# Evaluate Yearly based Forecasting Model of Wind Energy Production Capacities in India using NARX Neural Network

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## ABSTRACT

*Increasing integration of renewable energy into the electricity system, not only demands adequate planning of the generation system to meet the requirements of long-term capacity, but to deal with the sudden reduction of capacity during system operation. Due to its dynamic nature, wind is the most difficult of all sustainable resources and wind energy available more likely to be estimated. This paper proposed that a forecasting model of wind energy production capacities, integrated at the end of year of all wind farms in India. Proposed model is a neural network based time series forecasting, in which nonlinear autoregressive network with exogenous input (NARX) has been preferred to predict wind energy capacities for future. NARX model works on the basis of historical data, so the data of wind energy production capacities from 1997 to 2016 has been collected from wind power. MATLAB environment has been opted for implementation of proposed model.*

## KEYWORDS

*Neural network, Time series forecasting, NARX, Wind energy production, MATLAB*

## 1. INTRODUCTION

Energy has always played an important role in civilization, supplying the needs of mankind and modern society, whether at private, residential or industrial level. As is already known, the main problems with fossil fuel based energy are encoding for the production of natural sources of pollution, greenhouse gases, and global warming. In addition, the current instability in political relations between the oil producing countries has increased the need for permanent and renewable energy sources, of which wind power is the main. Wind power is used in ships, wind mills or water pumps etc. With the increasing number of wind turbines in wind farms, the progress of technology in the field of wind energy has become a reality, the main motivation for investing in the availability of this type of energy, the great potential of extraction, low maintenance cost and reduction in government taxes, among others [1].

As the world attempts to identify and develop permanent fossils of fundamental barriers to successful integration, it has been unable to make accurate estimation of possible yield from sustainable energy sources. Increasing integration of renewable energy into the electricity system, not only demands adequate planning of the generation system to meet the requirements of long-term capacity, but to deal with the sudden reduction of capacity during system operation. As a matter of fact, system operators have to set enough time for adequate operational reserves to avoid capacity deficit, which, for example, can make wind energy available more likely to be estimated. Due to its dynamic nature, wind is the most difficult of all sustainable resources.

There are currently plenty of Wind Energy Associations in India; including Indian Wind Energy Association, Indian Wind Power Association, Indian Wind Turbine Manufacturers Association, National Institute of Wind Energy etc. and 468 wind farms are installed in different places. According to those associations the total wind energy production capacities are shown in following table-1.

**Table 1** Wind energy production capacities of previous year

| At the end of year | Production of wind energy (MW) | % growth in production |
|---|---|---|
| 1997 | 940 | |
| 1998 | 992 | +5.3 % |
| 1999 | 1035 | +4.2 % |
| 2000 | 1267 | +18.3 % |
| 2001 | 1507 | +16 % |
| 2002 | 1702 | +11.5 % |
| 2003 | 2110 | +19.4 % |
| 2004 | 3000 | +30 % |
| 2005 | 4430 | +32.3 % |
| 2006 | 6270 | +29.4 % |
| 2007 | 7850 | +20.2 % |
| 2008 | 9587 | +18.2 % |
| 2009 | 10926 | +12.3 % |
| 2010 | 13065 | +16.4 % |
| 2011 | 15880 | +17.8 % |
| 2012 | 18421 | +13.8 % |
| 2013 | 20150 | +8.6 % |
| 2014 | 22465 | +10.3 % |
| 2015 | 25088 | +10.5 % |
| 2016 | 28700 | +12.6 % |

The following figure 1 use to illustrate the production of wind energy of previous year in the form of chart, which shows wind energy production capacities (in MW) with respect to the end of year.

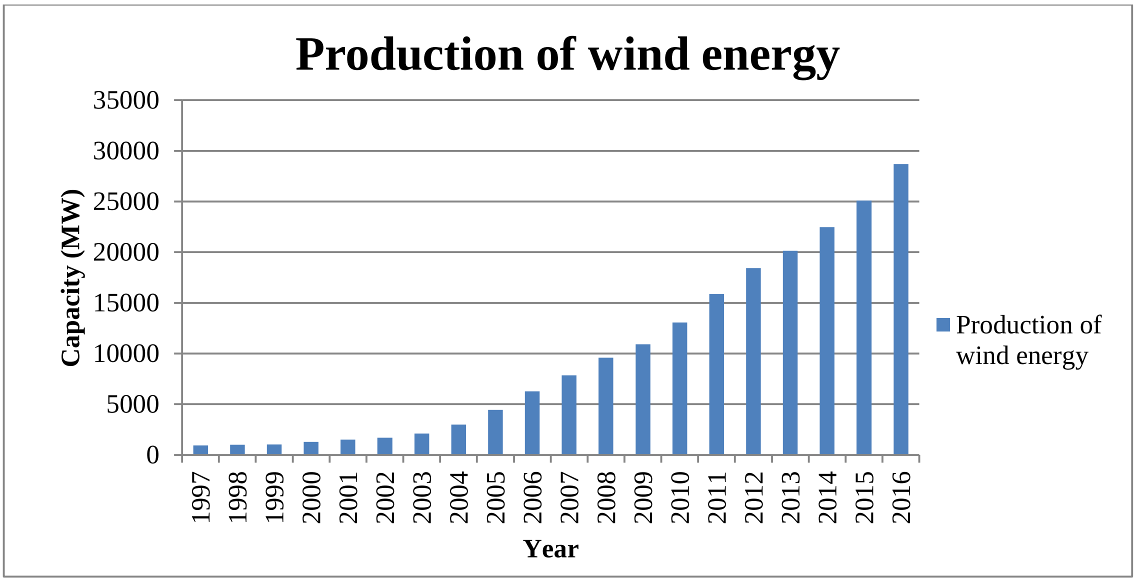



**Figure 1** Chart of wind energy production capacities of previous year

Wind energy production is the main contribution of India's annual energy production. Therefore, there is a great need to do forecasting of wind energy production capacities to estimate how much energy will be produced in future. In this paper neural network based time series forecasting is used in which NARX model has been preferred for prediction of future data of Wind energy production.

## 2. ARTIFICIAL NEURAL NETWORK FOR TIME SERIES PREDICTION

The artificial neural network (ANNs) [2, 3] has been successfully implemented for time series forecast and modeling tasks several times, including the prediction of financial time series, river flow forecast, biomedical time series modeling, communication network traffic prediction, chaotic time series forecast etc. [4]. In the one-step-forward forecast work, the ANN model needs to estimate the next sample value of the series of times, without giving it back to the input regressor of the model. In other words, the input regressor only has the actual sample points of the time series. If a user is interested in a long prediction horizon, then a process known as multi-step-forward or long-term forecasting, the output of the model should be fed back to the input regressor for a fixed but limited time stages. In this case, components of the input regressor, which were previously made from the actual sample points of the time series, are gradually replaced by the previous predicted values [4].

### 2.1 NARX NEURAL NETWORK

NARX network is a discrete-time non-linear model that can be represented as mathematical equation-1, and is usually used for time series forecasting [4, 5].

$$y(t+1) = f[y(t), y(t-1), \dots\dots, y(t-d_y+1); x(t), x(t-1), \dots\dots, x(t-d_x+1)] \quad (1)$$

Where,

y(t) = Output of the model.

x(t) = Input of the model.

t = number of time horizon.

$d_x \geq 1$, $d_y \geq 1$, and $d_x \leq d_y$, here $d_x$ is the input memory and $d_y$ is the output memory order.

Equation-1, shows that the forecasted values are depends on the previous inputs and their outputs. The following figure-2 shows the architecture of NARX model [8].

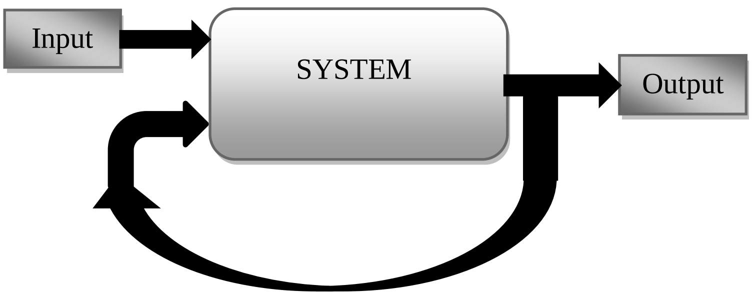



**Figure 2** architecture of NARX model

The following figure-3 illustrate the NARX Neural Network, which shows how the predicted output y(t+1) depends on the previous output and external input time series data.

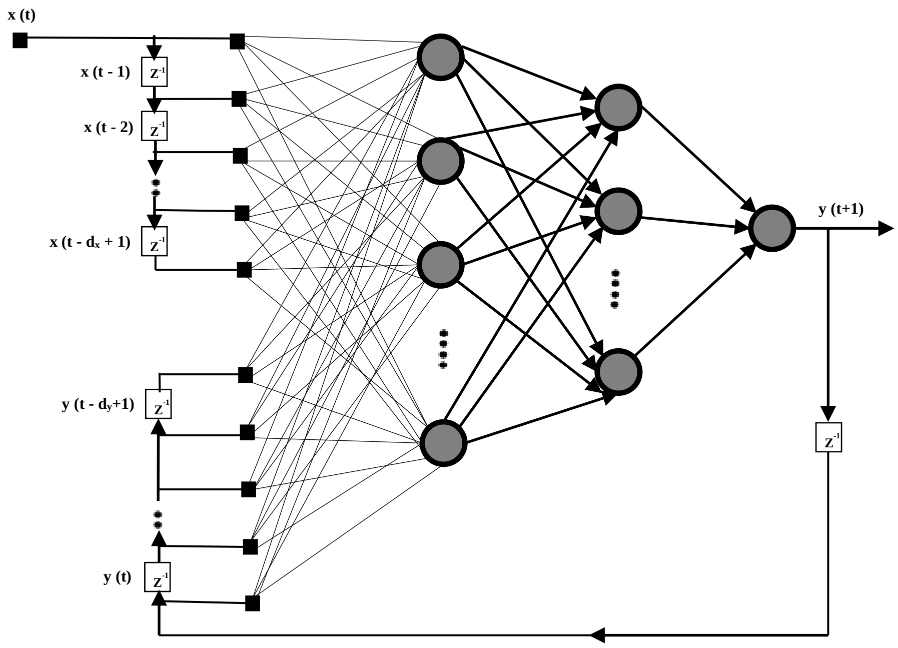



**Figure 3-** NARX neural network with $d_x$ delayed inputs and $d_y$ delayed outputs

## 3. LITERATURE SURVEY

Carlos Eduardo M. Barbosa et.al., proposed that energy made by wind farms is already accountable for a relevant portion of world's renewable energy and is a lot of turning into more necessary in trendy society. As energy made by wind farms is extremely obsessed with wind speed, it's not generated with regular output values requiring smart statement system to confirm smart electricity offer. They proposed that the Cuckoo Search could be a technique recently introduced as a promising improvement formula for parameter estimation in some applications and during this work it's investigated in wind energy statement [1].

Jyothi Varanasi et.al., proposed that Increasing energy demand and warming are forcing the planet towards the energy production from renewable energy sources. But, wind energy generation is very unsure and intermittent in its nature. To support grid integration of enormous capacity wind farms, wind energy prediction plays a significant role. Grid reliableness is greatly increased with the help of correct wind energy prediction. Their paper illustrates the implementation of NARX - ANN in wind speed & power prediction with the historical information accessible from United States of America wind farms [2].

Tomonobu Senjyu et.al., proposed that in recent years, there are issues like environmental pollution ensuing from consumption of fuel, e.g., coal and oil. Thus, introduction of energy supply like wind energy is predicted. Wind speed isn't constant and wind energy output is proportional to the cube of the wind speed. So as to predict the energy output for wind energy generators as correct as doable, it needs the tactic of wind speed prediction. In their paper, a method contemplates the wind speed of every month, and confirm the validity of Neural Network (NN) to predict wind speed by computer simulations. Since repeated Neural Network (RNN) is thought pretty much as good tool for time-series information forecasting, the authors propose associate degree application of RNN for the wind speed forecasting. The projected technique during their paper doesn't need difficult calculations and mathematical model [3].

Jose Maria P. Junior et.al., proposed that the NARX network may be a resurgent neural design usually used for input output modeling of nonlinear resurgent systems. Once used to time series forecasting, the NARX network is meant as a feed-forward Time Delay Neural Network (TDNN), i.e. while not the circuit of delayed outputs, reducing considerably its estimation performance. During their paper, we have a tendency to show that the first design of the NARX network is simply and efficiently applied to long-run (multi-step ahead) prediction of univariate statistic data. We have a tendency to value the projected approach using two real-world information sets, particularly the well-known chaotic optical maser statistic and a variable bit rate (VBR) video traffic statistic [4].

Lidong Zhang et.al., proposed that Wind prediction may be a key technique for the seamless integration of enormous penetration of alternative energy into the ability system. During their study, a nonlinear autoregressive model with exogenous inputs (NARX) is developed to predict the energy consumption of one turbine. The training information for the NARX models are collected from a 1.5MW turbine of a power station settled at Northeast of China. The accuracy of models victimisation totally different freelance inputs together with wind direction, speed in addition as engine room position, is compared. The results show that the resultant NARX models are capable of capturing the dynamic characteristics of turbine power consumption, and therefore the modelling accuracy with three inputs is best than of the model victimisation solely two inputs [5].

André Gabriel et.al., proposed that additional efforts are needed to promote the utilization of grid related photo-voltaic systems as a basic supply in energy systems at the higher penetration levels. They address the variability of photo-voltaic power generation and are constructed based on the management and the performance of tiny electrical networks can be improved once solar energy forecast data is employed. A neural specification system for the NARX model is enforced mistreatment not solely native-meteorologic information however additionally measurements of close PV systems. Input assortments are optimized and compare the estimation of the results of the model's prediction. When choosing the input assortments with the most effective network performance, predictions up to many hours before hand are tested to inquire the model predictive accuracy for various short-term time horizons and comparison occur through the persistence model [7].

Ke Meng et.al., proposed that while the progressive wind prediction platforms use similar inputs, the techniques could vary considerably from one forecast service supplier to a different. No single forecast can apply optimally to any or all prediction horizons and website locations. Therefore, facility operators deem many forecast service suppliers to hedge against the operational risk rising from the error in single-provider case. So as to accommodate the uncertainties in alternative energy forecast, every forecasting service supplier can deliver multiple alternative energy output eventualities with totally different initial conditions and model formulations, and one commitment call are going to be created. The key issue of their analysis work is to spot that generation schedule is probably going to perform higher beneath numerous conditions or for various kinds of choices [9].

E. V. Mc Garrigle et.al., proposed that Wind energy production is each unpredictable and variable in its nature. Wind energy prediction could be a means that of addressing each of those problems. They quantify the results of the accuracy of wind energy estimation on the operation of Irish electricity system of 2020. Through combined use of day ahead planning and time period simulations, it absolutely was found that there area-unit notable savings to be created which changes occur within the dispatch of generator technology sorts with enhancements in wind forecast accuracy. There area unit potential savings of on the average 0.27% of total power generation value for each decimal point decrease within the normalised mean absolute error (NMAE) of wind energy predictions [10].

## 4. METHODOLOGY

In this paper, MATLAB environment has been used for implementing the proposed model using neural network based NARX model. For this, data of wind energy production capacities from 1997 to 2016 has been collected from a Wind Energy Associations in India. The data of wind energy production capacities from 1997 to 2016 has been collected from the wind power. The entire data has been collected at the end of year, which is shown in table-1. All these data has been used in the model, in which year is set into input series and data of wind energy capacity is set into target series. Proposed model works on the following key points:-

1) Data collection.
2) Create Open loop neural network.
3) Train the data of open loop neural network.
4) Conversion of Open loop network into Close loop network.
5) Train the data of close loop neural network.
6) Simulate the data for prediction.

Parameters that were used in programming are described in table-2 below.

**Table 2** Parameters used in MATLAB Programming for proposed model.

| **Parameters** | **Values** |
|---|---|
| Nu. of previous data used in model | 20 |
| Nu. of input delays | 10 |
| Nu. of feedback delays | 10 |
| Nu. of hidden layer | 2 |
| Nu. of neurons in hidden layer 1 | 25 |
| Nu. of neurons in hidden layer 2 | 15 |
| Division of data % for training in open loop network | 90 |
| Division of data % for validation in open loop network | 5 |
| Division of data % for testing in open loop network | 5 |
| Division of data % for training in close loop network | 90 |
| Division of data % for validation in close loop network | 5 |
| Division of data % for testing in close loop network | 5 |
| Nu. of time horizon for forecasting (N) | 20 |

In NARX model, year 1997 to 2016 are used as input series, correspondingly we have total number of power data of 20, which is use in target series. 10 feedback delays used for the autoregressive function, and 10 input delays also used for the exogenous input. The double hidden layers were deemed adequate for this particular model with 25 hidden neurons and 15 hidden neurons respectively for hidden layer 1 and hidden layer 2.

The following figure-4 shows the flowchart of entire coding, which is implemented in MATLAB script for evaluate the NARX Model. It illustrates entire steps of NARX model.

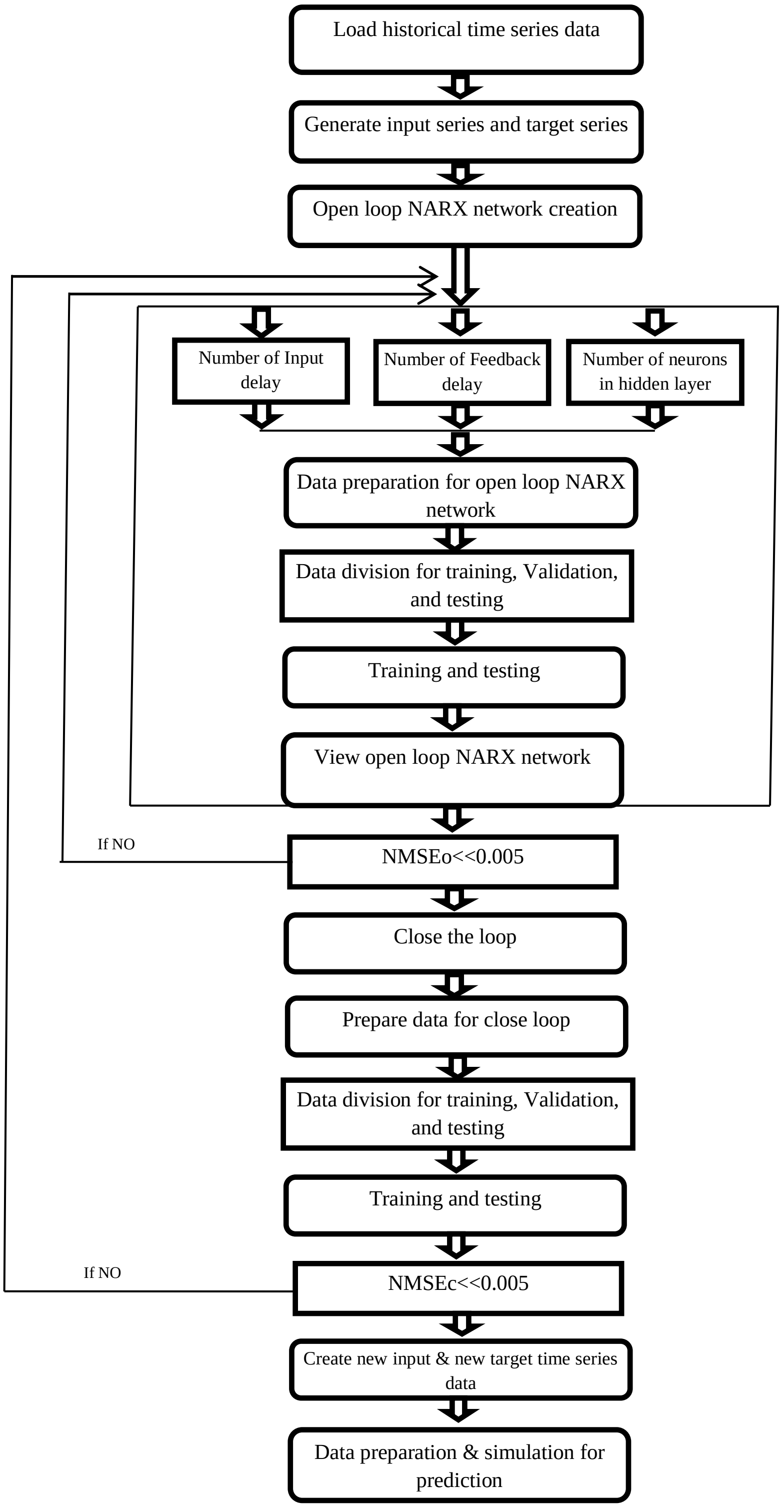
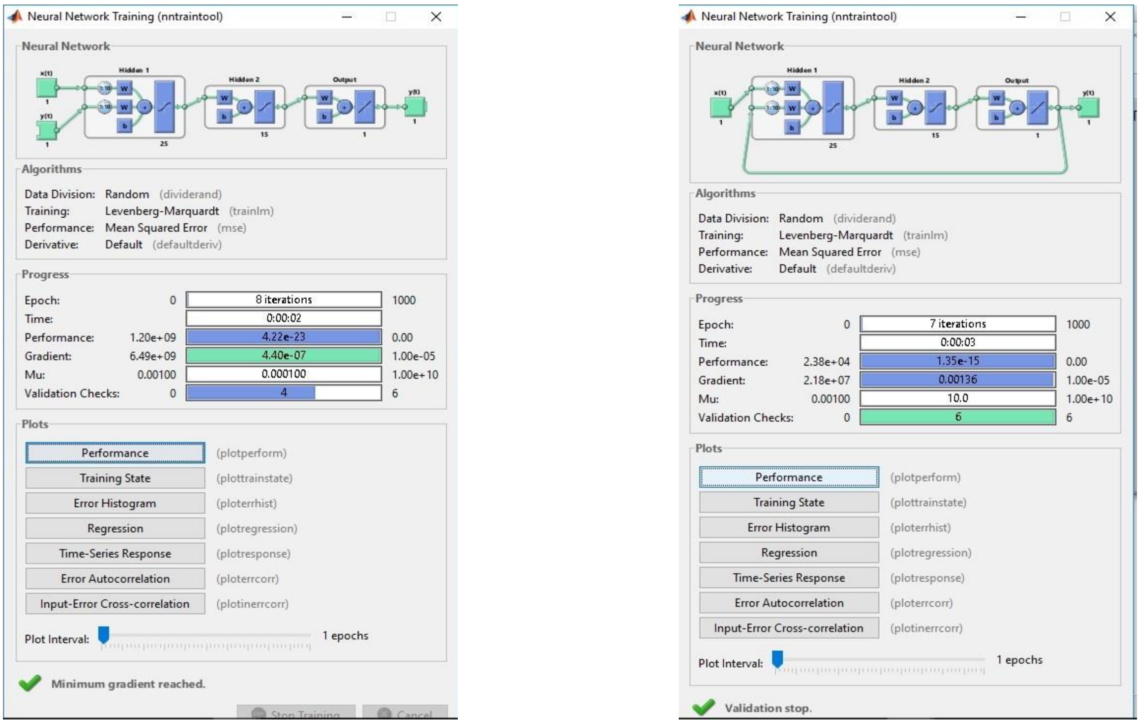



**Figure 4** Flowchart for coding of NARX Model

The collected data used in the model was trained by Levenberg-Marquardt (LM) algorithm [6, 7]. It is nothing but just a multiplication of bias and weight values with the input series and target series data. In LM algorithm, data was divided into 90 %, 5% and 5% respectively for training, validating and testing for both open loop and close loop data. In figure-5.a and figure-

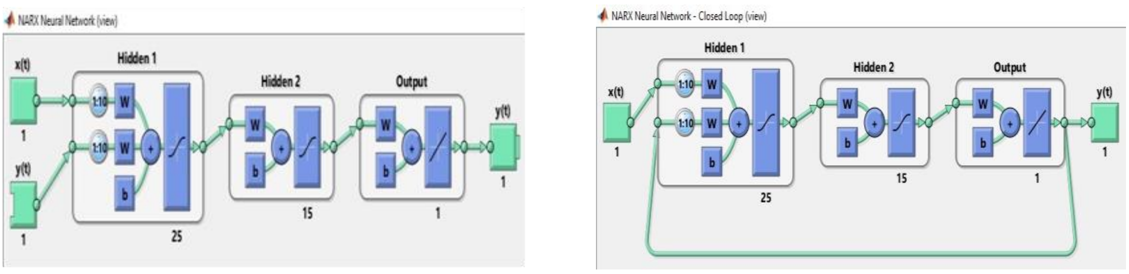
5.b, shows the training and performance for open loop and close loop neural network respectively, where training process time, number of epoch, number of delays, and number of neurons in hidden layer are shown.




a. Training tool for open loop b. Training tool for close loop

**Figure 5** Training tool for NARX Model

In figure-6.a & 6.b, shows the open loop and close loop architecture of NARX Network respectively, where input layer consist of x(t) and y(t), both are consisting single variable. x(t) is year data series and y(t) is wind energy data series. Architecture also consist two hidden layer, where hidden layer-1 have 10 feedback delays, 10 input delays, 25 hidden layer neurons with single bias node and hidden layer-2 have 15 hidden layer neurons with single bias node. Both hidden layer have tansig activation function (Symmetric sigmoid transfer function). It also consist single target (output) data series with purelin activation function (linear transfer function) [2].




a. Open loop architecture b. Close loop architecture

**Figure 6** Open loop and close loop architecture of NARX Model

In programming of model, normalised mean square error (NMSE) values should be lower from 0.005 for both open loop and close loop network. The neural network was trained using various parameters until NMSE received less than 0.005. After that data was simulated for receiving forecasted data. Mathematical formula of NMSE, used in MATLAB coding is shown in equation (2).

$$\mathrm{NMSE} = \frac{\text{MSE of error}}{\text{variance}} \tag{2}$$

Once the open loop network has been trained, are evaluated in the form of Normalized Mean Squared Error (NMSE) [4]. Equation (3) shows the NMSE for open loop:-

$$\mathrm{NMSE_o} = \frac{1}{M\,\sigma_{xo}^2} \sum_{t=1}^{M} (X_o(t+1) - Y_o(t+1))^2 \tag{3}$$

Where,

$NMSE_o$ = normalized mean squared error for open loop network.

$X_o$ = input data series for open loop network.

$Y_o$ = output of open loop network.

M = number of input data which provide to NARX model as a previous data.

$\sigma_{xo}^2$ = variance for open loop network.

Similarly for close loop network, NMSE shows as equation (4):-

$$\mathrm{NMSE_c} = \frac{1}{M\,\sigma_{xc}^2} \sum_{t=1}^{M} (X_c(t+1) - Y_c(t+1))^2 \tag{4}$$

## 5. Results and Discussion

After run the entire coding of proposed model in MATLAB, we received the following NMSE:-

NMSEo = $8.3198\times10^{-04}$

NMSEc = $6.6332\times10^{-04}$

Where, NMSEo and NMSEc are the normalised mean square error for open loop and close loop neural network respectively.

As seen in figure-7, curve in green colour shows the behaviour of available data that is used in the NARX Model as a target series and shows the behaviour of predicted data in the blue curve.

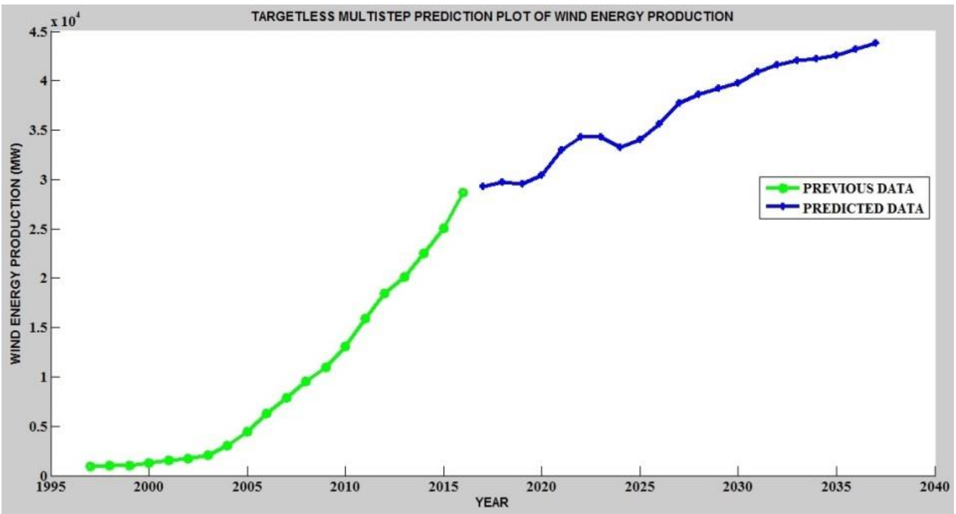



**Figure 7** Multistep prediction of wind energy production capacity

The following table-3 clearly describes the estimated values of wind energy production at the end of year from 2017 to 2037 and percentage growth of production is also shown in table-3.

**Table 3** Comparison of measured load data and predicted load data

| At the end of year | Production of wind energy (MW) | % growth in production |
|---|---|---|
| 2017 | 29241.89 | +1.9 % |
| 2018 | 29758.03 | +1.8 % |
| 2019 | 29501.6 | -0.86 % |
| 2020 | 30444.66 | +3.1 % |
| 2021 | 33019.55 | +7.8 % |
| 2022 | 34310.73 | +3.8 % |
| 2023 | 34312.02 | +0.01 % |
| 2024 | 33252.14 | -3.1 % |
| 2025 | 34069.21 | +2.4 % |
| 2026 | 35602.8 | +4.4 % |
| 2027 | 37748.39 | +5.7 % |
| 2028 | 38593.4 | +2.2 % |
| 2029 | 39241.56 | +1.7 % |
| 2030 | 39802.62 | +1.5 % |
| 2031 | 40903.51 | +2.7 % |
| 2032 | 41632.54 | +1.8 % |
| 2033 | 42035.93 | +1 % |
| 2034 | 42203.81 | +0.4 % |
| 2035 | 42611.86 | +1 % |
| 2036 | 43207.51 | +1.4 % |
| 2037 | 43771.03 | +1.3 % |

The following figure 8 shows the chart of wind energy production capacity, which describe the previous known data and predicted data.

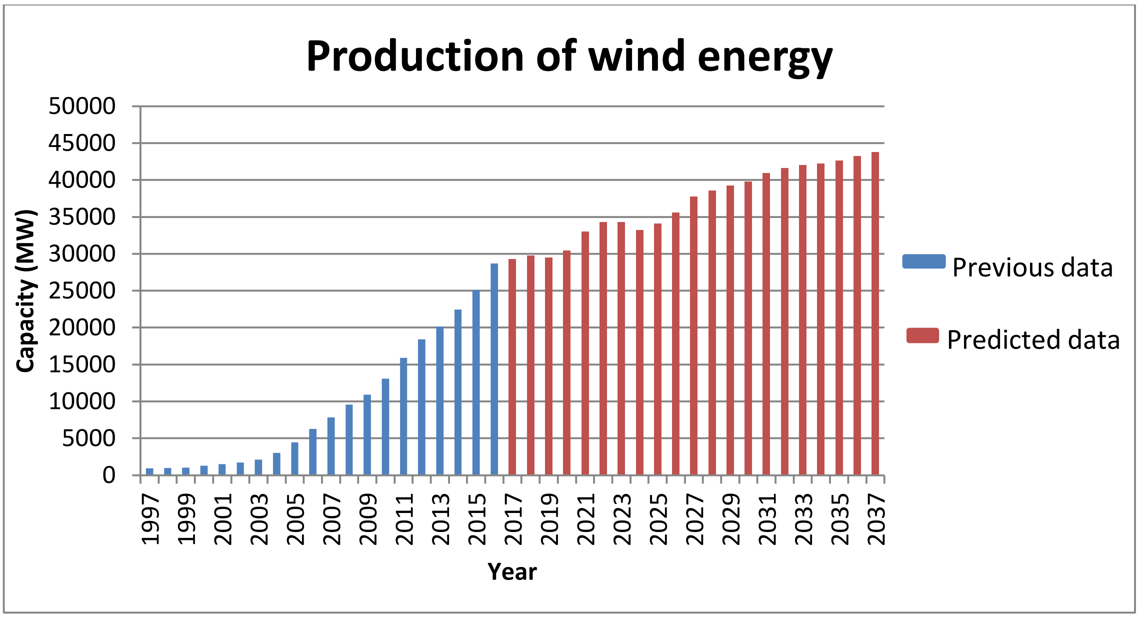



**Figure 8** Chart of previous data and predicted data of wind energy production capacity

## 6. CONCLUSION

In this paper, the annual based wind energy production has been predicted, using neural network based NARX time series forecasting model in the MATLAB environment. All the parameters used in the proposed model can be assessed analytically by the training process, as long as the

NMSE is not less than 0.005. The whole step of time series prediction like collection of data, creation of open loop network, construction of close loop network and data simulation for estimate the future values, are successfully done in this paper.

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