International Journal of Innovative Science and Modern Engineering (IJISME)
ISSN: 2319-6386 (Online), Volume-6 Issue-10, September 2020

Short-Term Solar Forecasting Model using Artificial Neural Networks

Naveen Kumar Dubey, M.P.S. Chawla

***Abstract:** in present context, Electrical Energy generation in India is mostly based on the conventional sources, but the time has come to be not depend on these conventional sources and to make renewable Energy sources capable of producing total energy demand by its own. So the focus has been shifted towards Wind, Hydro and photovoltaic (PV) power generation. Accurate forecasting of solar irradiance is required for effective and efficient power scheduling & dispatching. And this weather data is needed by the control engineers for planning their control strategies. In this paper a simple approach for weather prediction is proposed which relies on hourly weather data such as Temperature, Relative humidity, surface pressure, wind speed & direction and solar irradiance. The solar forecasting model to predict short-term solar irradiance & other weather parameters, is done by using Leven-berg Marquardt and Bayesian regularization back-propagation algorithms with standard non-linear autoregressive with external input NARXfeedforward Network. This approachis simple to implement fast in execution and provides good results for short-term time horizon predictions.*

***Keywords:** Solar power, Short-term forecasting, Artificial neural networks.*

I. INTRODUCTION

Energy generation from Renewable sources is growing very fast and india is generating large amount of electrical energy from photovoltaic sources. As of 31st march2020, 35.86% of total installed capacity of electrical energy, india's installed electricity generation capacity is from renewable sources only, producing total of 21.22% of total demand electricity in india. India is working with the target of achieving most of its total energy generation from renewable energy sources in coming years. Forecasting of solar power may result economic as well as nature friendly solution in many problems associated with increasing demand of electrical energy. Solar forecasting data can be used to increase the overall system stability and reliability along with to manage the power scheduling and dispatching problems.[1]

Artificial Neural Networks have been used in recent years for forecasting solar irradiance and for system modeling various statistical models are also used that comprises of non-learning and learning approaches.

In many case studies Statistical non-learning approach uses time series from historical time series data and direct statistical analysis is performed without considering physical conditions of the system. Various regression models & numerical weather prediction (NWP) models have been modeled as time series forecasting models. Many model includes (ARIMA) autoregressive integrated moving averages, and (MLR)multiple linear regression model for forecasting[2].

Revised Version Manuscript Received on September 15, 2020.
* Correspondence Author
Naveen Kumar Dubey*, Electrical Engineering Department, SGSITS,Indore(M.P.) – India Email: naveendubeyhtce@Gmail.com
M.P.S. Chawla, Electrical Engineering Department, SGSITS, Indore (M.P.) – India Email: mpschawla@Gmail.com

© The Authors. Published by Blue Eyes Intelligence Engineering and Sciences Publication (BEIESP). This is an open access article under the CC BY-NC-ND license (http://creativecommons.org/licenses/by-nc-nd/4.0/)

While statistical learning method uses applications of Artificial intelligence (AI) topology for learning best possible predicted weather conditions and output power relationship as time series. Unlike the non-learning approach where only statistical analysis on historic data is perform, Artificial Neural Network (ANN) uses some algorithms that are capable of explaining non-linear and complex relationship between input and target data. In general statistical models are simpler as compared to physical models because it requires less input information and less computation time for forecasting.[3] These methods, like (ARIMA), and (MLR)[2], (GRNN) generalized regression neural network, (CFNN) cascaded forward back-propagation, (FFNN)feed-forward back-propagation, and an (ELMNN) Elman back-propagation [4] findapplications of feed-forward neural network(FFNN) as multi-layer perceptron model[5], radial basis function (RBF) model for sizing of stand-alone photovoltaic (PV) power system[6], also for sample selections, LS-SVM methods[9] are used in previous work as learning methods to predict hourly short-term solar power forecasting.

II. ARTIFICIAL NEURAL NETWORK

A Neural Network is a group of interconnected artificial neurons same as the biological neural network present in the human brain. Multiple nodes are there in an artificial neural network and every neuron is interlinked with each other. Weight is assigned with each link so that ANN learns the target output by alternating weight values.[7]

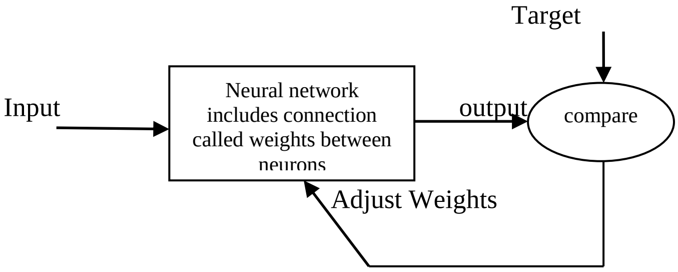

Fig. 1. Line diagram of Artificial neural network architecture

There are mainly two topologies of neural networks are used such as:

A. Feed-forward neural network (FFNN)

This topology has unidirectional flow of information that is one unit sends information to other unit but no information gets received back to it. No feedback paths are present in this type of networks. FFNN are used in classification, pattern generation and recognition problems.

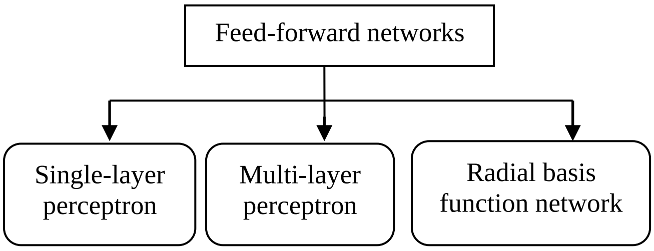

Fig. 2. Classification of Feed-forward Neural Networks.

B. Feedback / Recurrent networks:

In feedback or recurrent type of topology bidirectional flow of information takes place. Such that if one unit sends information to other unit then the other unit can send this information to first unit as well. Feedback paths are present in this type of topologies. The neural network is trained multiple times till it generates the desired target output, if the network produces undesired output then it changes its weights to improve subsequent results, and this process continues till the best accurate target output is achieved[8].

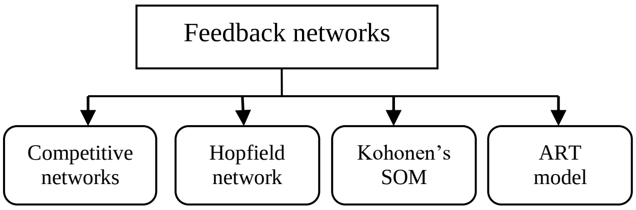

Fig. 3. Classification of Feedback networks.

III. MAJOR ASPECTS OF SOLAR FORECASTING

Selection of input parameters and forecasting time horizon affects the performance of overall forecasting model. Based on different forecasting time horizons different decision making activities are performed in the smart grid, these time horizon with their decision making activities are classified as follows:

1. Very short-term forecasting (up to {30-60}minutes ahead)

Very short-term forecasting data is used for photovoltaic and storage control and electricity market clearing for electricity markets.

2. Short-term forecasting (up to 48-72 hours ahead)

Short-term forecasting results are important to manage power system operations such as to plan their commitments and economic load dispatching problems.

3. Medium-term forecasting (up to weeks or a month)

With medium term forecasting data, scheduling of PV plants and maintenance of conventional power syspems and transmission lines could be performed.

4. Long-term forecasting (up to a year ahead)

Long –term forecasting information could be applied for planning of PV plants and for assessment of overall solar energy generation.

Different forecasting time horizon with their decision making activities are very useful for energy management and system operations. In this work short-term solar forecasting model is proposed which is very useful for real-time unit scheduling operations, storage control and electricity trading applications.

IV. METHODLGY ADOPTED

In this work Leven-berg Marquardt (trainlm) and Bayesian Regularization (trainbr) back-propagation algorithms with standard nonlinear autoregressive with exogenous (external) input NARX, 2-layer feedforward network, containing a (tansig) sigmoid transfer function in the hidden layer and linear transfer function in output layer is used to train the network. The model is trained using ANN toolbox of MATLAB. Mean squared error (MSE) and regression coefficient 'R' are the performance indices to evaluate the performance of the trained network.

V. DATA COLLECTION

The weather data used for this work is the hourly data of 2 weeks having total 360 sample values, and the data is taken via EUMETSAT for five different locations of MP-INDIAwhich are,

Dewas - latitude 22.9973^0 andlongitude 76.0229^0,
Indore - latitude 22.6959^0 and longitude 75.8082^0,
Bhopal- latitude 23.2995^0 and longitude 77.4352^0,
Jabalpur - latitude 23.1752^0 and longitude 79.935^0,
Neemuch- latitude 24.4876^0 and longitude 74.916^0.

And for each location Neural network is trained for forecasting of different parameters such as:

1. Temperature (2m) in ^{0}c.
2. Relative Humidity (2m) in %.
3. Pressure (mean sea level) in hPa.
4. Solar radiation in Watt/m^2.
5. Wind speed in km/h.
6. Wind direction in degree.

Through this dataset a short-term solar forecasting model is developed for predicting next step sample value.

VI. DEVELOPED MODEL

Fig. 4 shows the basic structure of the developed model, here standard NARX Non-linear autoregressive Exogenous model is used to predict the output variable [y(t)] based on 'd' past values of output and 'd' past values of an external exogenous input series. In This network topology tapped delay lines are used to store previous values of input x(t) and y(t) series. Correlation coefficient 'R' is used to express the accuracy of the predicted output variable along with an error term is also used to improve gauge predictive accuracy which is represented in the form of Mean squared error between target and output variable.

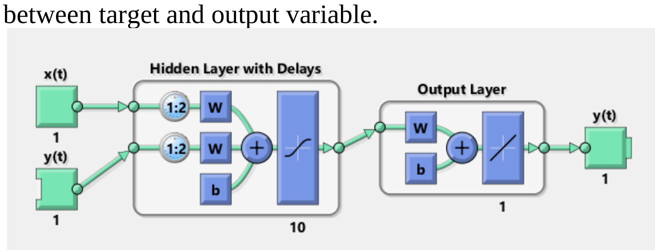

Fig. 4 Block diagram of neural network model.

© Copyright: All rights reserved.

International Journal of Innovative Science and Modern Engineering (IJISME)
ISSN: 2319-6386 (Online), Volume-6 Issue-10, September 2020

$$Y(t) = f(x(t-1),\ldots,x(t-d),y(t-1),\ldots,y(t-d)) \qquad (1)$$

VII. RESULTS AND DISCUSSION

The proposed network was trained using Leven-berg marquardt (trainlm) and also with bayesian regularization (trainbr) algorithms. Leven-berg marquardt typically requires more memory but less time. Training automatically stops when generalization of sample value stops improving[8], as shown by an increase in error MSE of the validation samples. While Bayesian regularization (trainbr) algorithm needs more time but it can provide better result, good generalization for difficult , small or noisy datasets, like in case of solar radiation dataset is having very different values in each step sample due to the overcast weather condition when cloud cover occurs the solar irradiance is having zero reading in the dataset or very low values and it is seen in next sample value the solar irradiance reading is quite high so it is preferred for such type of datasets, in this algorithm training stops according to adaptive weight minimization (regularization).

- Mean square error (MSE): is the average squared difference between output and target values.

$$MSE = \frac{1}{n}\sum_{j=1}^{n}(y_j - y_i)^2$$

- Regression 'R' value measures the correlation between output and target values.

TABLE I. TEMPERATURE FORECASTING RESULTS

LOCATION	ALGORITHM USED	NO. OF HIDDEN NEURONS	MSE	REGRESSION COEFFIENT 'R'
DEWAS	TRAINLM	10	0.178314	0.983277
INDORE	TRAINLM	10	0.307994	0.970925
BHOPAL	TRAINLM	10	0.179435	0.96897
JABALPUR	TRAINLM	8	0.311236	0.98175
NEEMUCH	TRAINLM	10	0.273658	0.980779

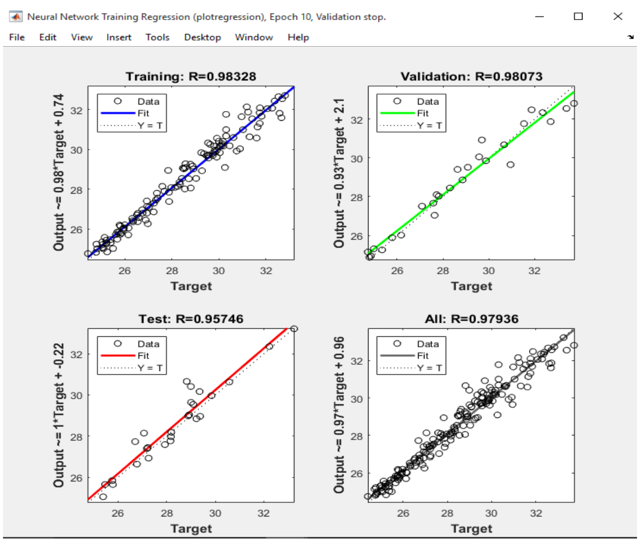

Fig. 5 Regression plot for temperature forecasting .

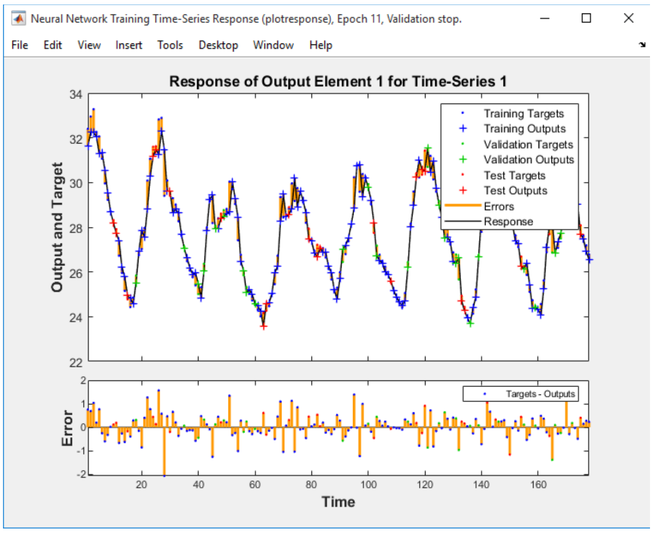

Fig. 6 time series response for temperature forecasting..

TABLE II. SURFACE PRESSURE FORECASTING RESULTS

LOCATION	ALGORITHM USED	NO. OF HIDDEN NEURONS	MSE	REGRESSION COEFFIENT 'R'
DEWAS	TRAINLM	20	0.0421053	0.994500
INDORE	TRAINLM	10	0.0913191	0.988738
BHOPAL	TRAINLM	10	0.0743243	0.98296
JABALPU R	TRAINLM	20	0.0483632	0.991692
NEEMUC H	TRAINLM	10	0.0953507	0.98776

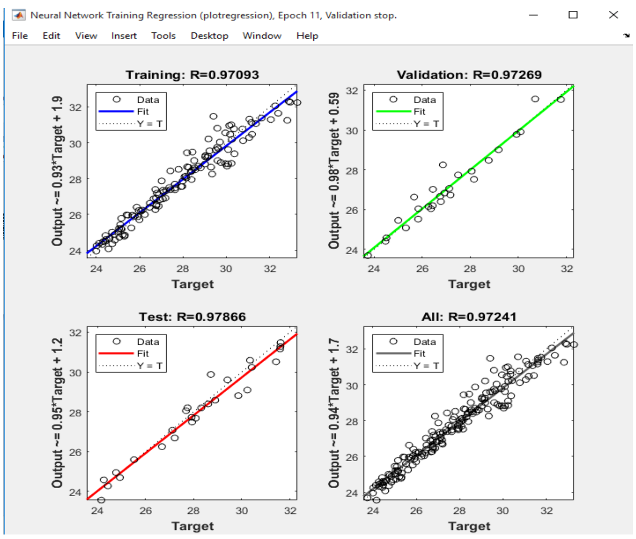

Fig. 7 Regression plot for surface pressure forecasting .

Retrieval Number:100.1/ijisme.J12590961020
DOI:10.35940/ijisme.J1259.0961020
Journal Website: www.ijisme.org

Published By:
Blue Eyes Intelligence Engineering
& Sciences Publication
© Copyright: All rights reserved.

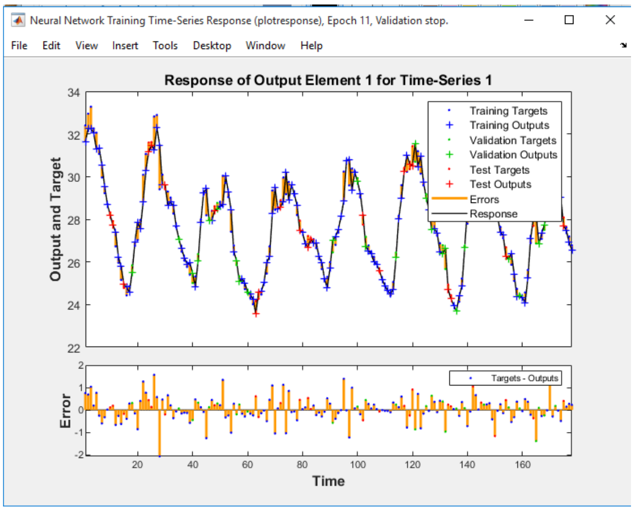

Fig. 8 time series response for pressure forecasting .

TABLE III. HUMIDITY FORECASTING RESULTS

LOCATION	ALGORITHM USED	NO. OF HIDDEN NEURONS	MSE	REGRESSION COEFFIENT 'R'
DEWAS	TRAINLM	10	4.71286	0.98155
INDORE	TRAINLM	10	7.61570	0.971140
BHOPAL	TRAINLM	10	5.03270	0.983732
JABALPUR	TRAINLM	16	4.02031	0.986344
NEEMUCH	TRAINBR	12	7.58969	0.974919

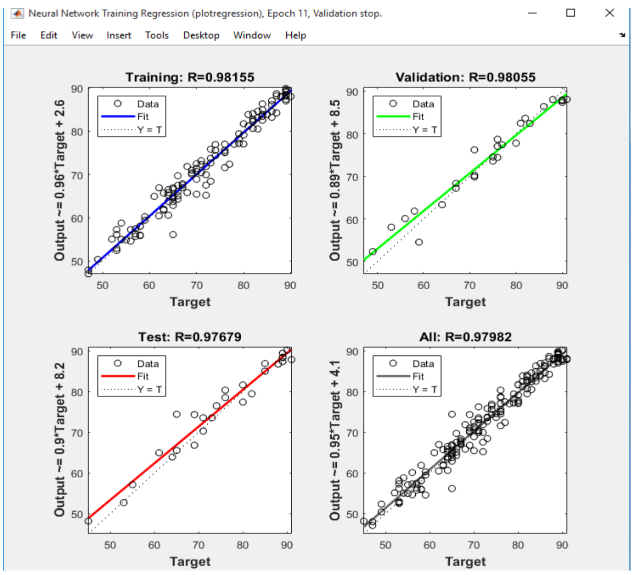

Fig. 9 regression plot for humidity forecasting.

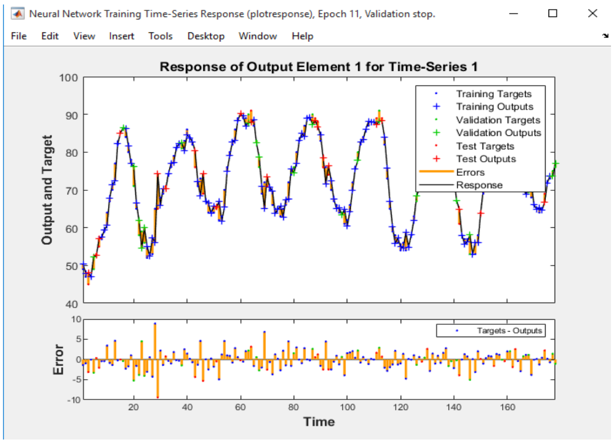

Fig. 10 time series response for humidity forecasting .

TABLE IV. SOLAR IRRADIANCE FORECASTING RESULTS

LOCATION	ALGORITHM USED	NO. OF HIDDEN NEURONS	MSE	REGRESSION COEFFIENT 'R'
DEWAS	TRAINLM	10	7775.0942	0.901242
INDORE	TRAINLM	12	6739.6185	0.900374
BHOPAL	TRAINLM	10	7096.8227	0.924311
JABALPUR	TRAINLM	10	6774.8705	0.944635
NEEMUCH	TRAINLM	12	4791.4159	0.956720

It is seen in the solar irradiance forecasting result MSE is very high as compared to other parameters MSE it is due to large variation in input data because solar radiation changes in every hourly sample value in overcast weather conditions which leads to sharp edges in its time series response also but regression coefficient is above 0.9 for each tested location which shows the correlation between output and target variable. This forecasting result could be much more accurate with large input database.

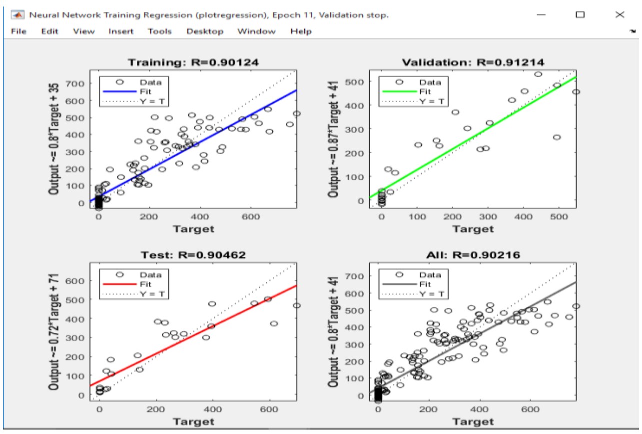

Fig. 11 Regression plot for solar irradiance forecasting .

© Copyright: All rights reserved.

International Journal of Innovative Science and Modern Engineering (IJISME)
ISSN: 2319-6386 (Online), Volume-6 Issue-10, September 2020

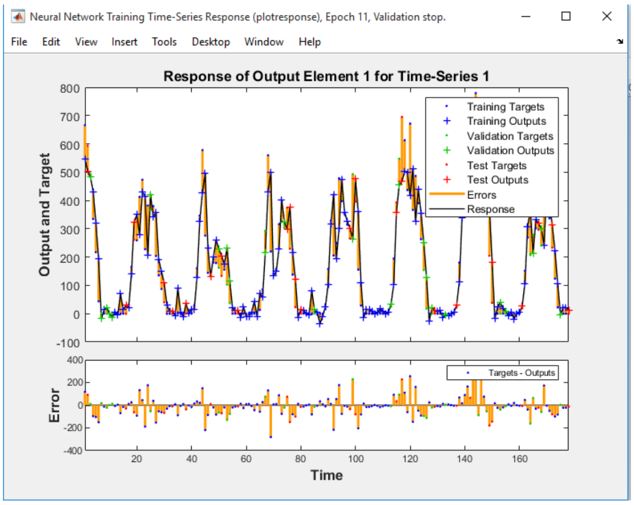

Fig. 12 time series response for solar irradiance forecasting.

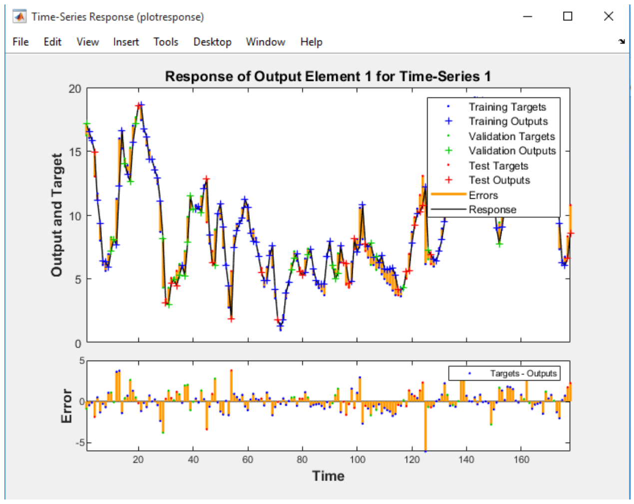

Fig. 14 time series plot for wind speed forecasting.

TABLE V. WIND SPEED FORECASTING RESULTS

LOCATION	ALGORITHM USED	NO. OF HIDDEN NEURONS	MSE	REGRESSION COEFFIENT 'R'
DEWAS	TRAINLM	10	1.53704	0.965399
INDORE	TRAINLM	10	1.26303	0.969568
BHOPAL	TRAINLM	10	1.11333	0.962476
JABALPUR	TRAINLM	16	0.690068	0.946236
NEEMUCH	TRAINLM	10	1.50215	0.960311

TABLE VI. WIND DIRECTION FORECASTING RESULTS

LOCATION	ALGORITHM USED	NO. OF HIDDEN NEURONS	MSE	REGRESSION COEFFIENT 'R'
DEWAS	TRAINBR	12	159.619	0.977707
INDORE	TRAINBR	10	16.14830	0.977549
BHOPAL	TRAINBR	8	94.53375	0.984759
JABALPUR	TRAINLM	10	175.5294	0.955749
NEEMUCH	TRAINLM	12	329.6400	0.958757

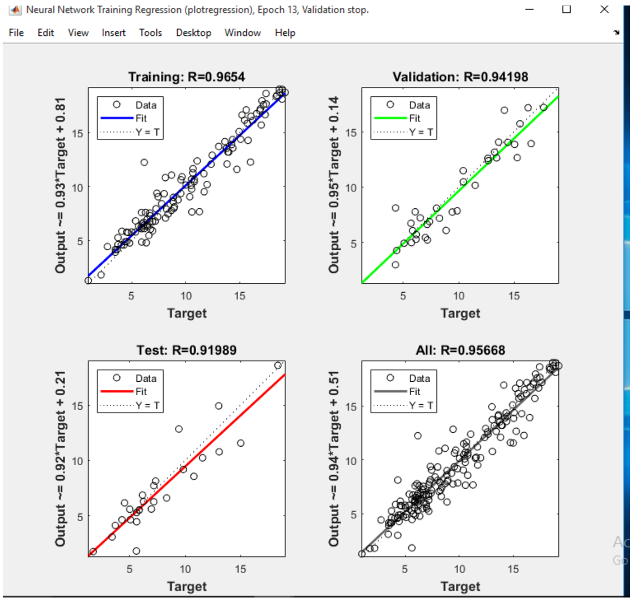

Fig. 13 Regression plot for wind speed forecasting .

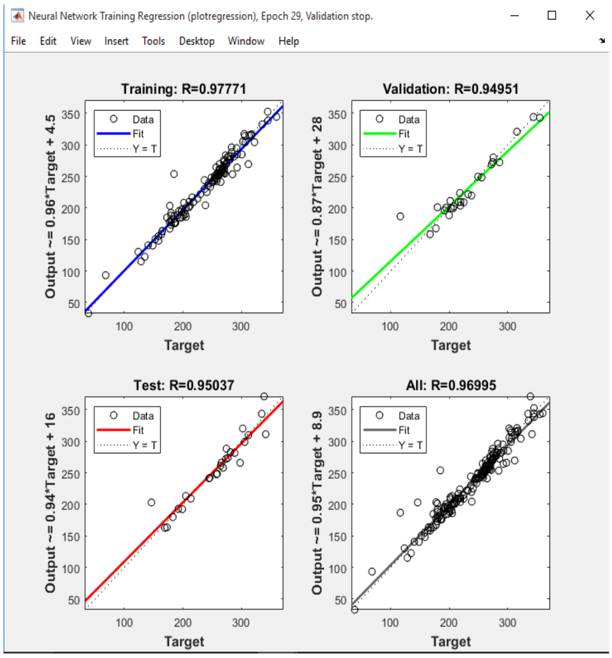

Fig. 15 Regression plot for wind direction forecasting .

Published By:
Blue Eyes Intelligence Engineering
& Sciences Publication
© Copyright: All rights reserved.

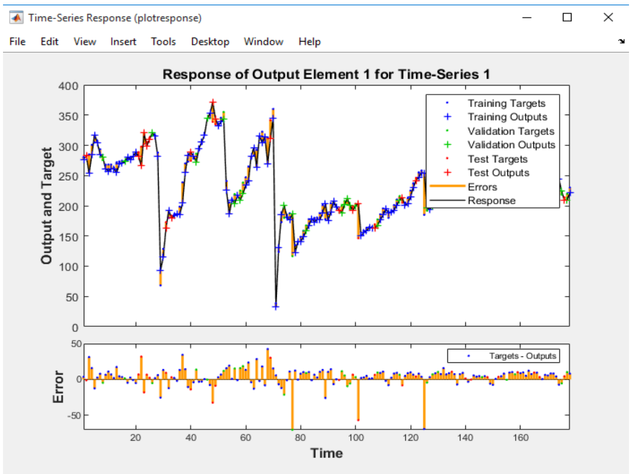

Fig. 16 Time series response for wind direction forecasting .

Wind direction is measured in degrees and for three stations dewas, indore and bhopal the network provides good results with bayesian regularization (trainbr) algorithm. Therefore it is used for generalizing the results with this algorithm in some case studies, the only disadvantage with (trainbr) algorithm is that it becomes time consuming approach with large databases, but here we are using limited number of sample values so no need to worry with this issue.

VIII. CONCLUSION

This work presents the one week ahead solar forecasting model by using NARX model. In the training process two weeks of solar irradiance data and meteorological data are used that is having total 360 hourly sample values and the model performs good forecasting results with minimum data available. Although the system is trained with complex data when the weather conditions were randomly changing in early monsoon period where weather conditions are very difficult to predict. Solar irradiance forecasting results can be improved by using large dataset of previous years. Working with neural networks for different type of datasets provide the most accurate predictions and feed-forward network with nonlinear inputs provide fast execution and better forecasting results for short-term solar forecasting model. Future work will include the neuro-fuzzy model for predicting with complex and noisy data and to find application of this model for sizing of PV standalone systems.

REFERENCES

1. P.A.G.M. Amarasinghe and S.K. Abeygunawardane, "An Artificial neural Network for solar Power Generation Forecasting Using Weather Parameters" IESL, pp.[431-438], 2018.
2. Mohamed Abuella and Badrul Chowdhury, "Solar Power Forecasting Using Artificial Neural networks" north American power symposium (NAPS), pages 1-5, oct 2015.
3. Fei Wang, ZengOiang Mi, Shi Su and Hongshan Zhao " Short-TermSolar Irradiance Forecasting Model Based on Artificial Neural Network using Statistical Feature Parameters" Energies 1355-1370, 2012.
4. Tamer khatib, Azah Mohamed, K. sopian and M. Mohmoud, "Assessment of Artificial Neural Networks for hourly Solar Radiation Prediction" international journal of photoenergy, 7 pages volume 2012.
5. S.Waterkam and S.Premrudeepreechacham "Forecasting of Solar Irradiance for Solar Power Plants by Artificial neural Network" chiang Mai50200Thailand7803-9156-X-IEEE,2005.
6. Mellit A., Benghanem m., Bendekhis M., "Artificial Neural Network Model for Prediction Solar Radiation data :application for sizing stand-alone Photovoltaic Power system" IEEE power engineering society General Meeting, 2005,pp. 40-44 Vol. 1.
7. H.parmar "Artificial Neural Network based modeling of photovoltaic system" (IJLTET) Vol.5 Issue 1 jan.2015.
8. M.W. Gardner & S.R. Dorling, "Artificial Neural Networks (The multilayer Perceptron) – A review of applications in the atmospheric sciences", vol.32 pp2627-2636, 1998.
9. Bernaedo penna Resedbe de Caryalho & wilian soares lacerda, Antono de Padua Barga. "RRS LS-SVM: a new strategy for 'a priori' sample selection". Neural comput & applications: pp.227-234 May 2007.

AUTHORS PROFILE

Naveen Kumar Dubey, Research Scholar in Power electronics, Electrical Engineering Department, SGSITS, 23 Park Road Indore-452003. He Received his Bachelor degree in the Electrical and Electronics engineering from Lakshmi Narain College of Technology, Indore-453331 in 2017. His research interests includes machine learning, artificial intelligence and renewable energy analysis.

Prof. M.P.S. Chawla Professor-Incharge (head), library, associate professor in electrical engineering department, sgsits, indore-452003 (m.p.)-india. immediate past chairman, 2017-2018, ieee mp sub-section. he received gold medals in be(electrical) and me (power electronics)degrees sgsits, indore, india from departments of electrical engineering in 1988 and 1992, respectively. he is appointed as "associated editor in chief chair", on 14th dec2018, in blue eyes intelligence engineering and sciences publication, india. his special research interests are in power electronics, devices, intelligent instrumentation, biomedical engineering, signal processing, advanced instrumentation systems, soft computing, higher order statistical techniques and control systems.

© Copyright: All rights reserved.