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Wind Speed & Power Forecasting using Artificial Neural Network (NARX) for new York Wind Energy Farm

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Abstract

Continuous Depleting conventional fuel reserves and its impact as increasing global warming concerns have diverted world attention towards non-conventional energy sources. Out of different non-conventional energy sources wind energy can be consider as one of the cleanest source with minimum possible pollution or harmful emissions and has the potential to decrease the relying on conventional energy sources. Today Wind energy can play a vital role to meet our energy demands; however, it faces various issues such as intermittent nature and frequency instability. To reduce such issues the knowledge of futuristic weather conditions and wind speed trend are required. This work mainly describes the implementation of NARX Artificial neural network for wind speed & power forecasting with the help of historical data available from wind farms.
Keywords: Wind Power Forecasting, Artificial Neural Network, Nonlinear Autoregressive with Exogenous Inputs, Mean Absolute Percentage Error, Statistical Method and YAR Model

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I. INTRODUCTION

The people of world today faces two, significant problem, first to enhance energy generation to meet the required demand and secondly to minimize the global warming effect due to energy generation and utilization by conventional sources. These significant problems can be minimize by increasing the contribution of non-conventional energy sources such as wind energy in electricity generation. As wind is highly unpredictable so reliability of wind energy generation is not up to mark [1], [2]. Therefore, accurate forecasting of wind speed will help in the improvement of reliable wind power generation, risk minimization and highly economical operation. Wind power generation is directly proportional to the cube of wind speed so small error in wind speed prediction will lead considerable error in power generation. For reliable power generation accurate wind speed prediction is essential. It is very difficult to estimate the future value of wind speed with certainty [3]. Currently various methods are used for wind speed and power forecasting such as Physical method, Numerical weather Prediction, artificial intelligence method, ARMA model, Persistence method, Statistical method, hybrid approach etc. Physical method is generally more suitable for long term forecasting which involved physical based equations for the conversion of data from certain period of time to forecasted value [4]. Statistical method is pattern based technique, more effective for short term forecasting and involve curve fitting for prediction [5]. Artificial intelligence (AI) method is also used for wind speed forecast; the main advantages of AI technique is that future time series data can be predicted without knowledge of any prior defined mathematical model. Probability of error can be minimized with the occurrence similar patterns simultaneously and accuracy significantly decreases with increase in time horizon [6]. In Numerical weather prediction (NWP) model, parameters selections are very crucial steps, and involve geographical area, special resolution, temporal resolution, time horizon and accuracy of computational time [7]. This work mainly describes the implementation of NARX Artificial neural network for wind speed & power forecasting with the help of historical data available from New York wind farms.

II. ARTIFICIAL NEURAL NETWORK APPROACH

In early days artificial neural network (ANN) was mainly used for the conventional load and price forecasting in power market. Now days it is widely used in wind power forecasting. Due to nonlinear nature of wind speed many researchers used ANN for wind speed and power forecasting as ANN is a great tool and easily understands the complication and non-linear bonding between the data without any prior assumption [8]. Its structure is composed basic element in parallel and work on the basis of biological nervous systems. To perform a particular function ANN can be trained by adjusting weights of connections between its basic elements. After receiving the input neuron it gives the output through the activation function then target is compared with its output and accordingly the weights of the connections are modified to meet the best output. Artificial neural networks can extract the dependency of the variable in training process by showing a nonlinear complex relationship [9]. For nonlinear function approximation, time series based estimation of climate variables in separate time horizon ANN gives better result as compare to traditional methods [10]. Trained ANN can support incomplete and noisy data to perform forecasting with higher rates [11]. ANN based forecasting approach is shown in figure1.

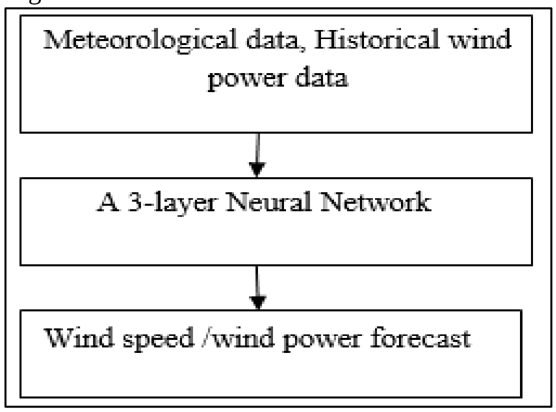

Fig. 1: ANN based Approach

For wind speed and power prediction Artificial Neural Network is a highly accurate technique. Feed forward and error back-propagation algorithm based model is us used by Lapedes for the wind speed prediction that gives the satisfactory result. [12]. On the other hand Song also proposed an ANN based model to estimate one-step ahead wind speed and power prediction and it provide good result when wind data variation rate is very low [13]. Figure 2 and figure 3 shows the Feed forward- back propagation (FFBP) and Radial basis function neural network structure.

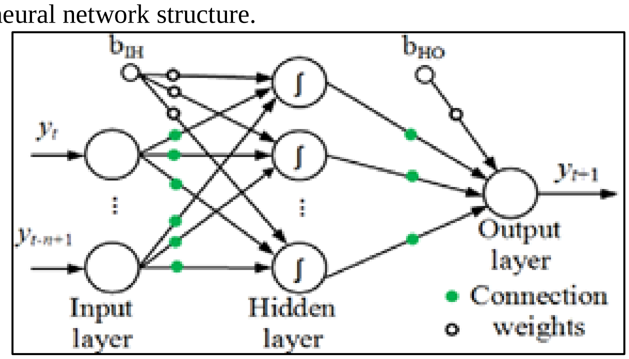

Fig. 2: Feed forward- back propagation network

Basic elements for the activation pattern or input vector can be supply by input layer source nodes that involve the input signal for the hidden layer neurons and output of hidden layer will work as input to output layer of the network.

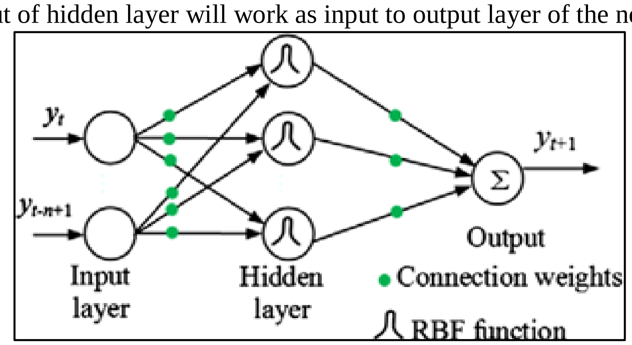

Fig. 3: Radial basis function neural network

The Radial basis function neural network takes multi-input and gives the single-output it have three basic layer such as input, hidden and output layer. The Radial basis function network output nodes shows linear relationship of a function called as basis function. The basis function gives nonzero response in hidden layer only when input ranges in small localized value of the input [14].

III. NARX NEURAL NETWORK

For time series modeling a nonlinear autoregressive exogenous model (NARX) is used, which associate exogenous input of the current value to the past value of same time series or current and past value of driving (exogenous) series. This model can be represented algebraically as equation 1.

$$Y_t = F\,(y_{t-1}, y_{t-2}, y_{t-3}, \ldots.., u_t, u_{t-1}, u_{t-2}, u_{t-3}, \ldots) + \varepsilon_t \ldots.(1)$$

Here y is the variable of interest, u is the externally determined variable and εt error .This structures has capacity to perform nonlinear modeling without any previous knowledge of relationships between input variables and output variables.

The figure 4 shows a multilayer artificial neural network. The bias unit is denoted by labeled "+1" and corresponds to the intercept term. The Layer1, Layer2 and Layer3 are called as input layer, hidden layer and output layer respectively. This network has 3 input 3 hidden and 1 output units. Its parameters are indicated as below.

(W, b) = ($W^{(1)}$, $b^{(1)}$, $W^{(2)}$, $b^{(2)}$) where $W_{ij}^{(l)}$ indicate weight associated with unit j in layer l , and i unit in layer l + 1, $b_i^{(l)}$ is the associated bias with unit i in layer l+1and $a_i^{(l)}$ indicate the activation of unit i in layer l.

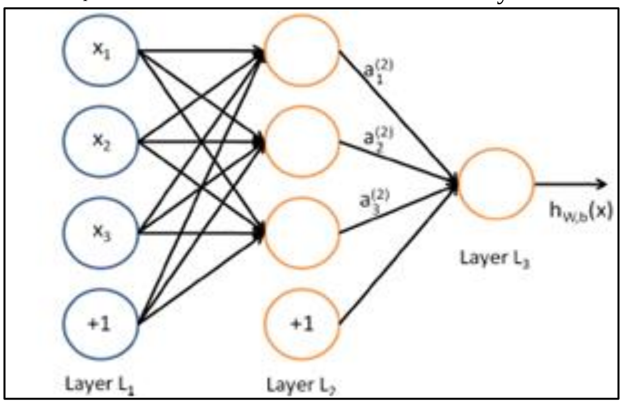

Fig. 4: Multilayer Artificial Neural Network

Neurons and network output are given by equations. 2, 3, 4 and 5.

$$a_1^{(2)} = f\,(\,W_{11}^{(1)} x_1 + W_{12}^{(1)} x_2 + W_{13}^{(1)} x_3 + b_1^{(1)}\,)\ldots(2)$$

$$a_2^{(2)} = f\,(\,W_{21}^{(1)} x_1 + W_{22}^{(1)} x_2 + W_{23}^{(1)} x_3 + b_2^{(1)}\,)\ldots(3)$$

$$a_3^{(2)} = f\,(\,W_{11}^{(1)} x_1 + W_{32}^{(1)} x_2 + W_{33}^{(1)} x_3 + b_3^{(1)}\,)\ldots(4)$$

$$h_{W,b}(x)= f(W_{11}^{(2)} a_1^{(2)} + W_{12}^{(2)} a_2^{(2)} + W_{13}^{(1)} a_3^{(3)} + b_1^{(2)}).$$

NARX neural network with exogenous inputs uses the previous actual time series data to be predicted and previous values of other inputs for prediction the future value of the target series [15].

IV. FORECASTING WITH NARX NEURAL NETWORK

NARX neural network uses the following procedure for wind speed and power forecasting.

A. Data Acquisition

Data has been taken from New York wind energy farms for the years of 2010 & 2011 and utilizes the following wind parameters such as speed, density, direction, temperature and power respectively to forecast the future value of wind speed and power.

B. Data Conversion and Normalization

Normalization of the data means that all the data (input parameters, target, output data) are scaled in the interval of {-1} to {+1}. The present work doesn't use Normalization.

C. Neural Network Design

For the complete neural network, design of three basic fields such as input neurons, hidden processing elements and output neurons are essential. Feed forward activity connections are used which connects every neuron in field 1 to field 2. Two sets of weights, one figuring for the of hidden layer neurons activations, second for determination of output neuron activations. Using Back Propagation (BP) algorithm, in each training set, the weights can be modified to reduce the error between the forecasted and the target value. These modifications are start from the output layer, via every hidden layer to the first hidden layer, up to the terminating condition is reached. Designing of a neural network involve the following steps.

– Decision of the weights
– Forward Processing of inputs data
– Error propagation toward backward
– Termination criteria

D. Training

This part consists training of neural network with the selected input parameters either wind speed or wind power as the target. Some of the input values are utilized for testing and validation purpose. Forecasted wind speed is used for the test input and compared with the actual data. Error can be minimize by adjusting the total hidden layers, delay, learning parameter, epochs for test, error tolerance, total neurons in different layers, etc. [16] & [17].
Figure 5 indicate the Procedure for forecasting wind speed and power.

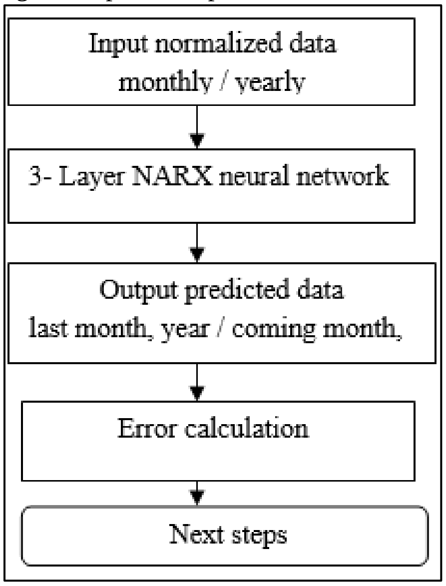

Fig. 5: Procedure for forecasting

E. Error Parameters

The performance of any forecasting model is evaluated by a variety of parameters such as root mean square error (RMSE), mean bias error (MBE) and mean absolute error (MAE). Equation 6, 7 and 8 shows the expression for these indicators.

1) Root mean square error (RMSE)

$$RMSE = \sqrt{\frac{1}{N}\sum_{j=1}^{N}(P_{mj} - P_{cj})^2} \quad (6)$$

2) Mean bias error (MBE)

$$MBE = \frac{1}{N}\sum_{j=1}^{N}\left(P_{mj} - P_{cj}\right) \quad (7)$$

3) Mean absolute error (MAE)

$$MAE = \frac{1}{N}\sum_{j=1}^{N}\left|(P_{mj} - P_{cj})\right| \quad (8)$$

Where P_{mj} is j^{th} measured value, P_{cj} is j^{th} calculated value and N is the number of measurement taken.
In this work, mean absolute percentage error (MAPE) is calculated for the forecasting error.

V. RESULTS & DISCUSSION

A. Wind Speed Forecasting

In this paper, forecasting of wind speed and power is carried out with NARX model. A three layer ANN is used and the optimum number of hidden neurons is obtained with repeated simulations to minimize the forecasting error (MAPE) and to improve regression. Input data used are wind direction, air density & temperature to forecast wind speed, after getting the forecasted wind speed it is further utilize to forecast the power. The accuracy of this prediction is estimated with the evaluation of MAPE. The wind speed forecasting has been carried by using month /year data of interval 5 minutes from New York wind farm. Regression plots for wind speed forecasting of year 2010, January 2010, February 2010, and MAPE of wind speed for month January and February 2010 as the function of each day, wind speed training and validation time response are shown in figure 6, 7,8,9 ,10, 11 and 12 respectively.

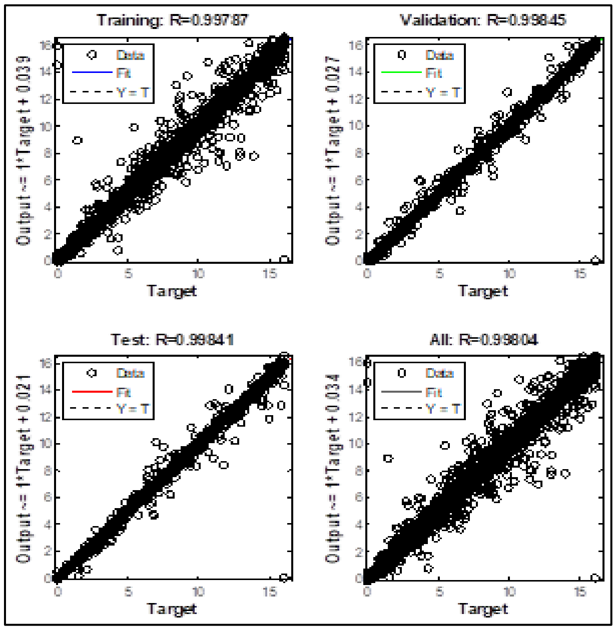

Fig. 6: Regression for wind speed forecast 2010

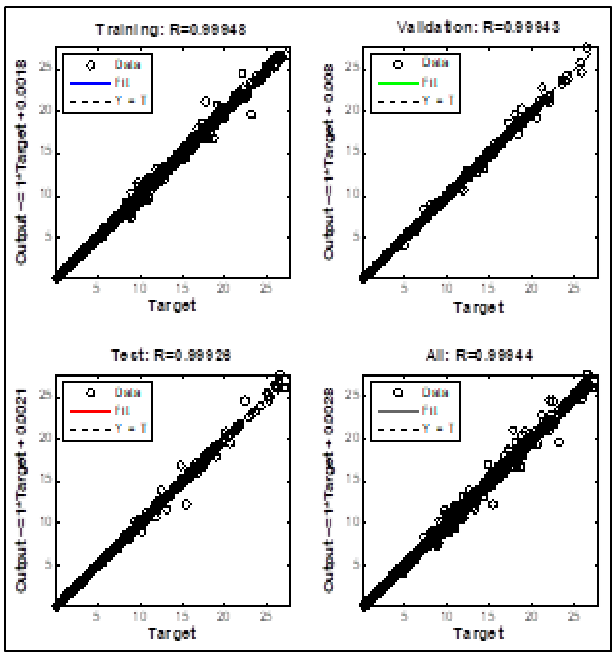

Fig. 7: Regression plot for wind speed forecast Jan 10

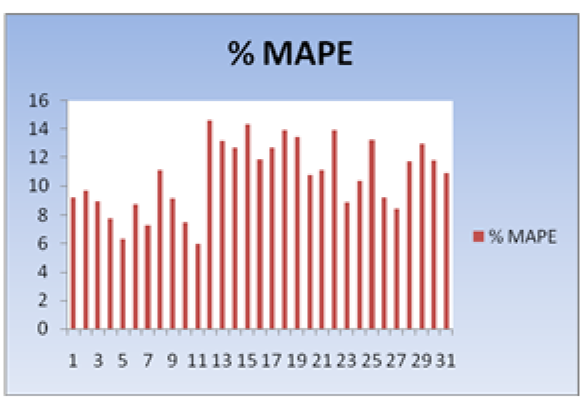

Fig. 8: MAPE for wind speed as function of day Jan 10

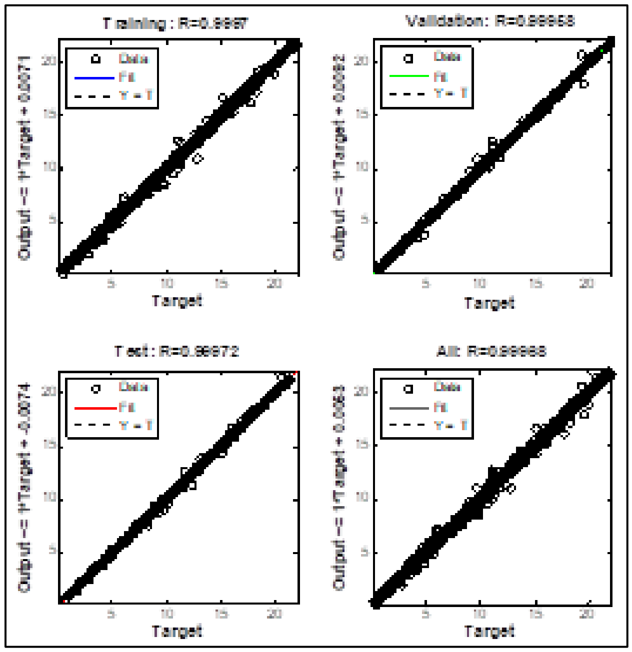

Fig. 9: Regression plot for wind speed forecast Feb 10

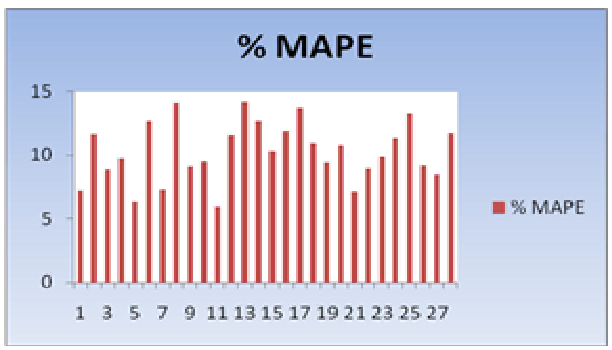

Fig. 10: MAPE for wind speed as function of day Feb 10

Regression plots clearly indicate that highly correlated data provide the better result for wind speed forecast. MAPE plot in figure 9 and 11 indicate about the accuracy of the wind speed forecasted.

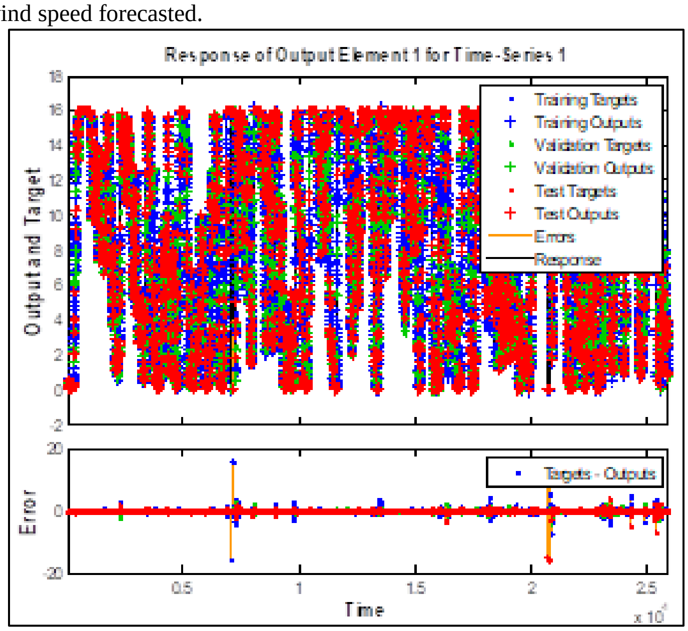

Fig. 11: Wind speed Training Time Response 2010

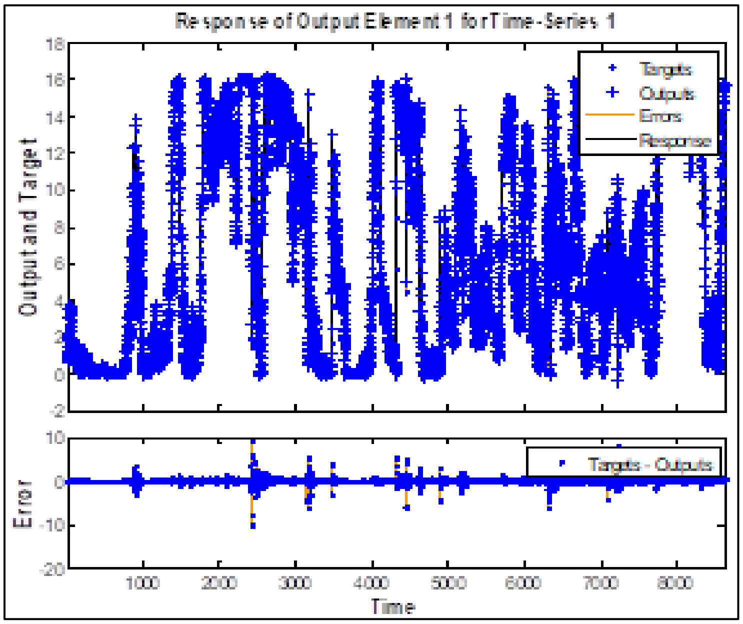

Fig. 12: Wind speed Validation Time Response 2010

B. Wind power Forecasting

By using the data sets of wind speed, direction, temperature and historical data of wind speed, power as input the future value of speed and power is forecasted. The data of 2010 & 2011 of New York wind farm is used in this paper. Prediction of wind power is carried by artificial neural network using NARX model. In this paper, the accuracy of wind power forecasting is evaluated in terms of the calculation of MAPE. The regression plot of wind power forecast suggests the utilization of moderately correlated data.

The monthly / yearly data of time interval of 5 minutes from New York wind farm has been used for the prediction of wind speed and power. Regression plots for wind power forecasting of complete year of 2010, January 2010, February 2010, and % MAPE for the same as the function of day are shown in figure 13, 14,15,16and 17 respectively.

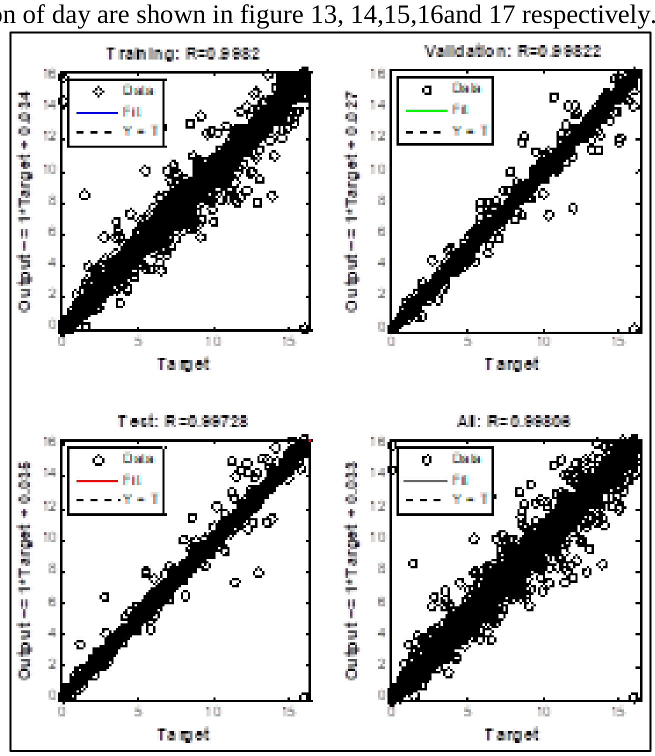

Fig. 13: Regression plot for wind power forecast 10

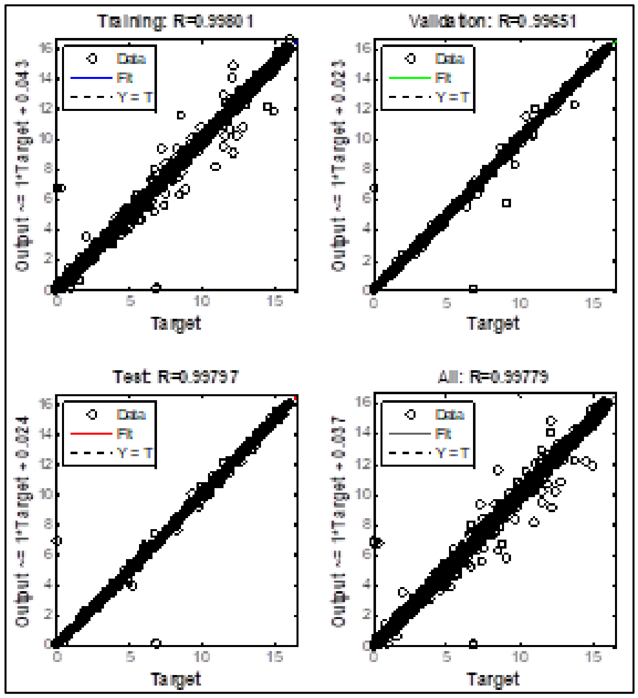

Fig. 14: Regression plot wind power forecast Jan 10

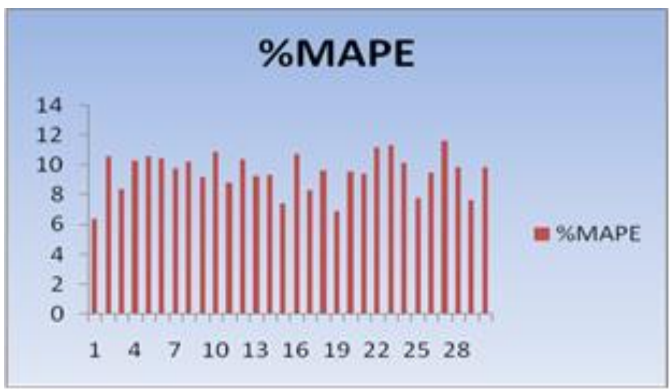

Fig. 15: MAPE for wind power as function of day January 2010

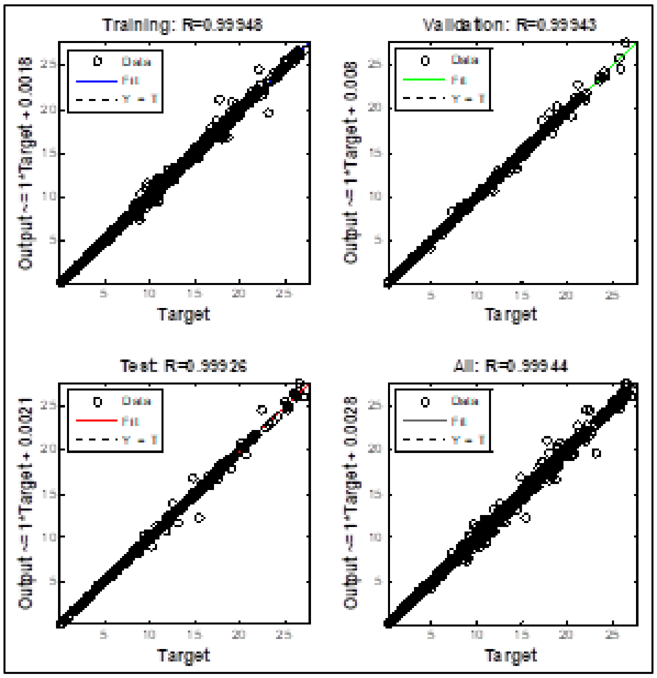

Fig. 16: Regression plot wind power forecast Feb 10

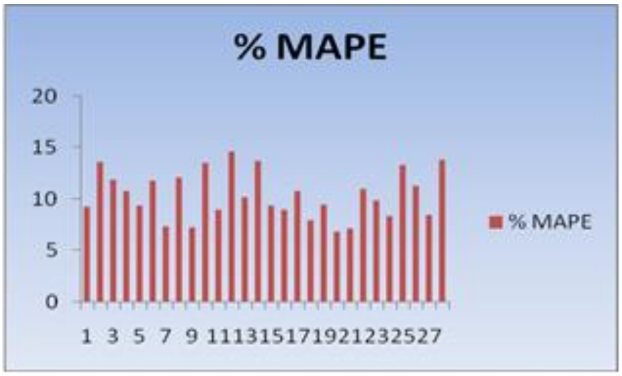

Fig. 17: MAPE for wind power as function of day February 2010

All the calculated MAPE values for wind speed & power forecasting are depicted in Table 1.

Table - 1
Table for MAPE values

Input parameters of Wind	*Forecasted parameters Wind*	*% MAPE*
Temperature, air Density, Wind Direction of 2010	*Wind speed of 2010*	*12.81*
Wind speed, Direction and Temperature of 2010	*Wind Power of 2010*	*15.21*
Historical wind speed & power of 2010	*Wind Power of 2011*	*18.79*
Air Density, wind Direction, and Temperature of January 2010	*Wind speed of January 2010*	*9.70*
Wind speed, Direction and Temperature of January 2010	*Wind Power of January 2010*	*13.79*
Historical wind power of January 2010	*Wind Power of January 2011*	*16.32*
Temperature, Air Density, Direction, of February 2010	*Wind speed of February 2010*	*10.29*
Wind speed, Direction and Temperature of February 2010	*Wind Power of February 2010*	*14.56*
Historical wind power of February 2010	*Wind Power of February 2011*	*17.64*

VI. CONCLUSION

In general, accuracy in wind speed and forecasts is crucial. In this work long-term wind speed and power forecasting is carried out using NARX neural network. The purpose of this work is to forecast the general trend of the wind speed and power for coming future year by analyzing the characteristics of the wind speed and power for the past few years that can improve the results of long term predictions. Prediction accuracy can also improve with the development of hybrid model to forecast wind power along with fuzzy system and data mining techniques such as support vector machine (SVM), relevance vector machine (RVM) to classify the available historical data.

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