Time series Based Prediction of Global Solar Radiation of Bhubaneswar, India, A Comparative Study and review

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Abstract- Solar energy is one of the most important renewable energy sources among all fossil fuels. For design of any solar energy device and for the use of solar energy in variety of applications, solar radiation data is the most important parameter. So for a particular location accurate measurement of solar radiation is most important.Especially for Indian context of view solar energy is an important factor and unlimited source of energy. As variation of solar radiation occurs by the changes of time, geographical locations and meteorological conditions, so the proposed system uses a Time series based neural network to predict global solar radiation. The meteorological parameters used by the model are sunshine duration, temperature, Humidity to estimate the daily global solar radiation of Bhubaneswar. The data for the period of 2002-2005 are used for training the while the data for the year 2006 is used for testing. The results of network are evaluated on the basis of mean square error (MSE) and regression coefficient (R).The global solar energy is modeled using Neural network Time series model with other neural networks i.e. Multi layered Perceptron (MLP), Adaptive neuro-fuzzy inference system (ANFIS) models, and comparison shows the superiority of Time series model.

Keywords – solar radiation, Sunshine duration, NARX, mean squared error (MSE), Neural Network (Multi layered perceptron), Adaptive neuro-fuzzy inference system.

I. INTRODUCTION

Solar energy is a vital source of energy produced by the sun on the earth surface. Solar radiation prediction is a difficult task, as in remote areas there are no measuring instruments and no meteorological stations installed to capture and record solar data. Also in developing countries like India, solar radiation data is scarce due to high costs involved in purchasing and maintaining solar measuring equipment. For this reason the long-term global solar radiation data are measured in very few locations, by installing the measuring instruments and then estimating radiation in other locations where there is no measuring instrument. Therefore some prediction techniques also are adopted for estimation of the solar radiation. Time series prediction is the most effective method used for predicting future values. The amount of solar radiation potential in the particular location is important for solar energy system design such as stand-alone PV, thermal and hybrid systems. The total solar radiation received at any points on earth is in the form of direct and diffuse radiation.

As solar radiation is not observed in any meteorological station experimentally, so some climatological /meterological parameters are needed to develop and estimate the global &diffuse solar radiation. To estimate the amount of solar energy incident on a horizontal surface, many models were developed by using various input parameters such as relative humidity, sunshine duration, temperature, latitude, longitude and altitude etc.

Several empirical models have been developed by many researchers by using meteorological/Climatological parameters to estimate monthly/daily global solar radiation. Angstrom [1] developed the first theoretical model for estimating global solar radiation based on input sunshine duration. The model was remodeled by Prescott [2] for calculating monthly average daily global radiation (MJ/m^2 day) on a horizontal surface from monthly average daily total insolation on an extraterrestrial horizontal surface using the following equation.

$$H/H_0 = a + b\left(S/S_0\right) \quad (1)$$

Solar radiation can also be estimated by using higher order correlations. Benson et al. [3] used a quadratic form of relationship between daily global/extraterrestrial radiation and actual/maximum possible hours of sunshine duration.

$$H/H_0 = a + b\left(S/S_0\right) + c\left(S/S_0\right)^2 \quad (2)$$

Researches also developed ANNs, Radial basis function network (RBFN), Fuzzy logic (FL) and the combination of neuro-fuzzy inference system (ANFIS) model to estimate solar radiation and its application as a function of meteorological/Geographical parameter.

AI-Alawi and AI-Hinai [4] used multilayer feed forward network, back propagation (BP) training algorithm for prediction of global radiation in Seeb. The inputs parameters used here are location, month, mean pressure, mean temperature, mean vapour pressure, mean relative humidity, mean wind speed and mean sunshine hours. The result shows MAPE varies from 5.43 to 7.30.Sözen et al. [5, 6] used ANN model based upon meteorological and geographical parameter for estimating solar radiation in Turkey. For prediction the model uses logistic sigmoid transfer function and conjugate gradient, Pola-Ribiere conjugate gradient Levenberg Marquardt learning algorithm. The MAPE value for MLP network is 6.73%. Bhardwaj et al. [7] generalized a hybrid approach which comprise hidden Markov models and generalized fuzzy models to estimate solar irradiation in India. For this they assessed the influence of different meteorological parameters for estimation of solar radiation.Wu et al. [8] combined the Autoregressive and Moving Average (ARMA) model with the controversial Time Delay Neural Network (TDNN) for prediction of hourly solar radiation. The result shows the hybrid model has higher capability in comparison to ARMA and TDNN model considered individual. Mohandes et al. [9] applied ANN for estimating global solar radiation in Saudi Arabia using latitude, longitude, altitude and sunshine duration as the input parameter. The result shows the network having 4,10,1 neurons in input, hidden, output layers perform best. So the MAPE changes from 6.5 to 19.1.

Hasni et al. [10] estimate global solar radiation based on inputs air temperature, relative humidity in south-western region of Algeria. The training is done by using LM feed-forward back propagation algorithm. The hyperbolic tangent sigmoid function used in hidden layer and the purelin transfer function in output layers. The MAPE, R^2 are 2.9971%, 99.99%.Lubna. B. Mohammed et al. [11] used Nonlinear Autoregressive Exogenous (NARX) model to predict hourly solar radiation in Amman, Jordan. The Meteorological data for the period of 2004 to 2007 were used for training while the data of the year 2008 were used for testing. The performance of NARX model was examined and evaluated on the basis of coefficient of determination (R^2), root mean squared error (RMSE) and mean bias error (MBE).The model using Marquardt–Levenberg learning algorithm gives minimum root mean squared error (RMSE) and maximum coefficient of determination (R). Rehman and Mohandes [12] developed models by combining the input parameters: day, maximum air temperature, mean air temperature, relative humidity, for estimating diffuse solar radiation for Abha city in Saudi Arabia. Among all the inputs the combination of relative humidity and daily mean temperature gives better results with mean square error (MSE) of 5.18107 than other combinations.

Rahoma et al. [13] uses artificial neuro-fuzzy inference system (ANFIS) to generate daily solar radiation data recorded on a horizontal surface in National Research Institute of Astronomy and Geophysics, Helwan, Egypt (NARIG) for a period of ten years (1991-2000).The paper uses ANFIS as it combines fuzzy logic and neural network techniques that are used to gain more efficiency. The prediction shows TS fuzzy model gave a good accuracy of approximately 96% and a root mean square error lower than 6%.The results shows that the identified TS fuzzy model provides better performances than other model. T. R. Sumithira et al. [14] used an adaptive neuro-fuzzy inference system (ANFIS) to predict the monthly global solar radiation (MGSR) in Tamilnadu of 31districts.Comparison of the predicted and measured value of monthly global solar radiation (MGSR) on a horizontal surface was evaluated by calculating root mean square error (RMSE), Mean bias error (MBE), and coefficient of determination (R^2).

Mohanty et al. [15] Used soft computing approaches (MLP, RBF, ANFIS) for comparison and prediction solar radiation data of eastern India for the period of 1984-1999 based on input Sunshine duration, Temperature and Humidity.Sandhya and Kavitha [16] applied a non-linear autoregressive exogenous input (NARX) network to estimate solar radiation based upon various climatic parameters such as minimum air temperature, maximum air temperature, air pressure and humidity.

The main objective of this paper is to predict global solar radiation of Bhubaneswar based upon various Meteorological parameters by using neural network time series tool called non-linear autoregressive neural network with exogenous input (NARX). Section II describes the different methodology adopted for prediction of solar radiation. Section III describes the Results and discussions. Section IV presents the conclusion followed by thereferences.

II. MATERIALS AND STEPS INVOLVED FOR DEVELOPING MODEL

The daily solar radiation data for the period of 2002-2006 are collected from Meteorological laboratory, IMD, Bhubaneswar. Data for the period of 2002-2005 are used for training while the data of 2006 is used for testing. For developing a model the following steps are needed.

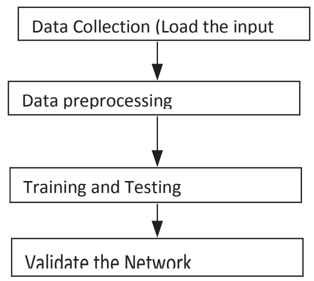


Figure.1.Steps involved for developing a model

To complete the data preprocessing, the data's were normalized between 0 and 1 as each dataset had different magnitudes. This process adjusts the measured values that have different scales and converts them to a common size; which is defined by using the equation:

$$X_{Normalized}=(x-x_{min})/(x_{max}-x_{min}) \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (3)$$

Before activating the network, the data's were divided into three different sets: training, testing and validation sets. The final evaluation of the performance of the network was completed using the validation set.Every time a network is trained and a different solution is achieved given the different initial weights and bias values, i.e. different outputs may be achieved with the same inputs to ensure good accuracy.

III. PROPOSED METHOD

This section describes and explains steps for designing of a Time series neural network (NARX) model for solar radiation forecasting and compares the result with other neural network for getting better performance. The nonlinear autoregressive neural network with exogenous inputs (NARX) is a recurrent dynamic network, having feedback connections enclosing several layers of the network. The NARX model is based on the linear ARX model, which is generally used in time-series modeling. The performance of the NARX model is verified for several types of chaotic or fractal time series applied as the input. The advantages of recurrent neural networks (RNN) model over other neural network models i.e. multi layered perceptron (MLP) and artificial neuro fuzzy inference systems (ANFIS) are not only useful for the forecasting of time series problem but also useful for the dynamic system. Comparison also has been done between NARX and MLP (Multilayered Perceptron) on the basis of MSE, RMSE and R^2.

A. Nonlinear Autoregressive Exogenous neural network(NARX) –

Nonlinear Autoregressive Exogenous (NARX) neural network, shown in Figure2. used to predict the daily global solar radiation data of Bhubaneswar for the period of 2002-2005.Three types of NARX neural network models are described here

Model1: Predict future values of a time series y(t) from past values of that time series and past values of a second time series x(t).

$$y(t)=f(x(t-1)\ldots\ldots x(t-d),y(t-1)\ldots\ldots y(t-d) \quad (4)$$

Model II: Predict future values of a time series y (t) from past values of that time series.

$$y(t)=f(y(t-1)\ldots\ldots\ldots\ldots y(t-d) \quad (5)$$

Model III: Predict future values of a time series y (t) from previous values of x (t) without knowledge of previous values of y (t).

$$y(t)=f(x(t-1)..............x(t-d) \quad (6)$$

The output is fed back to the input of the feed forward neural network (Parallel architecture), which is part of the standard NARX architecture. However, the true output is available during the training process; therefore, a series-parallel architecture can be created.

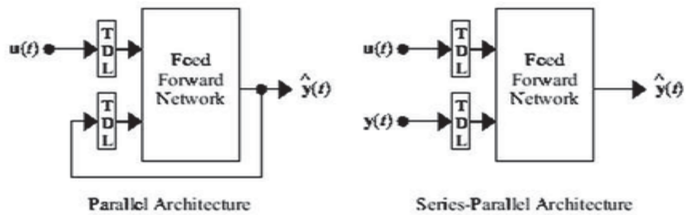


Figure 2. Series- parallel architecture of NARX network

B. Multi layered perceptron (MLP)–

A multilayer perceptron (MLP) is a feed forward artificial neural network shown in figure3.that maps sets of input data onto a set of appropriate outputs. An MLP consists of multiple layers of nodes in a directed graph, where each layer is fully connected to the next. For training the network MLP uses a supervised learning technique called back propagation.

Learning occurs in the MLP by changing the connection weights after each data is processed, based on the amount of error obtained in the output layer compared to the expected result. The error in output node j in the nth data point (training example) determined as

$$e_i(n) = d_i(n) - y_i(n) \quad (7)$$

where d is the target value and y is the value produced by the Perceptron. The error in the entire output can be minimized by using

$$\in(n) = \frac{1}{2}\sum_i e_i^n(n) \quad (8)$$

Using gradient descent, each weight is changed to be

$$\Delta w_{ji}(n) = -\eta \frac{\partial \in (n)}{\partial v_i(n)} y_j(n) \quad (9)$$

where y_i is the output of the previous neuron and η is the learning rate, which is selected to ensure that the weights converge to a response fast enough.

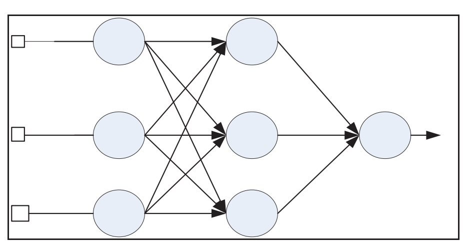


Figure 3.Neural Network (Multi layer perceptron)

C. Artificial neuro-fuzzy inference system(ANFIS) –

A non-linear mapping from input to output is called Fuzzy Inference System. It consists of three things a) a rule base containing fuzzy rules b) data base which defines membership functions applied for the fuzzy rules; c) rules of inferencences.

ANFIS is a multi layered structure where each node is connected to another. ANFIS is a hybrid soft computing model comprising of both neuro and fuzzy relation. The first-order Sugeno fuzzy model having two fuzzy if-then rules were described as

Rule 1: If x is A_1 and y is B_1 then $f_1=a_1x+b_1y+r$

Rule 2: If x is A_2 and y is B_2 then $f_2=a_2x+b_2y+t$

Five layer ANFIS architecture having two inputs x and y is shown in Fig.3.

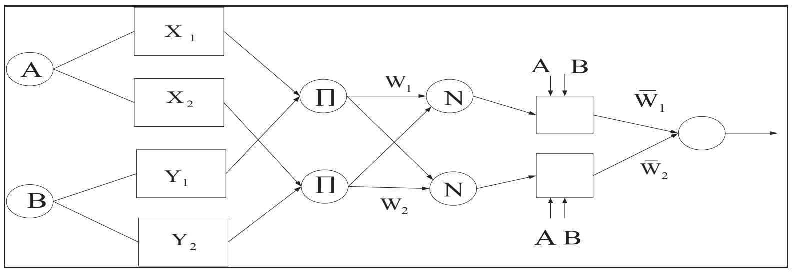


Figure 4. ANFIS architecture

Layer 1:

Every node *i* in this layer is a square node with a node function.The first layer comprises of input variables membership functions (MFs) and provides the input values to the next layer.

$$o_i^1 = \mu_{A_i}(x) \tag{10}$$

where *x* is the input to node *i* and A*i* is the linguistic label (small/ large) associated with this node function O_i^1 is the membership function of A*i* and it specifies the degree to which the given *x* satisfies the quantifier A*i*.

Layer 2:

The second layer (also called membership layer) multiplies the incoming signals from the first layer to produce an output.

$$w_i = \mu_{A_i}(x).\mu_{B_i}(y) \quad \text{where } i=1, 2\ldots \ldots\ldots\ldots\ldots \tag{11}$$

Layer 3:

The third layer (i.e. the rule layer) is a non-adaptive layer, where every node calculates the ratio of the rule's firing strength to the sum of all rules' firing strengths.

$$\varpi_i = \frac{\omega_i}{\omega_1 + \omega_2} \quad \text{where } i=1, 2\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots. \tag{12}$$

Layer 4:

Every node i in this layer is a square node with a node function

$$O_i^4 = w_i f_i = w_i(a_i x + b_i y + r_i) \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \tag{13}$$

Layer 5: The single node in this layer is a circle labelled by ∑ that computes the overall output i.e. the summation of all the incoming signals, i.e. the overall output is

$$o_i^5 = \sum_i \varpi_i f_i = \frac{\sum_i \omega_i f_i}{\sum_i \omega_i} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \tag{14}$$

In the proposed system Time series based neural network is trained and tested, and compare it with other model for getting better accuracy.

IV.RESULTS AND DISCUSSION

The model is tested and developed by using MATLAB software 12.0.The data for the period of 2002-2006 are collected from meteorological department, IMD, Bhubaneswar and Remote sensing data and information [17]. The data for the period of 2002-2005 are used for training while the data of 2006 is used for testing Here we evaluate and compare prediction by using NARX with other neural networks (MLP).The data is preprocessed and normalized within the network that is being created. The models are trained and tested by several algorithms. Three inputs at input layer, 10 neurons at hidden layer, and one output at output layer i.e. the estimated global solar radiation.

The performances of the approaches are examined by comparing the statistical analysis of the two models. The statistical analysis is performed by computing the Mean squared error and regression analysis. The Mean Squared Error (MSE) indicates the square of the average deviation of the estimated values from the corresponding target data. The regression analysis is used to understand the accuracy between the actual value and the predicted value. Performance graph for the models are shown in figures. (5-6).

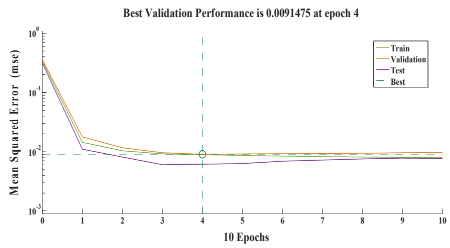


Figure5. Performance curve using Neural Network (MLP)

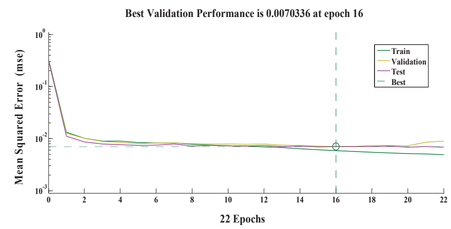


Figure 6.Performance curve using NARX1

Best validation for the model NARX1 is (MSE= 0.0070336 and R=0.85) found at epoch 16.Similarly for Feed forward neural network model (MSE=0.0091475 and R=0.77) found at epoch 4.

Table -1 Performance of different types of Network

MODEL	NO OF EPOCH	MSE	Training	Testing	Regression
NARX1	10	0.0070336	0.86749	0.81226	0.8502
NARX2	6	0.0083572	0.80124	0.77245	0.79245
NARX3	14	0.0080359	0.78256	0.73478	0.76023
NEURAL NETWORK (MLP)	4	0.0091475	0.81418	0.70818	0.77112
ANFIS	15	0.0089457	0.83452	0.75124	0.78456

The result shows that NARX1 model gives better result in comparison to other two NARX model and neural network model (Multi layer Perceptron). Lower MSE gives accurate prediction. Training, Testing and Regression plot of NARX and Neural network (MLP) are shown below.

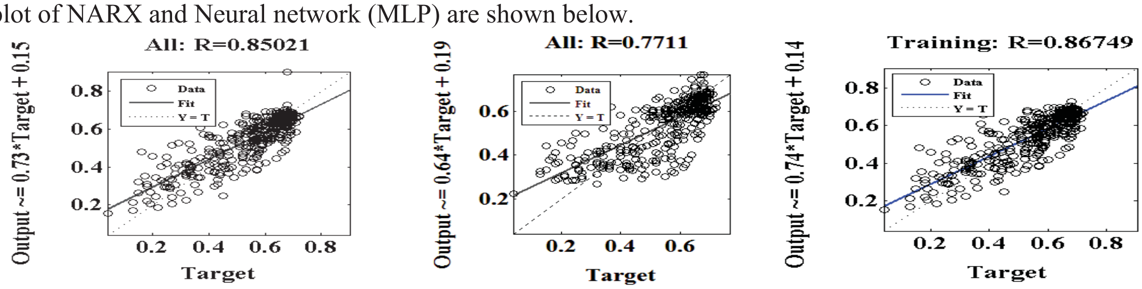
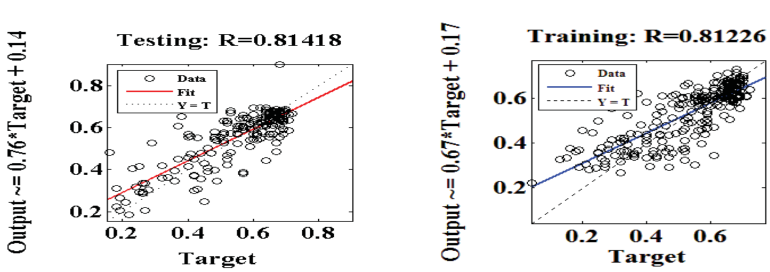


Figure7. Regression plot of NARX and Multilayered perceptron



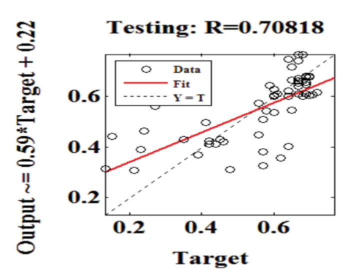
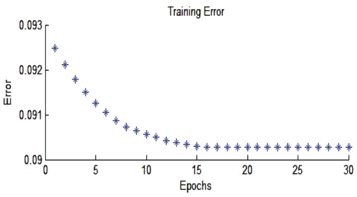


Figure 8. Training and testing plot of NARX network Figure 9. Training and Testing curve of Multi layered Perceptron

The regression plot shows the accuracy between the measured and predicted solar radiation.



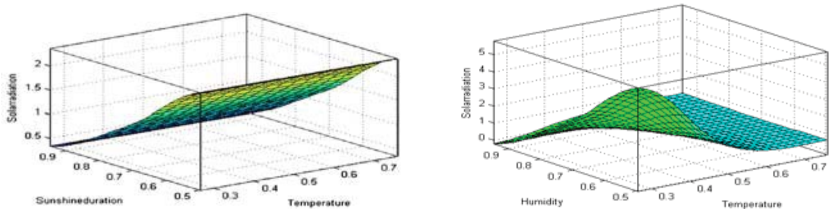
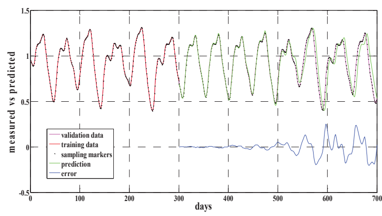
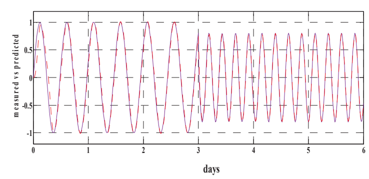


Figure10. Training curve of ANFIS (Artificial neuro-fuzzy inference system) Figure 11. Surface plot of solar radiation estimation using ANFIS

Figure10. shows the Training curve of artificial neuro-fuzzy inference system. This figure contains the training data of solar radiation using ANFIS model.The ANFIS decision surface for solar radiation estimation using the three input parameters is shown below.Figures. (12-14).shows the comparison between measured and predicted solar radiation using NARX, Multilayered Perceptron (Artificial neural network) and Artificial Neuro-fuzzy inference system.





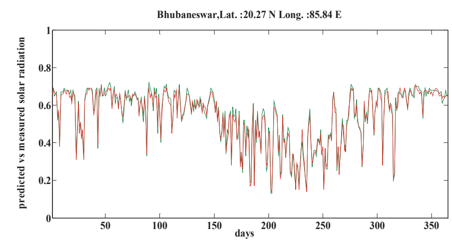


Figure12. Measured vs predicted using nonlinear auto regressive neural network (NARX1) Figure13. Measured vs predicted using Multi layered perceptro Figure14.Measured vs predicted using Artificial Neuro-fuzzy inference system

For getting better accuracy, the models are trained by using different training algorithms i.e. Levenberg-Marquardt(train lm), Conjugate Gradient with Powell/Beale Restarts(train cgb), Fletcher-Powell Conjugate Gradient (train cgf), Resilient Back Propagation (train rp), Scaled Conjugate Gradient (train scg), Polak-Ribiere Conjugate Gradient (train cgp), The results produced by the training algorithms of the two models are shown below.

Table-2 .Performance evaluation of models with different Algorithms

Nonlinear Auto regressive neural network				Artificial neuro-fuzzy			Multi layered perceptron		
Algorithms	MSE	Epoch	Regression	MSE	Epoch	Regression	MSE	Epoch	Regression
trainlm	0.00525	10	0.83	0.00598	15	0.81	0.00645	12	0.82
traincgb	0.00866	12	0.75	0.00845	10	0.79	0.00857	18	0.80
traincgf	0.01091	29	0.76	0.00987	14	0.81	0.00178	25	0.79
trainrp	0.00911	35	0.77	0.00879	23	0.80	0.09452	32	0.75
trainscg	0.01000	16	0.74	0.01234	18	0.78	0.01978	19	0.78
traincgp	0.00922	21	0.76	0.00894	12	0.73	0.01245	23	0.72

The result shows the NARX model trained with Levenberg-Marquardt algorithm (train lm) gives better result in comparison to Multilayer Perceptron (Neural network). The model having lower MSE and higher regression value obtained at epoch 10 i.e. (MSE=0.00525 and R=0.83).Figure.15. shows the Response of output and error of NARX model with Levenberg-Marquardt algorithm.

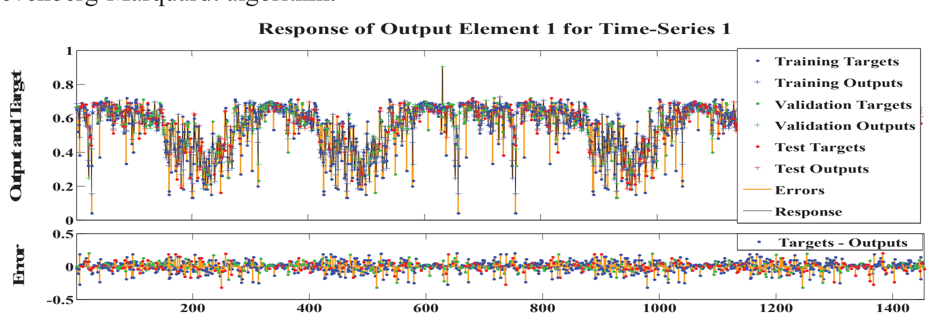


Figure15. Response curve using NARX

V.CONCLUSION

In this work, prediction of solar radiation using different NARX model and Multi layered Perceptron (neural network) has been employed. For better accuracy the models are trained by using different training algorithms. The comparative analysis between the estimated data and measured data are evaluated by comparing the statistical value after prediction. The Marquardt-Levenberg learning algorithm of NARX model1 produces a maximum regression coefficient with lower gradient value and lower MSE value. Hence this present work can be used to predict solar data in the locations where measuring instruments are not used. Further work can be extended on solar thermal and solar pv performances based on predicted solar data using NARX models.

NOMENCLATURE

ANFIS	**Artificial neuro fuzzy inference system**	**GSR**	**Global Solar Radiation**
SD	**Sunshine Duration**	**NPV**	**NET Present Value**
MLP	**Multilayer Perceptron**	**ANN**	**Artificial Neural Network**
RBF	**Radial basis Function**	**FL**	**Fuzzy Logic**
MAPE	**Mean Absolute percentage error**	**MSE**	**Mean squared Error**
RMSE	**Root means squared Error**	**SWH**	**Solar water Heater**
SPP	**Simple payback period**	**DP**	**Discounted Payback**
ECO	**Energy Conservation Option**	**PI**	**Profitability Index**
BCR	**Benefit Cost Ratio**	**MF**	**Membership Function**
GNN	**Generalized Neural Network**	R^2	**Coefficient of determination**

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