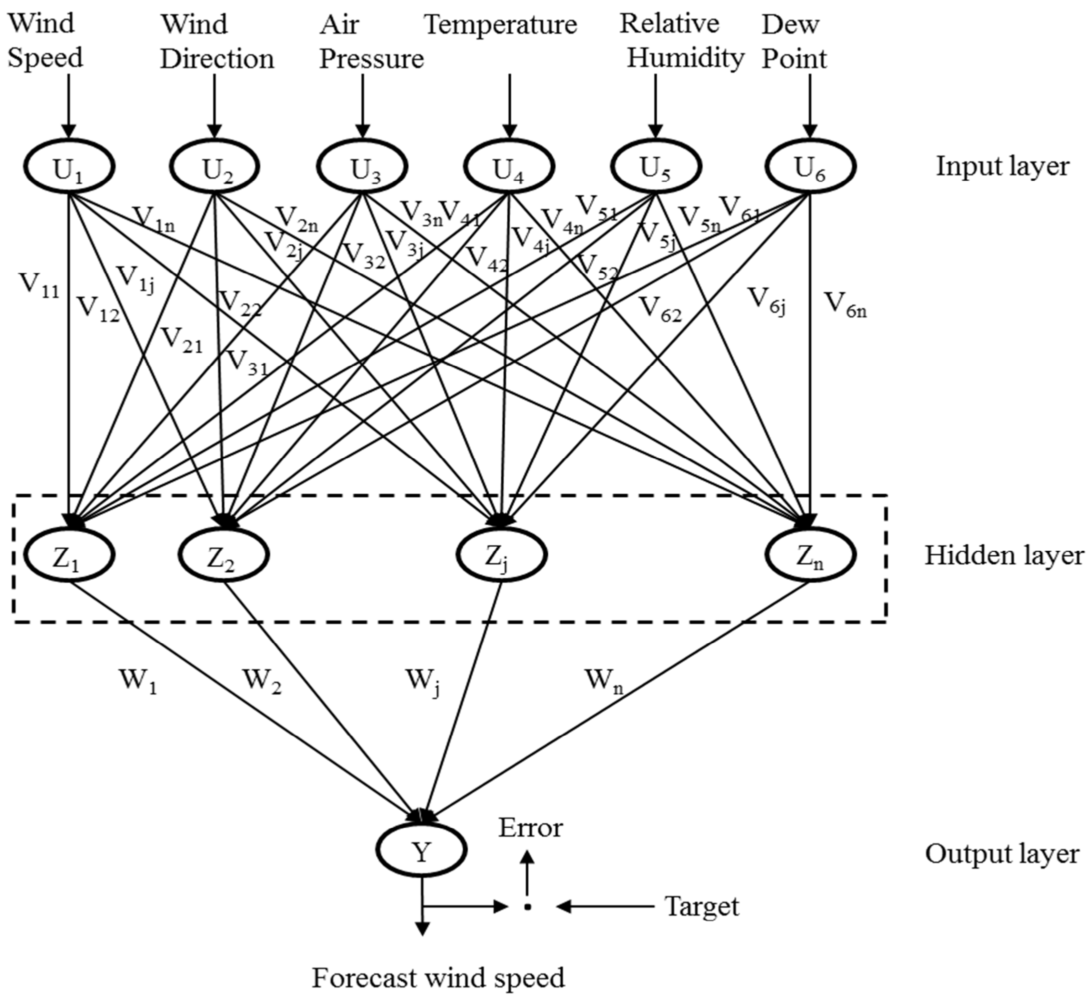

Fig. 1. Architecture of the implemented back propagation network based forecasting model

Weight vectors of input to the hidden vector,

$$V = [V_{11}, V_{12}, ..., V_{1n}, V_{21}, V_{22}, ..., V_{2n}, V_{31}, V_{32}, ..., V_{3n}, V_{41}, V_{42}, ..., V_{4n}, V_{51}, V_{52}, ..., V_{5n}, V_{61}, V_{62}, ..., V_{6n}] \quad (5)$$

Hidden layer net input, $Z_{in\,j} = \sum_{i=1}^{6} \sum_{j=1}^{n} U_i V_{ij}$ (6)

Tangent sigmoid activation function adopted over the net input to compute the output.

Hidden layer output, $Z_j = f\left(\sum_{i=1}^{6} \sum_{j=1}^{n} U_i V_{ij} \right)$ (7)

Where, U - input, V - weights between input and hidden layer, n - number of hidden neurons.

Weight vectors of hidden to output vector, $W = [W_1, W_2, ..., W_n]$ (8)

Output layer net input, $Y_{in} = \sum_{j=1}^{n} (Z_j W_j)$ (9)

Output, $Y = f\left(\sum_{j=1}^{n} (Z_j W_j) \right) \quad , j = 1,2,.....,n$ (10)

Where, W - weight between hidden and output layer.

f - Activation function.

Output layer error, $\delta = (t_n - Y) f^{'}(Y_{in})$ (11)

Where, $f^{'}(Y_{in})$ - derivative of the net input of output layer.

Computed error (δ) back propagated to the hidden layer.

Each hidden neuron (Z_j, $j = 1,2,....,n$) sums its delta inputs from output layer neurons,

$$\delta_{in\,j} = \sum_{j=1}^{n} \delta W_j \tag{12}$$

Hidden layer error, $\delta_j = \delta_{in\,j}\ f^{'}(Z_{in\,j})$ (13)

Where, $f^{'}(Z_{in\,j})$- derivative of the net input of hidden layer.

Calculated error (δ_j) propagated backward to the input layer.

Output layer error, $E = [\delta]$ (14)

Hidden layer error, $E_j = [\delta_j]$ (15)

Weight modifying equation, $W_j(t+1) = W_j(t) + \eta \delta Z_j$ (16)

$$V_{ij}(t+1) = V_{ij}(t) + \eta \delta_j u_i \tag{17}$$

Where, η - Learning rate.

3.2 MULTI-LAYER PERCEPTRON NETWORK BASED FORECASTING MODEL

Multi-layer perceptron network (MLPN) is a feed-forward neural network with supervised learning rule to search the weight for binary and linear activation function to solve the complex task. The multi-layer perceptron network has three different layers such as input layer, hidden layer and output layer, it is fully connected networks. Multi-layer perceptron is outperforming than that of single layer perceptron because it eliminates limitations of single layer perceptron and posses higher computational efficiency. The multi-layer perceptron network learns linear and nonlinear relationship between input and output vector because hidden layer neuron has the nonlinear transfer function. In general hyperbolic tangent sigmoid activation function is used as nonlinear transfer function which is applied over a net input of the hidden layer. Back propagation learning rule is incorporated in Multi-layer perceptron network for training process. Hidden layer neurons are activated by means of the hyperbolic tangent sigmoid activation function and output layer neuron is activated by purelin activation function. Proposed multi-layer perceptron network model architecture for wind speed forecasting is depicted in Fig. 2.

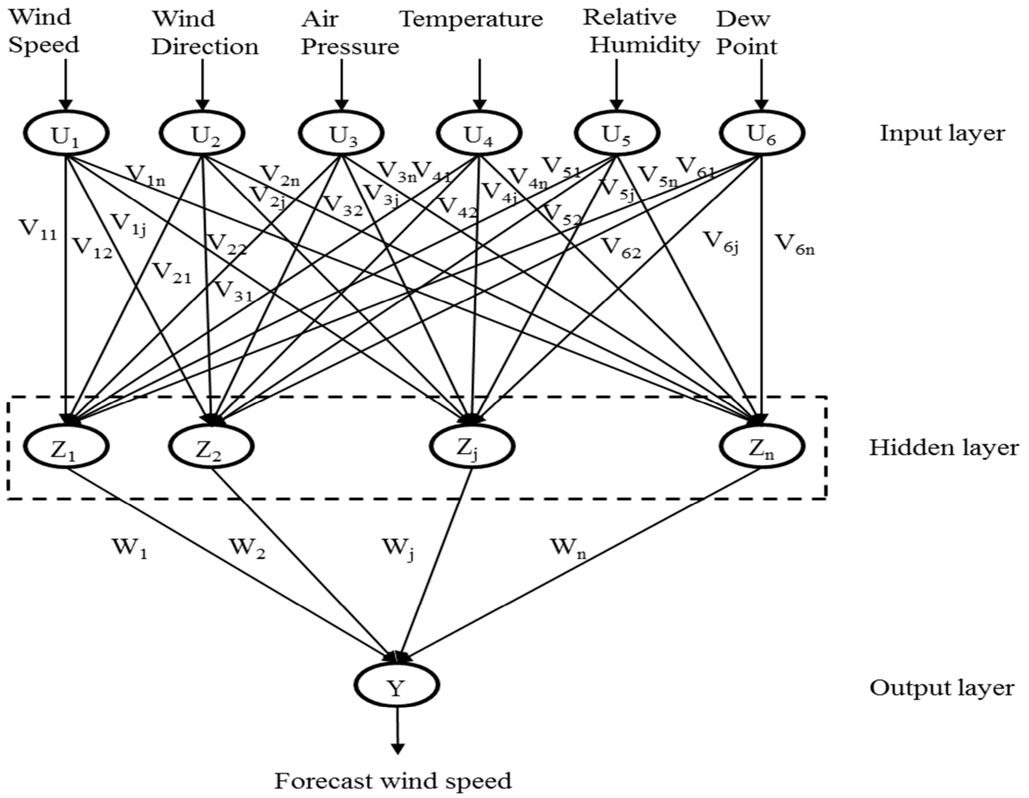

Fig. 2. Architecture of the implemented multi-layer perceptron network based forecasting model

Weight vectors of input to the hidden vector,

$$V = [V_{11}, V_{12}, ..., V_{1n}, V_{21}, V_{22}, ..., V_{2n}, V_{31}, V_{32}, ..., V_{3n}, V_{41}, V_{42}, ..., V_{4n}, V_{51}, V_{52}, ..., V_{5n}, V_{61}, V_{62}, ..., V_{6n}] \quad (18)$$

Hidden layer net input, $Z_{in\,j} = \sum_{i=1}^{6} \sum_{j=1}^{n} U_i V_{ij}$ (19)

Hidden layer output, $Z_j = f\left(\sum_{i=1}^{6} \sum_{j=1}^{n} U_i V_{ij} \right)$ (20)

where, U - input, W - weights between input and hidden layer, n - number of hidden neurons.

Weight vectors of hidden to output vector, $W = [W_1, W_2, ..., W_n]$ (21)

Output layer net input, $Y_{in} = \sum_{j=1}^{n} (Z_j W_j)$ (22)

Output, $Y = f\left(\sum_{j=1}^{n} (Z_j W_j) \right) \quad , j = 1,2,....., n$ (23)

where, W - weight between hidden and output layer.

f - Activation function.

3.3 RADIAL BASIS FUNCTION NETWORK BASED FORECASTING MODEL

Radial basis function network (RBFN) comprises the input layer, hidden layer and output layer. The radial basis function is applied for hidden nodes to compute the input and the output computed by Gaussian activation function. Radial basis function emphasize on data exist a region of input space. Radial basis function network improves convergence faster and better function approximation. Fig. 3 depicts the architecture of the proposed radial basis function networks model for wind speed forecasting.

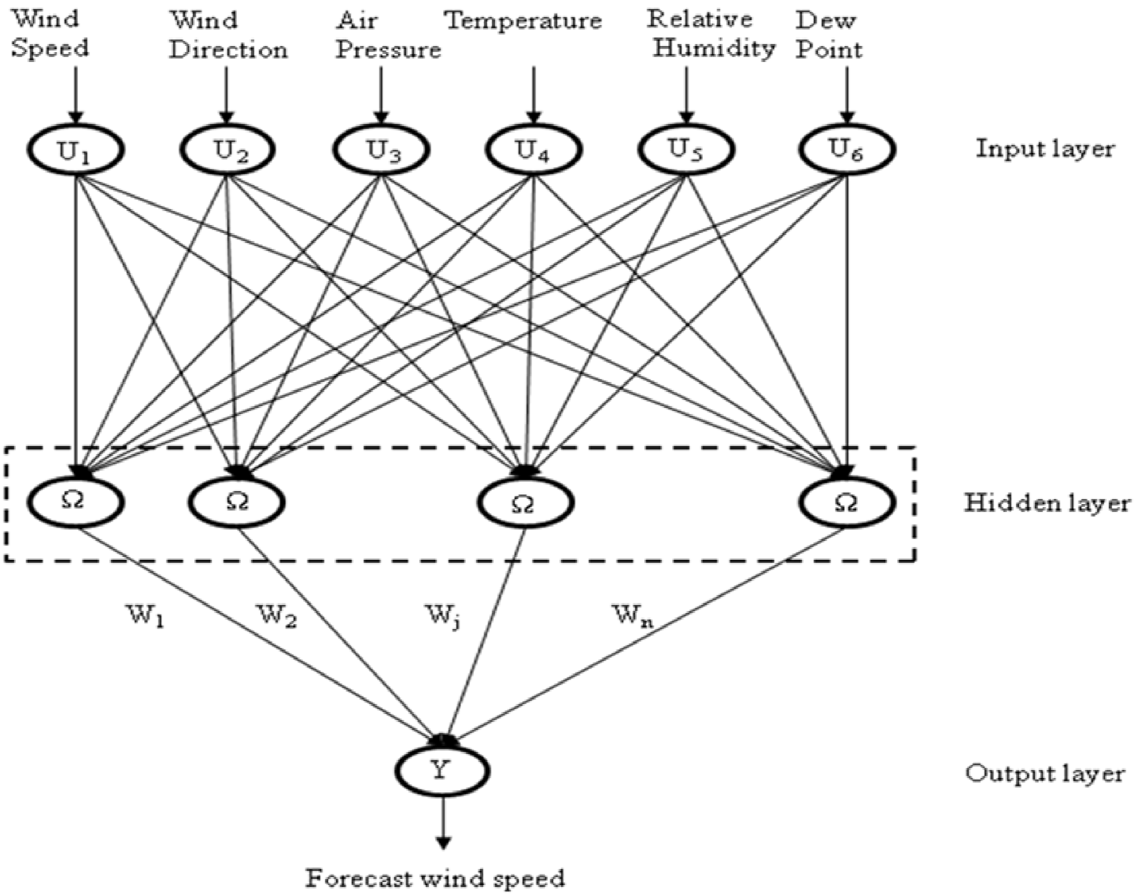

Fig. 3. Architecture of the implemented radial basis function network based forecasting model

Weight vectors of hidden to output vector, $W = [W_1, W_2, ..., W_m]$ (24)

Gaussian activation function, $f(Y_{in}) = e^{(-Y_{in}{}^2)}$ (25)

where, Y_{in} - net input.

Radial basis function network output,

$$Y_{in} = \sum_{i=1}^{n} f(\|U - C_i\|) * W_{ik} \quad , k = 1,2,....,m \tag{26}$$

where, n - number of hidden neurons.

U - Input vector.

C_i - i th Center node in hidden layer.

$\|U - C_i\|$ - Euclidean distance between C_i and U .

f - Activation function (Gaussian function).

W_{ik} - Weight between hidden and output layer.

3.4 ELMAN NETWORK BASED FORECASTING MODEL

ELMAN neural network is a feedback neural network and widely used for different application such as time series prediction, modeling, control and speech recognition. Output is get from the hidden layer. Recurrent link layer stores the feedback and retains the memory. Hidden layer neurons are activated by hyperbolic tangent sigmoid activation function and output layer neuron activated by satlins activation function. Architecture of the proposed ELMAN network based wind speed forecasting model is presented in Fig. 4.

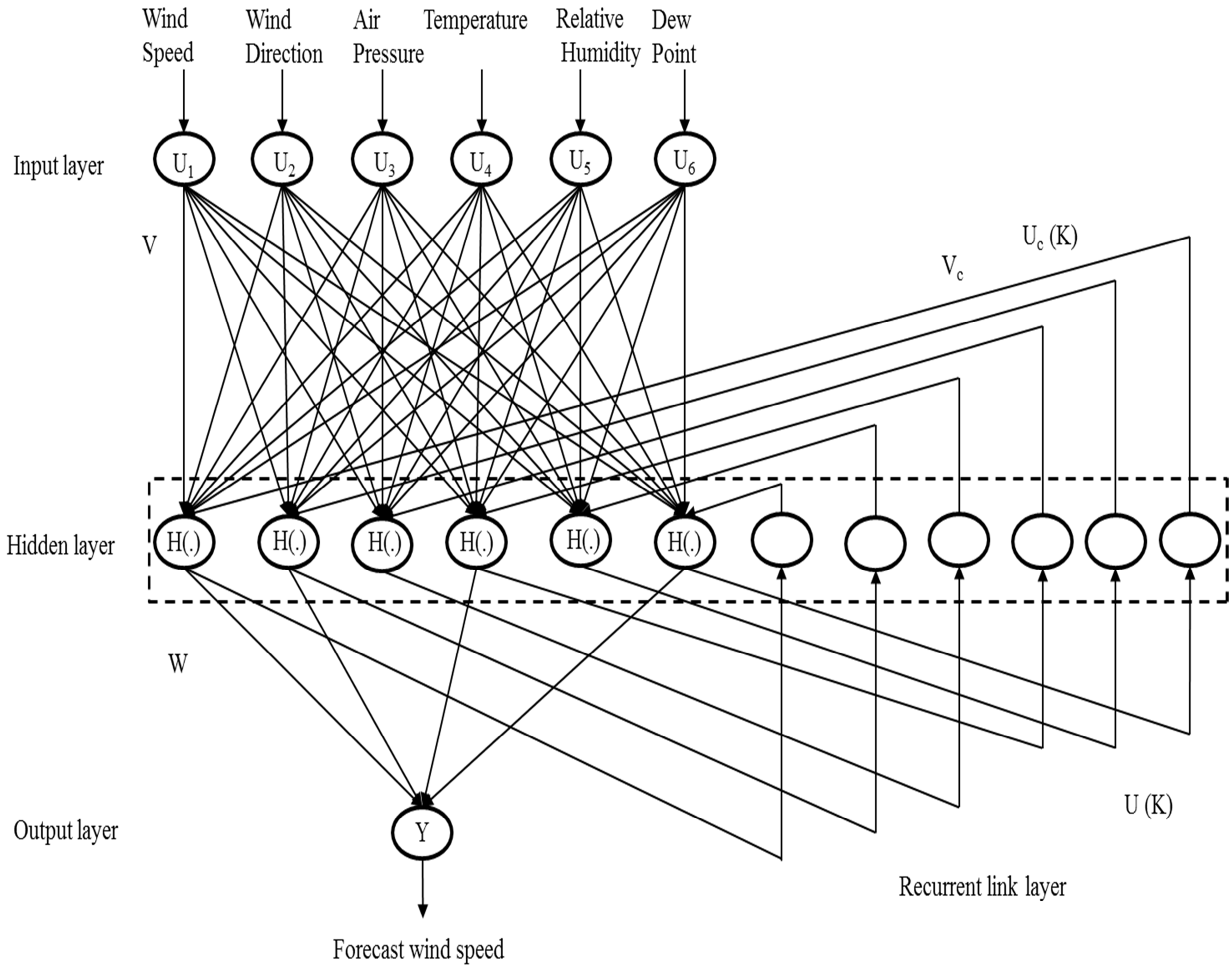

Fig. 4. Architecture of the implemented ELMAN network based forecasting model

Weight vectors of input to the hidden vector,

$$V = [V_{11}, V_{12}, ..., V_{1n}, V_{21}, V_{22}, ..., V_{2n}, V_{31}, V_{32}, ..., V_{3n}, V_{41}, V_{42}, ..., V_{4n}, V_{51}, V_{52}, ..., V_{5n}, V_{61}, V_{62}, ..., V_{6n}] \quad (27)$$

Weight vectors of recurrent link layer vector, $W = [W_{21}, W_{22}, ..., W_{2n}]$ (28)

Weight vectors of recurrent link layer to input vector,

$$V_c = [V_{c11}, V_{c12}, .., V_{c1n}, V_{c21}, V_{c22}, .., V_{c2n}, V_{c31}, V_{c32}, .., V_{c3n}, V_{c41}, V_{c42}, .., V_{c4n}, V_{c51}, V_{c52}, .., V_{c5n}, V_{c61}, V_{c62}, .., V_{c6n}] \quad (29)$$

Input, $U(K)=H\left(V_c U_c(K)+VU(K-1)\right)$ (30)

Output, $Y(K)=f\left(WU(K)\right)$ (31)

Recurrent link layer input, $U_c(K)=U(K-1)$ (32)

Let V_c be the weight between context layer and input layer, V be the weight between input and hidden layer, W be the weight between hidden and recurrent link layer, $H(\cdot)$ is hyperbolic tangent sigmoid activation function and is symmetric saturating linear activation function.

3.5 IMPROVED BACK PROPAGATION NETWORK BASED FORECASTING MODEL

Among the six artificial neural networks improved back propagation is a newly proposed method by Madhiarasan M and Deepa S N 2016 [24]. Improved Back propagation network (IBPN) is a multi-layer feed-forward network which adapts the back propagation (error) learning algorithm in order to obtain balance between the network's memorization and its generalization ability. Generally improved back propagation networks are composed of three various layers such as input layer, hidden layer and output layer. Stages associated in improved back propagation training are feed-forward stage, error computation stage and weight modification stage. Feed-forward network consisting of neurons (processing elements) which perform independent computation based on given set of input data and weights with continuous differential activation function and computed result transferred to the next layer and lastly network output (forecast wind speed) computed then error calculated based on the difference between the real target and forecast output. Calculated error propagated backward to the hidden layer and then transferred to the input layer. For a given set of training inputs and target pairs the weights get modified and are updated to the improved back propagation network to obtain the correct forecast wind speed with the lowest error. Presented improved back propagation networks achieve speed up convergence by incorporation of the momentum factor (μ). Improved back propagation network outperform than back propagation network in terms of reduced statistical error and faster convergence. Architecture of the proposed improved back propagation networks model for wind speed forecasting shown in Fig. 5

Input to the hidden weight vectors,

$$V=\left[V_{11},V_{12},\ldots,V_{1n},V_{21},V_{22},\ldots,V_{2n},V_{31},V_{32},\ldots,V_{3n},V_{41},V_{42},\ldots,V_{4n},V_{51},V_{52},\ldots,V_{5n},V_{61},V_{62},\ldots,V_{6n}\right] \quad (33)$$

Hidden layer net input, $Z_{in\,j}=\sum_{i=1}^{6}\sum_{j=1}^{n}U_iV_{ij}$ (34)

The tangent sigmoid activation function adopted over the net input to compute the output.

Hidden layer output, $Z_j=f\left(\sum_{i=1}^{6}\sum_{j=1}^{n}U_iV_{ij}\right)$ (35)

where, U - input, V - weights between input and hidden layer, n - number of hidden neurons.

Weight vectors of hidden to output vector, $W=\left[W_1,W_2,\ldots\ldots,W_n\right]$ (36)

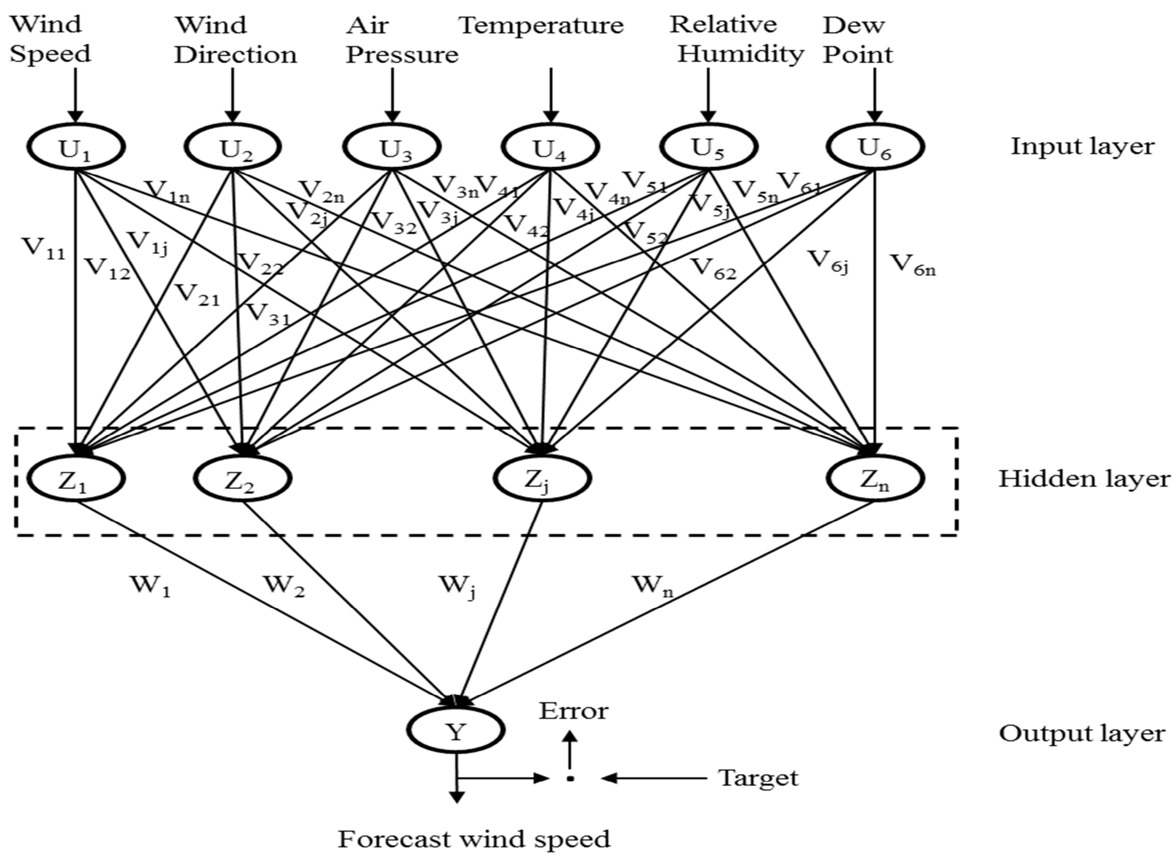

Fig. 5. Architecture of the implemented improved back propagation network based forecasting model

Output layer net input, $Y_{in} = \sum_{j=1}^{n} \left(Z_j W_j \right)$ (37)

Output, $Y = f\left(\sum_{j=1}^{n} \left(Z_j W_j \right) \right) \quad , j = 1,2,.....,n$ (38)

where, W - weight between hidden and output layer.

f - Activation function.

Output layer error, $\delta = \left(T - Y \right) f^{'}\left(Y_{in} \right)$ (39)

where, $f^{'}\left(Y_{in} \right)$- derivative of the output layer net input.

Evolved error (δ) back propagated to the hidden layer.

Each hidden neuron (Z_j, $j = 1,2,....,n$) sums its delta inputs from output layer neurons,

$$\delta_{in\,j} = \sum_{j=1}^{n} \delta W_j \quad (40)$$

Hidden layer error, $\delta_j = \delta_{in\,j}\ f^{'}\left(Z_{in\,j} \right)$ (41)

Where, $f^{'}\left(Z_{in\,j} \right)$- derivative of the net input of hidden layer.

Evolved error (δ_j) propagated backward to the input layer.

Output layer error, $E=[\delta]$ (42)

Hidden layer error, $E_j=[\delta_j]$ (43)

Weight modifying expression, $W_j(t+1)=WE_j(t)+\eta\delta Z_j+\mu[W_j(t)-W_j(t-1)]$ (44)

$$V_{ij}(t+1)=V_{ij}(t)+\eta\delta_j u_i+\mu[V_{ij}(t)-V_{ij}(t-1)] \quad (45)$$

Where, η - Learning rate, μ - momentum factor.

3.6 RECURSIVE RADIAL BASIS FUNCTION NETWORK BASED FORECASTING MODEL

Among the six artificial neural networks recursive radial basis function network is a proposed novel method. Recursive Radial Basis Function network is a multi-layer feed-forward neural network. Recursive radial basis function network composed of three different layers namely input layer, hidden layer and output layer. In recursive radial basis function network, the solution for complex problem is generally obtained by transforming it into a high dimensional space in a nonlinear form. The Proposed recursive radial basis function networks achieve the least statistical errors by means of the recursive weight modification. Based on the computation of distance between the inputs and hidden layer center, output of the input layer is obtained. Input layer outputs signals are passed to the hidden layer as a nonlinear form. Hidden layer has a large dimension because all input layer neurons directly interlinked to the hidden layer. Each hidden neurons in the hidden layer has parameters such as width and center place. Each and every hidden neuron in the hidden layer has activation function; in this network radial basis function is applied. The network parameter namely spread value is modified in order to fine tune Gaussian radial basis function (i.e.) shape the Gaussian radial basis function curve. At zero distance the Gaussian activation function curve has a peak value and further minimized as distance from the center increase. The weighted form of hidden layer output is interlinked to the output layer as a linear form. Weights are modified recursively to make the least output error. Weights modification stage associated with gradient descent rule. Architecture of the proposed recursive radial basis function network based wind speed forecasting model is shown in Fig. 6.

Weight vectors of hidden to output vector, $W=[W_1,W_2,....,W_m]$ (46)

Output from hidden layer, $Y_h(u)=e^{\left(-Y^2{}_h/2B^2{}_h\right)}$ (47)

$$Y_h=R(\|U-C_h\|)=\sqrt{\sum_{i=1}^{6}\sum_{h=1}^{n}(U_i-C_{ih})^2} \quad (48)$$

where, Y_h - net input, B - width, h - hidden layer neurons, C_h - Center vector, $i=1\,to\,6$ - number of inputs, $h=1to\,n$ - number of hidden neurons

Output from output layer,

$$Y=\sum_{h=1}^{n}Y_h(u)*W_{hk} \qquad ,k=1,2,....,m \quad (49)$$

where, n - number of hidden neurons.

U - Input vector.

C_{ih} - Center node in hidden layer.

$\|U-C_h\|$ - Euclidean distance between center and input vector.

R - Activation function (Gaussian radial basis function).

W_{hk} - Weight between hidden and output layer.

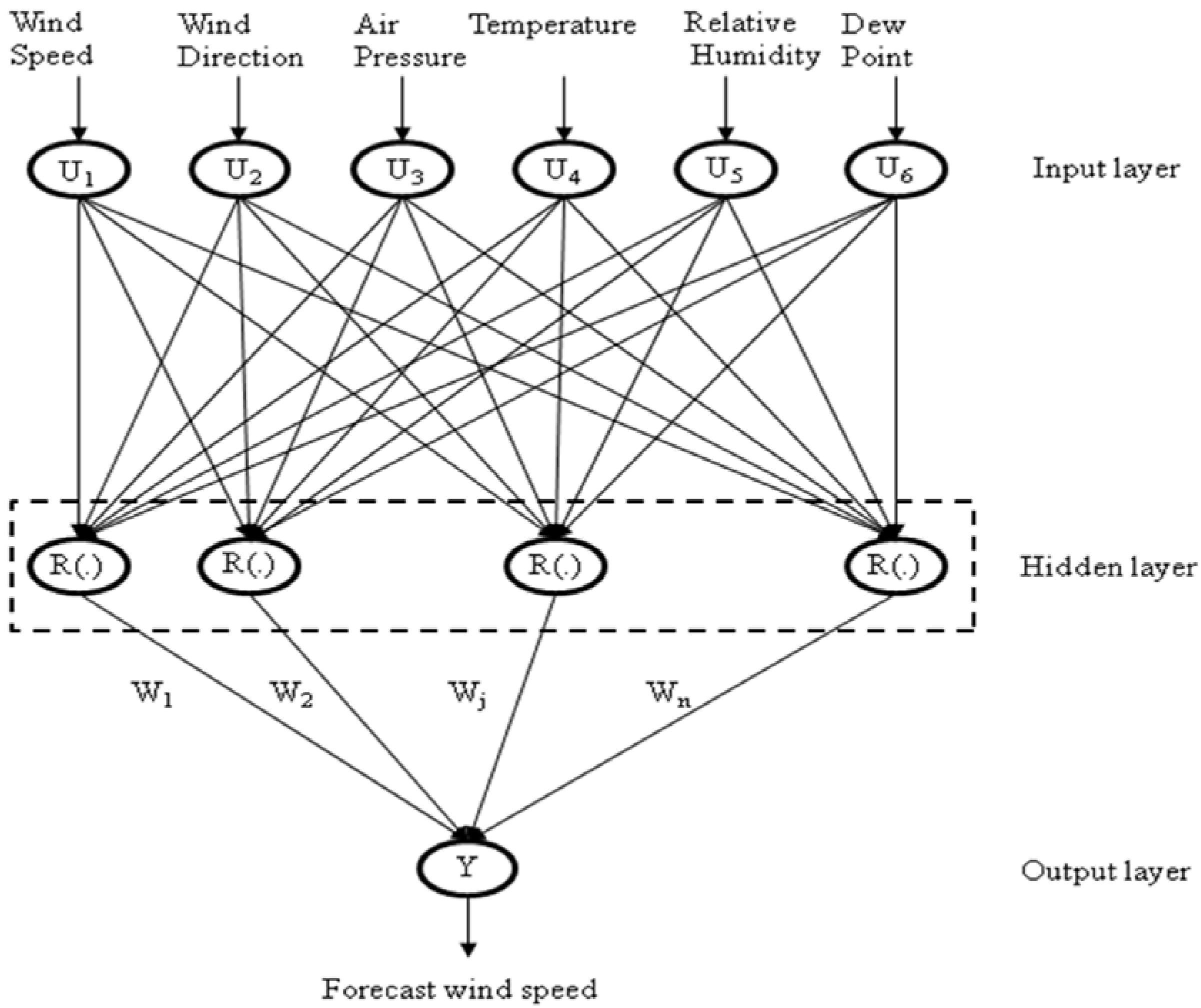

Fig. 6. Architecture of the implemented recursive radial basis function network based forecasting model

4 Forecasting Model development and training

4.1 Data Acquisition

Three real-time wind farm data sets used in this research corresponds to the 1 minutes mean average values acquired during the period from January 2009 to December 2015 in Coimbatore regions namely Udumalaipettai, Poolavadi and Edayapalayam locations. On careful analysis of the real-time data sets, it was noticed that wind speed ranges from 0.5 m/s to 18 m/s, wind direction ranges from 0.2 degree to 356 degree, temperature ranges from 20 ºC to 38 ºC, air pressure ranges from 845 mbar to 1020 mbar, relative humidity ranges from 46 % to 98 % , and dew point ranges from 10 ºC to 32 ºC, the complexity and deviation in the real-time data sets are found to be minimum and since they fall between the specified minimum and maximum range. All wind farm data sets consists of 1, 20, 000 data samples for each input variables. Acquired some of real-time input data samples are tabulated in Table 3.

Table 3. Acquired real-time input data samples (from Suzlon Energy Pvt. Ltd)

Wind Speed (m/s)	Wind Direction (Degree)	Temperature ($°C$)	Air Pressure (mbar)	Relative Humidity (%)	Dew Point ($°C$)
8.9	285.5	26.4	1011	71	22
8.6	285.5	25.9	1013	48	21
7.7	279.8	25.8	1010	44	22
6.9	286.9	26.1	1008	15	24
6.8	298.1	30.4	1009	17	16
5.9	277	32.4	1011	68	15
3.8	315	27.5	1006	19	20
1.9	299.5	26.6	1012	75	18
9.2	112.5	25.2	1007	21	17
15.9	111.1	26.4	1015	90	19

4.2 Data Preprocessing

Normalization (data preprocessing) is very important and most required for dealing with real-time data; the real-time data has different range and different units. Hence, the normalization used to scale the real-time data within the range of 0 to 1. Data preprocessing helps to obtain the correct numeric computation and improve output accuracy. Proposed approaches employed the min-max normalization technique. Following transformation equation used for normalization of the real-time data.

$$\text{Normalized input,} U_i' = \left(\frac{U_i - U_{\min}}{U_{\max} - U_{\min}}\right)\left(U'_{\max} - U'_{\min}\right) + U'_{\min} \tag{50}$$

Where, U_i is real input data, $U_{\min}$ is the least input data, $U_{\max}$ is the greatest input data, $U'_{\min}$ is the least target value, $U'_{\max}$ is the greatest target value.

4.3 Design Specification

The proposed six artificial bases wind speed forecasting models designed parameter includes dimensions and epochs presented in Table 4. Dimensions such as input layer neurons, hidden layer neurons and output layer neurons are represented in the network design. Developed all forecasting model posses single hidden layer only because its have sufficient capacity to solve any complex task with reduce computational complexity.

Designed Back Propagation network (BPN) based forecasting model input signals are transmitting to the hidden layer neurons over weighted interlinks utilizing hyperbolic tangent sigmoid activation function and output signals from the hidden layer are transmitting to the output layer neuron over a weighted interlink (W) using tangent sigmoid activation function. Training algorithm used for BPN is gradient decent training algorithm.

Implemented Multi-layer Perceptron network (MLPN) based forecasting model inputs passed to the hidden layer that multiplies weight V using hyperbolic tangent sigmoid activation function and output from the hidden layer passed to the output layer that multiplies with weight W using purelin activation function. Training algorithm used for MLPN is Levenberg-Marquardt training algorithm.

Constructed Radial Basis Function network (RBFN) based forecasting model input layer and hidden layer is connected by means of the hypothetical connection. The hidden layer neurons activated by means of the Gaussian function. Hidden layer and output layer is connected with weighted connection. Output layer has linear function.

Table 4. Implemented wind speed forecasting models designed parameters

Proposed Neural Network	Parameters	Parametric Values
Back propagation network (BPN)	Input layer neurons Number of hidden layer Output layer neuron Number of epochs Threshold Learning Rate	6 1 1 1000 1 0.9
Multi-layer perceptron network (MLPN)	Input layer neurons Number of hidden layer Output layer neuron Number of epochs Threshold Learning Rate	6 1 1 1000 1 0.9
Radial basis function network (RBFN)	Input layer neurons Number of hidden layer Output layer neuron Number of epochs Spread	6 1 1 1000 2.1
ELMAN network (EN)	Input layer neurons Number of hidden layer Output layer neuron Number of epochs Threshold Learning Rate	6 1 1 1000 1 0.9
Improved Back propagation network (IBPN)	Input layer neurons Number of hidden layer Output layer neuron Number of epochs Threshold Learning Rate Momentum Factor	6 1 1 1000 1 0.9 0.9
Recursive radial basis function network (RRBFN)	Input layer neurons Number of hidden layer Output layer neuron Number of epochs Spread	6 1 1 1000 2.1

Designed ELMAN network inputs weighted (V) interconnect to the hidden layer using hyperbolic tangent sigmoid activation function and output from the hidden layer linked to the output layer with weight linkages W using satlins activation function. As a result of training, pervious information reflected to the ELMAN network. Training algorithm used for ELMAN network is gradient descent with momentum and adaptive linear back propagation training algorithm.

Developed Improved back Propagation network (IBPN) based forecasting model input signals are transmitting to the hidden layer neurons over a weighted connection utilizing hyperbolic tangent sigmoid activation function and output signals from the hidden layer are transmitting to the output layer neuron over a weighted connection (W) using tangent sigmoid activation function. Training algorithm used for IBPN is Levenberg-Marquardt back propagation training algorithm. Convergence is speed up by means of the inclusion of momentum factor μ.

Implemented Recursive Radial Basis Function network (RRBFN) based forecasting model use hypothetical connection between input and hidden layer. Radial basis function is introduced for hidden layer in order to activate the neurons in the hidden layer. Weighted connections exist between hidden layer and output layer. Output layer has linear function. In order to get the minimal output error weights are modified recursively. Gradient descent rule is used for weights modifying stage. Recursive back propagation training algorithm is introduced for training process of RRBFN.

4.4 TRAINING AND TESTING

Wind speed forecasting models developed based on training data while the effectiveness of the proposed models evaluated by means of the testing data. The acquired three wind farm data sets are used for training and testing phase, each wind farm data set contained $1,20,000$ real-time data samples are classified in to the training and testing sets. Acquired 70% of data samples ($84,000$) used for training phase and 30% of the acquired data samples ($36,000$) used for testing phase of the each network. Testing data samples are distinct from training data samples. Implemented all artificial neural network performance is estimated based on the statistical errors such as MSE, RMSE, MAE, MRE and MAPE.

4.5 EVOLUTION ERROR METRICS

The designed forecasting models based on artificial neural network effectiveness are investigated by means of the evolution error metrics namely Mean Square Error (MSE), Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Mean Relative Error (MRE) and Mean Absolute Percentage Error (MAPE). Evolution error metrics formulas are given as below:

$$\text{MSE} = \frac{1}{N}\sum_{t=1}^{N}(Y_t^{'} - Y_t)^2 \qquad (51)$$

$$\text{RMSE} = \sqrt{\frac{1}{N}\sum_{t=1}^{N}(Y_t^{'} - Y_t)^2} \qquad (52)$$

$$\text{MAE} = \frac{1}{N}\sum_{t=1}^{N}(Y_t^{'} - Y_t) \qquad (53)$$

$$\text{MRE} = \frac{1}{N}\sum_{t=1}^{N}\left|(Y_t^{'} - Y_t)/\overline{Y_t}\right| \qquad (54)$$

$$\text{MAPE} = \frac{100}{N}\sum_{t=1}^{N}\left|(Y_t^{'} - Y_t)/\overline{Y_t}\right| \qquad (55)$$

where N is a number of data samples, $Y_t^{'}$ is target output, $\overline{Y_t}$ is average target output, Y_t is forecast output. The evolution error metrics are used to check quality of forecast wind speed obtained by six ANN bases wind speed forecasting models.

5 STATISTICAL ANALYSIS OF RESULTS AND DISCUSSION

The presented six ANN bases wind speed forecasting design runs on an Acer laptop computer with Pentium (R) Dual Core processor running at 2.30GHZ with 2GB of RAM and were simulated using MATLAB. Three real-time data sets, each with 1, 20,000 data samples initially classified into the training and testing sets. Training set used for neural network learning, and testing set used to calculate the error. All artificial neural networks (i.e. BPN, MLPN, RBFN, EN, IBPN and RRBFN) based wind speed forecasting models are trained with 70% o acquired data samples and tested with 30 % of acquired data samples, effectiveness is validated in terms of evaluation error metrics.

5.1 FORECASTING MODELS ASSESSMENT WITH VARIOUS HIDDEN LAYER NEURONS

All ANN based wind speed forecasting models are examined individually with varying number of hidden neurons from 1 to 30 using three wind farm data sets and obtained results are tabulated in Table 5, 6 and 7. From the simulation results, it can be observed that hidden neurons play an important role in neural network for the best performance.

Table 5. Sensitivity analysis of six ANNs based forecasting models with different hidden neurons using wind farm1 data set

Model	Structure	MSE	RMSE	MRE	MAE	MAPE
BPN	6-5-1	0.1944	0.4409	0.0342	0.2768	3.4162
	6-10-1	0.9744	0.9891	0.2125	0.7870	21.2538
	6-15-1	0.2087	0.4568	0.0383	0.3102	3.8289
	6-20-1	0.1772	0.4209	0.0367	0.2973	3.6698
	6-25-1	0.3384	0.5817	0.0482	0.3907	4.8222
	6-30-1	0.2231	0.4723	0.0418	0.3385	4.1785
MLPN	6-5-1	4.3422e-08	2.0838e-04	8.6264e-06	7.7640e-05	8.6264e-04
	6-10-1	5.3631e-07	7.3233e-04	4.9230e-05	2.4179e-04	0.0049
	6-15-1	9.9937e-07	9.9968e-04	2.1196e-04	7.2747e-04	0.0212
	6-20-1	3.3416e-09	5.7807e-05	6.5243e-06	3.2043e-05	6.5243e-04
	6-25-1	5.5532e-08	2.3565e-04	2.5797e-05	1.2670e-04	0.0026
	6-30-1	5.8104e-07	7.6226e-04	2.0574e-04	7.0610e-04	0.0206
RBFN	6-5-1	9.6003e-06	0.0031	4.7691e-04	0.0016	0.0477
	6-10-1	1.8812e-05	0.0043	6.9436e-04	0.0024	0.0694
	6-15-1	9.2549e-10	3.0422e-05	2.4989e-06	2.0903e-05	2.4989e-04
	6-20-1	8.7143e-07	9.3351e-04	1.9955e-04	6.8488e-04	0.0200
	6-25-1	9.1277e-08	3.0212e-04	6.3857e-05	2.1916e-04	0.0064
	6-30-1	1.9697e-07	4.4381e-04	8.8889e-05	3.0507e-04	0.0089
EN	6-5-1	0.0360	0.1896	0.0152	0.1234	1.5237
	6-10-1	0.0299	0.1728	0.0152	0.1233	1.5221
	6-15-1	0.0038	0.0613	0.0056	0.0457	0.5636
	6-20-1	0.0076	0.0874	0.0067	0.0546	0.6734
	6-25-1	0.0061	0.0780	0.0076	0.0618	0.7625
	6-30-1	0.0106	0.1030	0.0082	0.0664	0.8193
IBPN	6-5-1	0.0255	0.1597	0.0068	0.0548	0.6760
	6-10-1	0.2091	0.4572	0.0376	0.3048	3.7622
	6-15-1	0.0026	0.0510	7.8120e-04	0.0063	0.0781
	6-20-1	0.0737	0.2714	0.0079	0.0639	0.7891
	6-25-1	5.8606e-04	0.0242	3.7802e-04	0.0031	0.0378
	6-30-1	6.5041e-05	0.0081	6.2435e-05	5.0583e-04	0.0062
RRBFN	6-5-1	5.8692e-07	7.6611e-04	1.8000e-04	6.1776e-04	0.0180
	6-10-1	1.8122e-08	1.3462e-04	2.6223e-05	9.0001e-05	0.0026
	6-15-1	5.1650e-09	7.1868e-05	2.8289e-06	2.1336e-05	2.8289e-04
	6-20-1	9.0673e-08	3.0112e-04	1.7261e-05	1.5535e-05	0.0017
	6-25-1	1.3642e-11	3.6935e-06	2.8456e-07	2.3385e-06	2.8456e-05
	6-30-1	3.9063e-10	1.9764e-05	2.5277e-06	1.2089e-05	2.5277e-04

Table 6. Sensitivity analysis of six ANNs based forecasting models with different hidden neurons using wind farm2 data set

Model	Structure	MSE	RMSE	MRE	MAE	MAPE
BPN	6-5-1	0.1481	0.3848	0.0366	0.2761	3.6602
	6-10-1	0.7778	0.8820	0.0956	0.7743	9.5576
	6-15-1	0.1791	0.4232	0.0374	0.2818	3.7365
	6-20-1	0.1430	0.3782	0.0308	0.2324	3.0812
	6-25-1	0.3666	0.6055	0.0531	0.4007	5.3131
	6-30-1	0.1459	0.3819	0.0387	0.2920	3.8713
MLPN	6-5-1	3.4982e-08	1.8704e-04	1.7083e-05	1.2884e-04	0.0017
	6-10-1	4.7365e-07	6.8822e-04	1.5271e-04	5.2412e-04	0.0153
	6-15-1	8.8600e-07	9.4128e-04	2.0124e-04	6.9068e-04	0.0201
	6-20-1	1.9889e-09	4.4597e-05	3.1808e-06	2.8628e-05	3.1808e-04
	6-25-1	4.5554e-08	2.1343e-04	4.4364e-05	1.5226e-04	0.0044
	6-30-1	4.2127e-07	6.4905e-04	1.5800e-04	5.4226e-04	0.0158
RBFN	6-5-1	9.2071e-06	0.0030	4.9562e-04	0.0017	0.0496
	6-10-1	1.7836e-05	0.0042	6.9237e-04	0.0024	0.0692
	6-15-1	8.6474e-10	2.9407e-05	2.1289e-06	1.9161e-05	2.1289e-04
	6-20-1	8.5368e-07	9.2395e-04	1.9770e-04	6.7852e-04	0.0198
	6-25-1	8.8008e-08	2.9666e-04	6.3585e-05	2.1823e-04	0.0064
	6-30-1	1.7136e-07	4.1395e-04	8.3560e-05	2.8678e-04	0.0084
EN	6-5-1	0.0401	0.2003	0.0170	0.1285	1.7041
	6-10-1	0.0378	0.1944	0.0187	0.1409	1.8684
	6-15-1	0.0033	0.0571	0.0056	0.0424	0.5628
	6-20-1	0.0097	0.0983	0.0077	0.0578	0.7661
	6-25-1	0.0035	0.0592	0.0062	0.0466	0.6184
	6-30-1	0.0146	0.1208	0.0102	0.0768	1.0177
IBPN	6-5-1	0.0402	0.2005	0.0176	0.1326	1.7578
	6-10-1	0.3783	0.6151	0.0537	0.4052	5.3730
	6-15-1	5.5824e-04	0.0236	4.7750e-04	0.0036	0.0477
	6-20-1	0.0013	0.0361	0.0028	0.0208	0.2757
	6-25-1	2.9979e-04	0.0173	3.2271e-04	0.0024	0.0323
	6-30-1	1.6383e-05	0.0040	1.2479e-04	5.5754e-04	0.0125
RRBFN	6-5-1	5.4097e-07	7.3550e-04	1.6938e-04	5.8134e-04	0.0169
	6-10-1	1.5256e-08	1.2352e-04	2.4624e-05	8.4513e-05	0.0025
	6-15-1	4.6445e-09	6.8151e-05	4.0360e-06	3.2698e-05	4.0360e-04
	6-20-1	7.4147e-08	2.7230e-04	1.7662e-05	1.5896e-04	0.0018
	6-25-1	9.9233e-12	3.1504e-06	2.0739e-07	1.7043e-06	2.0739e-05
	6-30-1	1.0450e-10	1.0222e-05	5.0095e-07	4.1904e-06	5.0095e-05

Table 7. Sensitivity analysis of six ANNs based forecasting models with different hidden neurons using wind farm3 data set

Model	Structure	MSE	RMSE	MRE	MAE	MAPE
BPN	6-5-1	0.1286	0.3586	0.0292	0.2200	2.9167
	6-10-1	0.6739	0.8209	0.0935	0.7055	9.3539
	6-15-1	0.1383	0.3719	0.0625	0.1852	6.2525
	6-20-1	0.1141	0.3377	0.0257	0.2084	2.5718
	6-25-1	0.3413	0.5842	0.0645	0.4862	6.4459
	6-30-1	0.1503	0.3877	0.0626	0.3060	6.3640
MLPN	6-5-1	1.4458e-08	1.2024e-04	2.6217e-06	1.2876e-05	2.6217e-04
	6-10-1	3.1454e-07	5.6084e-04	1.2724e-04	4.3669e-04	0.0127
	6-15-1	8.1435e-07	9.0241e-04	2.0569e-04	7.0593e-04	0.0206
	6-20-1	1.3865e-09	3.7236e-05	1.9835e-06	1.6592e-05	1.9835e-04
	6-25-1	2.4698e-08	1.5715e-04	7.4821e-06	6.7341e-05	7.4821e-04
	6-30-1	3.8703e-07	6.2212e-04	1.5185e-04	5.2116e-04	0.0152
RBFN	6-5-1	9.1183e-06	0.0030	5.2984e-04	0.0018	0.0530
	6-10-1	1.5690e-05	0.0040	6.6167e-04	0.0023	0.0662
	6-15-1	5.6178e-10	2.3702e-05	2.4270e-06	1.1608e-05	2.4270e-04
	6-20-1	8.0905e-07	8.9947e-04	1.9908e-04	6.8327e-04	0.0199
	6-25-1	8.4443e-08	2.9059e-04	6.0850e-05	2.0884e-04	0.0061
	6-30-1	1.1304e-07	3.3622e-04	6.5574e-05	2.2506e-04	0.0066
EN	6-5-1	0.0365	0.1910	0.0249	0.1113	2.4908
	6-10-1	0.0429	0.2072	0.0267	0.1194	2.6731
	6-15-1	0.0031	0.0554	0.0055	0.0415	0.5539
	6-20-1	0.0080	0.0892	0.0147	0.0656	1.4685
	6-25-1	0.0040	0.0636	0.0071	0.0349	0.7098
	6-30-1	0.0111	0.1053	0.0155	0.0692	1.5495
IBPN	6-5-1	0.0211	0.1452	0.0162	0.0723	1.6185
	6-10-1	0.6854	0.8279	0.0364	0.1627	3.6423
	6-15-1	6.6176e-04	0.0257	8.1425e-04	0.0036	0.0814
	6-20-1	0.0011	0.0339	0.0034	0.0151	0.3373
	6-25-1	1.8427e-04	0.0136	0.0013	0.0057	0.1272
	6-30-1	1.1368e-05	0.0034	2.7034e-04	0.0012	0.0270
RRBFN	6-5-1	5.0564e-07	7.1108e-04	1.6052e-04	5.5091e-04	0.0161
	6-10-1	1.2852e-08	1.1337e-04	2.2910e-05	7.8629e-05	0.0023
	6-15-1	3.4725e-09	5.8928e-05	3.8508e-06	3.1198e-05	3.8508e-04
	6-20-1	2.4698e-08	1.5715e-04	7.4821e-06	6.7341e-05	7.4821e-04
	6-25-1	1.1982e-12	1.0946e-06	1.2229e-07	6.3774e-07	1.2229e-05
	6-30-1	1.0371e-10	1.0184e-05	4.7252e-07	4.2528e-06	4.7252e-05

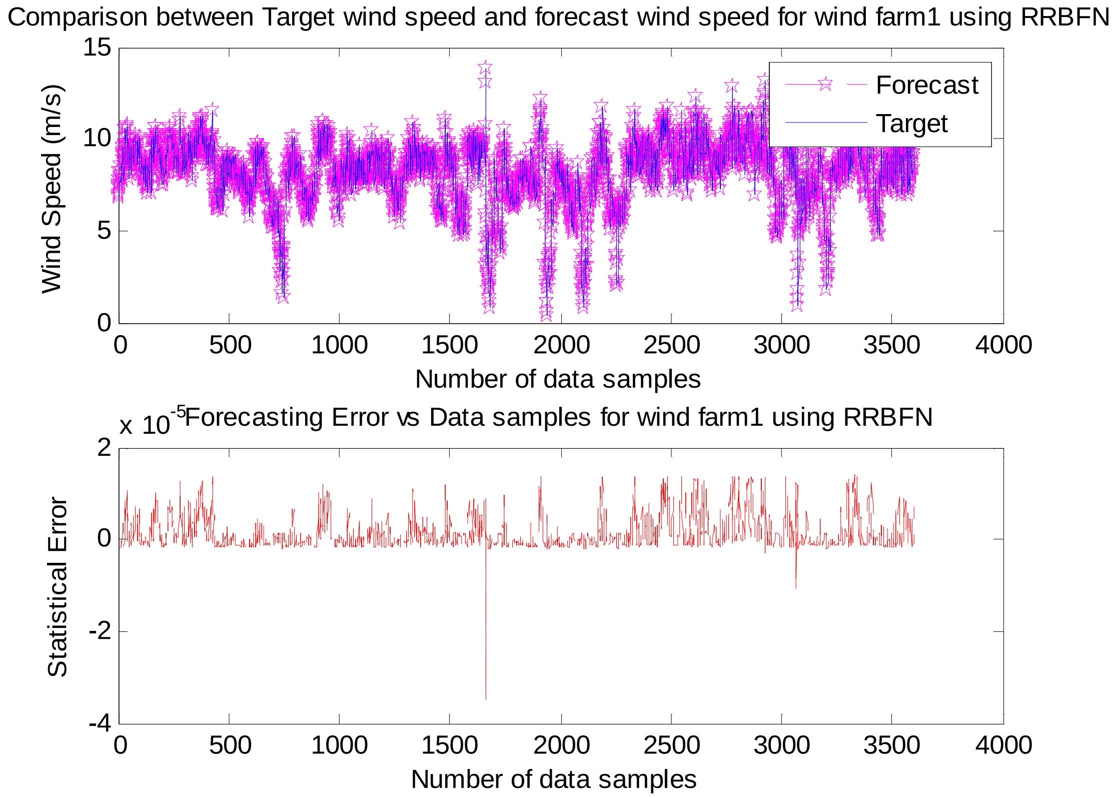

Fig. 7. Comparison between target and forecast wind speed and forecasting error vs. number of data samples for wind farm1 using RRBFN

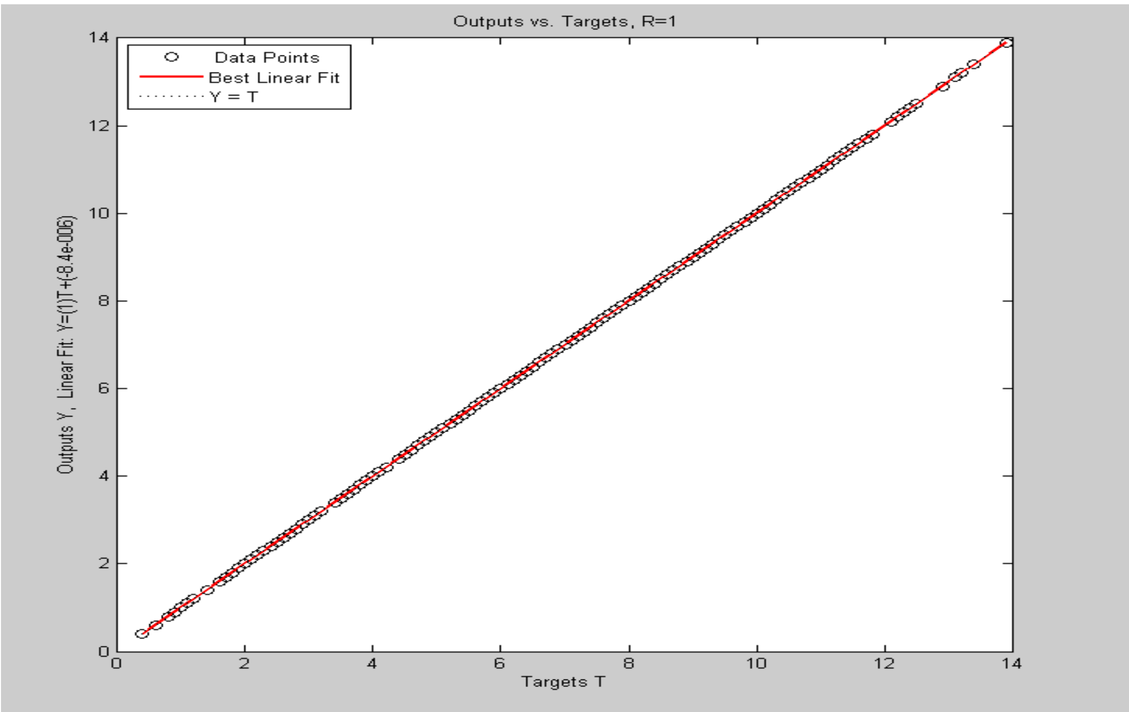

Fig. 8. Outputs vs. Targets for wind farm1 using RRBFN

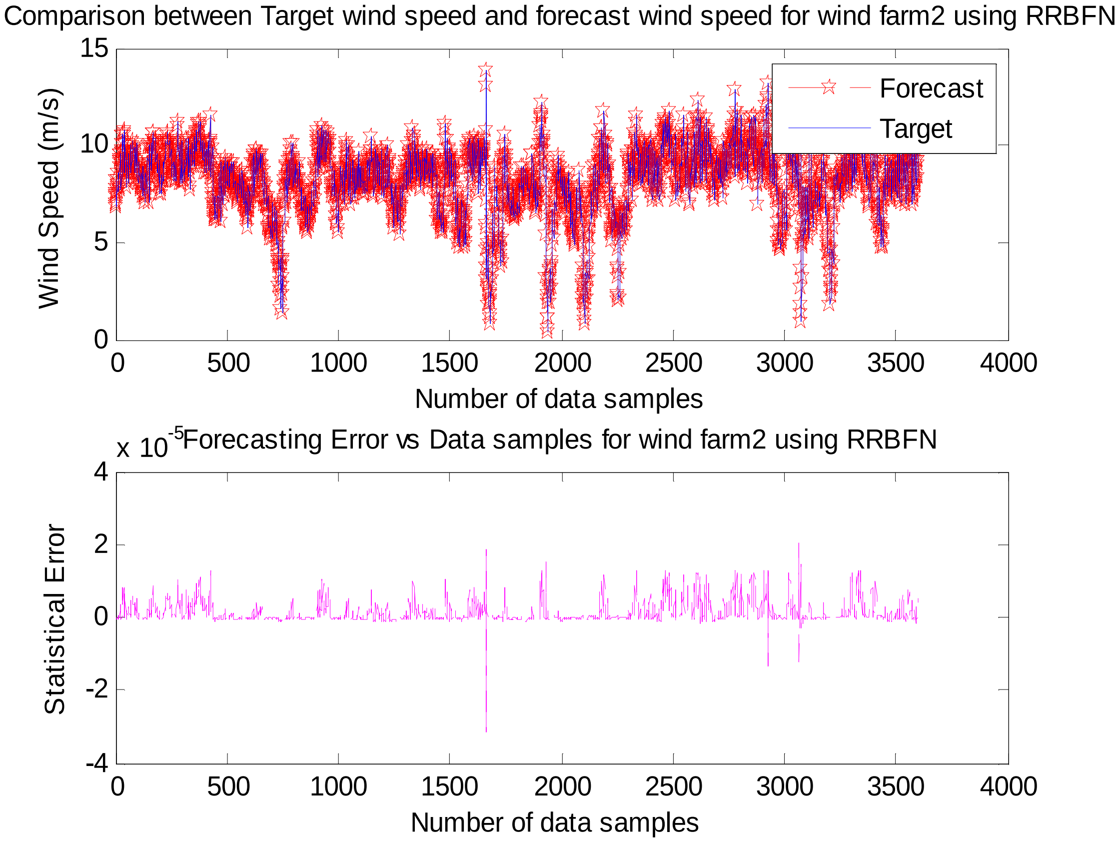

Fig. 9. Comparison between target and forecast wind speed and forecasting error vs. number of data samples for wind farm2 using RRBFN

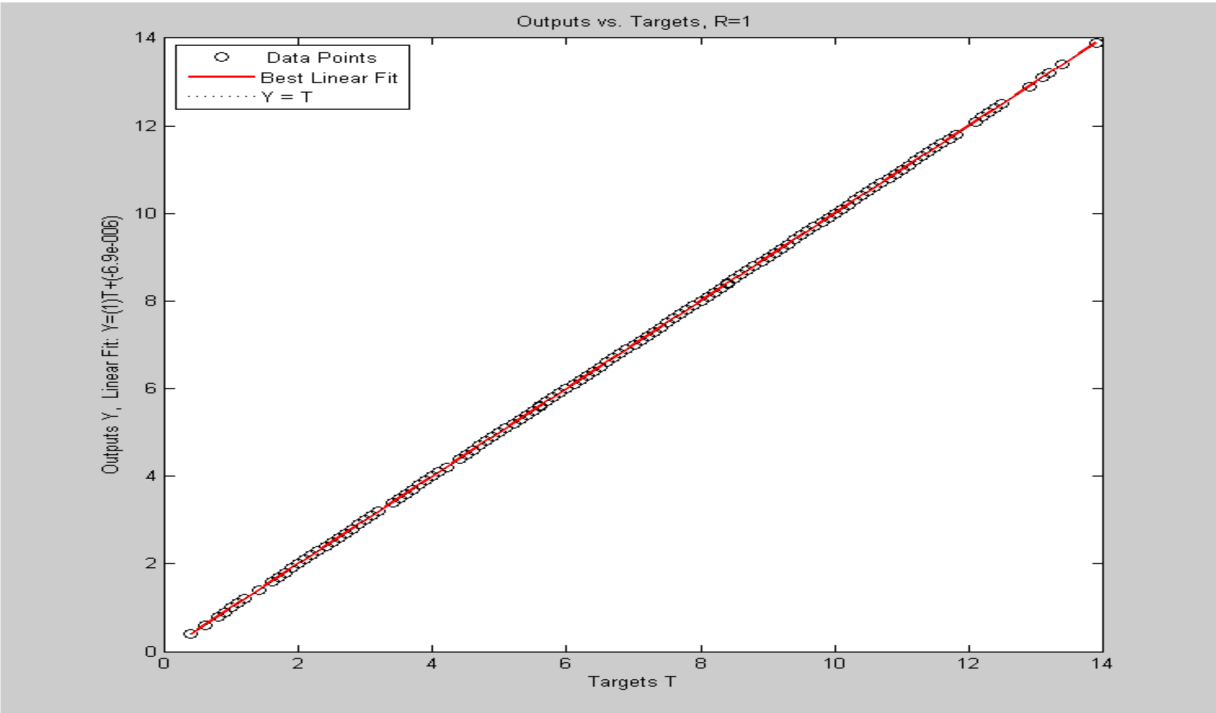

Fig. 10. Outputs vs. Targets for wind farm2 using RRBFN

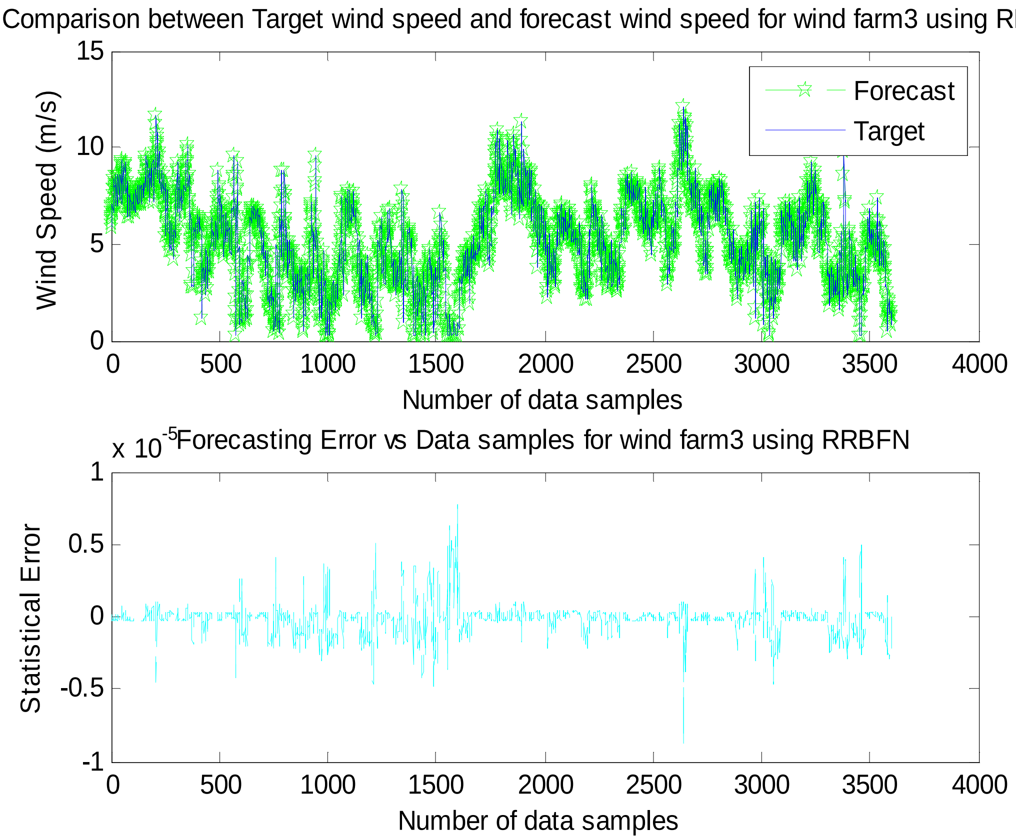

Fig. 11. Comparison between target and forecast wind speed and forecasting error vs. number of data samples for wind farm3 using RRBFN

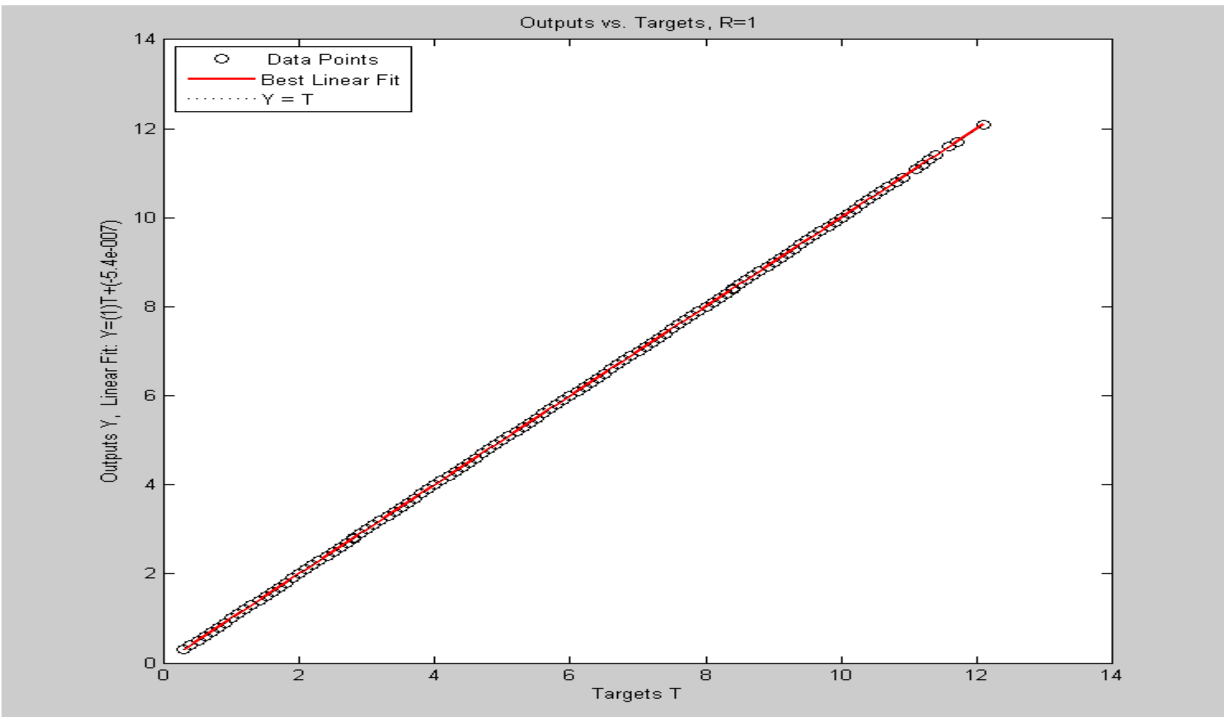

Fig. 12. Outputs vs. Targets for wind farm3 using RRBFN

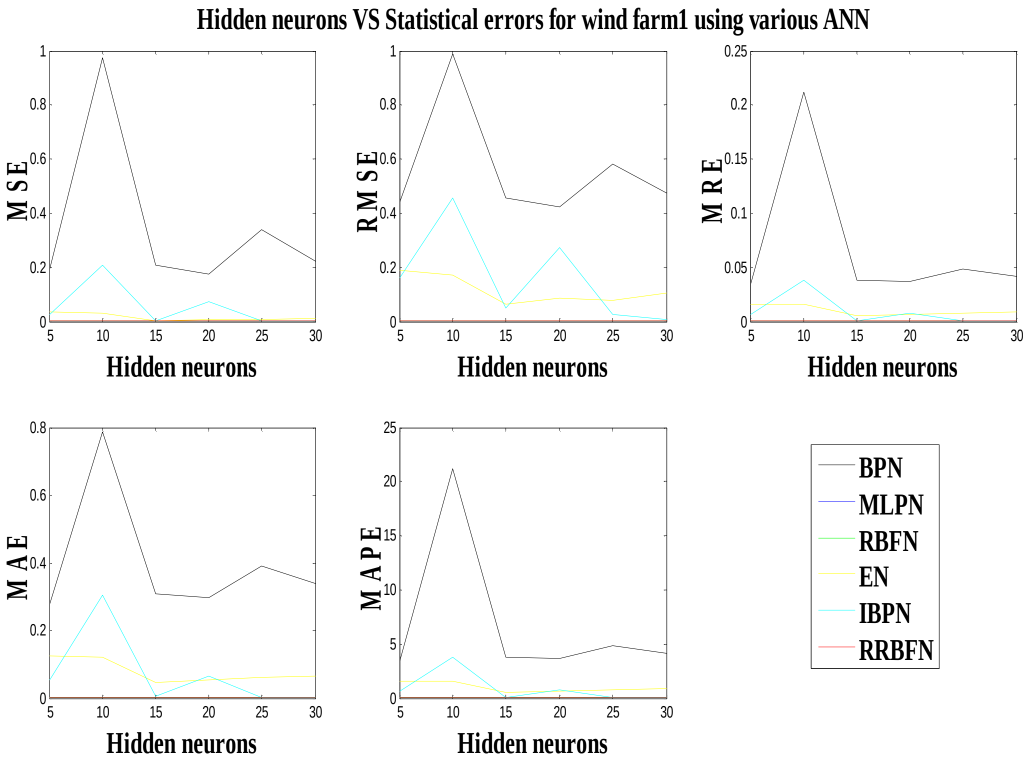

Fig. 13. Hidden neurons vs. Statistical errors for wind farm1 using various ANN

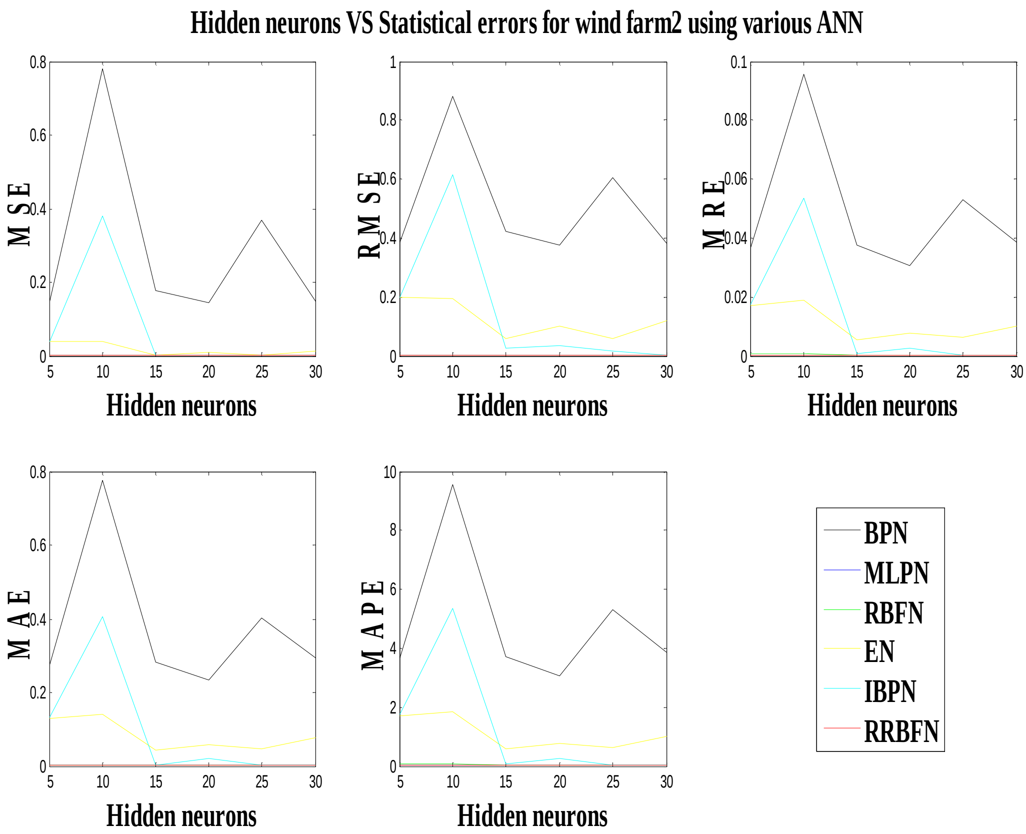

Fig. 14. Hidden neurons vs. Statistical errors for wind farm2 using various ANN

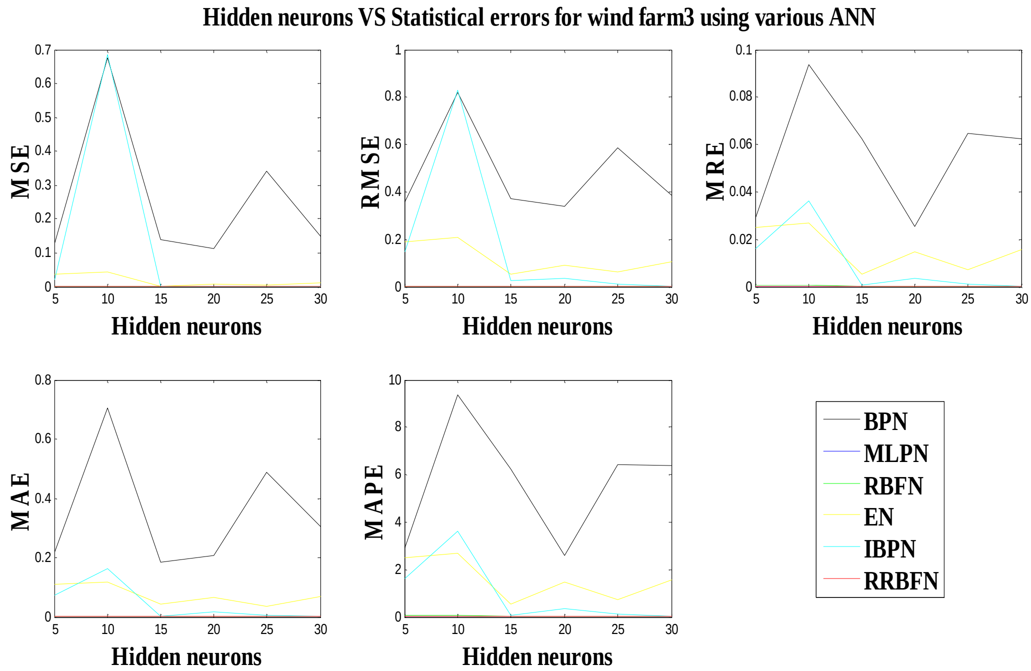

Fig. 15. Hidden neurons vs. Statistical errors for wind farm3 using various ANN

The discrepancy noticed in the Table 5, 6 & 7 because of the improper selection of hidden neurons. Back propagation network based forecasting model with 20 hidden neurons achieve consistent statistical error on three wind farm data sets than that of other hidden neurons. Forecasting model based on multi-layer perceptron network posses 20 hidden neurons in hidden layer obtain the better forecasting accuracy in terms of reduced evolution error metrics on three wind farm data set compared to other hidden neurons. Radial basis function network based forecasting model with 15 hidden neurons outperform than other hidden neurons on three wind farm data sets. Forecasting model based on ELMAN network posse's 15 hidden neurons tested on three wind farm data sets made acceptable performance compared to other hidden neurons. Improved back propagation network with 30 hidden neurons in the hidden layer based forecasting model through the validation on three wind farm data sets get the minimal evolution error metrics than that of other hidden neurons. Simulation on three wind farm data sets using recursive radial basis function network based forecasting model with 25 hidden neurons achieve the best performance in terms of the lowest evolution error metrics than that of other hidden neurons. It can be seen from the results that wind speed forecasting based on six ANNs with different hidden neurons illustrate varying levels of forecasting accuracy with varying statistical errors. The best hidden neurons for one neural network may not obtain the superior performance for other networks. Each types individual neural outperform with different number of hidden neurons.

Table 5, 6 and 7 depicts that among the six tested wind speed forecasting model best and suitable model for three data sets acquired from different location in Coimbatore region RRBFN with 6 neurons in the input layer, 25 hidden neurons in the hidden layer and single neuron in the output layer will be observed as 6-25-1 is recommended as the best wind speed forecasting model. For purpose of better understating only part of result with 3600 data samples are shown for all wind farm data sets, Fig. 7 and 8 depicts the comparison between target and forecast wind speed and forecasting error vs. number of data sample for wind farm1 using RRBFN and outputs vs. targets for wind farm1 using RRBFN respectively. Similarly, Fig. 9 and 10 presents the comparison between target and forecast wind speed and forecasting error vs. number of data sample for wind farm2 using RRBFN and outputs vs. targets for wind farm2 using RRBFN respectively. Fig. 11 and 12 shows the comparison between targets and forecast wind speed and forecasting error vs. number of data sample for wind farm3 using RRBFN and outputs vs. targets for wind farm3 using RRBFN respectively. Simulation results revealed that the forecast wind speed is in the best agreement with the experimental measured values. Merits of the recursive radial basis function network are it does not need much training time, avoid local mini ma issue, easy to implement and compact. Hence, proposed novel recursive radial basis function network suitable for various applications such as forecasting, function approximation and pattern recognition.

Evolution on three wind farm data sets, comparison of statistical errors such as MSE, RMSE, MRE, MAE and MAPE vs. number of hidden neurons for BPN, MLPN, RBFN, EN, IBPN and RRBFN based wind speed forecasting models are depicted in Fig. 13, 14 and 15 respectively. From Fig. 13–15 it can be noticed that compared to back propagation network the proposed improved back propagation network outperforms with minimal statistical error because demerits of back propagation network (convergence problem, unable to reach acceptable results, and issue of local mini ma) are avoided. Radial basis function network perform better than that of BPN and MLP. Compared to BPN, MLP, RBFN, EN, and IBPN recursive radial basis function network (RRBFN) achieve superior forecasting accuracy with minimal statistical error and forecast wind speed has the best agreement with the real target.

5.2 Models assessment with different Time scale Forecasting

Based on the sensitivity analysis the optimal number of hidden neurons in the hidden layer is identified for all wind speed forecasting models. The best number of hidden neurons based six artificial neural networks are evolved for different time-scale wind speed forecasting namely very short-term, short-term, medium-term and long-term wind speed forecasting. Different time scale wind speed forecasting is performed in order to further evaluate the capability of the six artificial neural network based wind speed forecasting models. All wind farm data sets are utilized for wind speed forecasting and the simulation results are tabulated in Table 8. RRFBN based wind speed forecasting model is significantly achieved the best forecasting performance in all forecasting ranges than other models. Based on this investigation, it can be concluded that the proposed novel RRBFN based forecasting model could be the best alternative for various time scale wind speed forecasting.

For clarity of result, comparison of artificial neural network based forecasting model for different time scale ranges such as very short-term, short-term, medium-term and long-term are shown for all wind farm data sets in Fig. 16, 17, 18 and 19 respectively. It was clear that the compared to other forecasting model RRBFN proves with extremely higher forecasting accuracy.

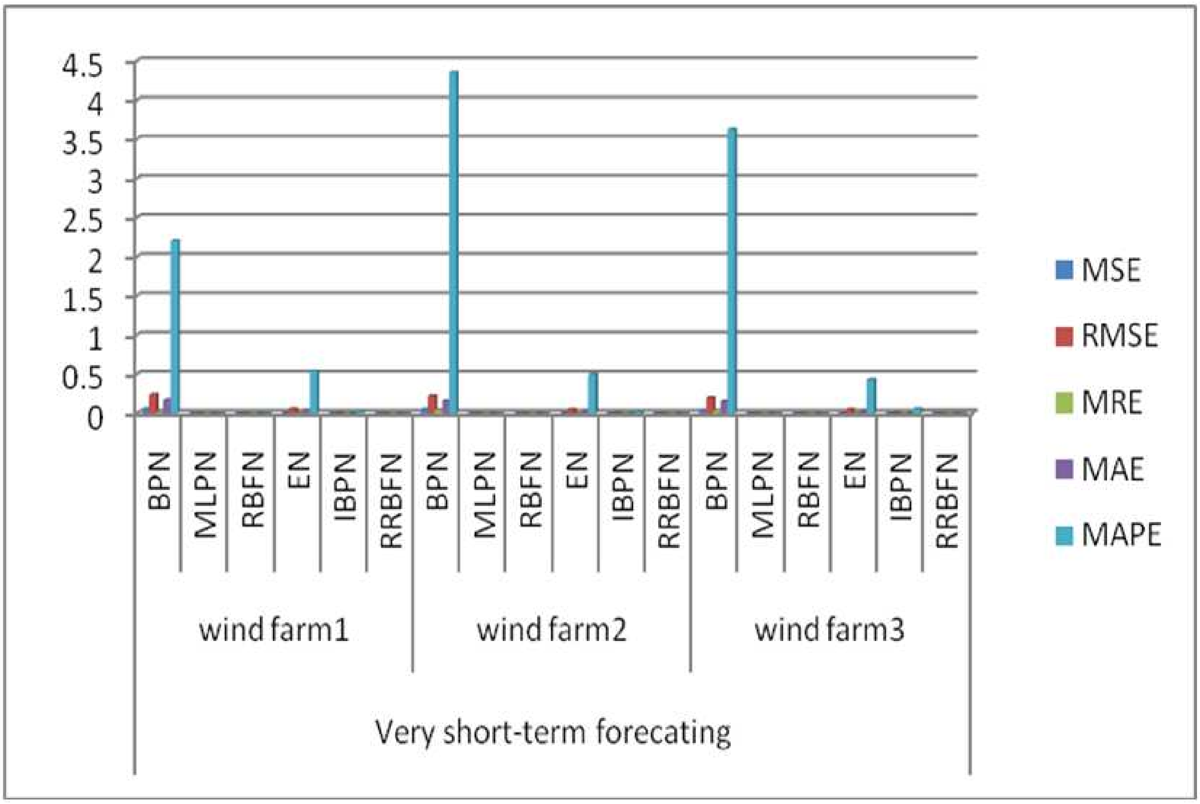

Fig. 16. Comparison of ANN based forecasting models for very-short-term forecasting

Table 8. Performance analysis of implemented six forecasting models based on different time scale ranges using 3 wind farm data set

Time scale	Data sets	Model	MSE	RMSE	MRE	MAE	MAPE
Very short-term	Wind farm1	BPN	0.0572	0.2391	0.0221	0.1755	2.2070
		MLPN	2.0784e-09	4.5589e-05	2.5094e-06	2.2585e-05	2.5094e-04
		RBFN	4.7510e-10	2.1797e-05	2.0798e-06	1.0010e-05	2.0798e-04
		EN	0.0030	0.0550	0.0054	0.0414	0.5423
		IBPN	2.8854e-05	0.0054	2.5015e-04	0.0011	0.0250
		RRBFN	7.1113e-12	2.6667e-06	1.1543e-07	7.5613e-07	1.1543e-05
	Wind farn2	BPN	0.0516	0.2271	0.0436	0.1650	4.3578
		MLPN	1.0254e-09	3.2022e-05	2.7461e-06	1.1289e-05	2.7461e-04
		RBFN	3.6701e-10	1.9158e-05	1.7805e-06	6.3703e-06	1.7805e-04
		EN	0.0027	0.0520	0.0050	0.0348	0.5013
		IBPN	1.0472e-05	0.0032	2.1911e-04	0.0010	0.0219
		RRBFN	5.8549e-12	2.4197e-06	1.0032e-07	7.4154e-07	1.0032e-05
	Wind farm3	BPN	0.0412	0.2029	0.0363	0.1565	3.6272
		MLPN	9.1437e-10	3.0239e-05	1.0318e-06	1.0033e-05	1.0318e-04
		RBFN	1.9212e-10	1.3861e-05	2.3447e-06	9.0771e-06	2.3447e-04
		EN	0.0024	0.0488	0.0043	0.0312	0.4315
		IBPN	7.8466e-06	0.0028	5.5286e-04	0.0018	0.0553
		RRBFN	8.2353e-13	9.0749e-07	9.8905e-08	9.8701e-08	9.8905e-06
Short-term	Wind farm1	BPN	0.0927	0.3044	0.0285	0.2109	2.8474
		MLPN	2.4741e-09	4.9741e-05	7.8167e-06	3.7274e-05	7.8167e-04
		RBFN	6.0930e-10	2.4684e-05	3.5031e-06	1.2400e-05	3.5031e-04
		EN	0.0032	0.0565	0.0056	0.0439	0.5582
		IBPN	3.9105e-05	0.0063	0.0011	0.0038	0.1108
		RRBFN	9.3439e-12	3.0568e-06	2.8451e-07	9.7645e-07	2.8451e-05
	Wind farm2	BPN	0.0797	0.2824	0.0446	0.1923	4.4592
		MLPN	1.2100e-09	3.4785e-05	3.6761e-06	1.3422e-05	3.6761e-04
		RBFN	5.0169e-10	2.2398e-05	2.1183e-06	7.2703e-06	2.1183e-04
		EN	0.0029	0.0542	0.0051	0.0385	0.5108
		IBPN	1.2010e-05	0.0035	3.0738e-04	0.0013	0.0307
		RRBFN	7.2562e-12	2.6937e-06	1.1966e-07	8.5390e-07	1.1966e-05
	Wind farm3	BPN	0.0612	0.2475	0.0400	0.2146	3.9961
		MLPN	1.0672e-09	3.2668e-05	1.0949e-06	1.1021e-05	1.0949e-04
		RBFN	3.2444e-10	1.8012e-05	2.7803e-06	9.5423e-06	2.7803e-04
		EN	0.0026	0.0505	0.0045	0.0315	0.4511
		IBPN	9.7650e-06	0.0031	6.0583e-04	0.0019	0.0606
		RRBFN	1.0371e-12	1.0184e-06	1.0252e-07	4.2528e-07	1.0252e-05
Medium-term	Wind farm1	BPN	0.1301	0.3608	0.0483	0.2592	4.8263
		MLPN	3.1924e-09	5.6501e-05	7.6095e-06	2.6116e-05	7.6095e-04
		RBFN	8.5950e-10	2.9317e-05	6.0713e-06	2.0837e-05	6.0713e-04
		EN	0.0035	0.0592	0.0056	0.0466	0.5584
		IBPN	5.2012e-05	0.0072	0.0012	0.0040	0.1160
		RRBFN	1.0048e-11	3.1699e-06	2.8905e-07	1.2089e-05	2.8905e-05
	Wind farn2	BPN	0.1035	0.3217	0.0453	0.2438	4.5313
		MLPN	1.6095e-09	4.0119e-05	8.0005e-06	2.7458e-05	8.0005e-04
		RBFN	7.5864e-10	2.7543e-05	5.7187e-06	1.9627e-05	5.7187e-04
		EN	0.0030	0.0550	0.0054	0.0454	0.5423
		IBPN	1.4417e-05	0.0038	4.6600e-04	0.0016	0.0466
		RRBFN	8.5737e-12	2.9281e-06	1.8490e-07	1.0074e-06	1.8490e-05

	Wind farm3	BPN	0.1028	0.3206	0.0372	0.2102	3.7191
		MLPN	1.2864e-09	3.5867e-05	1.5579e-06	1.3032e-05	1.5579e-04
		RBFN	4.8769e-10	2.2084e-05	3.3535e-06	1.1510e-05	3.3535e-04
		EN	0.0029	0.0542	0.0051	0.0385	0.5108
		IBPN	1.0472e-05	0.0032	6.1911e-04	0.0021	0.0619
		RRBFN	1.1449e-12	1.0700e-06	1.2002e-07	6.3447e-07	1.2002e-05
Long-term	Wind farm1	BPN	0.1772	0.4209	0.0367	0.2973	3.6698
		MLPN	3.3416e-09	5.7807e-05	6.5243e-06	3.2043e-05	6.5243e-04
		RBFN	9.2549e-10	3.0422e-05	2.4989e-06	2.0903e-05	2.4989e-04
		EN	0.0038	0.0613	0.0056	0.0457	0.5636
		IBPN	6.5041e-05	0.0081	6.2435e-05	5.0583e-04	0.0062
		RRBFN	1.3642e-11	3.6935e-06	2.8456e-07	2.3385e-06	2.8456e-05
	Wind farm2	BPN	0.1430	0.3782	0.0308	0.2324	3.0812
		MLPN	1.9889e-09	4.4597e-05	3.1808e-06	2.8628e-05	3.1808e-04
		RBFN	8.6474e-10	2.9407e-05	2.1289e-06	1.9161e-05	2.1289e-04
		EN	0.0033	0.0571	0.0056	0.0424	0.5628
		IBPN	1.6383e-05	0.0040	1.2479e-04	5.5754e-04	0.0125
		RRBFN	9.9233e-12	3.1504e-06	2.0739e-07	1.7043e-06	2.0739e-05
	Wind farm3	BPN	0.1141	0.3377	0.0257	0.2084	2.5718
		MLPN	1.3865e-09	3.7236e-05	1.9835e-06	1.6592e-05	1.9835e-04
		RBFN	5.6178e-10	2.3702e-05	2.4270e-06	1.1608e-05	2.4270e-04
		EN	0.0031	0.0554	0.0055	0.0415	0.5539
		IBPN	1.1368e-05	0.0034	2.7034e-04	0.0012	0.0270
		RRBFN	1.1982e-12	1.0946e-06	1.2229e-07	6.3774e-07	1.2229e-05

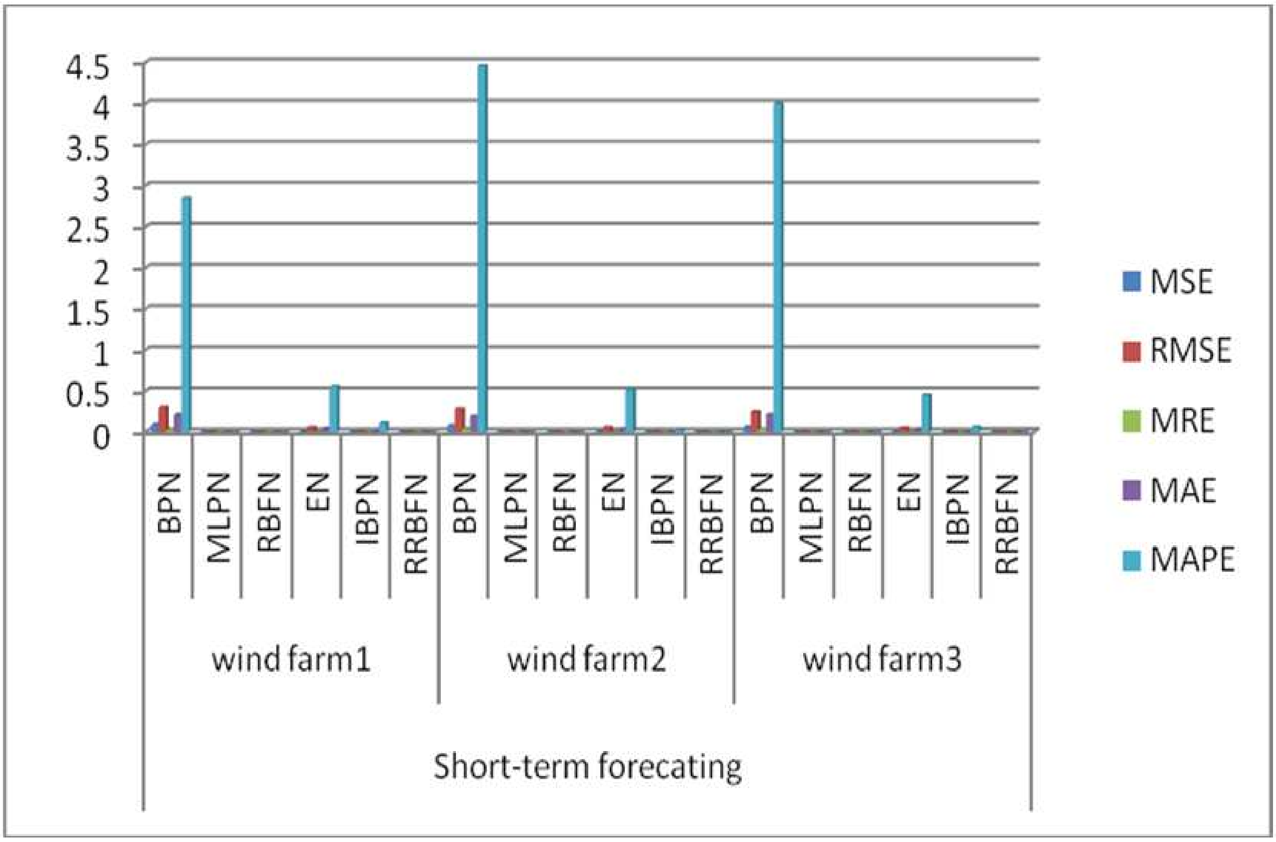

Fig. 17. Comparison of ANN based forecasting models for short-term forecasting

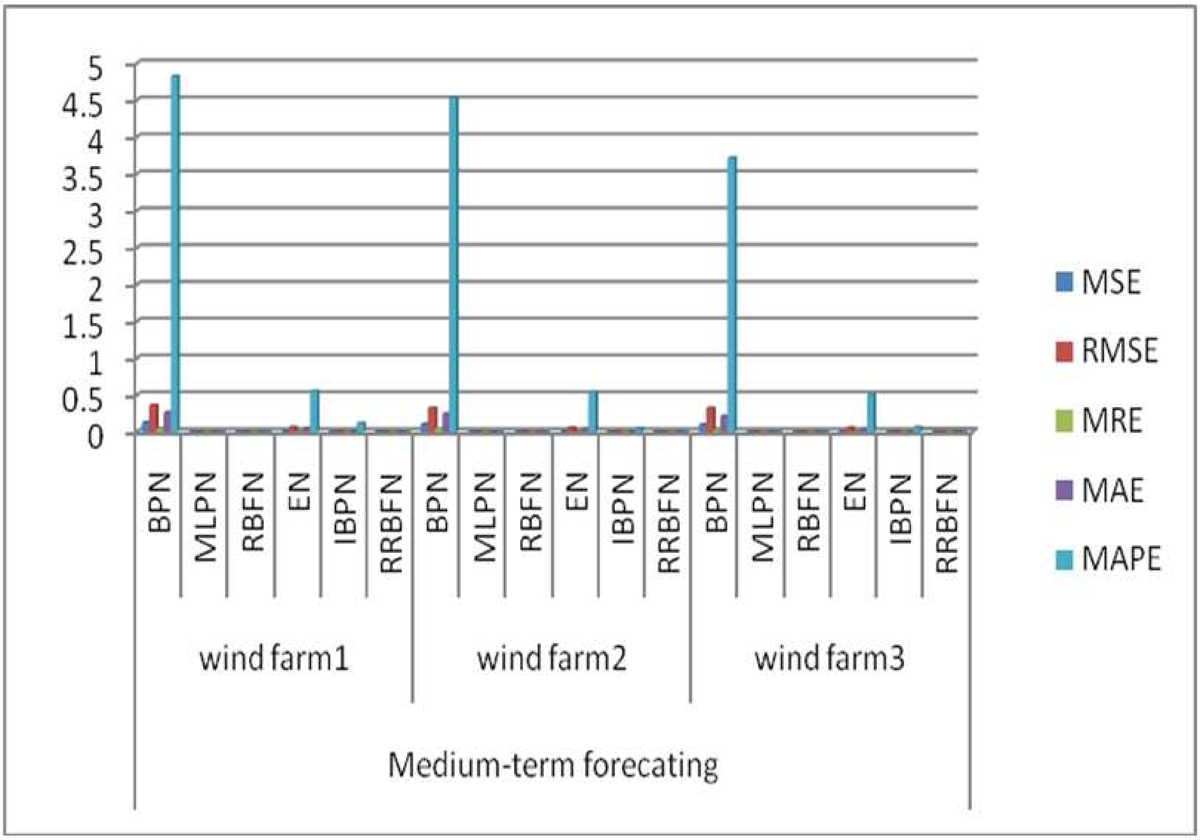

Fig. 18. Comparison of ANN based forecasting models for medium-term forecasting

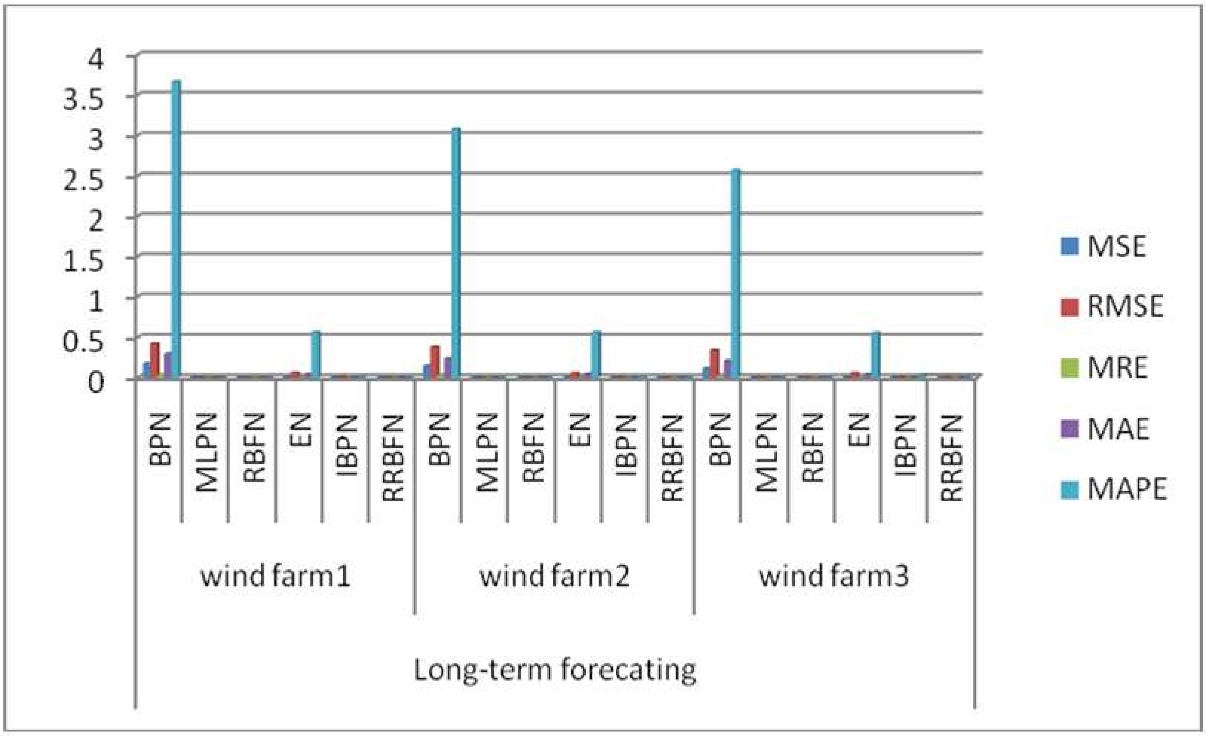

Fig. 19. Comparison of ANN based forecasting models for long-term forecasting

6 CONCLUDING AND REMARKS

In this work number of various artificial neural networks based forecasting models namely back propagation network, multi-layer perceptron network, radial basis function network, ELMAN network, improved back propagation network and recursive radial basis function network are developed for forecasting the wind speed. Implemented forecasting models are applied to simulate on three wind farm data sets and forecast the wind speed based on the different time scale such as very short-term, short-term, medium-term, long-term. The optimal hidden neurons for six artificial neural networks are identified. The ultimate goal is to find the best wind speed forecasting model, which can forecast the wind speed with minimal evolution error metrics and suitable for other wind farms. According to the wind farm data sets from three acquisition location in Udumalaipettai, Poolavadi and Edayapalayam; six artificial neural networks based forecasting models are tested. From the simulation results it is discovered that each forecasting model could forecast the wind speed with modest accuracy. However, the RRBFN based wind speed forecasting model rigorously outperforms with the best forecasting accuracy and the least evolution error metrics for different time scale forecasting on three different wind farm data sets in comparison to other forecasting models.

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