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Short Term Wind Speed Forecasting through ANN

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Abstract

Wind energy is one of the most promising renewable energy resources since it is widely available and can be converted into electric energy with highest efficiency. But the wind speed is highly intermittent in nature as it weather dependent. Due to this the wind power generated poses a problem when high power is injected into the system. So prediction of wind speed acts as a solution. To predict the wind speed, Nonlinear Autoregressive network with exogenous inputs (NARX) model is developed. To train and validate the developed model, an hourly collected data of a month is used except the last 2 days which is used for the prediction. ME, MSE, NMRSE are used as evaluation parameters to test the developed model.

Keywords— ANN, narx, Netc, Hybrid method, Wind power forecasting

I. INTRODUCTION

Due to growing concerns about the rapid depletion of conventional fossil fuel resources and global environmental pollution, power generations based on renewable energy sources are increasing significantly throughout the world. In recent years, wind energy has become one of the most promising renewable energy sources. According to the Global Wind Energy Council (GWEC), the global cumulative wind energy installed capacity has reached almost 194 GW at the end of 2010 with a growth rate of 22.5% than that in the previous year [1].

India is the fifth largest wind power producer in the world, according to the world report, 2008. As of 31st March 2015 the installed capacity of wind power in India was 22644.63 MW [8]. Within two years of span from 2011 to 2013, the wind power installed increased by 25.27% which acts as an evidence for the fast growing demand for wind energy.

In a power system, power production and consumption must be equal at all times. Because of the intermittent and volatility nature of Wind speed, the integration of large scale wind power into power system is a big challenge for the development of electric power industry. So, Wind power forecasting technology plays an important role in handling of this challenge, and the accurate forecasting helps power system operators make the power production schedules and dispatch decisions and directly relates to the need for balancing energy and hence to the cost of wind power integration [1-4]. However the wind power generated directly depends on the wind speed which in turn depends on the atmospheric conditions such as temperature, air pressure, density of air, friction and Coriolis Effect.

There are various methods to solve the problem of wind speed prediction such as persistence method, statistical method and hybrid method. Among these methods, hybrid method gives the best results since the advantages of both methods can be used to predict the further values. Based on these methods, different models such as Auto Regressive Models (ARMA, ARIMA), Nonlinear Autoregressive network with exogenous inputs (NARX), fuzzy logic, Neuro-fuzzy, etc… are developed to predict the future values of which some could be found in literatures [5, 6].

The main objective of the present study is to predict the wind speed by using NARX based model. The proposed system uses the Numerical Weather Prediction (NWP) data, which collected at the Energy Department of K L University. The data collected is one month data which hourly collected. All the data available except last 2 days, is used for the training the NARX model and the last 2 days data is used for the prediction of the wind speed.

The Mean Error (ME), Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) are used as performance indices. Using them the deviation between the actual value and predicted value are calculated. The combination which shows least deviation and more similar is the index more is the performance of that combination.

II. ANALYSIS OF INPUT DATA

Wind speed is highly intermittent in nature since it depends on the atmospheric factors. The factor on which the wind speed depends is atmospheric pressure, temperature and density of air. These factors are interdependent on each other.

$$air\ density\ \alpha\ \frac{1}{temperature}$$

And

$$wind\ speed = \left(\frac{2 * air\ pressure}{density * shape\ factor}\right)^{\frac{1}{2}}$$

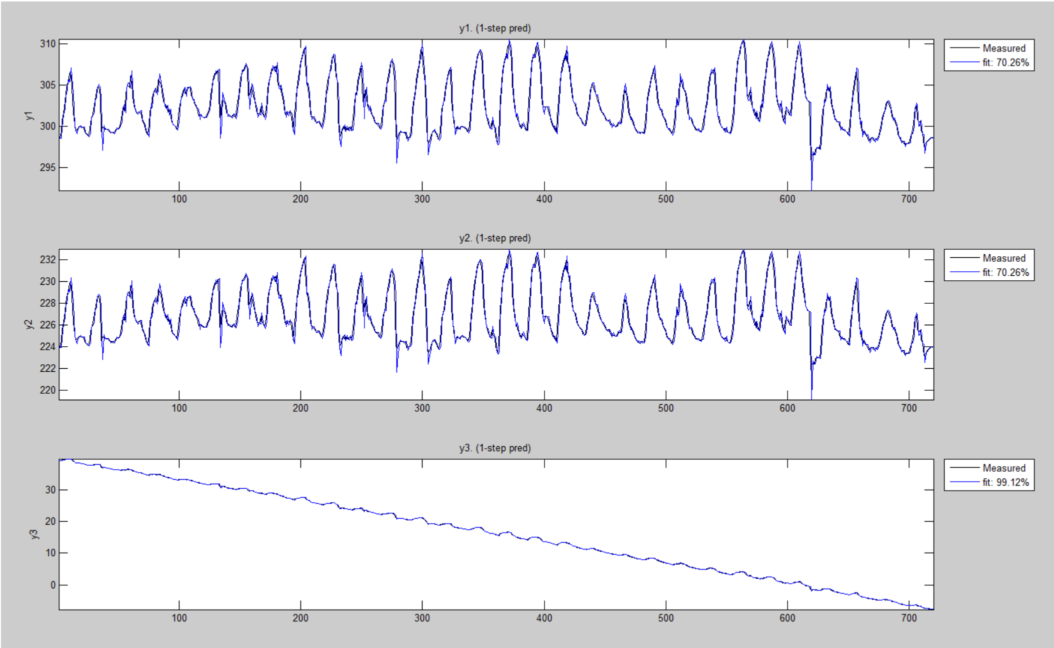


Figure1: Plot between temperature, pressure, air density vs time (hours)

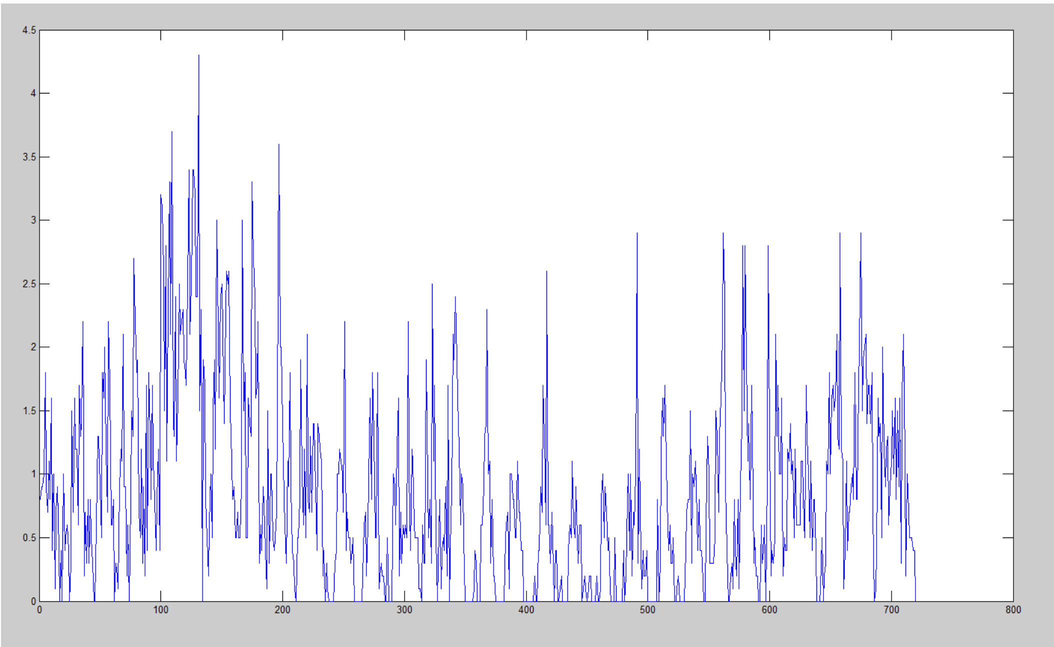


Figure2: Plot between wind speed vs time (hours)

III. MODELING APPROACH

Since the wind speed is highly intermittent in nature, a dynamic network could solve the problem of prediction in best possible way; hence Nonlinear Autoregressive network with Exogenous inputs (NARX) based model is used in the present paper.

NARX:

The NARX is a dynamic recurrent network which means its output not only depends on the present input but also on the past outputs. The past outputs are obtained using the feedback path and several layers in the network. The NARX model is based on ARX model and it is defined by the equation:

$$y(t) = f(y(t-1), y(t-2), --y(t-n), u(t-1), u(t-2), --u(t-n))$$

Where,

- Y(t), u(t) represents the output and input to the network respectively,
- y(t-1), y(t-2), y(t-3), y(t-4),- - - - - - - - - - - - - - - - - y(t-n) represents the previous output states and
- u(t-1), u(t-2), u(t-3), u(t-4),- - - - - - - - - - - - - u(t-n) represents the previous input states.

So because of its dynamic nature it can be used for prediction of the nonlinear time series variable such as wind speed.

There are two architectures in NARX model, namely

a. Series parallel architecture

b. Parallel architecture

Series parallel architecture:

In this architecture, both the input and target values are given to the network. The network calculates the output using the inputs and initial weights. Then the target value is given to the network so that error can be calculated and weights could be adjusted accordingly. This architecture is called series parallel architecture. This architecture is used in training the given network since it yields better performance as actual (target) values are present. Back propagation technique can be used to correct the weights.

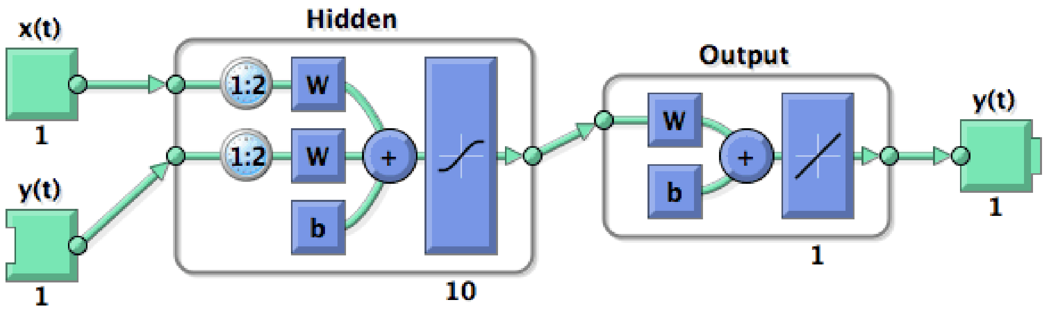


Figure3: Block diagram of series parallel architecture.

Parallel architecture:
In this architecture, the input values are given and the output values are feedback to the input without any target values as shown in the below figure. This architecture is mainly useful in predicting the future value. The number of previous values fed back to the network is adjusted by the feedback delays. The network also depends on the previous input values and these are adjusted by using input delays.

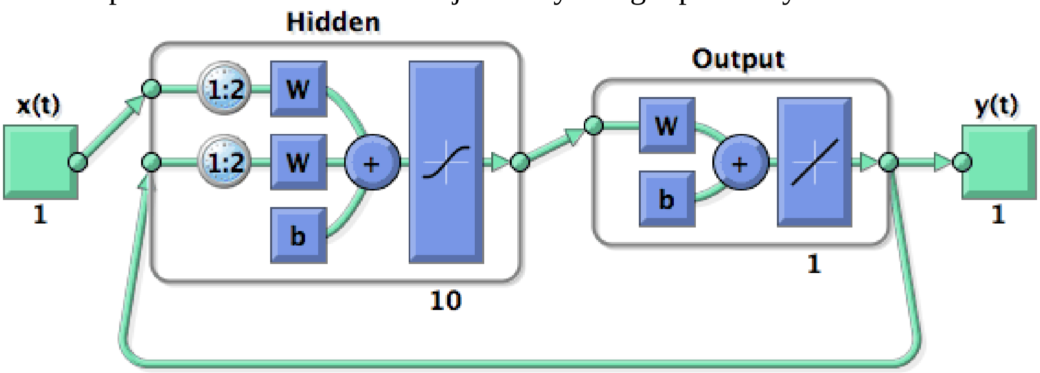


Figure4: Block diagram of parallel architecture.

IV. RESULTS AND ANALYSIS

The results are analysed by using the performance indices ME, MSE, RMSE, NRMSE and standard deviation between them.

The errors can be calculated by using the formulae:

Mean Error (ME):

$$ME = \frac{1}{N} i = 1NTi - Pi$$

Table1: Assessment of NARX model with different hidden layer size and different delay

ANN hidden layer size	Delay	ME	MSE	RMSE	NRMSE	Standard Deviation
3	2	0.65	0.64	0.80	0.39	0.16
	4	1.20	1.85	1.36	0.57	0.52
	6	2.62	7.62	2.76	0.71	2.94
	8	0.91	1.13	1.06	0.54	0.26
5	2	0.61	0.58	0.76	0.49	0.11
	4	4.39	21.61	4.64	0.64	9.37
	6	1.62	5.16	2.27	0.43	2.00
	8	0.67	0.77	0.88	0.40	0.20
10	2	0.68	0.69	0.83	0.48	0.14
	4	0.74	0.82	0.90	0.45	0.19
	6	2.42	7.92	2.81	0.59	3.14
	8	0.62	0.58	0.76	0.49	0.11

Mean Square Error (MSE):

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(Ti - Pi)^2$$

Root Mean Square Error (RMSE):

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(Ti - Pi)^2}$$

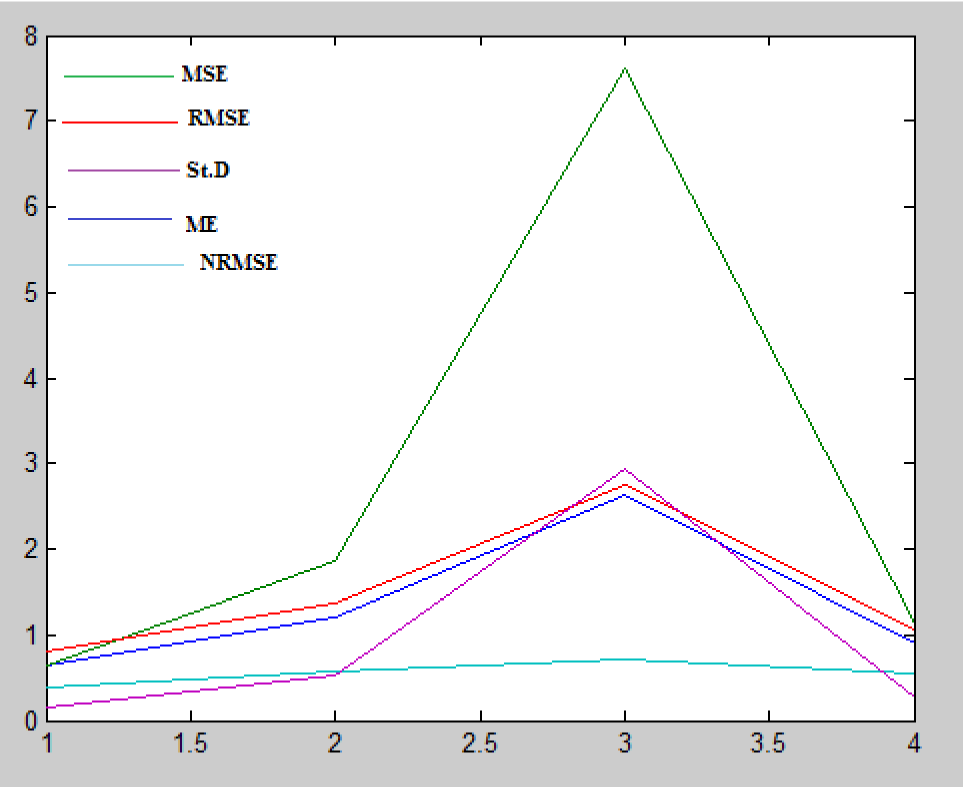
Normalized Root Mean Square Error (NRMSE):

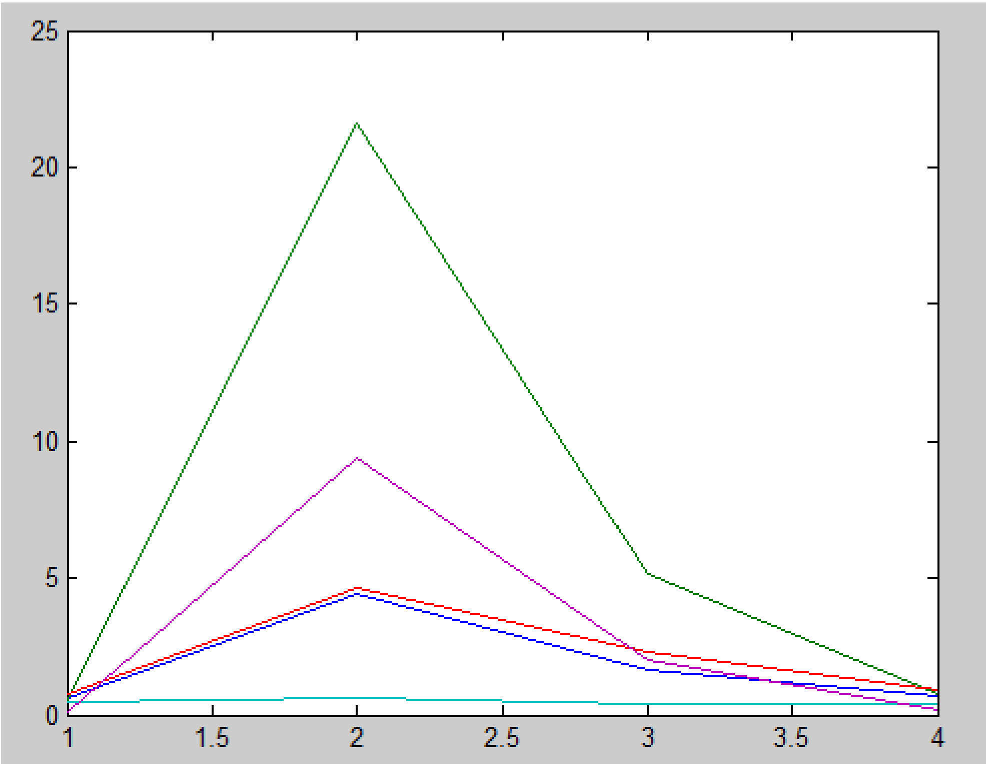
$$NRMSE = \frac{1}{maximum\ \ value - minimum\ value}\sqrt{\frac{1}{N}\sum_{i=1}^{N}(Ti - Pi)^2}$$

Where
N – Number of samples
T – Target Output
P - Predicted Output

The collected input data is given to the NARX modeled network. All the data except last 2 days is used for training the network and the last two days is used for the prediction. The data is given to the network with different hidden layer size and different input and feedback delays.

Among the results the network with 5 neurons in the hidden layer and with delay 2 is having the best performance since it's standard deviation is 0.11. the same result can be observed even with the hidden layer size 10 and delay 8 but it is complex and need high number of inputs in the form of delays.


MSE
RMSE
St.D
ME
NRMSE
0
1
2
3
4
5
6
7
8
1
1.5
2
2.5
3
3.5
4


0
5
10
15
20
25
1
1.5
2
2.5
3
3.5
4

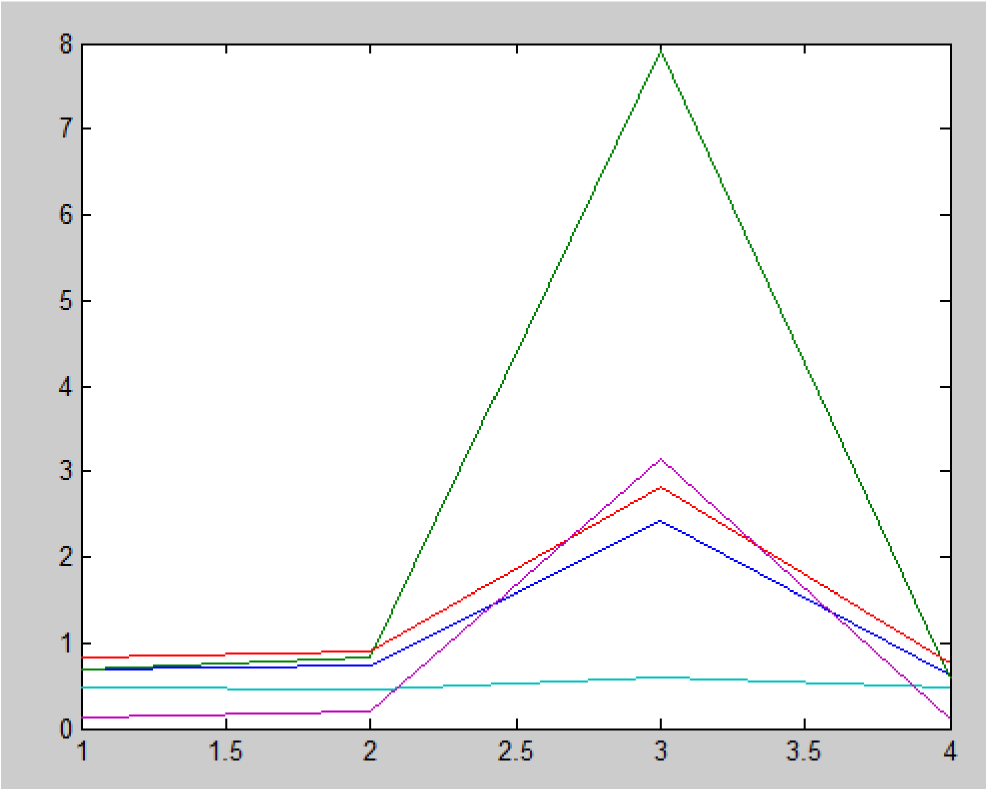


Figure5: Graphs representing the ME, MSE, RMSE, NRMSE and standard deviation of hidden layers 3, 5 and 10.

The performance indices of that network are as follows, ME=0.61, MSE=0.58, RMSE=0.76, NMRSE=0.49. it is clear from the values that the deviation between them is minimum, which is observed in the standard deviation column.

From the tabular column it is clear that for a given hidden layer size, as the delays get varied the standard deviation increases gradually and then decreases. Considered the delay, for any hidden layer size the standard deviation is maximum for the delay 6 except for hidden layer size 5 which is maximum for delay 4.

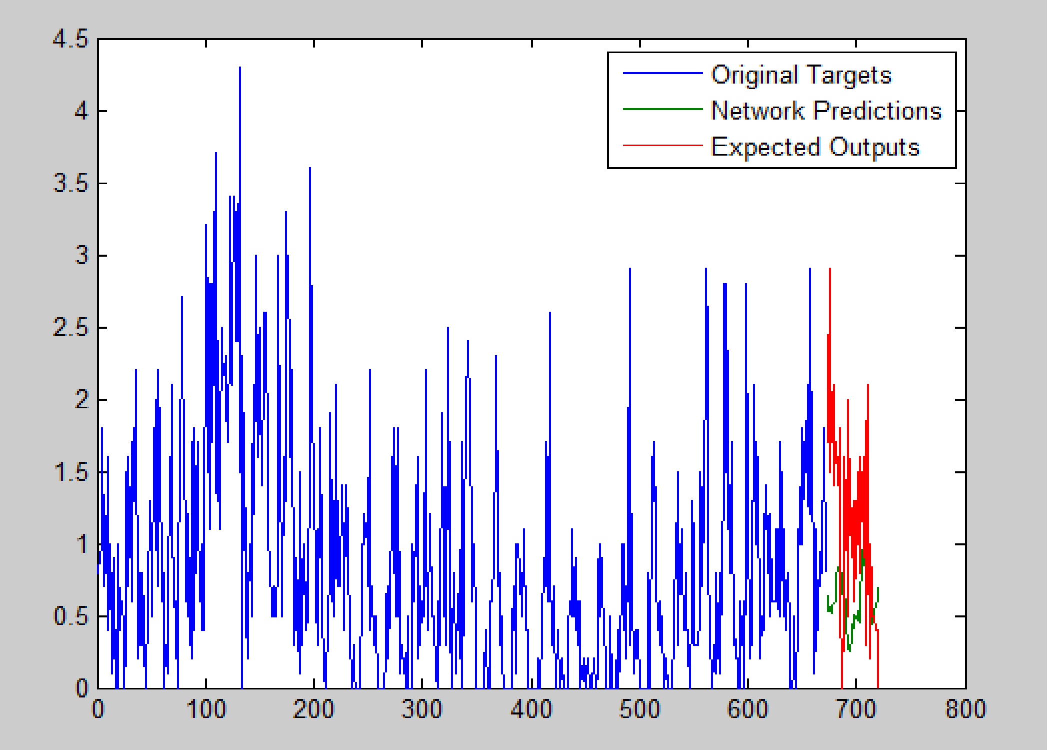
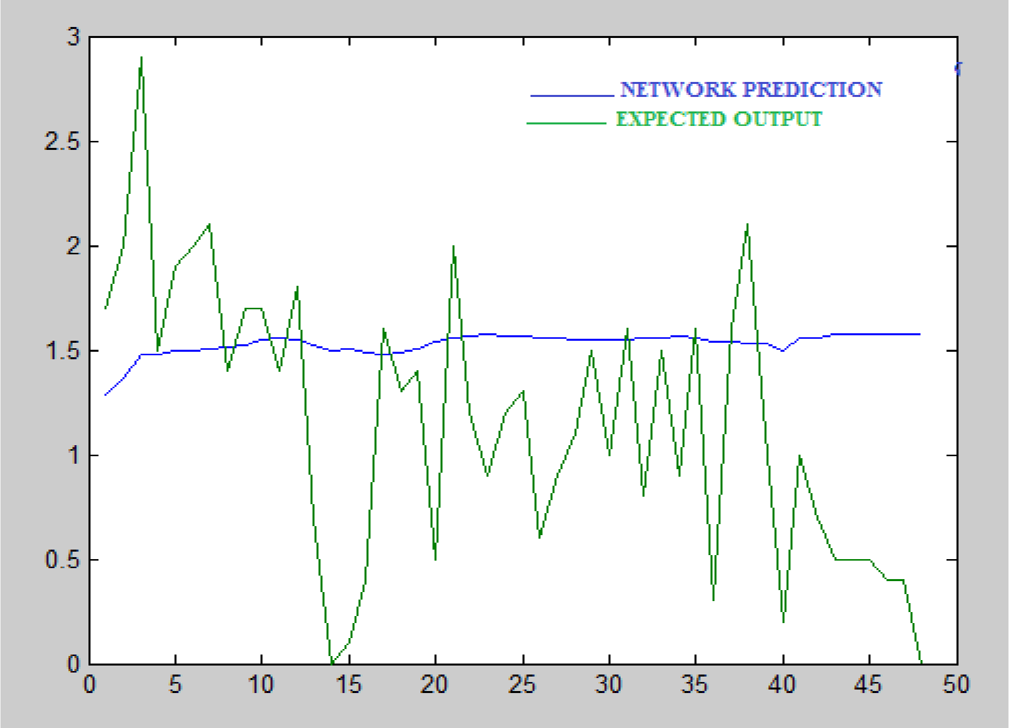


Figure6: calculated and prediction plot of the NARX network with hidden layer size 5 and delay2.



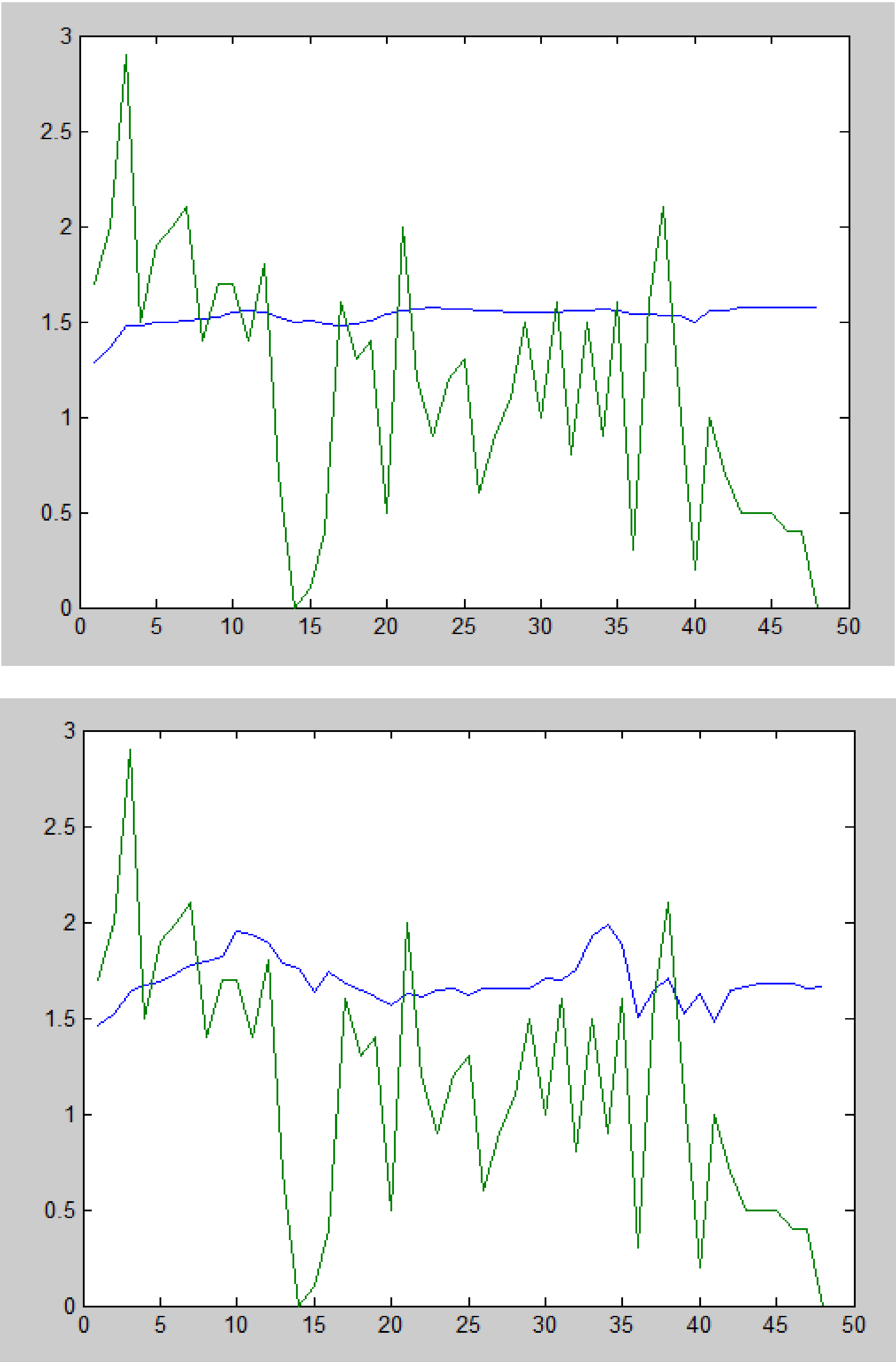


Figure6: Calculated and prediction plot of the NARX network with hidden layer size 3, 5,10 at delay2.

V. CONCLUSION

The model has been developed to predict the wind speed in advance so that when this is applied to the turbine model gives us the wind power and hence the variations in the power can be predicted in advance. The NARX network irrespective of the hidden layer size whether it is 3, 5 or 10 has shown comparatively better performance when there is a delay of 2. The performance indices ME, MSE, RMSE and NMRSE are used to estimate the network of different hidden layer size and delays and we obtained the network with hidden layer size 5 and delay 2 has shown the best performance among these combinations.

VI. FUTURE SCOPE

The wind speed prediction when applied to the turbine model gives us the wind power in advance which can be used by power engineers for the load scheduling and operation of the system. The prediction can be made more accurate when combination of techniques are deployed such as Neuro fuzzy, wavelets with artificial neural networks, etc… but these combinations are more complex and employs high mathematical computations.

VII. ACKNOWLEDGMENT

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VIII. REFERENCES

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