Rain–Induced Flood Prediction for Niger Delta Sub-Region of Nigeria Using Neural Networks

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***Abstract*—Climate change generates so many direct and indirect effects on the environment. Some of those effects have serious consequences. Rain-induced flooding is one of the direct effects of climate change and its impact on the environment is usually devastating and worrisome. Flood is a commonly naturally occurring disaster, its effect is very devastating and caused enormous damage to life mostly in terms of agriculture and economy. Floods usually occur where there is high volume of rainfall and there are no proper drainage systems. The study uses Feedforward Multilayer Neural Network to perform short-term prediction of the amount of rainfall flood for the Niger Delta sub region of Nigeria given previous rainfall data for a given time duration. The dataset used in this study for training and consequently testing the Neural Network was sourced from Weather Underground official web site https://www.wunderground.com. An iterative Methodology was used and implemented in MATLAB. We adopted multi-layer Feedforward Neural Networks. The study accurately predicts the rain-induced flood for the Niger Delta sub region of Nigeria.**

***Index Terms*—Climate Change, Feedforward Multilayer, Neural Networks, Niger Delta, Rain-Induced Flood.**

I. Introduction

Climate change generates so many direct and indirect effects on the environment. Some of those effects have serious consequences. Rain-induced flooding is one of the many direct effects of climate change and its impact on the environment is often known to be devastating and worrisome. In recent time, Niger Delta sub region and Nigeria in general has been experiencing flooding with a steady increase in the frequency of its occurrence. It is now an established record that flood is among the most commonly naturally occurring disaster that regularly affect Nigeria (Global Facility for Disaster Reduction and Recovery (GFDRR) [1]. In 2012 Nigeria was shocked with a widespread flooding that affected almost the entire country and caused a damage computed by the Post-Disaster Needs Assessment (PDNA) of GFDRR and estimated to be more or less at 17 billion US Dollar. This estimate did not cover other undocumented losses and damages to livelihood and the low end Agro industry often driven by the peasant and vulnerable. And majority of the occurrence of the flooding in Nigeria are caused and started by rain.

GFDRR PDNA reported large scale of damage and destruction caused by flooding to the means of living and activities of the poor, and low-income earners whose major sustenance is in subsistence agriculture. Thus, majority of these low-income households are rural dwellers who are mostly defenseless and lack capacity to manage natural disasters caused by weather related factors. With high damaging impact by flood on agriculture which forms more than 70% of income of the rural dwellers particularly the Niger Delta Region of Nigeria comes an upsurge in poverty and hunger [1].

Flooding has also caused and justify some agencies of government receiving more funding, resources and capacity build up with inputs coming from both within the country and foreign donor government. A good example is National Emergency Management Agency (NEMA) and Federal Ministry of Environment (setup during the President Olusegun Obasanjo administration) which attribute rain fall that are heavy and with high run-off as the primary and most identifiable cause of flood. Bulk of the funding of these government agencies are targeted at mitigating the after effect of the flood on the society.

Rain-induced flooding simply refers to floods are caused by rainfall. Rain-induced flooding may also be referred to as pluvial flooding or pluvial flash flood. Pluvial flooding occurs when the duration of the rainfall in a particular geographical area is lengthy or in continuous fashion thus generating high volume of water. While pluvial flash flooding occurs when the duration of the rainfall is very brief yet the volume of the sudden rain is also high [2]. Pluvial floods are therefore dangerous Pluvial flash floods are natural occurring disaster that are seen as heavy surface running water causing discharge of high volume of water flow within a region. [2]. Heavy rainfall is discovered to be the sole and major culprit that is responsible for the frequent occurrence of this type of flood thus the description pluvial flash flood is often used. In another word, pluvial flooding takes place when rainfall produces a high volume or concentration of water or high amount of rainfall take place within a very short duration of time and the volumes overpowers the ability of the soil to absorbed the floods but exceeds it penetration capacity. It may also be caused by where there is no sufficient means to discharge the high volume of flood quickly through existing sewage and drainage systems. The resultant flood then flows through an area without control. The weather, climatic conditions and terrain are factors that contribute to making the flow course to be so complicated in nature and having varying constituents as in space and time.

Rain-induced flooding is a natural hazard that must be avoided. Applying various weather forecasting models and

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applications help to reduce the post-flood impact on environment, people and businesses. Consequently, Early Warning Systems (EWS) that are designed to provide efficient alarm protocols must constantly be reviewed and improved upon to reduce error or failure rate of the EWS. This is critical to ensuring that reaction time to alarm time is enough for optimal preparation that will contribute to dropping the degree of damages resulting from flood and most importantly save lives in the event of flood. Therefore, in view of the forgoing, the paper seeks to address how we can determine the volume of rainfall for the next 24-hours for a particular location. To attend to the problem, we:

(i) Design a feed forward multilayer neural network architecture to handle the prediction.
(ii) Make the neural network to be adaptive having the ability to incorporate new data and update it structure.
(iii) Implement and utilize official weather data for training and testing of the networks.
(iv) Implement the Neural Networks design in MATLAB.

II. Background

A. Neural Networks (NNs)

Neural networks are computational data processing structure conceived in accordance with the underlying principles that governs the human nervous systems. Hence the term neural network. Recently many different types of neural networks have evolved resulting to different theories, some are simple and easy to understand and implement while some are of complex nature. This is the case because there now exist different kinds of interpretation and understanding of the biological neural network processing as to what kind of problems to be solved [3].

Neural Networks has ability to learn and the outcome of the training is reliable and useful only in a situation where dataset used in training of the NNs are made up of good samples. Thus, the quality or type of data used in training of the NNs also affects its performance. When data for training is not reliable and good, we are bound to also experience "garbage in-garbage out". Therefore, extreme diligence and caution should be applied when collating, preparing and presenting the correlated data for inputs, and as much as possible all previous knowledge and understanding should be applied when harnessing relevant data supposed to serve as training data inputs. Additional steps and consideration must be put in place to ensure that the dataset used in training NN is a true and realistic characteristic of the object under study since a neural network training cannot obtain reliable and accurate learning from an inadequate few sample. Thus, the efficiency and reliability of a NN is measured by the adequacy, realistic and quantity of the data submitted for its training.

NNs is characterized by the following: -

i. NNs can be used for pattern matching. That is, they can find and report patterns that are matching in many samples in which it is given.
ii. NN can be used in financial applications. In many volatile, unpredictable and complex financial applications, NNs systems are using non-correlated inputs and trading systems and are presently giving reasonable results.
iii. In simple NNs models data that are not randomly distributed can be easily processed and useful information obtained from it.
iv. NNs learn(acquired) information by training and not by programming.
v. Knowledge in NNs are store in the interconnections between processing elements called neurons.
vi. Knowledge in the NNs id distributed throughout the networks and not stored in specific memory locations.
vii. NNs is immune to distorted data as it is generalized and extract the essence of the knowledge.
viii. In NNs knowledge recall is made in response to inputs similar to those used during training.
ix. In NNs, generalization enabled to recognize patterns in new input data, even when the networks have not been presented with the data before.
x. Flexibility in NNs is obtained through its ability to be trained at any point.
xi. Future-centric designed algorithm in NNs enabled it adjust to new realities within the shortest possible time.

B. Weather Predictions Model and Neural Networks

Among the most complicated and tasking topics in academic areas in the world is rainfall forecasting. Presently, weather forecasting unlike traditional methods used before, involves a hybrid of knowledge and technology. Using the present-day technology, accurate forecasting has been made possible.

Combination of support vector machine (SVM) and fuzzy logic was used by Indrabayu and his colleagues. In their paper, they investigated the performance of their proposed hybridized method to Neural Networks _ Fuzzy method. Meteorological data for ten (10) years from 2001 to 2010 was collected from BMKG Indonesia for Makassar City and used. The Climatological Data is Obtained from PT Lapan Bandung and The Meteorology, Climatology and Geophysics Region IV Makassar Indonesia for 10 Years (2001-2010) and is analyzed by MATLAB 7.6 [4].

Rainfall prediction using fuzzy rule base and fuzzy logic was done by Somia et al. [5], They used five parameters as input variables, which are direction of wind, temperature, relative humidity, cloud cover and atmospheric pressure. The output percentage approximately around eighty percent is considered as success forecast. Their result clearly indicates that there is still some degree of uncertainty associated with models for rainfall prediction. For future work, they suggested that the use of hybrid intelligent approach by merging the fuzzy inference system with neural network may give the ability to learn and reduce the need for the experts.

Their result clearly indicates that there is still some degree of uncertainty associated with models for rainfall prediction. For future work, they suggested that the use of hybrid intelligent approach by merging the fuzzy inference system with neural network may give the ability to learn and reduce the need for the experts.

The used of clustering and classification techniques which is a data mining technique for rainfall prediction carried out by Jyothis and Ratheesh [6]. The paper describes empirical method technique belonging to classification and clustering approach. NNs was used to implement these techniques. The NNs not only analyze the data but also learn from it for future predictions making them suitable for weather forecasting. The paper outlined the use of NNs as a means to providing a methodology for solving many types of non-linear problems that are difficult to be solved through traditional methods. The paper presented the values of rainfall are clustered and using subtractive clustering and the states of the rainfall are classified as heavy, medium and low and these are given as outputs for training. They divide their data sets to form the data set for training and the one for testing which they said separating the data into training sets and testing sets is a significant aspect of modeling data mining models. They applied subtractive clustering, and the optimum numbers of clusters obtained was 3. The rainfall values were categorized as low, medium and heavy. Rainfall Prediction gave the accuracy of 87%.

Michaelides and his colleagues compares the success of NN in estimating missing rainfall figures over Cyprus with several linear regressions [7]. Wong and his colleagues constructed fuzzy rule bases by SOM and back-propagation neural networks, and developed a spatial interpolation predictive rainfall model over Switzerland using the rule base [8]. Toth and his colleagues compared real-time models of flood forecasting for short-term rainfall [9]. Koizumi used a Neural Networks model with radar, satellite and weather station data along with numerical products created by the Asian Spectral Model by the Japan Meteorological Agency (JMA) and 1-year data was used in training the model. Neural Networks skills were established to be higher compared to the persistence prediction, linear regression predictions and a computational model of precipitation forecasting [10].

Abraham and his colleagues used a NN for the determination of precipitation time series by using a Scaled Conjugate Gradient Algorithm (ANN-SCGA). Input data used was monthly precipitation for training the model in the analysis [11].

The Artificial NN (ANN) technology has equally been applied for rain forecasting. In [12], generated synthetically rainfall storms was used to calibrate an Artificial NNs model and then plausible rainfall pattern that could occur over a subregion was generated and a physically based rainfall was used to validate the ANN. ANN has major advantage in situations where nonlinearity intrinsic situation in the dynamics prevent providing solution of solvable models. But in most cases, all of these criteria are present in the sense that the dynamics are inherently nonlinear and prediction is one of the main goals.

Using technology and scientific theories to forecast the atmospheric condition of the earth in the future for particular region is referred to as rainfall prediction. Modern days rainfall prediction is done using computer-assisted modeling. Using computer-assisted model has assisted the prediction but 100% success rate has not been achieved. So, there is still possibility of false positive and true negative. There is serious need for accurate rainfall prediction as this information is needed in various fields, especially in such areas as agriculture and aviation fields [13].

A research was conducted with learning rate 0.01, the architectural topology has (4-5-3) that is 4 inputs, 5 hidden layers, and 3 outputs with a maximum of iterations 1500 and a tolerance error 0.01 obtained the best result stops at maximum iteration conditions (1500) with the value of MSE 0.34165862738135266. The design configuration of neural network used the four (4) input variables namely air temperature, air humidity, wind speed, and sunshine duration and 3 output variables which are low rainfall, medium rainfall, and high rainfall. The network shows a reasonable result, as evidenced by the results of the prediction of the system precipitation is the same as the results of manual calculations in Microsoft Excel [14].

C. Common NN Types Used for Rainfall Predictions

The common types of Neural Networks so far designed and used by different researchers for rainfall predictions are: - Back Propagation Network (BPN), Radial Basis Function Networks (RBFN), Support Vector Machine (SVM) and Self Organizing Map (SOM) [15].

One of the most outstanding developments in neural networks is the back-propagation learning algorithm. With this algorithm, this network is still the most popular and most effective model for complex, multi layered networks in many areas of application. The back-propagation learning algorithm is applied to multilayer feed-forward NNs consisting of many processing elements with continuous differentiable activation functions. The networks associated with back-propagation learning algorithm are also called back-propagation networks (BPNs). It is a supervised learning method. For a given set of training input-output pair, this algorithm provides a procedure for changing the weights in a Back- Propagation -Network fashion to classify the given input patterns correctly.

Another category of nonlinear feed forward networks is RBF Networks. Seeing the construction of neural network as a curve fitting problem in a high dimensional space brought the approach which is the RBF networks. The hidden layers enable a set of executions that constitute an arbitrary basis for the input patterns (vectors). As the hidden space are expanded, the resulting model are called radial-basis functions. The modeling of an RBF network involves 3-layers with entirely different functions: the input layer, the only hidden layer, and the output layer.

One of the important categories of multi-layer feed forward network is the Support Vector Machine (SVM). In the same category of multi-layer perceptrons and radial basis function networks, support vector machines can be used for pattern classification and nonlinear regression. SVM has been established to be an important technique that can solve many problems in classifications domain in the recent years. Very few people of this this field used support vector machine for rainfall prediction and got satisfactory result.

There is a network said to be special class of artificial neural network and that is the Self Organizing Map. These models of NNs are opined to be based on competitive learning. The output neurons of NNs compete among themselves to be fired or activated, with the result that only one output neurons are on at any time. The one that is on is called winning neuron. The weight vector associate with winning neurons only updated in the scheme similar "winner takes all" analogy. It is based on unsupervised learning, that is human intervention is not needed during the learning and that little need to be known about the characteristics of input data. In Self Organizing Map the neurons are organized in two- or one- dimensional lattice.

III. METHODOLOGY

The study uses previous rainfall data for a specific period of time to predict volume of rainfall and consequently flood or no flood. An iterative methodology was adopted and implemented in MATLAB using multilayer feedforward Neural Networks.

The historical weather data for the area under study was source from Weather Underground official web site (https://www.wunderground.com). Weather Underground is powered by IBM and it is one of the respected weather data centres that captures, archive and report weather data on minute by minute basis. Weather Underground also have over 250,000 on ground personal weather stations including more than 8000 additional international weather stations and more than 5000 automated weather networks operated at different airports and other government facilities.

Weather underground weather data is suitable for research and weather forecasting applications and they have been providing this public service on weather information since 1993.

Sample of the weather data which was divided and used for training, testing and validation is shown in table1. The first column is the week number (WK). This was not used in the network. Day1 to Day7 are the days of the week. Entries in these columns are volume of rain fall in millimetre per minute in the region. These were the actual input to the system.

TABLE I: SAMPLE OF WEATHER DATA

WK	Day 1	Day 2	Day 3	Day 4	Day 5	Day 6	Day 7
1	0	0	0	0	0	0	0
2	0	0	0	0	0	0	0
3	0	0	0	0	0	0	0
4	0	0	0	0	0	0	0
5	0	0	0	0	0	0	0
6	0	0	0	0	0.04	0	0.83
7	0	0	0	0	0	0	0
8	0	0	0	0	1.38	0	0.04
9	0.04	0	0	0	0	0	0
10	0	0	0.12	0	0	0	0
11	0	0	0	0	0.04	0	0.83
12	0	0	0	0	0	0	0
13	0	0	0	0	1.38	0	0.04
14	0.04	0	0	0	0	0	0
15	0	0	0.12	0	0	0	0

(Source: https://www.wunderground.com)

The architectural topology of the network was designed to have 7 inputs since there are 7 days in a week. After some iteration processes, a 7 hidden layer was decided as the hidden layer and a target value was set for firing flood or no flood. This give the architectural design for the Neural Network for Flood Prediction System (NNFPS).

Fig. 1 shows the Neural Network architecture for the NNFPS.

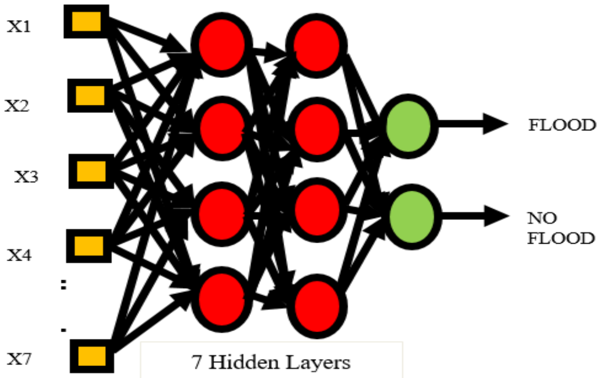

Fig. 1. Architectural Design for the NNFPS

IV. RESULTS AND DISCUSSION

The neural network with 7 inputs for daily reading of volumes of rain fall in a day, seven hidden layers and output indicating the volume of rain fall on the next target day which may be low or high was then implemented. The network was trained and tested on data presented from Weather Underground official web site (https://www.wunderground.com). The target mean-squared error (MSE) rate for training was 0.001. The network was able to exceed this threshold and training was halted once an error of 7.69775e-005 was obtained.

The network was then presented with rainfall data for the previous week and to predict the next day's downfall, if any. High intensity rains are categorized as high volume where the rate of downfall is greater than 0.13mm/min. Consequently, consecutive high intensity rain fall implies flood and the reverse is the case. Fig. 2 shows the high intensity rainfall during the decade from 2009-2018 in Port Harcourt in the Niger Delta. Y-axis is the intensity of rain fall and X-axis is the year from 2009 to 2018.

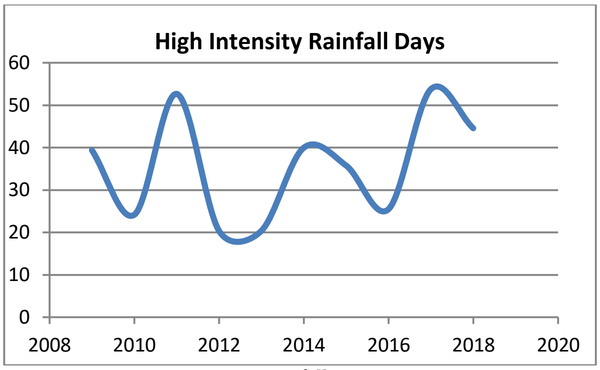

Fig. 2. Port Harcourt Rainfall Intensity, 2009 - 2018

The network was trained and finally performance goal met. An extract of the program running is shown in Fig 3.

```
Select one:
  1) Train Network
  2) Test Network
  0) Exit
>>1
Running Training Mode:
 Enter train data file name>> training_wk
A = 7    52
C =  1    52
 Select one:
  1) Existing network
  2) New network
>>2
```

Fig. 3. Running Program Extract

Extracts from the training sessions are shown in Fig. 4, Fig. 5 and Fig. 6 from different iterations until performance goal was met.

```
TRAINLM-calcjx, Epoch 0/1000, MSE 4.45299/0.001, Gradient 11.9693/1e-010
TRAINLM-calcjx, Epoch 1/1000, MSE 0.727205/0.001, Gradient 3.30124/1e-010
TRAINLM-calcjx, Epoch 2/1000, MSE 0.515955/0.001, Gradient 2.10659/1e-010
TRAINLM-calcjx, Epoch 3/1000, MSE 0.182824/0.001, Gradient 1.00417/1e-010
TRAINLM-calcjx, Epoch 4/1000, MSE 0.109335/0.001, Gradient 0.272273/1e-010
TRAINLM-calcjx, Epoch 5/1000, MSE 0.09443/0.001, Gradient 0.108719/1e-010
TRAINLM-calcjx, Epoch 6/1000, MSE 0.0824052/0.001, Gradient 0.0679127/1e-010
TRAINLM-calcjx, Epoch 7/1000, MSE 0.0723397/0.001, Gradient 0.0955641/1e-010
TRAINLM-calcjx, Epoch 8/1000, MSE 0.0649889/0.001, Gradient 0.0476807/1e-010
TRAINLM-calcjx, Epoch 9/1000, MSE 0.0604788/0.001, Gradient 0.0644534/1e-010
TRAINLM-calcjx, Epoch 10/1000, MSE 0.0588266/0.001, Gradient 0.366894/1e-010
TRAINLM, Validation stop.
```

Fig. 4. Training Session1

```
Select one:
 1) Continue
 2) Save
 0) Done
>>1
TRAINLM-calcjx, Epoch 0/1000, MSE 0.234676/0.001, Gradient 0.166341/1e-010
TRAINLM-calcjx, Epoch 1/1000, MSE 0.193009/0.001, Gradient 0.809487/1e-010
TRAINLM-calcjx, Epoch 2/1000, MSE 0.144965/0.001, Gradient 0.111827/1e-010
TRAINLM-calcjx, Epoch 3/1000, MSE 0.125861/0.001, Gradient 0.0496624/1e-010
TRAINLM-calcjx, Epoch 4/1000, MSE 0.111325/0.001, Gradient 0.0448054/1e-010
TRAINLM-calcjx, Epoch 5/1000, MSE 0.0993383/0.001, Gradient 0.0625852/1e-010
TRAINLM-calcjx, Epoch 6/1000, MSE 0.0908264/0.001, Gradient 0.147429/1e-010
TRAINLM, Validation stop.
```

Fig. 5. Training Session 2

```
Select one:
 1) Continue
 2) Save
 0) Done
>>1
TRAINLM-calcjx, Epoch 0/1000, MSE 0.125854/0.001, Gradient 0.825614/1e-010
TRAINLM-calcjx, Epoch 1/1000, MSE 0.0863846/0.001, Gradient 2.00552/1e-010
TRAINLM-calcjx, Epoch 2/1000, MSE 0.0463409/0.001, Gradient 0.457577/1e-010
TRAINLM-calcjx, Epoch 3/1000, MSE 0.0426037/0.001, Gradient 0.649067/1e-010
TRAINLM-calcjx, Epoch 4/1000, MSE 0.0381038/0.001, Gradient 0.0352408/1e-010
TRAINLM-calcjx, Epoch 5/1000, MSE 0.0366403/0.001, Gradient 0.10387/1e-010
TRAINLM-calcjx, Epoch 6/1000, MSE 0.0351698/0.001, Gradient 0.0133468/1e-010
TRAINLM-calcjx, Epoch 7/1000, MSE 0.0338057/0.001, Gradient 0.00929126/1e-010
TRAINLM-calcjx, Epoch 8/1000, MSE 0.0324645/0.001, Gradient 0.00760088/1e-010
TRAINLM, Validation stop.
```

Fig. 6. Training Session3

Fig. 7 shows when the performance goal was met and the program finally terminated.

```
Select one:
 1) Continue
 2) Save
 0) Done
>>1
TRAINLM-calcjx, Epoch 0/1000, MSE 0.0631287/0.001, Gradient 0.822905/1e-010
TRAINLM-calcjx, Epoch 1/1000, MSE 0.0303255/0.001, Gradient 0.376343/1e-010
TRAINLM-calcjx, Epoch 2/1000, MSE 0.0242001/0.001, Gradient 0.856958/1e-010
TRAINLM-calcjx, Epoch 3/1000, MSE 0.00574386/0.001, Gradient 0.148258/1e-010
TRAINLM-calcjx, Epoch 4/1000, MSE 0.00195052/0.001, Gradient 0.337704/1e-010
TRAINLM-calcjx, Epoch 5/1000, MSE 0.00181001/0.001, Gradient 0.200241/1e-010
TRAINLM-calcjx, Epoch 6/1000, MSE 7.69775e-005/0.001, Gradient 0.0354515/1e-010
TRAINLM, Performance goal met.
 Select one:
 1) Continue
 2) Save
 0) Done
>> 0
```

Fig. 7. Performance Goal Met

After the training and performance met, the network was tested on the weather data and the results in Fig. 8 was obtained. Y-axis is the error and X-axis is the Time in seconds.

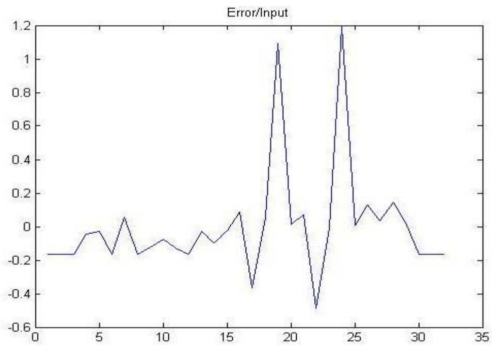

Fig. 8. Testing Results

The testing results hover around 0 and peak at 1.2 MSE (mean-squared error). Although, these is not as impressive at the training results, it is still significant. Based upon these extremely low values for daily input rainfall data presented weekly it is reasonable to assume that smaller intervals, which translates to more precise data would yield even better results. As BPN networks have been shown to benefit from increased data set size, as well as pre-processing schemes (none were applied here due to the values of the data), it is likely that these results can be improved.

However, if greater accuracy is desired, a smaller interval; such as hourly could be used. This would of course increase the size of the network and potentially require more optimization procedures be performed for the best results. In that case, those undertakings will be relegated to further research and beyond the scope of this report.

The neural network training and performance in Graphic User Interface(GUI) are shown in Fig. 9 and Fig. 10 respectively.

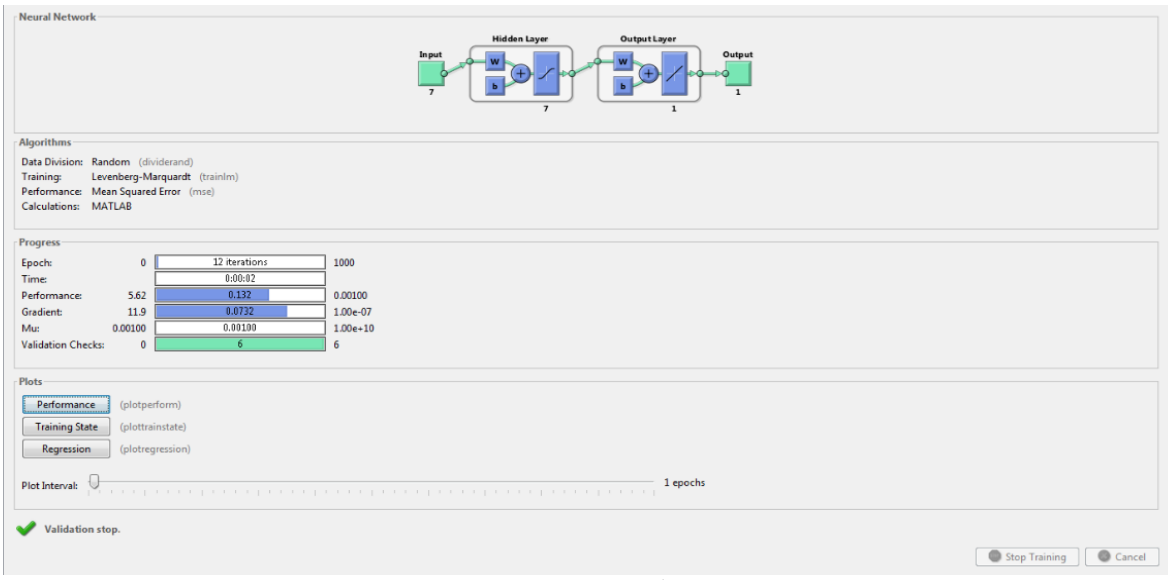

Fig. 9. GUI Training session of the Network

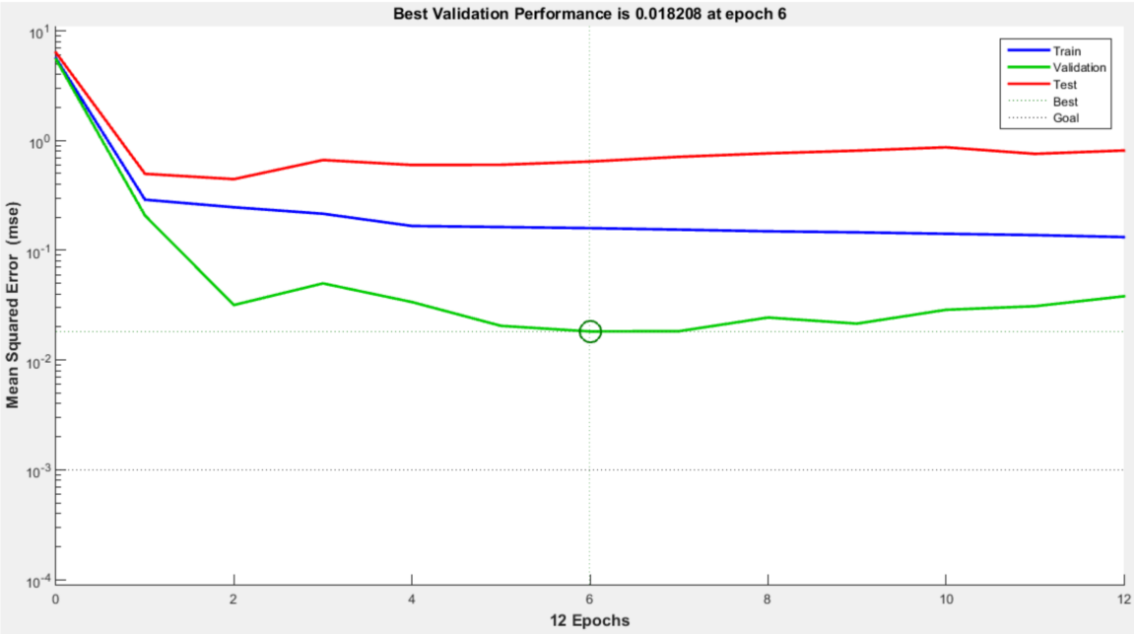

Fig. 10. GUI Performance of the Network

V. Conclusions

Rain-induced flooding is one of the direct effects of climate change and its impact on the environment is usually devastating and worrisome. In recent time flooding has become a frequent occurrence in the Niger Delta sub region and Nigeria in general. According to Global Facility for Disaster Reduction and Recovery (GFDRR), floods regularly affect Nigeria.

Rain-induced flooding is a natural hazard that must be avoided. Applying various weather forecasting models and applications help to reduce the post-flood impact on environment, people and businesses. The work thus designs and implement rain-induced flood prediction system using neural networks. We design a feed forward multilayer neural network architecture to handle the prediction and make the neural network to be adaptive having the ability to incorporate new data and update it structure. We implement the Neural Networks design in MATLAB and utilize official weather data for training and testing of the networks source from weather underground official web site (https://www.wunderground.com)

The study thus designs Neural Network-based model that can accurately predict upcoming weather in the short-term. To this end, the network is presented with rainfall data for the previous week and tasked with predicting the next day's downfall, if any. Successfully meeting this objective should serve as tangible evidence of the ability of a prediction system; such as the NFPS to be pursued.

We observed that the relationship between Ministry of Environment and Nigerian Emergency Management Agency (NEMA) is seen as a critical to advancing the abilities of the Niger Delta people to cope with Rain-induced floods, hence we wish to recommend that the two bodies should work together in this regard of rain-induced flood.

We equally, recommend that The Government of the Niger Delta States should sponsor works like this so that more detailed jobs can be done to alleviate the problems of Niger Delta people.

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