Nonlinear Autoregressive External Input (NARX) for Prediction of All Sky Radiation

Abdullahi Sada*, Najashi Bara'u Gafai[1], Halima Bello Kawuwa[1]
[1]*Dept. of Electrical/Computer Engineering, Baze University, Abuja, Nigeria*

(E-mail: najashi.gafai@bazeuniversity.edu.ng)

Abstract— Additional efforts are required to promote the use of Grid-Connected Photovoltaic system as a fundamental source in electric power systems at the higher penetration levels worldwide, therefore, many researchers are interested in its modeling and its prediction to enhance the management of the electrical systems which include Photovoltaic (PV) arrays. Amongst the current existing techniques, Artificial Neural Networks (ANN) have proven their performance in the prediction of the all-sky downward radiative flux. ANN is characterized by its capacity for learning and generalizing and as such, it represents a very powerful tool that provides multiple solutions to different complex problems. This research work aims to predict the future values of all-sky radiation. The developed solution predicts the direct all-sky downward radiative flux using a Nonlinear Autoregressive Exogenous (NARX) neural network from MATLAB/SIMULINK taking into account the specific conditions of tracking maximum power operation. The results show that the most effective prediction performance is obtained when the training phase of the neural network is performed periodically. The best results are obtained for a dataset of 20 years with NARX model providing better predictions.

Keywords: *Prediction; All-Sky Longwave Radiative Flux; Artificial Neural Network (ANN); Nonlinear Autoregressive Exogenous (NARX) model, PV arrays.*

I. INTRODUCTION

The core of development in any community or society is the supply of electrical energy. Inadequate supply of electrical energy would imply that communities are thrown into a darkness that will invariably affect essential services like healthcare and education as well as cause businesses to operate at a loss. Energy makes attainable investments, innovations, and new industries that spur the creation of jobs and growth for the entire economy. Universal access to cheap, reliable, and proper energy; Sustainable Development Goal (SDG) 7; is important for the success of the other SDGs and is at the center of global efforts against climate change [1][2]. Nowadays, electrical grids are mostly centralized, transferring power between big power plants towards end-users; however, decentralized production units are expected to increase significantly. Approaches to increase electricity transfers amongst grids at different levels and penetration of renewable energies may provide more efficient grid management. The challenge for electrical grid operators is to synchronize, continuously, the demand with energy supply [3].

NARX model, as a type of dynamic neural network, is employed to predict future values of the All-Sky Longwave Radiative Flux of the PV array by using measured environmental data. To have more accurate results large dataset should be used. A neural network is important because the elements operating in parallel while the function of the network is determined by the connections between elements. Neural networks have the potential to provide an improved method of deriving non-linear models, which can be used as conventional techniques, thus making them suitable for modeling systems. MATLAB/SIMULINK is used in this paper to establish a PV system model with the Maximum Power Point Tracking (MPPT) function.

The NARX network can be used as a predictor, to predict the electricity pricing, the air pollution prediction [4][5], and the next value of the input signal. In [6] the authors, analyze and configure appropriately the input vectors to enhance the performance of NARX models to forecast solar radiation one hour ahead. Energy Conservation Methods (ECM) program was executed at one floor of a university building, a NARX-ANN was then used to model the baseline energy consumption and determine the energy savings following the International Performance Measurement and Verification Protocol (IPMVP) [7]. It can also be used for nonlinear filtering, within which the target output could be a noise-free version of the input signal. Here, before showing the training of the NARX network, an important configuration that is useful in training needs explanation. We can consider the output of the NARX network to be an estimate of the output of some nonlinear dynamic system that you simply are trying to model. The output is fed back to the input of the feedforward neural network as part of the standard NARX structure. However, because the true output is available during the training of the network, a series-parallel architecture can be created in which the true output is used instead of feeding back the estimated output. This has two advantages.

- The input to the feedforward network is more accurate.

- The resulting network has a pure feedforward architecture, and static backpropagation can be used for training [6].

A. SOLAR PHOTOVOLTAIC SYSTEMS

Solar photovoltaic systems convert sunlight directly into electricity [6]. These power systems are outlined to supply utilizable solar power through the process of photovoltaic. It consists of several components arranged such as solar panel/module which acts as a means of absorption and converting sunlight into electricity, an inverter, a battery charge controller, maximum power point tracking controller and some switchgear components of the low voltage, a solar tracking system perhaps and other electrical devices to make up the system [8].

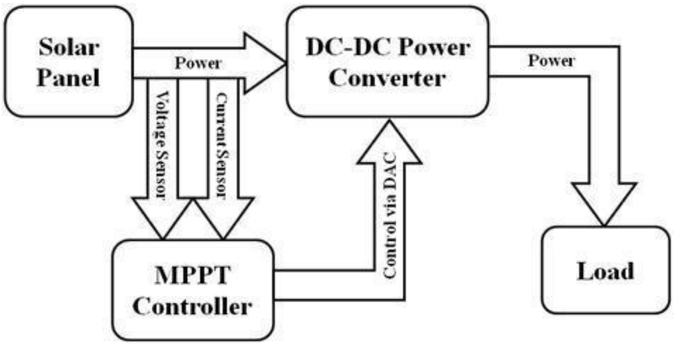

Figure 1: PV System

From the output characteristics of PV panels, the output of PV panels is a function of solar irradiation and temperature, and it presents nonlinear characteristics of photovoltaic panel output power (PPV) vs. output current or voltage (IPV or VPV). It is desirable to predict an accurate future value of the ALL sky radiation. This could be done by using the historical data of the All-sky radiation. Research has been done in nonlinear models that show more flexibility in capturing the data underlying characteristics.

II. MATERIALS AND METHOD

A. Maximum Power Point Tracking

Maximum power point tracking (MPPT) operates on a specific tracking algorithm and it is situated on a control system. The maximum power point or peak power voltage is the voltage at which the photovoltaic module produces maximum power. Maximum power alters with solar radiation, ambient temperature, and solar cell temperature. It is most effective under winter, cloudy days when more power is needed [6].

B. Artificial Neural Network Method

Artificial neural networks (ANN) commonly have three (3) layers which are: input, hidden, and output layers [9]. The number of nodes in each layer varies and its user-dependent. The algorithms used by the hidden layer depends on how close the operating point gets to the MPP and how well the ANN has been trained.

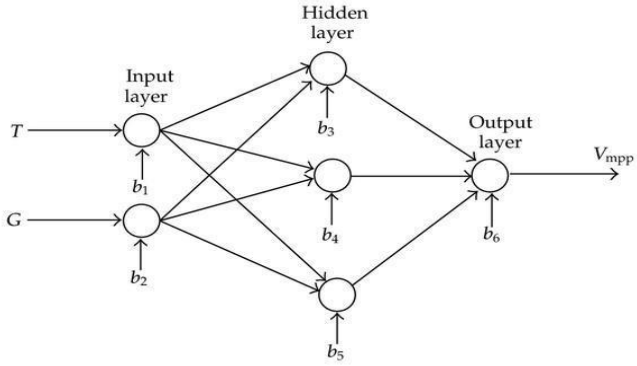

Figure 2: Structure of neural networks [7]

ANN searches MPP exactly when solar irradiance changes sharply or under partial shading conditions, and it can make the system work under a stable mode. Here, the ANN-based PV model method is the fast MPP approximation according to the parameters. Its advantages are robust operation, fast-tracking, and off-line training [12] [13]. In this method, the features of a photovoltaic (PV) array also changes with time, as the neural network has to undergo a training process, the photovoltaic (PV) array is tested over months or years and the patterns between the input and output of the neural network are recorded to ensure accurate MPPT.

C. Nonlinear Autoregressive With External Input (NARX)

Nonlinear autoregressive with external input (NARX) is a type of nonlinear time series problem in which networks can learn to predict one-time series given past values of the same time series, the feedback input, and another time series called the external time series. It is a recurrent dynamic network, with feedback connections enclosing many layers of the network. NARX consists of a linear ARX model with two delays. Compared to other neural network types, the NARX model is characterized by good learning, fast convergence, and better generalization [14].

The defining equation for the NARX model is

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

where the next value of the dependent output signal $y(t)$ is regressed on former values of the output signal and previous values of an independent input signal. NARX predicts series given past values of series and another external series, which can be single or multidimensional.

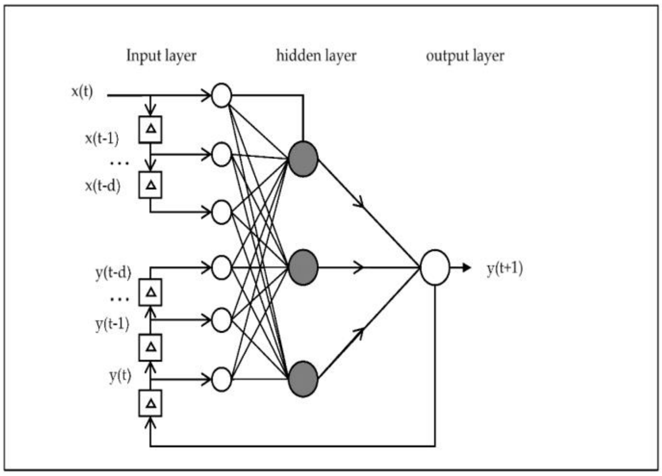

Figure 3: NARX model architecture

D. Simulation

The prediction was done using MATLAB/SIMULINK 2016a where we deploy the Neural Network Application. Figure 4 shows the startup page for the neural network application. Several complex problems could be solved using this application. As highlighted in figure 4, the Time series app was used in our case.

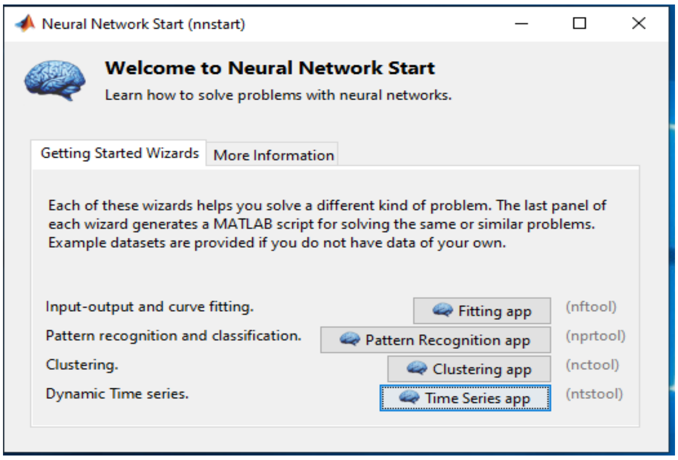

Figure 4: Neural network startup page

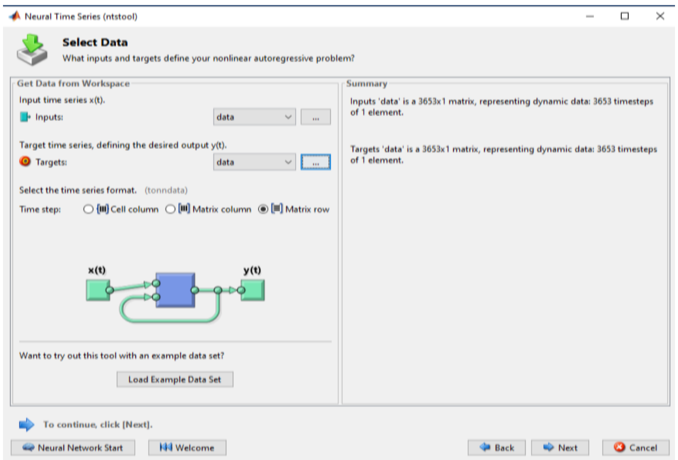

Figure 5: Defining input and target time-steps

The next step involves defining the input and target time-steps as indicated in Figure 5. This is achieved by either importing the data from excel to MATLAB workspace or by directly importing the data. The input defines the past values of the data and the target defines the desired output. The time-series format will be in a matrix row for better representation of the dynamic data.

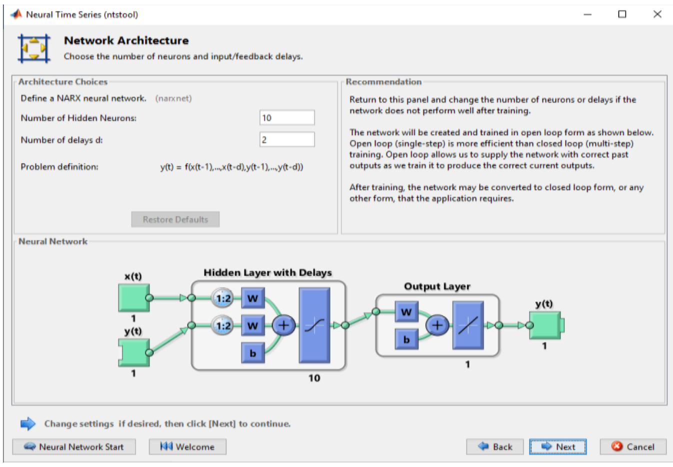

Figure 6: Network architecture; defining the number of hidden neurons and time delays

Figure 6 shows the network architecture, defines the number of hidden neurons (n) and the time delay (d). Different values for both hidden neurons and time delay were used to ascertain the performance of the model.

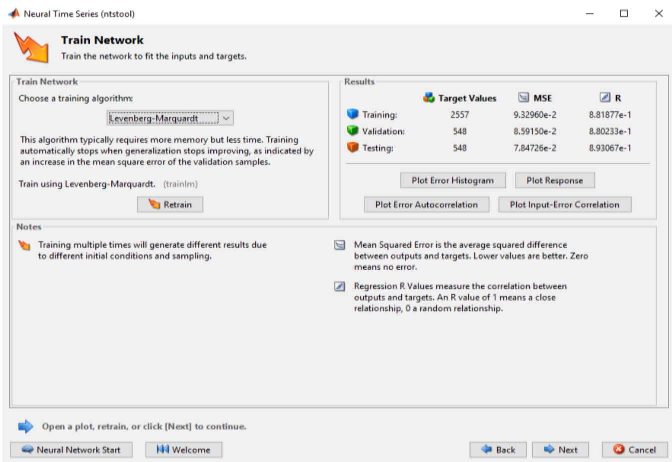

Figure 7: Training the network

The network is trained as shown in Figure 7 to fit in the input and target data. The training algorithm used is the Levenberg Marquardt (this algorithm typically requires more memory but less time). Training automatically stops when generalization stops improving, as indicated by an increase in the mean square error of the validation samples. However, the mean squared error on the training network is the average squared difference between outputs and targets. Lower values are better. Zero means no error. Regression R values measure the correlation between outputs and targets. An R-value of 1 means a close relationship, 0 indicates a random relationship.

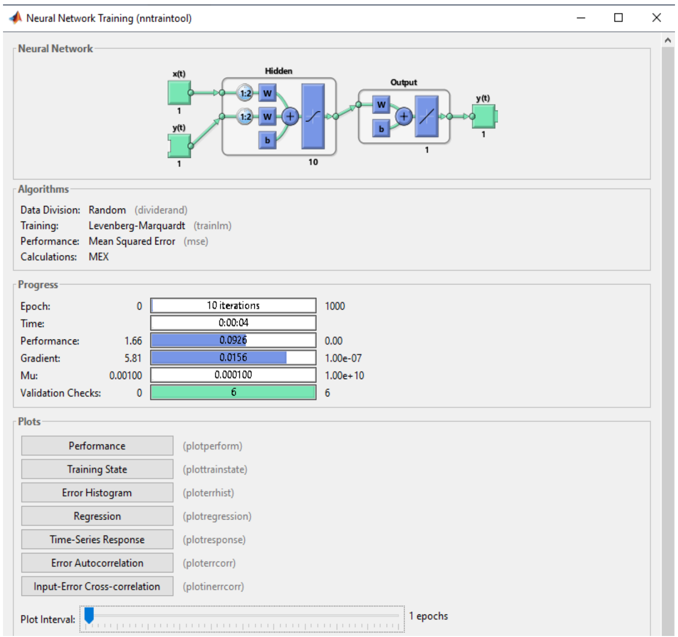

Figure 8: Training result

Figure 8 shows the training result of the neural network architecture. The progress includes the following:

- Epoch: An epoch is a measure of the number of times all of the training vectors are used once to update the weights set.
- Iteration: describes the number of times a batch of data passed through the algorithm.
- Time: the number of seconds performed during an iteration.
- Gradient: The gradient is the gradient of the square of the error function concerning the unknown weights and biases.
- MU: Momentum update is a training gain and is between 0 and 1.

III. RESULTS AND DISCUSSION

Tables 1 to 4 indicates the performance of the model using different values of n and d as shown below.

Table 1: Result of NARX parameters: n=5, d=1 (train and retrain)

	Training	**Validation**	**Testing**
MSE	9.73E-02	8.15E-02	7.34E-02
R	8.75E-01	8.97E-01	8.99E-01
EPOCH	41		
TIME	0:00:00		
Performance	0.0973		
Gradient	0.0114		
MU	1.00E-06		
Validation check	6		

Table 2: Result of NARX with parameter: n=10, d=2 (train and retrain)

	Training	**Validation**	**Testing**
MSE	9.29E-02	8.75E-02	7.92E-02
R	8.81E-01	8.87E-01	8.93E-01
EPOCH	11		
TIME	0:00:02		
Performance	0.0926		
Gradient	0.00537		
MU	0.0001		
Validation check	6		

Table 3: Result of NARX with parameters: n=15, d=3 (train and retrain)

	Training	**Validation**	**Testing**
MSE	8.64E-02	8.59E-02	9.10E-02
R	8.92E-01	8.87E-01	8.63E-01
EPOCH	13		
TIME	0:00:00		
Performance	0.0861		
Gradient	0.0879		
MU	1.00E-05		
Validation check	6		

Table 4: Result of NARX with parameters: n=20, d=4 (train and retrain)

	Training	**Validation**	**Testing**
MSE	8.73E-02	8.91E-02	7.21E-02
R	8.89E-01	8.77E-01	9.06E-01
EPOCH	11		
TIME	0:00:03		
Performance	0.0858		
Gradient	0.0725		
MU	0.0001		
Validation check	6		

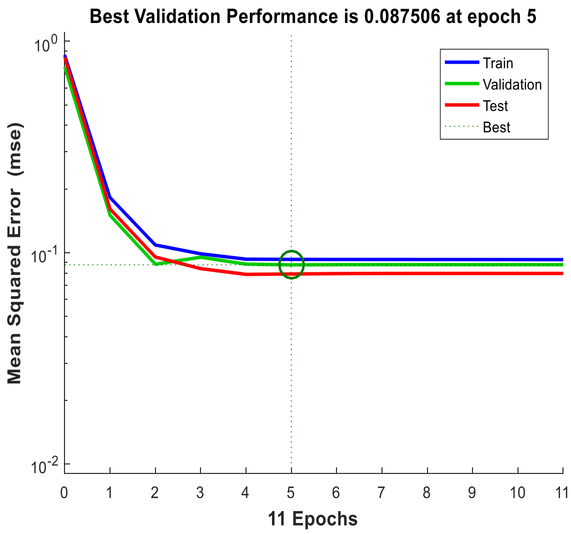

Figure 9: Performance Plot (training, testing, and validation of NARX model)

Figure 9 shows a decrease in training error, validation, and testing until iteration 11 is attained which depicted that there is no element of the occurrence of overfitting. The best performance was taken from the epoch with the lowest validation error. The training, validation, and testing are done in an open-loop likewise, the R values are also computed based on the open-loop training results.

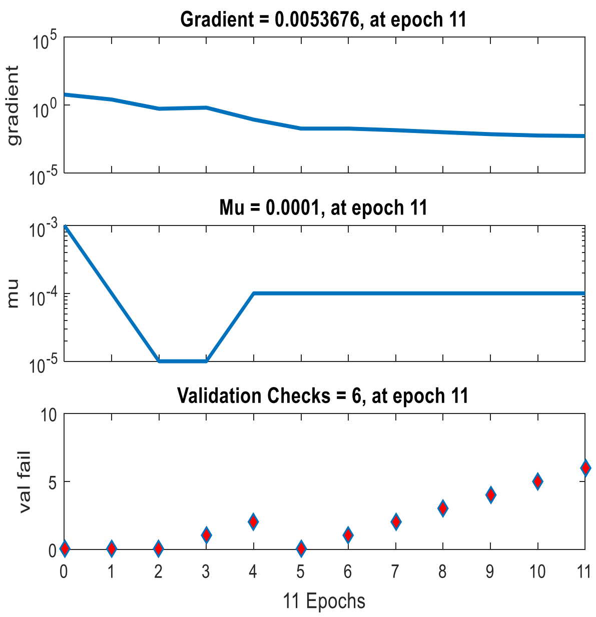

Figure 10: Training State

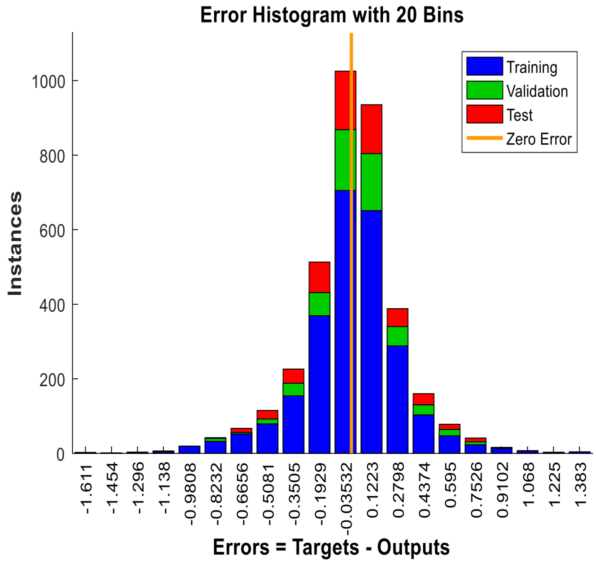

Figure 11: Error Histogram

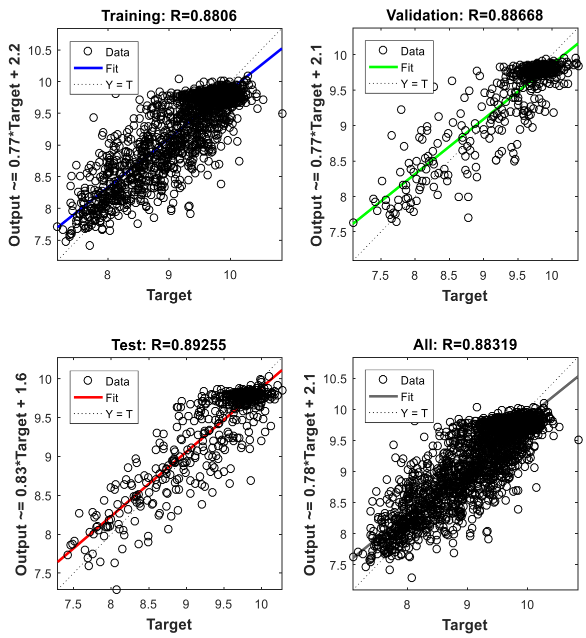

Figure 12: Regression Plot

Figure 12 is the regression of four different plots, which represent the training, validation, and testing and output data. This scatter plot of NARX shows that certain data points have good or poor fits. The solid straight lines represent the best fit linear regression line between outputs and targets of training (blue), validation (green), testing (red), and output of all (black) while the dashed line for each plot represents the perfect result – outputs = targets. The regression (R) value indicates the relationship between the outputs and targets. Here, with R=0.8806 for training, R=0.88668 for validation and R=0.89255 for testing, when we put all together R=0.88319. So, If R is close to zero, it means there is no linear relationship between outputs and targets but, if R = 1, it indicates that there is an exact linear relationship between outputs and targets.

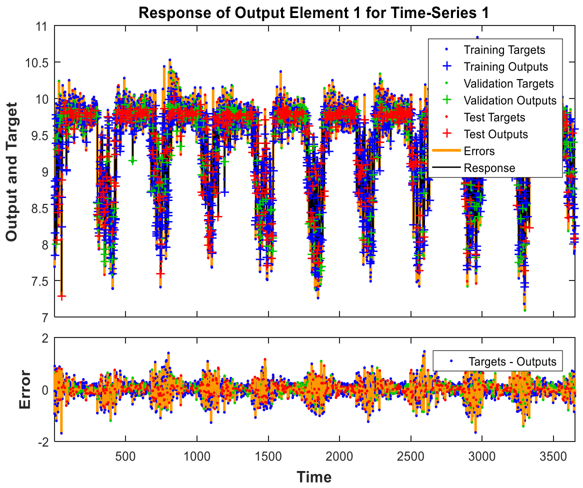

Figure 13: Time series response

Figure 13 shows the Time Series Response which gives a clear indication where time points were selected for training, testing, and validation. Time Series Response helps in displaying the inputs, targets, and errors versus time of a given problem. It takes a target time series t and an output time series y, and plots them on the same axis showing the errors between them. It takes multiple target pairs, typically defining training, validation and testing targets, and the output.

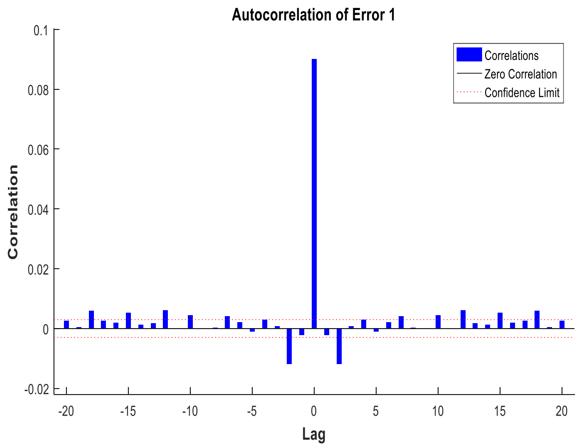

Figure 14: Error Autocorrelation

Figure 14 shows the error autocorrelation function to validate the performance of the trained network which describes how the prediction errors are related in time. It was observed that there was a significant correlation in the prediction errors, the most of the trained network falls within the red confidence limits, which can create rooms for possible improvement (maybe by increasing the number of neurons and delays further). If the network has been trained well, all the other lines will be much shorter, if not, all will fall within the red confidence limits.

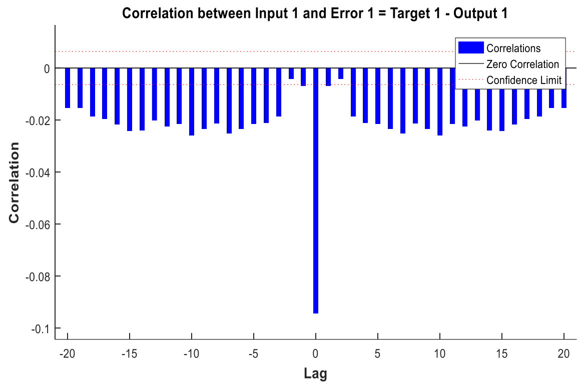

Figure 15: Input-Error Cross-correlation

Figure 15 shows the input-error cross-correlation function that assists in obtaining additional verification of network performance in the sense that it investigates how the errors are correlated with the input sequence x(t). It was observed that the input is correlated with the error which also indicated that there is room for prediction improvement by increasing the number of delays in the tapped delay lines.

IV. CONCLUSION

The main finding of this research study is that the training phase of the neural network is performed periodically, taking into consideration several parameters, such as the cloud cover and temperature. The results show that the most effective prediction performance is obtained when the training phase of the neural network is performed periodically.

Several simulations carried out with different evaluation criteria are performed and evaluated using MSE and R. The best results (0.087506 for MSE) are obtained for a dataset of 20 years, a NARX model which randomly divides the training, validation and testing set, consisting of 10 number of neurons and 2 number of delays in the hidden layers, using a training algorithm *trainlm* function, and a random initialization of weights.

Moreover, the research work found that the NARX model possesses high and strong potential to be considered as a reliable alternative to conventional techniques. The NARX model discussed in this research had provided better predictions. This is because the NARX employs the use of additional information contained in the previous values of y(t). In conclusion, it was observed that NARX can effectively learn complex sequences and outperform some well-known, existing models.

ACKNOWLEDGMENT

The authors will like the express their gratitude to the Faculty of Engineering, Baze University for the support rendered during this research.

REFERENCES

[1] The World Bank project on Booting Renewable Energy in Africa (Feb. 2019) [Online]. Available: https://www.worldbank.org/en/news/feature/2019/02/26/this-is-what-its-all-about-boosting-renewable-energy-in-africa [Accessed].

[2] Bruce, S., & Stephenson, S. (2016). SDG 7 on Sustainable Energy for All: Contributions of International Law, Policy and Governance. *Policy and Governance (August 2016)*.
[3] Energy Access Database. [Online]. Available: https://www.iea.org/energyaccess/database/.
[4] E. Pisoni, M. Farina, C. Carnevale, L. Piroddi, (2009). Forecasting peak air pollution levels using NARX models. Engineering Applications of Artificial Intelligence. 22:593-602
[5] Rangel, E., Cadenas, E., Campos-Amezcua, R., & Tena, J. L. (2020). Enhanced Prediction of Solar Radiation Using NARX Models with Corrected Input Vectors. *Energies*, *13*(10), 2576.
[6] A. Arash, F. Atry, (2009). Multi-step ahead forecasts for electricity prices using NARX: A new approach, a critical analysis of one-step ahead forecasts. Energy Conversion and Management. 50(3):739-747
[7] Mustapa, R. F., Dahlan, N. Y., Yassin, A. I. M., & Nordin, A. H. M. (2020). Quantification of energy savings from an awareness program using NARX-ANN in an educational building. *Energy and Buildings*, 109899.
[8] Mathworks.com. (2019). Design Time Series NARX Feedback Neural Networks- MATLAB & Simulink. [online]. Available: https://www.mathworks.com/help/deeplearning/ug/design-time-series-narx-feedback-neural-networks.html. Apricus.com. (2019).
[9] Solar PV Systems, PV Power System – Apricus Solar PV System. [online]. Available: http://www.apricus.com/solar-pv-systems-29/
[10] S. Sumathi, L. Ashok Kumar, P. Surekha, ‘‘Solar PV and Wind Energy Conversion Systems_ An Introduction to Theory, Modeling with MATLAB_SIMULINK’’
[11] Kaliasgoldmedal.yolasite.com. (2019). NEURAL NETWORK BASED MAXIMUM POWER POINT TRACKING. [online]. Available: http://kaliasgoldmedal.yolasite.com/resources/Project/PV_Project/chapter%203%20.pdf
[12] N. Khaehingtung, P. Sirisuk, W, Kurutach; (2003) ‘A novel ANFIS controller for maximum power point tracking in photovoltaic systems’. Fifth Int. Conf. on Power Electronics and Drive Systems, 2003. PEDS 2003, vol. 2, pp. 833-836.
[13] M.D. Singh, V.J. Shine, V. Janamala; (2014, Nov. 27-29) ‘Application of artificial neural networks in optimizing MPPT control for standalone solar PV system’. 2014 Int. Conf. on Contemporary Computing and Informatics (IC31), pp. 162-166.
[14] Zhang, T., Barthorpe, R. J., & Worden, K. (2020). On Treed Gaussian Processes and piecewise-linear NARX modelling. *Mechanical Systems and Signal Processing*, *144*, 106877.