Wind Power Forecasting using Artificial Neural Networks

This paper aims at predicting the power output of wind turbines using artificial neural networks,two different algorithms and models were trained and tested using open source data and a detailed comparison has been done based on the results.

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***Abstract*—The paper gives anaccurate way of predicting the power output of a wind turbine or an entire wind farm through artificial neural networks .MATLAB and its neural network toolbox has been used to build and simulate the network .The data used to train and test the neural network is open source and was obtained primarily through, ELIA-A Belgium based transmission system operator. This paper is divided into two parts; the first part defines the problem statement and proposes a ANN based solution to it while the second part presents a comparative study of the various ANN techniques, models and regressions.**

Keywords*—ANN(artificial neural netwroks);Wind energy;NAR(non linear autoregression);NARX(non linear autoregression with exogenous input);BPA(back propagation algorithm),MSE(Mean square error),LM(Lavenberg macquardt),GDA(gradient descent algorithm).

I. INTRODUCTION

Wind energy is increasingly being seen as the most potential form of renewable energy due to its easy and abundant availability i.e. both onshore and offshore, lower cost compared to other forms of energy, particularly solar and easy grid integration features. The maximum extractable energy from the 0-100 m layer of air has been estimated to be of the order of 10^{12} kWh per annum, which is of the same order as hydroelectric potential.[1] However, it is often criticized for its non-reliable nature largely due to unpredictability of weather.The dependence of wind power output on various parameters like wind speed, air density, temperature, turbine swept area, power coefficient etc. makes it's forecasting a challenging task.An accurate forecasting of wind power output will not only help producers and utility companies in optimizing their power generation schedule, but will also result in ease of grid operations and stability of interconnected power systems, particularly in countries with high wind power penetration.

Wind power forecasting can be broadly classified intophysical prediction methods and statistical prediction methods [2]. Most of the conventional wind power forecasting techniques follow the physical approach whichuses the wind flow pattern around the wind farm along withthe turbine's power curve, for proposing an estimation of the wind power output. The forecasters based on physical approach uses mathematical models for all the relevant physical processes that might affect the power output and rely very heavily on metrological forecasts and numerical weather prediction models (NWPs)hence,the performance of physical wind power forecasts and the forecast accuracy depends heavily on the availability of good NWP forecasts, the complexity of the terrain, and the availability of real-time weather and power plant data. Another drawback of purely physical models is the fact that it requires huge amount of data related to all the relevant processes and parameters.A statistical prediction method on the other hand does not take into consideration the physical wind power conversion process [2] but instead tries to establish a statistical relationship between historical values of wind powergenerationor between power generation data and other relevant input data such as meteorological variables like wind speed, temperature etc.This paper describes a statistical wind power predictor based on ANN.

ANN isa nonlinear combination of small elements operating in parallel. These elements try to mimic the biological nervous systems. Just like a biological neural network, the connections between various elements called weights largely determine the network function. They can be used in any application where a relationship exists between input and output variables; even if the relationship is complex and hard to articulate using traditional methods [3].ANN's can be broadly classified as static and dynamic [4], the major difference between the two is the fact that dynamic ANN's have memory and therefore, they can be trained to learn sequential or time varying patterns [5]. Thestatic multilayer feed forward neural network topology is usually used, for function fitting problem while dynamic network is used for time series prediction.Fig1 describes the work flow for the general neural network design process.

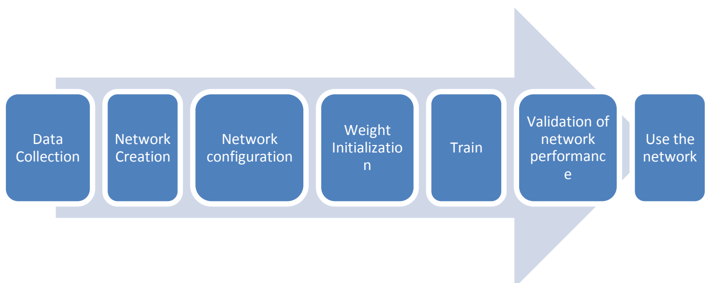


Fig.1-Artificial neural network design stages.

II. METHODS AND TECHNIQES

A. Wind energy data

Most of the data was obtained from ELIA's Belgium situated onshore wind farms[6], thirteen month data from January, 2013 to February 2014 was used to train, test and validate the network's performance using MATLAB and its neural networks toolbox. The data was evenly time stamped, with a spacing of 15 minutes. The data used for NAR consisted of past measured power output, while for NARX power output was predictedusing previous year's power generation data as exogenous input to the NAR net.

B. Neuaral Network model training algorithm

A number of ANN models and training algorithms have been proposed various applications. However, in this paper two fundamental problems are being tackled. First, the wind energy output fitting problem; where a mapping is done between a wind energy parameter data set and target power output. Second is power output time series prediction; where power output is forecasted using previous output data Multilayer feed forward network has been used in both the cases; it consists of an input layer, hidden layer and an output layer. . Due to the non-availability of a specific algorithm for finding the numbers of hidden neurons in a network, different ANN architecture have been tested to identify the numbers of neurons .A large number of hidden neurons may deteriorate the performance of the network as it requires huge storage memory for network variables, which in turn complicates the training. However, if very few numbers of neurons are used in the hidden layer, the network will not be able to adjust the weights and biases properly during training, resulting in over fitting. Over fitting makes the network excessively complex, generating random error and providing very poor classification.

The Lavenberg marquardt (LM) back propagation training algorithm has been followed in both the cases.It is a combination of gradient descent algorithm (GDA) and Gauss-newton iteration which does not require the calculation of hessian matrix(involving second order partial derivatives)[8].The LM algorithm tries to minimize the MSE i.e. the performance function to be minimized is form of a sum of squares

$$F = mse = \frac{1}{N}\sum_{i=1}^{N}(e_i)^2 = \frac{1}{N}\sum_{i=1}^{N}(t_i - a_i)^2$$

Therefore, the Hessian matrix can be approximated as

$$\mathbf{H} = \mathbf{J}^T\mathbf{J}$$

andthe gradient can be computed as

$$\mathbf{g} = \mathbf{J}^T\mathbf{e}$$

Where J is the Jacobian matrix that contains first derivatives of the network errors with respect to the weights and biases, and e is a vector of network errors [8]. The computation of Jacobian matrix can be done using a standard back propagation technique which is much less complex than computation of Hessian matrix.

The Levenberg-Marquardt algorithm uses this approximation to the Hessian matrix in the following Newton-like update:

$$\mathbf{x}_{k+1} = \mathbf{x}_k - [\mathbf{J}^T\mathbf{J} + \mu\mathbf{I}]^{-1}\mathbf{J}^T\mathbf{e}$$

After proper training back propagation networks can be used to solve a problem even when presented with a new set of input data. This makes it suitable for forecasting in power systems.

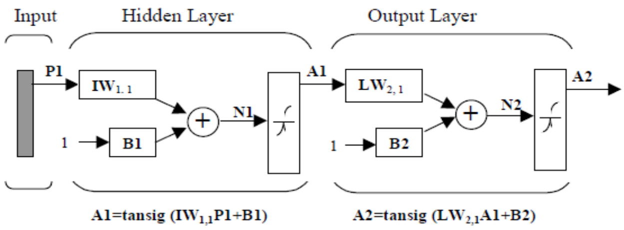


Fig2. A three layer back propagation network.

III. RESULTS AND DISCUSSION

A. Non linear regression with external input: -Previous year's generation data was given as an exogenous input to the network along with the target data i.e. present year power output data. The defining equation for the NARX model is

$$y(t) = f(y(t-1), y(t-2), \ldots, y(t-n_y), u(t-1), u(t-2), \ldots, u(t-n_u))$$

where the next value of the present year's power output y(t) is regressed on previous values of the output signal y(t) and previous year data i.e. input signal u(t).

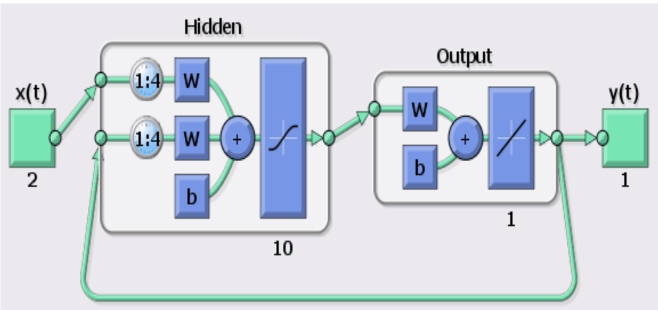


Fig3.The closed loop NARX neural network layout

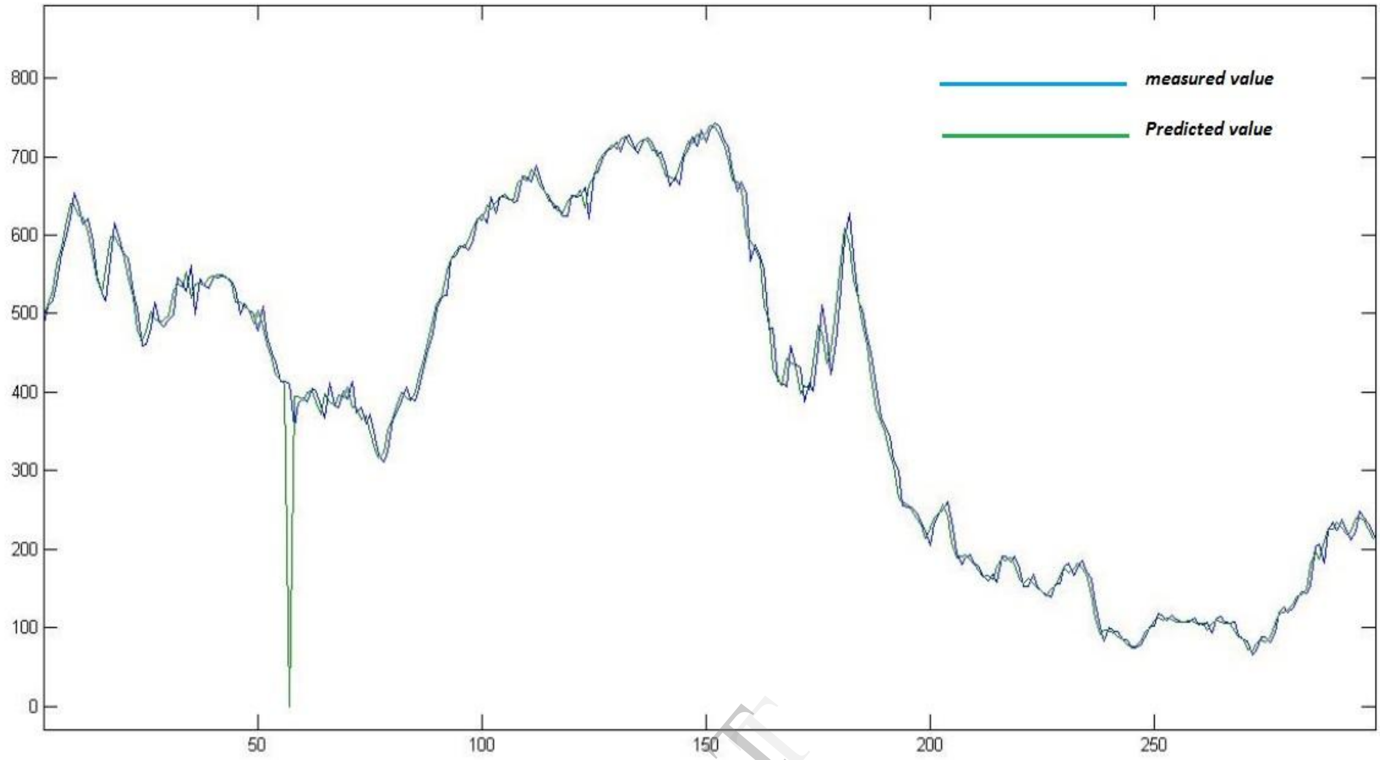


Fig.4.300 timestamp ahead forecast-NARX.

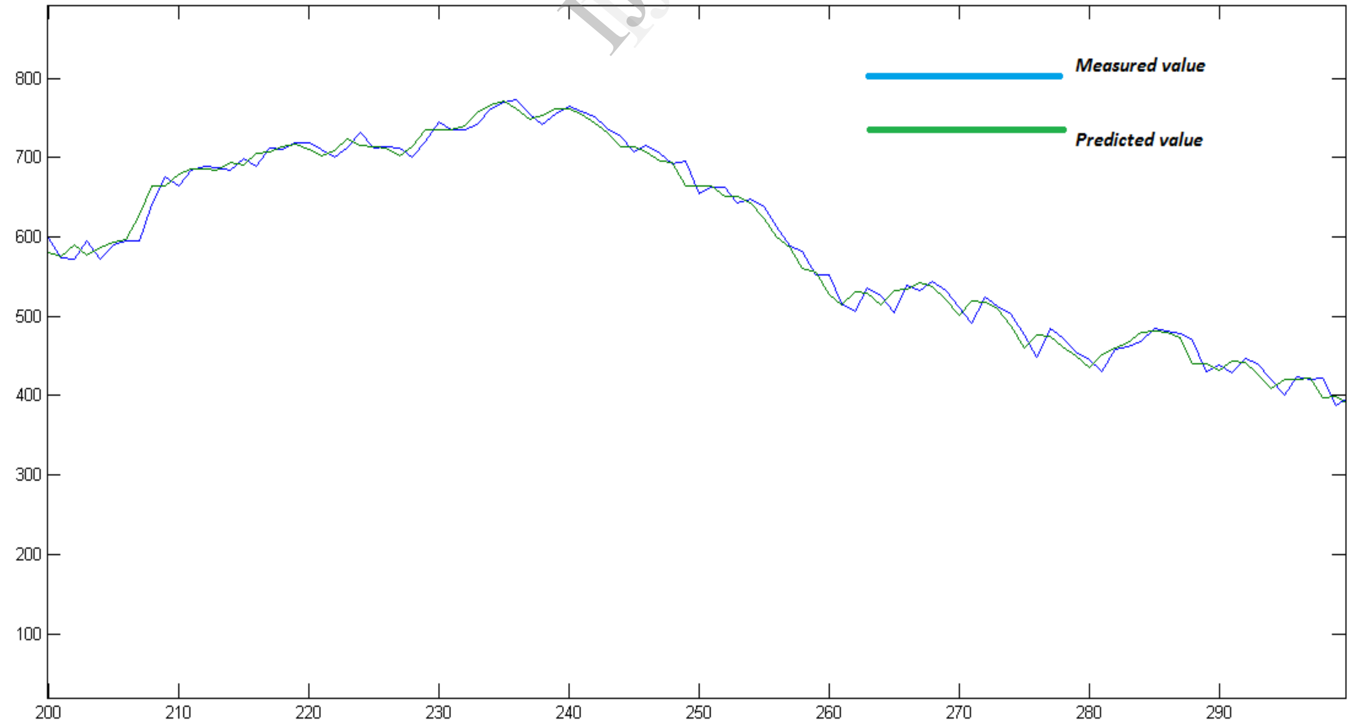


Fig.5. one day (100 timestamps) ahead forecast-NARX

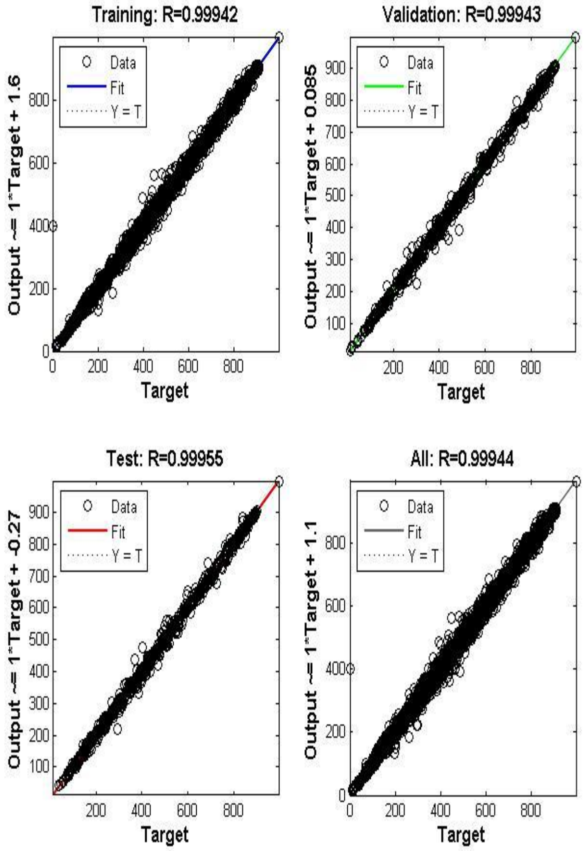


Fig.6. Regression values for training, validation and testing-NARX model

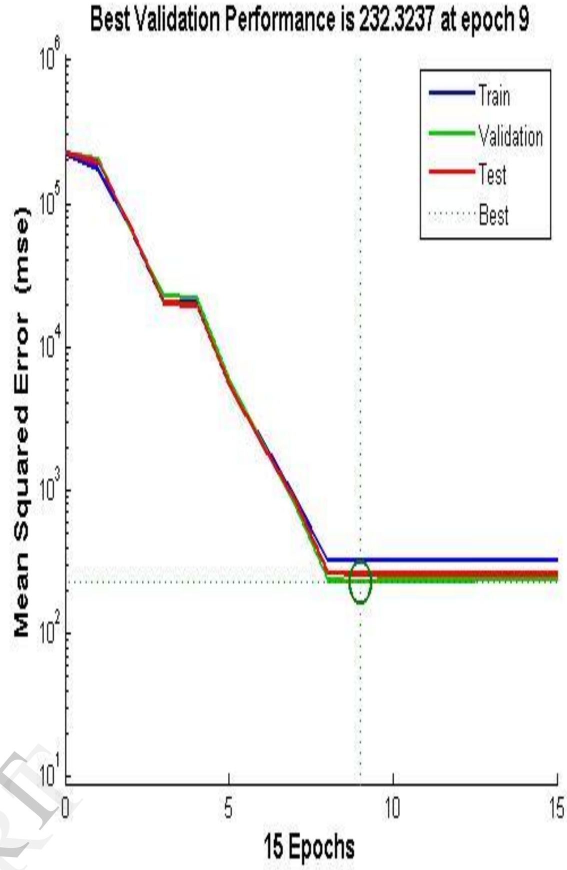


Fig.7. Performance during training, validation and testing based on mean square error-NARX

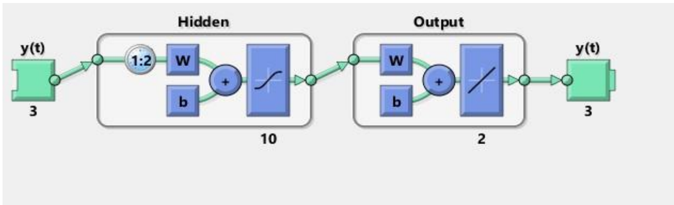
Fig.4 and Fig.5 shows actual and predicted data plotted together for 300 and 100 timestamps respectively. The time series prediction neural network is trained with an open loop, where instead of feeding the predicted data as the next input to the model, an actual value is fed from the available data in order to ensure better accuracy, but such a model can only do one step prediction and hence the loop is closed for doing multiple time series prediction like in this particular case.

Fig.6.Shows the decreasing mean square error of the model as the training advances, the training stops when mean square error goes below a specified value. Regression value gives an estimate of the relationship between the actual data and our model output. For a highly accurate model, the data points should lie completely over the 45 degree fit line [7] and the R value should be equal to 1.Fig.7 shows the presence of almost all the data points very close to the fit line. The R value of the model ranged around 0.9995 during testing of NARX based model and 0.99818 for NAR model.

B.**Nonlinear regression**:-It predicts the future values of the time series using the previously known values of the series. In this case no external input is fed along with the target data. The equation defining NAR model is

$$y(t) = f(y(t-1), y(t-2), \ldots, y(t-n_y)),$$

Where y(t) is computed using previous values of power output y(t).



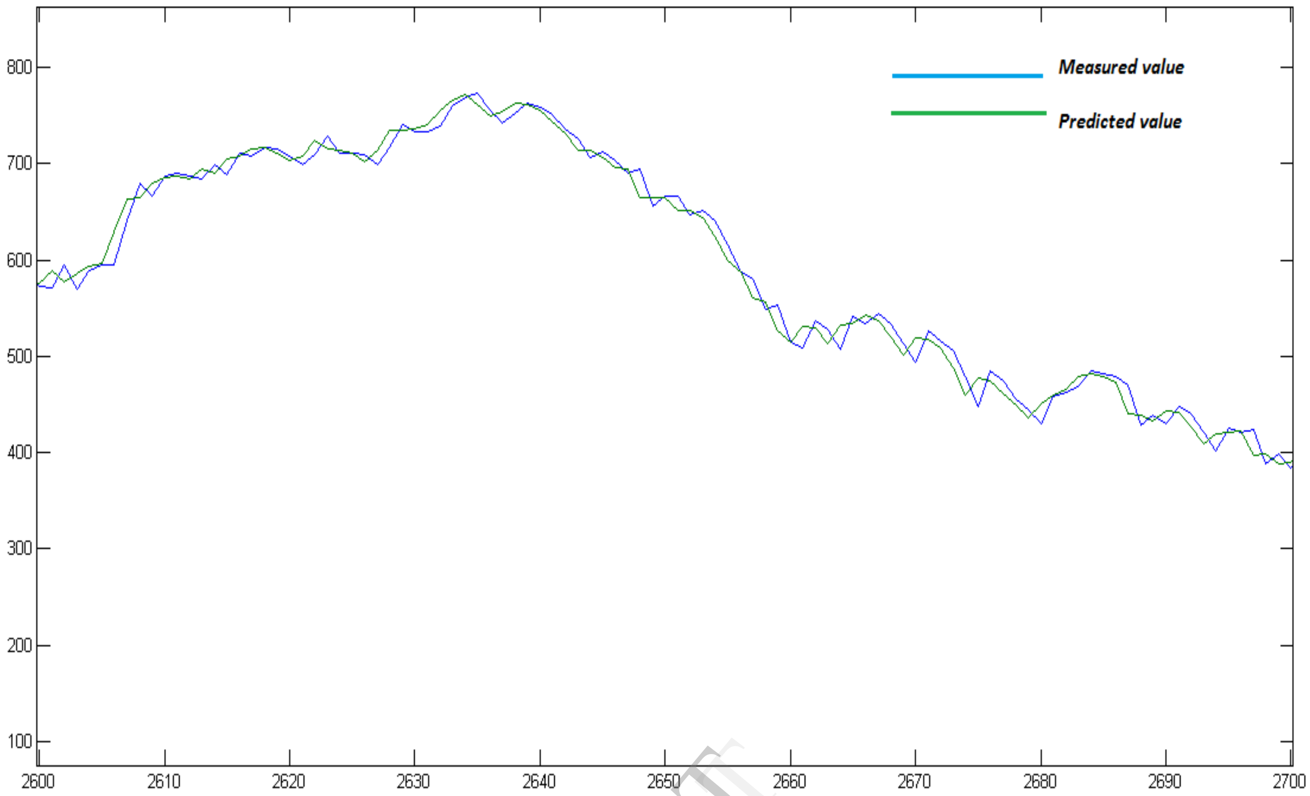


Fig.8. 1day (100 timestamps) ahead forecast-NAR model.

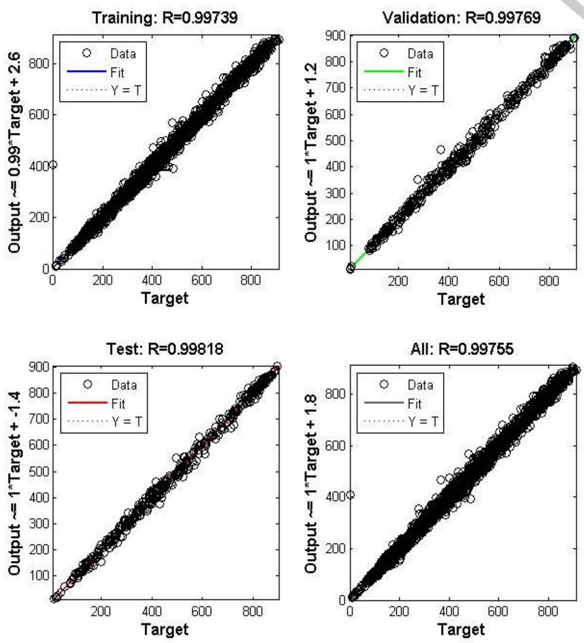


Fig.9. regression values for training, validation and testing-NAR model.

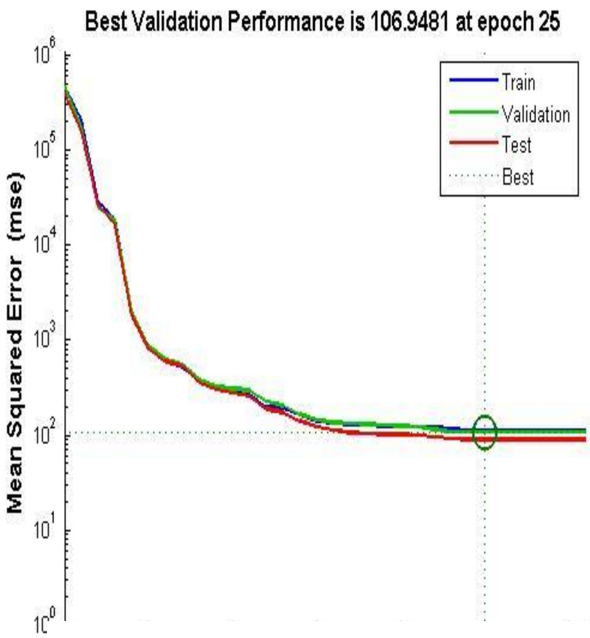


Fig.10.Performance during training, validation and testing based on mean square error-NAR model.

IV.CONCLUSION

The paper proposed and discussed a statistical wind power predictor based on ANN. The neural network was designed, trained and tested using the Lavenberg marquardt back propagation training algorithm with open source data .It is evident from the results that the wind power forecasting model based on NARX; with exogenous input as previous year output is slightly more accurate and reliable as compared to the NAR model without any external input, the external input can be wind speed, temperature, terrain characteristics etc. Despite having slightly lower accuracy compared to NARX, NAR model is more versatile since it can be used in cases where only a single parameter like power output, is available. The choice of model to be used for a particular case thus depends on a variety of factors such as nature of data available, volume of data available and required accuracy.

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