ASSESSMENT OF NEURAL NETWORKS PERFORMANCE IN MODELING RAINFALL AMOUNTS

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ABSTRACT

This paper presents the evaluation of performance of Neural Network (NN) model in predicting the behavioral pattern of rainfall depths of some locations in the North Central zones of Nigeria. The input to the model is the consecutive rainfall depths data obtained from the Nigerian Meteorological (NiMET) Agency. The neural networks were trained using neural network toolbox in MATLAB with fifty years (1964–2014) total monthly historical data of five locations while two other locations, Abuja and Lafia with twenty-nine years (1986-2014) and eleven years (2004-2014) total monthly data respectively. Analysis showed the variation in the values of correlation coefficients (R) for each location of the study area in response to change in number of hidden neurons. The average R values of 0.80, 0.62, 0.65, 0.67, 0.79, 0.76 and 0.81 with corresponding mean square errors of 2.12, 0.23, 0.26, 0.36, 2.61, 1.18 and 1.03 were obtained for Abuja, Makurdi, Ilorin, Lokoja, Lafia, Minna and Jos respectively. The results showed some slight variability in the performances of NN due to changes in the number of hidden neurons during the network training. These values of R indicated that the networks are fit to be used for the subsequent quantitative prediction of rainfall depths in each location which is useful for safeguarding against future flood and drought occurrence in the North Central zone, Nigeria.

Keywords: Rainfall depths, NN, coefficient of correlation, mean square errors.

1.0 INTRODUCTION

Rainfall is one of hydro-meteorological elements whose prediction is challenging as the world continues to witness ever changing climatic conditions. Its forecast plays an important role in water resources management and agricultural production, which contributes significantly to the economy growth of any nation (Abdulkadir *et al.*, 2012). French *et al.* (1992) highlighted that rainfall is complex and difficult element of hydrological cycle to understand and model due to the tremendous variations that occurs over a wide range of space and time. The complexity of the atmospheric processes that generate rainfall makes its quantitative forecasting extremely difficult task (Hung *et al.*, 2008). However, accurate rainfall forecasting is one of the greatest challenges in operational hydrology, despite many advances in weather forecasting in recent decades (Gwangseob and Ana, 2001). Flood and drought are hazards that often caused respectively by excessive and insufficient rainfall amounts. Rainfall aggressiveness could lead to extreme land degradation such as gully erosion and water quality deteriorations (Abdulkadir *et al.*, 2016). Flood phenomenon is one of the most devastating natural disasters in Nigeria and many other developing and developed countries. In 2012, several states across the country were ravaged by the flood, in which many lives and properties were lost. Federal Ministry of Environment reported that floods affected more than seven million people, while more than 363 persons lost their lives and about 597,476 houses were destroyed. Floods due to heavy rainfall amidst other factors have killed over 360 people and displaced 2,100,000 people in Nigeria with the states in the North Central mostly affected in 2012 (Wikipedia, 2013). National Emergency Management Agency reported that about 25,000 persons in 14 communities were displaced in Benue State following the overflow of river Benue in 2012. Premiumtimes (2015) reported flood hazards that occurred in Nigeria in the early month of September 2015 resulted to death of 53 people and 100,420 people displaced. The detailed records of significant flood hazards in Nigeria between 1985 and 2014 were reported by Nkwunonwo (2016). The details of historical floods provided information about the location, size of affected landmass, duration of flood, causes, causalities, number of affected properties and economic losses involved. This situation could have been arrested with adequate rainfall prediction and early warning mechanisms. In the past, several empirical and computational methods of modeling have been proposed to accurately predict rainfall (Khaing and Thinn, 2008). According to Karim (2009), these models, regardless of their structural diversity generally fall into three broad categories: black-box or system theoretical models, conceptual models and physically-based models. The physically based models describe the natural system using the basic fluid-flows derived from the energy and water budgets. The models have set of partial differential equations together with various parameters which have direct physical significance (Hogue *et al.,* 2006). Conceptual models operate with different and mutually interrelated storages representing physical elements in a catchment area. In this parameters and variables represent mean values over the entire catchment areas and the description of the hydrological processes cannot be based directly on the equation derived for the individual soil columns (Junsawang *et al.,* 2007). Hence, the equations are regarded as semi-empirical, but with a physical basis. Therefore, the model parameters cannot usually be assessed from field data, but have to be obtained through calibration. Black-box models are empirical in nature involving mathematical equations that have been assessed. This model is not concerned with the physical processes in the catchment area, but from analysis of concurrent input and output time series of data. Examples of black-box models are the unit hydrograph model (Yue *et al.,* 2000) and the Artificial Neural Network (ANN) model (Tan *et al.,* 2006; Abdulkadir *et al.,* 2012; 2013).

The development of ANN model has recently become an important alternative tool to conventional methods like regression methods in modeling of non-linear functions. In recent decades, various commercially available algorithms such as MATLAB toolbox, NuExpert, NeuNet, Easy NN, ALYUDA-Forecaster, SPSS, etc have been developed to overcome a number of limitations in the early networks (Abdulkadir *et al.,* 2013). This makes the practical applications of ANN more appreciable in the field of climate science. An ANN provides the users a model free tool, which can generate input-output mapping for any set of data as complex pattern recognition can be attempted without making any initial assumptions. In addition, it could learn and generalize from examples to produce meaningful solution even when the input data contain errors or are incomplete (Luk *et al.,* 2000). Haykin (1994) identified the following areas of application of ANN model: pattern matching, adaptive learning, prediction, data compression, self-organization and functions optimization. Training of the network with the relevant data enable the neural network ability of making predictions based on the input fed into it (Kumarasiri and Sonnadara, 2006). Based on the structure of the learning algorithm, various neural network models have been proposed and applied to solve different modeling problems. Karim (2009) demonstrated ANN's ability as a universal approximator when applied to complex systems that may be poorly described or understood using mathematical equations. According to Adya and Collopy (1998), among the forty eight (48) studies conducted using ANN, it was found that neural network models produced superior predictions. The results of effectively implemented and validated neural network models out-performed all comparative methods such as linear regression, stepwise polynomial regression, multiple regression, discriminant analysis, logic models and rule-based system (Adya and Collopy, 1998). Owing to the efficacy of ANN models and complexity in rainfall prediction, there is need to evaluate response of models' output to the available number of hidden layers in the training network. Thus, this study is aimed at evaluating ANN performance in modeling the rainfall amount (depths) in the North central Nigeria.

2.0 MATERIALS AND METHOD

2.1 Data Collection

Rainfall data (in depths) were obtained from synoptic weather stations in North Central Nigeria. This comprises of Ilorin (Kwara State), Markurdi (Benue State), Lafia (Nasarawa State), Jos (Pleteau State), Lokoja (Kogi State), Minna (Niger State) and Federal Capital Territory (Abuja) as shown in Figure 1. These areas are characterized by two major seasons: wet and dry seasons. The location map of the study areas is as shown in Figure 1. The rainfall data required for this study were obtained at the Nigerian Meteorological Agency (NiMET), Lagos, Nigeria. The description in terms of geographical locations and some meteorological information of the locations are presented in Table 1.

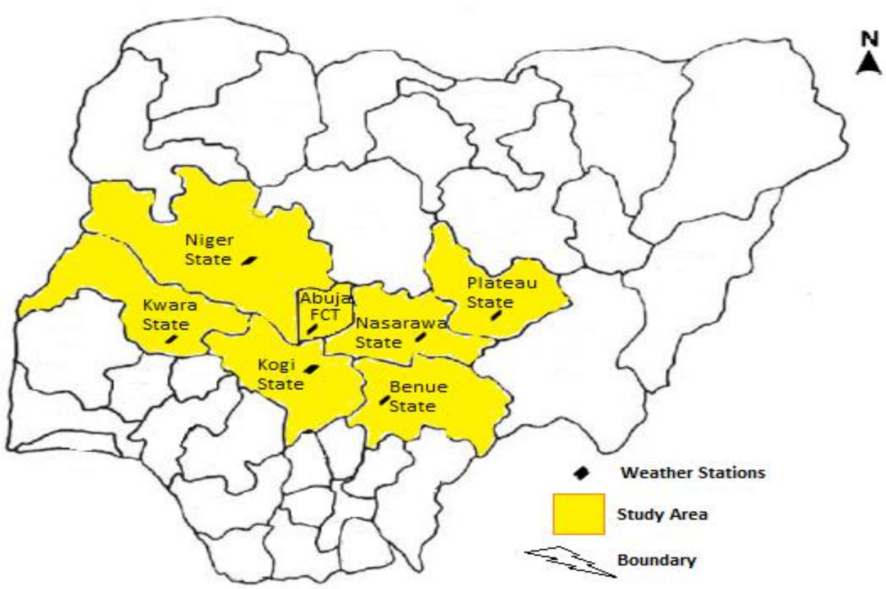

Figure 1:Location of the study areas (Yellow Regions)

Table 1: Description of locations of study area

S/No.	Towns	State Capital	Latitude (N)	Longitude (E)	Average annual rainfall depth (mm)	Approx. Average annual temperature range (^{0}C)
1	Ilorin	Kwara	$8^{0}30^{1}$	$4^{0}35^{1}$	1200	25.00 – 28.90
2	Makurdi	Benue	$7^{0}43^{1}$	$8^{0}33^{1}$	1290	21.00 – 35.00
3	Minna	Niger	$10^{0}00^{1}$	$6^{0}00^{1}$	1312	25.10 – 30.50
4	Lafia	Nasarawa	$8^{0}32^{1}$	$8^{0}18^{1}$	1288	22.70 – 36.80
5	Jos	Plateau	$9^{0}56^{1}$	$8^{0}53^{1}$	1400	21.00 – 25.00
6	Lokoja	Kogi	$7^{0}49^{1}$	$6^{0}45^{1}$	1216	22.80 – 32.22
7	Abuja	FCT	$9^{0}40^{1}$	$7^{0}29^{1}$	1221	18.45 – 36.05

2.2 Data Analysis

For this study, historical rainfall data were obtained from NiMET for period of fifty years (1964–2014) for all locations except Abuja with twenty nine years (1986-2014) and Lafia with eleven years (2004-2014). The total monthly rainfall values from several successive observations are computed for each location and fed into the neural network model via MATLAB. The statistical analysis of data such as mean, standard deviation (Stdev), skewness, minimum and maximum were estimated for rainfall values for each of the locations of the study area for period of data availability and the results presented as shown in Table 2.

Table 2: Statistical analysis of the data

	Abuja	Makurdi	Ilorin	Lokoja	Lafia	Minna	Jos
Mean	120.564	102.595	100.645	101.636	38.702	104.461	108.839
Maximum	554.9	884.2	382.5	448.6	258.9	533.9	426
Minimum	0	0	0	0	0	0	0
Stdev	122.737	106.689	106.689	99.139	55.584	109.821	113.824
Skew	0.834	1.392	1.392	0.830	1.627	0.872	0.703

2.3 Application of ANN Model

2.3.1 ANN Model

Many tasks involving intelligence or pattern recognition are extremely difficult to automate but appear to be performed very easily by humans (Dongare *et al.*, 2012). ANN is a computing system whose central idea was borrowed from the analogy of biological neurons in the human brain (Andy *et al.*, 2004; Hung *et al.*, 2008; Kumarasiri and Sonnadara, 2006; Luk *et al.*, 2001). ANNs are made up of many simple and highly interconnected processing units called neurons, each of which performs two functions: aggregation of its inputs from other neurons or the external environment and generation of an output from the aggregated inputs. In a neural network, each node performs some simple computations and each connection conveys a signal from one node to another, labeled by a number called the connection strength or weight (Abdulkadir *et al.*, 2012). This indicates the extent to which a signal is amplified or diminished by connections. Through this simple structure, neural networks have been shown to be able to approximate most continuous functions to any degree of accuracy, by choosing an appropriate number of neuron units (Kurban and Yildirim, 2003). Neural networks essentially involve a nonlinear modeling approach that provides a fairly accurate universal approximation to any function. Its approximation power comes from the parallel processing of the information from the data. No prior assumption of the model form is required in the model building process. The model is characterized by a network of three layers of simple processing units, which are connected to one and other. The layers are input, hidden and output layer as shown in Figure 2.

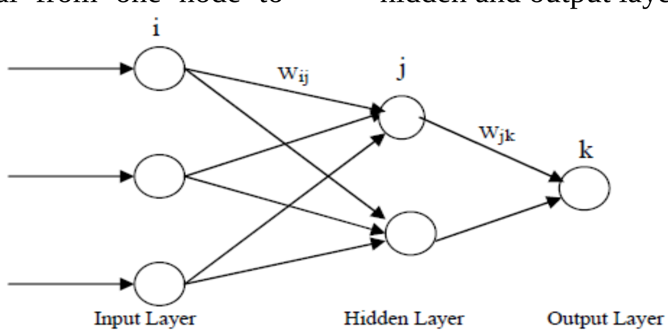

Figure 2: Typical ANN structure (Kristen and Lee, 2003)

The number of nodes in the input layer and the output layer are determined by the number of input and output parameters. The first layer ***i***, (independent variables) that receive input information, is called an input layer. The last layer $\boldsymbol{k}$, (dependent variables) which produces output information, is called an output layer. There exists between the output and input layers the hidden layers $\boldsymbol{j}$. There can be one or more hidden layers with many nodes. Information is transmitted through the connections between nodes in different layers with the aid of connection weights w_{ij} and w_{jk}. The connection between nodes in the network architecture fundamentally determines the behavior of the network. For most forecasting and other applications, all nodes in one layer are fully connected to all nodes in the next higher layers. However, it is possible to have sparsely connected networks or include connection from input to output nodes (Duliba, 1991).

Artificial neural network has been widely applied in modeling of many nonlinear hydrologic processes such as numerical weather and global climate model (Kang and Ramirez, 2009); rainfall-runoff model (Hsu *et al.,* 1995; Shamseldin, 1997); stream flow model (Zealand *et al.,* 1999; Modarres, 2008; Karim, 2009); precipitation prediction (Kevin, 2008; Khaing and Thinn, 2008); rainfall modeling (Sunyoung *et al,* 1998; Hung *et al.,* 2008; Somvanshi *et al.,* 2006); and simulation of daily temperature (Ricardo and Jean, 1999). Various ANN models have been proposed for the rainfall modeling since its inception. Multilayer perceptron (MLP) otherwise known as feed forward back propagation (FFBP) and the radial basis function (RBF) network are the most widely used model. Others such as ridge polynomial networks and wavelet networks are very useful in some applications due to their function approximating ability. MLP maintains high level of research interest due to its inherent capability to map any function to arbitrary degree of accuracy (Modarres, 2008). It is composed of multiple simple processing nodes or neurons assembled in several different layers. Each node computes a linear combination of weighted inputs (including a bias terms) from the links feeding into it (Ricardo and Jean, 1999). The summed value (net input) is transformed using a non-linear function called log-sigmold or hyperbolic tangent (tan h) functions. This function map any input to a finite output range usually between 0 and 1, or -1 and 1. Among these functions, the most widely used is log-sigmold function shown in Equation 1. Then, the output obtained serves as an input to other nodes.

In modeling of hydrological variables such as rainfall, a set of variables is divided into three prior to the model building: the training, validation and testing sets. A set is used for training and the others are used to evaluate the accuracy of the model derived from the training set. In validation phase, the model output is compared with the actual output using statistical measurements such as sum of square error (RMSE). This is used as criteria in the back-propagation training algorithm. The mean absolute percent error (MAPE) and the coefficient of correlation (R) are some of the statistical parameters used to examine the model performance (Somvanshi *et al.*, 2006; Khaing and Thinn, 2008; Hung *et al.*, 2008; Karim, 2009). The validation sample is also utilized to avoid over fitting problems or to determine the stopping point for the training process (Wang *et al.*, 1992). It is a common practice to use one test datasets for both validation and testing purpose particularly with small data set.

$$\boldsymbol{y_{i}} = \frac{\mathbf{1}}{\mathbf{1} + e^{-x_i}} \text{ ----------(1)}$$

Where:

y_i = model output,

x_i = model input,

e = exponential function

The training of the network, supervised or unsupervised, is aimed at determining the main control parameters of ANN called “weights”. The processes of estimating these parameters are known as training where optimal connection weights are determined by minimizing an objective function (Somvanshi *et al.*, 2006). The most famous self-organizing neural network (unsupervised) is the Kohonen’s Self-Organizing Map (SOM) classifier, which divides the input-output space into a desired number of classes (Karim, 2009). In supervised training, the network compares the generated values with the target values. The error resulting from the comparison is propagated backward through the network, and the weights are adjusted to minimize this error. The procedure continues until network generates value of error closer to the validation value. Thus, the performance criterion is the minimization of square error and this is expressed in Equation 2.

$$error = \sum_{p,i}(t_{ip} - y_{ip})^2 \text{-----------(2)}$$

Where:
i indexes unit of output,
p indexes the input – output pairs to be learned.
t_{ip} = desired output,
y_{ip} = learned (network) output.
The standard training algorithm used in most hydrological applications is the back-propagation algorithm. The full mathematical derivation of this can be found in several neural networks textbooks (Abdulkadir *et al*, 2012).

In the case of explanatory or casual forecasting problems, the inputs to an ANN model are usually the independent or predator variables. The functional relationship estimated by the ANN can be written as in Equation 3

$$\mathbf{y= \mathit{f}(x_1, x_2, x_3, x_4 \ldots\ldots x_p)} \text{-----------(3)}$$

where:
$x_1, x_2, \ldots x_p$ are p independent variables and
y is a dependent variable. In this sense,
the neural network is functionally equivalent to a nonlinear regression model. On the other hand, for an extrapolative or time series forecasting problems, the inputs are typically the past observation of the data series and the output is the future values for the dataset. The ANN performs the mapping as in shown Equation 4.

$$\mathbf{y_{t+1}= \mathit{f}(y_t, y_{t-1}, y_{t-2} \ldots \ldots y_{t-p})} \text{-----------(4)}$$

where:
y_t is the observation at time t.

Thus, the ANN is equivalent to nonlinear autoregressive model for time series forecasting problems. In this study, the model is trained using the data format of the form in Equation 4. After the network is adequately trained as demonstrated in Figure 2, it has to be tested for its ability to produce accurate outputs.

2.3.2 Rainfall Modeling Using ANN

The neural network training of the rainfall data was automated in MATLAB 2012b toolbox. According to the early stopping method, the dataset for each of the location were divided into 80%, 10% and 10% of total volume of the data for the training, validation and testing sets respectively. The training set of each of the location was used to train the network whereas its validation set was used to monitor or test the network performance at regular stages of the training. During the training, connection weights of input and hidden layer nodes were adjusted by checking the training and testing stage performances of neural network as automated in MATLAB. The training stopped when the error on the validation set reached the minimum. Finally, the performance of the network was evaluated on the test data set. The training was repeated for 5, 10, 15, 20, 25 and 30 hidden neurons in the hidden layer. The coefficient of determination and the mean square error were used as the performance criteria for the testing stage. The coefficients of correlations for the training for each of the locations are as shown in Table 3. Figure 3 shows the variations of coefficient of correlations with number of hidden neurons in the hidden layer for the training of each dataset for various locations. Figures 4 and 5 show the performance reports of the network generated error with the output and target against time respectively for Abuja and Makurdi while the same plots for other locations are done but not presented in this reported to avoid been cumbersome. This shows the fluctuation of errors between the output and target rainfall data for the training, validation and test stages during the training of the network.

Table 3: Results of ANN training for different number of neurons in the hidden layer

Location	Dataset	Data Used	Values of R for a Given Number of Neurons in Hidden Layer						Average R-values
			5	10	15	20	25	30	
Abuja	Training	278	0.77	0.81	0.77	0.79	0.84	0.80	0.80
	Validation	35	0.85	0.81	0.74	0.85	0.75	0.60	0.77
	Testing	35	0.76	0.67	0.56	0.68	0.71	0.80	0.70
Makurdi	Training	480	0.62	0.63	0.57	0.61	0.63	0.65	0.62
	Validation	60	0.57	0.66	0.65	0.69	0.58	0.57	0.62
	Testing	60	0.60	0.32	0.50	0.62	0.19	0.19	0.40
Ilorin	Training	474	0.66	0.65	0.67	0.63	0.66	0.65	0.65
	Validation	59	0.72	0.58	0.40	0.69	0.65	0.67	0.62
	Testing	59	0.52	0.54	0.45	0.63	0.57	0.57	0.55
Lokoja	Training	490	0.63	0.66	0.67	0.69	0.65	0.70	0.70
	Validation	61	0.61	0.69	0.62	0.54	0.63	0.67	0.63
	Testing	61	0.66	0.60	0.69	0.64	0.61	0.67	0.64
Lafia	Training	106	0.73	0.74	0.86	0.89	0.67	0.84	0.84
	Validation	13	0.81	0.97	0.81	0.78	0.68	0.40	0.74
	Testing	13	0.84	0.93	0.58	0.20	0.84	0.94	0.72
Minna	Training	490	0.72	0.76	0.78	0.77	0.78	0.77	0.77
	Validation	61	0.78	0.66	0.51	0.76	0.66	0.57	0.66
	Testing	61	0.81	0.67	0.61	0.73	0.52	0.69	0.67
Jos	Training	490	0.79	0.81	0.81	0.81	0.84	0.83	0.83
	Validation	61	0.83	0.86	0.77	0.81	0.88	0.87	0.84
	Testing	61	0.79	0.74	0.84	0.80	0.69	0.81	0.78

Table 4 shows the average values of R and MSE for each location of the study areas during the model training. While the Abuja and Lafia have higher average MSE values due to relatively fewer dataset for the training compare to other locations.

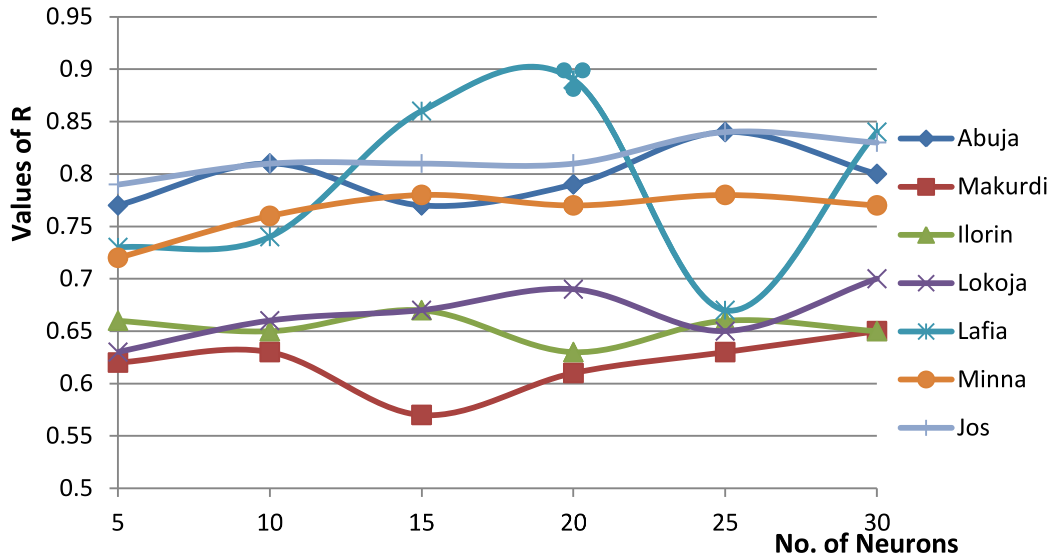

Figure 3: Variation of values of R with number of neurons in the training datast

Table 4: Average value of coefficient of correlation and MSE for each of the location

Location	Average Correlation Coeff. (R)	Average MSE
Abuja	0.80	2.12
Makurdi	0.62	0.23
Ilorin	0.65	0.26
Lokoja	0.70	0.36
Lafia	0.79	2.61
Minna	0.77	1.18
Jos	0.83	1.03

3.0 RESULTS AND DISCUSSION

Statistical analysis of the rainfall data for all the areas under consideration in this study indicated that FCT Abuja has the highest average rainfall values of 120.564mm compared to others. Other statistical parameters of interest are also evaluated and the results are presented in Table 2. Neural network toolbox available in MATLAB package was used in this study for the training of the network. The software used the most common neural network model which is the three layer feed-forward model with back-propagation neural network (BPNN) learning algorithms. In the BPNN architecture, each node at input and hidden layers receive input values, process it and pass it to the next layer. This process is conducted by the weights which are the connection strength between the nodes. Application of ANN model to rainfall data in MATLAB environment automatically generated best network structure. This topology produced a good forecast in the training, validation and testing data set. The values of coefficient of correlations (R) measure the correlation between the forecasted and actual rainfall values. Table 3 shows that variations in the number of neurons in the hidden layer gives different values of R and the graphs of performance reports generated in MATLAB toolbox are different for each training exercise. The average correlation coefficients obtained for the training, validation and testing were evaluated and presented in Table 3 with Jos having the highest value and Makurdi having the lowest value of R for training dataset. However, all locations under consideration yielded better rainfall prediction owing to the fact that the values of *R* are greater than 0.5 but Abuja and Jos results have stronger values than other locations. The results showed that increase in number of hidden neurons have significant effect on the values of R for each training exercise as shown in Figure 3.

The performance report of the network generated errors with output and target against time are shown in Figures 4 and 5. The same plots were generated for other locations but not shown in this report. These Figures show the variations of errors with training time for training, validation and test outputs and targets for different locations of the study area.

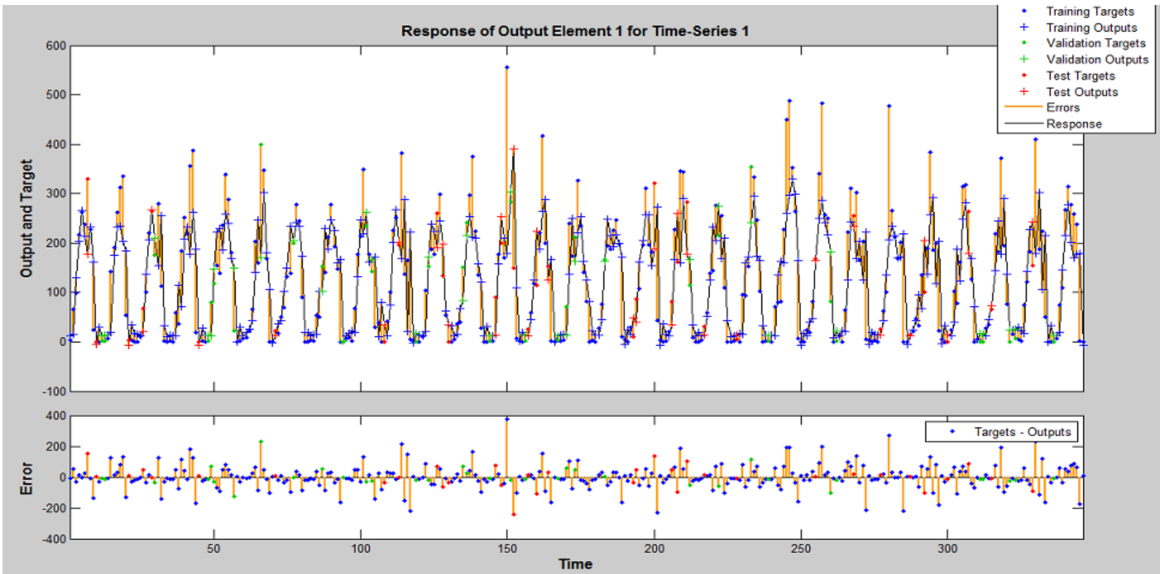

Figure 4: Output and Target against Time and Error against Time for FCT, Abuja

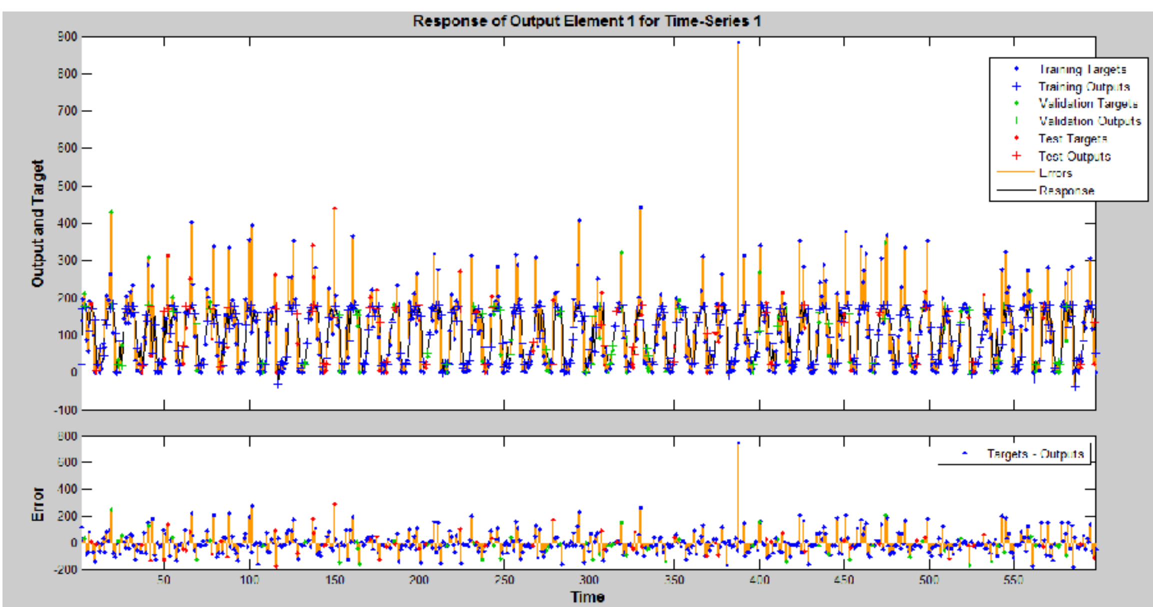

Figure 5: Output and Target against Time and Error against Time for Makurdi

CONCLUSION

Rainfall is one of the key entities of hydrological cycle that strongly influence the operations of dams and reservoirs, flood control, drought and flood mitigation, operation of sewer systems, agricultural practices and other human activities. As a result, accurate modeling of rainfall plays an important role in the management and sustainability of water resources. ANN modeling of rainfall data of North Central Nigeria using NN toolbox in MATLAB showed that ANN is a good forecasting tool for all the locations since values of R are greater than 0.5. However, the reliability of the trained networks for Jos, Abuja, Lafia and Minna is slightly better than Ilorin, Lokoja and Makurdi. The results showed that increase in number of hidden neurons for network training have significant effect on the values of R. ANN is therefore a good method of optimization, since error observed in the comparison of target and model outputs is minimal. The trained network is reliable and fit to be used for the subsequent quantitative prediction of rainfall in each State of North Central Nigeria.

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