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A RAIN- STIMULATED FLOOD PREDICTION FOR RIVERS STATE USING NEURAL NETWORKS.

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ABSTRACT:
This project is to study the ability of neural networks to perform short-term prediction of the amount of rainfall of Rumudara River flooding for a specified area given previous rainfall data for a specified period of time. Short-term, in this case, means predicting the total rainfall for the next 24-hr period. The literature provides examples of neural networks being able to generate future averages of weather data if provided with data over a reasonably long range prior to the period being predicted. 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. Thus, for this project, the ability of a neural network to predict next day rainfall given a short range of precious days' data is investigating.

KEY WORDS: Weather Prediction, Feedforward Multilayer, Neural Networks Rivers State, Rain-Stimuted Flood.

INTRODUCTION

River 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. In 2012 alone there was a widespread flooding that affected almost the entire country and caused a damage computed by the post-disaster needs assessment (PDNA) (of GFDRR) and valued at 17 billion US Dollar plus various losses. And majority of the occurrence of the flooding in Nigeria are caused and started by rain. GFDRR PDNA also discovered that "Low-income households are the most vulnerable to weather-related natural disasters. Agriculture, which is heavily impacted by flooding and drought, serves as the main source of income for 80 percent of the rural poor. Furthermore, the rapid rise of urban poverty increases potential flood risk."

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 agrees that "in Nigeria, the basic causes of floods are heavy and intense rainfall associated with high run-off". Bulk of the funding of these government agencies are targeted at mitigating the after effect of the flood on the society. In some instances, flood caused the premature death of some businesses and lives. The actual value of the loss incurs during and after flooding can only be estimated in billions of naira. More worrisome is the fact that flooding now appears to be a recurring experience with little done to provide a precautionary measure that can help to reduce or eliminate the damage associated with flooding especially that which occurs during rainfall.

Since 2009 till date, several budgetary efforts have been exacted towards providing reliable flood forecasting mechanism for the entire country. While government effort in this direction is yet to be felt on large scale, this project is seeking to produce a solution that can be adapted and used by individual and software developers to produce solutions that are portable and easy to apply by all. More so, data set targeted are immediate past weather conditions and not the long historical weather data set.

Rain-induced flooding simply refers to floods caused by rainfall. According to Hofmann and Schüttrumpf (2019), rain-induced flooding may also be referring 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.

Pluvial floods are dangerous. Hofmann and Schüttrumpf (2019) maintained that Pluvial "flash flood are natural hazards that are defined as fast surface flows with high peak discharge values, often limited in their spatial extent. The most frequent cause of this type of flood is heavy rainfall events, hence the expression pluvial flash flood is used. Pluvial flooding occurs when rainfall with a high intensity (high amount of precipitation during a very short period) exceeds the infiltration capacity of soil, or the discharge capacity of sewage and drainage systems, and water flows uncontrolled through urban areas. The rainfall-induced runoff and flow processes are highly complex and vary in space and time with respect to terrain and climate conditions". Floods are natural occurrences that have fatal potentiality. According to the World Meteorological Organization (WMO), flash floods are among the natural hazards with the highest mortality rate (deaths/people affected) and because devastating property damage every year. Due to the physical characteristics of convective heavy rainfall cells, the forecasting time of pluvial flash floods is, unlike river (fluvial) floods, very short.

Consequently, as we continue to experience frequent extremes weather variables, couple with expanding vulnerable settlements and business locations, a significant risk to civilian security is posed by heavy rainfall induced floods. In contrast to river floods, pluvial flooding can occur anytime, anywhere and vary enormously due to both terrain and climate factors. Thus, it is vital to continually "…strengthening flood forecasting and national early warning capacity".

WEATHER PREDICTION

Weather forecasting is considered in many circles as the description or computation of what the weather pattern will be in future.

Existing flood forecasting systems (FFS) rely largely on long-range weather data representing measurements of rainfall occurrence, intensity or monitoring water levels collected over a long period of time. Whereas, using short-range weather forecasting is to provide information on the expected weather with forecast projection times ranging from a few hours to two or three days for both particular locations and areas covering a few million square kilometers. Almost all currently used short-range forecasting techniques involve dynamic prediction models based on an application of compressible fluid mechanics equations to the atmosphere.

Weather prediction is as old as humanity. Many of human activities are controlled by weather situations. Activities greatly impacted by weather conditions and which requires high degree of reliability in predictions are not limited to agriculture, civil constructions, transportations, games and entertainment, aviation and many others. Hence there have evolved a lot of different methods of forecasting, interpreting and reporting the weather behaviours.

All weather forecasting can be classifying under the following categories:

NOW CASTING:

Now Casting in which the details about the current weather and forecasts up to a few hours ahead are given.

SHORT RANGE FORECASTS (1 TO 3 DAYS):

Short range forecasts in which the weather (mainly rainfall) in each successive 24 hrs. Intervals may be predicted up to 3 days.

MEDIUM RANGE FORECASTS (4 TO 10 DAYS):

Medium range forecasts Average weather conditions and the weather on each day may be prescribed with progressively lesser details and accuracy than that for short range forecasts.

LONG RANGE /EXTENDED RANGE FORECASTS (MORE THAN 10 DAYS TO A SEASON):

There is no rigid definition for Long Range Forecasting, which may range from a monthly to a seasonal forecast.

RAINFALL PREDICTION MODELS:

A wide range of rainfall forecast methods are employed in weather forecasting at regional and national levels. There are two approaches to predict rainfall. They are Empirical method and dynamical methods.

GENERAL FORECASTING MODEL

Making a weather forecast involves five steps:

1. observation,
2. collection and transformation of data,
3. plotting of weather data,
4. analysis of data and extrapolation to find the future state of the atmosphere, and
5. Prediction of particular variables.

DYNAMICAL MODEL

In dynamical approach, predictions are generated by physical models based on systems of equations that predict the evolution of the global climate system in response to initial atmospheric conditions. The Dynamical approaches are implemented using numerical rainfall forecasting method.

USE OF FLUID MECHANICS IN WEATHER PREDICTION

The purpose of short-range weather forecasting to-day is to provide various users with information on the anticipated weather over forthcoming two or three days for the sites in the areas of a few million square kilometers to take necessary precautions beforehand and thus to reduce the damage of adverse weather conditions, as well as to gain maximum advantage from those favourable for various kinds of the human activity.

Attempts to predict weather on the basis of simple qualitative rules and subjective judgments have a multi-century history. From the ancient times on, human civilizations have tried to find relationships between various weather and celestial events and to use them in weather forecasting, mainly for sailing and crop production purposes. However, the quantitative and fully objective approach to weather forecasting has proved to be feasible only by describing the atmospheric weather-producing mechanisms using the basic laws of the fluid dynamics. Advances in the application of fluid dynamics to the investigation of various processes and motions in fluids and gases have attracted the scientists' attention to the dynamical weather prediction already in the 19th century. In this context, the earth's atmosphere should be considered as a viscous and compressible baroclinic fluid, which is exposed to the thermal and dynamical effect of the underlying surface, to the absorption and emission of the radiation in various spectral domains and to the heating and cooling due to phase transformations of atmospheric moisture. The equations describing evolution of this fluid are constructed on the basis of three fundamental physical laws: the laws of the conservation of momentum, mass, and energy. The first of these laws leads to three equations of motion for a fluid exerting action of the gravity force and the Coriolis force that results from the earth's rotation, the second one leads to the equations of continuity for air and water vapour, and the third one leads to the thermodynamic energy transfer equation (or the first law of the thermodynamics) which describes the air temperature, pressure, and density variations in both the presence and absence of external sources and sinks of heat (radiation emission and absorption, water phase transformations, and turbulent heat exchange). The principal problem arising when these equations are applied to the dynamical weather forecasting lies in the necessity to define and separate the atmospheric weather-producing processes among the variety of other processes occurring in the atmosphere and described by these equations (e.g., propagation of acoustic waves). This necessity has been understood only after a number of unsuccessful attempts to use the equations for straightforward prediction of the weather elements.

Predicting is making claims about something that will happen, often based on information from past and from current state.

Everyone solves the problem of prediction every day with various degrees of success. For example, weather, harvest, energy consumption, movements of forex (foreign exchange) currency pairs or of shares of stocks, earthquakes, and a lot of other stuff needs to be predicted.

In technical domain predictable parameters of a system can be often expressed and evaluated using equations - prediction is then simply evaluation or solution of such equations. However, practically we face problems where such a description would be too complicated or not possible at all. In addition, the solution by this method could be very complicated computationally, and sometimes we would get the solution after the event to be predicted happened.

It is possible to use various approximations, for example regression of the dependency of the predicted variable on other events that is then extrapolated to the future. Finding such approximation can be also difficult. This approach generally means creating the model of the predicted event.

Neural networks can be used for prediction with various levels of success. The advantage of then includes automatic learning of dependencies only from measured data without any need to add further information (such as type of dependency like with the regression).

The neural network is trained from the historical data with the hope that it will discover hidden dependencies and that it will be able to use them for predicting into future. In other words, neural network is not represented by an explicitly given model. It is more a black box that is able to learn something.

Hence the object of this project centre around the need to determining the amount of rainfall in a location if we are given some previous rainfall data.

1.2 STATEMENT OF THE PROBLEM

Rainfall of River 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. 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 problem the project seek to address is: How can we determine the volume of rainfall for the next 24-hours for a particular location.

1.3 AIM AND OBJECTIVES

The aims to evaluate the ability of neural networking to be used to predict the amount of future rainfall of River flooding over a defined period (less than or equal to one month) based on previous rainfall data. The program will be designed, built and tested in Matlab which is a software capable of implementing the concept of neural network.

1.4 SIGNIFICANCE OF THE STUDY

Weather forecasting is constantly providing avenue of averting dangers and helping to reduce the devastating impact of floods and associated hazards upon the people and businesses. The significance of this research is to provide solutions that are suitable, beneficial and useful for theoretical understanding and practical applications.

In this research, one of the core technologies of Neural network is back propagation which is evaluated and applied in designing the flood forecasting system. Back propagation is the technique used by computers to find out the error between a guess and the correct solution, provided the correct solution over this data. Theoretically this project will demonstrate the effectiveness of using Backpropagation method of neural network in carrying out prediction.

Physically, the findings of this study shall provide model and solutions which can be applied to solving flood prediction. The type of people and organizations that shall benefit from adapting the solutions are not limited to: Travelers, Tourists, Businesses, Ministry of environment, National Emergency Management Agency, Risk Management experts, Trip planners and logistics officers and many others.

Software developers and designers can also adapt the algorithm and source codes to developing mobile applications that can be of great benefit to mobile phone users.

1.5 SCOPE OF THE STUDY

This research covers the Rumudara Area of Port Harcourt sub region of Rivers State in the Niger Delta.

The data utility of the analysis and development of this system is mostly about Port Harcourt and its environs.

Port Harcourt is notorious for rainfall and therefore, the high frequency of the rainfall in port Harcourt also form a suitable data collection spot by which the efficiency of back propagation tool of neural network can be properly tested to see how it handles and uses previous locational data to predict the amount of rainfall in short range of time.

2.0 LITERATURE REVIEW

2.1 NEURAL NETWORK

Kumar Abhishek et al (2012) describe neural network as a computational structure inspired by the study of biological neural processing. We currently have many different types of neural networks, from relatively simple to very complex, just as there are many theories on how biological neural processing takes place. In some text it is refer to as artificial neural network (ANN) and just neural Network (NN). In this work, the word ANN and NN refers to the same neural network.

The advantage of the usage of neural networks for prediction is that they are able to learn from examples only and that after their learning is finished, they are able to catch hidden and strongly non-linear dependencies, even when there is a significant noise in the training set.

When relating to the biological process that gives rise to neural network some other experts describe Neural networks as relatively crude electronic networks of neurons model after the neural structure of the brain. They treat, examine, analyses and process records one at a time, and learn the features, characteristics, relationships and other attributes of that one record by comparing their assessment, assumption and prediction of the record (largely arbitrary) with the known actual record. The errors from the initial prediction of the first record is then fed back to the network and used to modify the network's algorithm for the second iteration. These steps are repeated multiple times.

TRAINING AN ARTIFICIAL NEURAL NETWORK

In the training phase, the correct class for each record is known (i.e., supervised training), and the output nodes can be assigned correct values -- 1 for the node corresponding to the correct class, and 0 for the others. Results have been found using values of 0.9 and 0.1, respectively. As a result, it is possible to compare the network's calculated values for the output nodes to these correct values, and calculate an error term for each node. These error terms are then used to adjust the weights in the hidden layers so that the next time around the output values will be closer to the correct values.

THE ITERATIVE LEARNING PROCESS

A key feature of neural networks is an iterative learning process in which records (rows) are presented to the network one at a time, and the weights associated with the input values are adjusted each time. After all cases are presented, the process often starts over again. During this learning phase, the network trains by adjusting the weights to predict the correct class label of input samples. Advantages of neural networks include their high tolerance to noisy data, as well as their ability to classify patterns on which they have not been trained. The most popular neural network algorithm is the back-propagation algorithm proposed in the 1980s.

Once a network has been structured for a particular application, that network is ready to be trained. To start this process, the initial weights are chosen randomly. Next, the training begins.

The network processes the records in the training data one at a time -- using the weights and functions in the hidden layers -- then compares the resulting outputs against the desired outputs. Errors are then propagated back through the system, causing the system to adjust the weights for the next record. This process occurs again as the weights are continually tweaked. During the training of a network, the same set of data is processed many times as the connection weights are continually refined.

Note that some networks never learn. This could be because the input data does not contain the specific information from which the desired output is derived. Networks also will not converge if there is not enough data to enable complete learning. Ideally, there should be enough data available to create a Validation Set.

FEEDFORWARD, BACK-PROPAGATION

The feedforward, back-propagation architecture was developed in the early 1970s by several independent sources (Werbor, Parker, Rumelhart, Hinton, and Williams). This independent co-development was the result of a proliferation of articles and talks at various conferences that stimulated the entire industry. Currently, this synergistically developed back-propagation architecture is the most popular and effective model for complex, multi-layered networks. Its greatest strength is in non-linear solutions to ill-defined problems. The typical back-propagation network has an input layer, an output layer, and at least one hidden layer. Theoretically, there is no limit on the number of hidden layers, but typically there are just one or two. Some studies have shown that the total number of layers needed to solve problems of any complexity is five (one input layer, three hidden layers, and an output layer). Each layer is fully connected to the succeeding layer.

The training process normally uses some variant of the Delta Rule, which starts with the calculated difference between the actual outputs and the desired outputs. Using this error, connection weights are increased in proportion to the error times, which are a scaling factor for global accuracy. This means that the inputs, the output, and the desired output all must be present at the same processing element. The most complex part of this algorithm is determining which input contributed the most to an incorrect output and how to modify the input to correct the error. (An inactive node would not contribute to the error and would have no need to change its weights.) To solve this problem, training inputs are applied to the input layer of the network, and desired outputs are compared at the output layer. During the learning process, a forward sweep is made through the network, and the output of each element is computed layer by layer. The difference between the output of the final layer and the desired output is back-propagated to the previous layer(s), usually modified by the derivative of the transfer function. The connection weights are normally adjusted using the Delta Rule. This process proceeds for the previous layer(s) until the input layer is reached.

2.2 BACKPROPAGATION IN NEURAL NETWORK

Based on review of several neural paradigms and their strengths, it has been determined that the multilayer feedforward fully connected neural network structure will be utilized employing the backpropagation (BPN) algorithm. This algorithm has continuously displayed superior ability to perform prediction and adjust to non-linear relationships among various input parameters.

Backpropagation may be regarded as supervised learning procedure, which Multi-Layer Perceptron’s in an neural network must learn or be trained upon.

The training and learning angle are one of the core features of any neural network and so cannot be abandoned. Backpropagation is an algorithm that justifies the training of the NN.

Backpropagation was introducing in neural network because when designing a Neural Network, we initialize weights in the beginning, with some random values or any variable for that fact.

Since we are often prone to errors it’s not necessary that whatever weight values, we have selected will be correct, or it fits our model the best.

Thus, we have to choose some weight values in the beginning, but our model output is way different than our actual output i.e. the error value is huge. Therefore, we must find a way to reduce the error. In order to eliminate and or reduce the error, we simply need to somehow explain the model to change the parameters (weights), such that error becomes minimum. Or in another words we say we are training our model and one way to train our model is Backpropagation.

The Backpropagation steps can be summarizing as follows:

- **Calculate the error** – How far is your model output from the actual output.
- **Minimum Error** – Check whether the error is minimized or not.
- **Update the parameters** – If the error is huge then, update the parameters (weights and biases). After that again check the error. Repeat the process until the error becomes minimum.
- **Model is ready to make a prediction** – Once the error becomes minimum, you can feed some inputs to your model and it will produce the output.

2.3 USE OF NEURAL NETWORK IN PREDICTING WEATHER

Weather forecasting is a complex operation performed by meteorological services all over the world. It includes numerous specialized fields of knowledge how. The task is complicated because in the field of meteorology all decisions are to be taken in the visage of uncertainty. Different scientists over the globe have developed stochastic weather models which are based on random number of generators whose output resembles the weather data to which they have been fit.

This project however demonstrates, the ability of neural network to utilized short-range weather data to forecast pluvial flooding in order to reduce the scale of damage to the environment, loss of lives, crippling effects on investment and businesses which demands that preventive approach is critical to curtail and reduced the level of loss and to protect lives in the event of eventualities resulting from rain-induced flooding.

The reason is that NN (Neural Network) model is based on 'prediction' by smartly 'analyzing' the trend from an already existing voluminous historical set of data. Apart from NN, the other models are either mathematical or statistical.

These models have been found to be very accurate in calculation, but not in prediction as they cannot adapt to the irregularly varying patterns of data which can neither be written in form of a function, or deduced from a formula.

These real-life situations have been found to be better interpreted by 'artificial neurons' which can learn from experience, i.e by back-propagation of errors in next guess and so on. This may lead to a compromise in accuracy, but give us a better advantage in 'understanding the problem', duplicating it or deriving conclusions from it.

Amongst all weather happenings, rainfall plays the most imperative part in human life. Human civilization to a great extent depends upon its frequency and amount to various scales. Several stochastic models have been attempted to forecast the occurrence of rainfall, to investigate its seasonal variability, to forecast yearly/monthly rainfall over some geographical area.

The project endeavors to develop a system solely driven by an NN model to forecast the volume of rainfall in the next 24 hours and up to 2 or 3 days in Port Harcourt.

Port Harcourt is the capital city of Rivers State, dubbed the Treasure base of Nigeria's. It plays host to major economic drivers of the nation and with its known irregular and frequent rainfall pattern the issue of prediction of rainfall is a challenging topic to

Atmospheric experts in Nigeria.

2.4 SOME HISTORICAL REVIEW OF VARIOUS WEATHER PREDICTION MODEL IN RELATION TO NEURAL NETWORK

Kumar Abhishek et al (2012) provide some historical perspective of neural network and its initial application when they said that Hu (1964) initiated the implementation of NN, an important soft computing methodology in weather forecasting. Since the last few decades, NN a voluminous development in the application field of NN has opened up new avenues to the forecasting task involving environment related phenomenon (Gardener and Dorling, 1998; Hsiesh and Tang, 1998). Michaelides et al (1995) compared the performance of NN with multiple linear regressions in estimating missing rainfall data over Cyprus. Kalogirou et al (1997) implemented NN to reconstruct the rainfall over the time series over Cyprus. Lee et al (1998) applied NN in rainfall prediction by splitting the available data into homogenous subpopulations. Wong et al (1999) constructed fuzzy rules bases with the aid of SOM and back-propagation neural networks and then with the help of the rule base developed predictive model for rainfall over Switzerland using spatial interpolation. Toth et al. (2000) compared short-time rainfall prediction models for real-time flood forecasting. Different structures of auto-regressive moving average (ARMA) models, NN and nearest-neighbor's approaches were applied for forecasting storm rainfall occurring in the Sieve River basin, Italy, in the period 1992-1996 with lead times varying from 1 to 6 h. The NN adaptive calibration application proved to be stable for lead times longer than 3 hours, but inadequate for reproducing low rainfall events. Koizumi (1999) employed an NN model using radar, satellite and weather-station data together with numerical products generated by the Japan Meteorological Agency (JMA) Asian Spectral Model and the model was trained using 1-year data. It was found that the NN skills were better than the persistence forecast (after 3 h), the linear regression forecasts, and the numerical model precipitation prediction. As the NN model was trained with only 1-year data, the results were limited. The author believed that the performance of the neural network would be improved when more training data became available. It is still unclear to what extent each predictor contributed to the forecast and to what extent recent observations might improve the forecast.

Abraham et al. (2001) used an NN with scaled conjugate gradient algorithm (ANN-SCGA) and evolving fuzzy neural network (EfuNN) for predicting the rainfall time series. In the study, monthly rainfall was used as input data for training model. The authors analyzed 87 years of rainfall data in Kerala, a state in the southern part of the Indian Peninsula. The empirical results showed that neuro-fuzzy systems were efficient in terms of having better performance time and lower error rates 5 compared to the pure neural network approach. Nevertheless, rainfall is one of the 20 most complex and difficult elements of the hydrology cycle to understand and to model due to the tremendous range of variation over a wide range of scales both in space and time (French et al., 1992).

3.0 METHODOLOGY

At this stage of the Research, we shall discuss the procedure that is adopted in carrying out this project. The discussion shall focus on the research design, area of the study, procedures followed and resources used to develop the system

The area of research is Port Harcourt. On 25 July 2017, GardaWorld reported that as a result of flooding in Port Harcourt, Rivers State, Nigeria three people had lost their lives and severe damage to infrastructure had occurred (GardaWorld). These results are indicative of what can occur when extreme rains coupled with inadequate contingency planning coincide. As Port Harcourt is subject to this type of weather, especially during the annual rainy season from March.

Port Harcourt, which is an important trading center for Nigeria, lies in the Niger Delta at a low elevation. Waterways, such as the Bonny River and creeks, are subject to flooding during periods of “high intensity” rains. According to (K. C. Chiadikobi), high intensity rains are categorized as high volume events where the rate of downfall is greater than 0.13mm/min. And during the decade from 1998-2007, the following high intensity rainfall occurred (see figure 3.1).

At least two conclusions can be drawn from this. First, the area is at a reasonable risk of flooding even when the number or percentage of rainfall days during the rainy season is moderate to low. Second, there are other factors contributing to the flood events themselves.

The second conclusion stated above is the focus of research performed by Akukwe in *Determinants of Flooding in Port Harcourt Metropolis, Nigeria*. By gathering data from a number of sources; including persons living in the affected areas, the author analyzed and ranked nine factors according to their documented or presumed causality for flooding. The results obtained ranked rainfall as the second most important factor behind inadequate drainage facilities. **Source and reliability of historical weather data_** the historical data is critical to this kind of project. 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 centre 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.

The network of Weather Underground generates weather data also from Meteorological Assimilation Data Ingest System (MADIS) which is managed by the National Oceanic and Atmospheric Administration (NOAA) and other satellite observatory agencies like NASA and their observations are reported on hourly basis.

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.

consequently, the backpropagation (BPN) algorithm has continuously displayed superior ability to perform prediction and adjust to non-linear relationships among various input parameters.

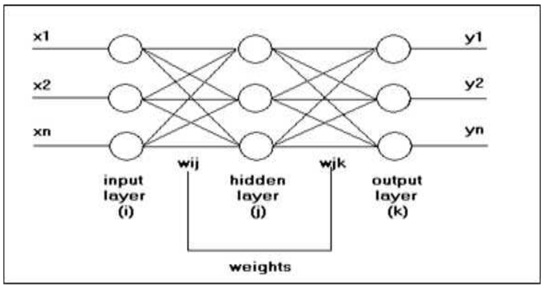

Figure1: Neural network architecture

3.1 Determination of neural structure and parameters

A general view of the BPN network is shown in Figure, above. The network consists of three layers and several parameters that need to be determined. In order to determine a suitable network architecture for the neural network FPS or Neural Network Flood Prediction System (NFPS), the process defined in *"An Optimal Design Method for Multilayer Feedforward Networks"* (Cooke) is relied upon. In this work, the author presents a systematic method for arriving at an optimal neural network architecture based on the problem to be solved. Here a portion of that strategy is implemented to determine the boundaries for the Neural Network Flood Prediction System.

Let's define the target date for prediction to be x, then we want to know if the Neural Network Flood Prediction System can accurately determine the risk of flooding or the level of rainfall for days x-1, x-2, …, x-7 or up to one week before the target. Thus, our network needs to be able to accept the actual rainfall for the seven days before the target and provide a single output of the predicted rainfall for the target day. This indicates that the Neural Network Flood Prediction System should have seven neurons in the input layer and one output layer neuron. According to Cooke in *"An Optimal Design Method for Multilayer Feedforward Networks",* the maximum number of hidden layer neurons would be seven. Thus, this will be the network architecture for this initial investigation of the Neural Network Flood Prediction System.

3.2 Result and Discussion

This research used the following hardware and software tools:

- Hardware: Desktop Computer
- Software: Matlab *(Matlab is an industry leader in mathematical and scientific modeling and analyses distributed by **The MathWorks, Inc.**)*

The neural network was implemented using Mathlab. The program created with Mathlab is saved as npfs.m as the filename. By building the NFPS using this platform, extensions, enhancements or modifications can be performed and tested easily. Moreover, the program can be converted to executables for other operating systems; such as Windows and Linux.

3.3 Training and Testing Data

Experimentation:

In order to evaluate the ability of neural networks to perform short-term rainfall prediction, a BPN network will be modelled in Matlab and tested for various short-term input periods. These results will be compared, and the best model will be determined. Successful prediction will be measured as the network's ability to match the actual next day rainfall within a present tolerance, which is yet to be determined.

Table1: Training Data Sample

0	0	0	0	0	0	0
0	0	0	0	0	0	0
0	0	0	0	0	0	0
0	0	0	0	0	0	0
0	0	0	0	0	0	0
0	0	0	0	0.04	0	0.83
0	0	0	0	0	0	0
0	0	0	0	1.38	0	0.04
0.04	0	0	0	0	0	0
0	0	0.12	0	0	0	0
0	1.46	0	0	0	0	0
0	0	0.75	0.94	0.08	0	0
0	0	0	0	0	0	0
0	0	0.04	0	0	0	0
0.04	0.43	0	0	0	0	0.24
0	0	0.63	0	0.08	0	0
0.04	0	0	0	0	0	0
0	0	0	0	0	0	0
0	1.73	0	3.39	0	0	0

Table2: Testing Data Sample

0	0	0	0	0	0	0
0	0	0	0	0	0	0
0	0	0	0	0	0	0
0	0	0	0	0	0	0
0	0	0	0	0	0	0
0	0	0	0	0.04	0	0.83
0	0	0	0	0	0	0
0	0	0	0	1.38	0	0.04
0.04	0	0	0	0	0	0
0	0	0.12	0	0	0	0
0	1.46	0	0	0	0	0

0	0	0.75	0.94	0.08	0	0
0	0	0	0	0	0	0
0	0	0.04	0	0	0	0
0.04	0.43	0	0	0	0	0.24
0	0	0.63	0	0.08	0	0
0.04	0	0	0	0	0	0
0	0	0	0	0	0	0
0	1.73	0	3.39	0	0	0
0	0	0.28	0	0	0	0
0	0	0.39	0	0.12	0	0
0	0.91	0	0	0	1.26	0
0	0	0.16	1.14	0	0	0
0	0	0.08	0.24	0	0	0
0	0.51	1.77	0	0	0.75	0
0	1.1	0	0	0	0	0
0	0.43	0	0	0.35	0	0
0.12	0	0	2.2	0.71	0	0
0	0.04	0.12	0	0	0	0.01
1.3	4.57	0	0	1.42	0.04	0
0	0	0	0	0	0.01	0.02
0.31	0.39	0.12	0.31	0	0.08	0.16
0	0	0.35	0.12	0.12	0.67	0.2
0.47	0.16	0.79	0.12	0	0	0
0.43	2.36	0.24	0.35	1.34	0.01	0.31
0	0.01	2.2	1.57	0.08	0	0
0	0.12	3.15	0	0.01	0	0
0.02	0	0	2.52	0.35	0	0.24
1.97	0.31	0	0.28	0	0	0
0.2	0.08	0.87	1.3	0	0.39	0
0.04	0.47	0	0.04	0	0	0.08
1.73	0	1.02	0	0.04	0	0
0.28	0	0	0	0	0.87	0
0.28	0	0.03	0.51	1.1	0	0
0.04	0.01	0	0	0	0	0
0.28	0	0	0	0	0.35	0
1.65	0	0	0	0	0	0
0	0	0	0	0	0	0

Year	Pct. of High Intensity Rainfall Days
1998	24.2
1999	52.7
2000	20.4
2001	20.4
2002	40
2003	35.8
2004	25.5
2005	53.8
2006	44.6

Flooding actually occurred for seven of the ten-years illustrated in chart below, Fig. 3.1: 1998, 2000, 2002-2004, 2006 and 2007.

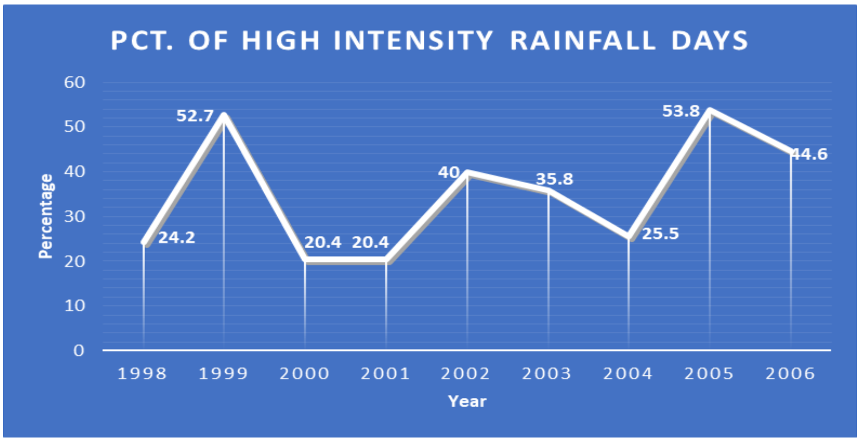

Figure 2: Review of Port Harcourt Rainfall Intensity, 1998-2007

Port Harcourt, which is an important trading centre for Nigeria, lies in the Niger Delta at a low elevation.

4.0 SOURCE CODE LISTING

This source is purely a Math lab source code:

%This program implements the ANN rainfall prediction module of the NFPS. This %module implements a multilayer feedforward architecture running the BPN

%paradigm. It accepts as input data files for:

% Option 1: Training a Network

% Option 2: Testing a Network

%and generates files consisting of learning/training and testing results.

%The ANN structure is also saved, if desired by the user, for further

%training/testing. The user is able to select both input files and output

%file names.

```
%%
```

DEFINE VARIABLES

```
%net current network being built/trained/tested.
%option indicates training (1) or testing (2) mode.

%% INITIALIZE
Clear all;
Fprintf ('\n\n Starting module NFPS:');
%% GET USER INPUT
Option=9;
While option ~= 0
 Option=input ('\n\n Select one: \n 1) Train Network\n 2) Test Network\n 0) Exit\n  >>');
   if option == 0
      break;
   elseif option ~= 1 && option ~= 2
      fprintf('\n INVALID OPTION! PLEASE REENTER!');
   else
%% GET INPUT DATA
      if option == 1
         fprintf('\n Running Training Mode:');
         trainin=input('\n Enter train data file name>> ','s');
         load (trainin);
         x=x';
%           A=size(x)
         y=y';
%           C=size(y)
%% BUILD/EDIT ANN
         usropt=input('\n Select one:\n  1) Existing network\n  2) New network\n  >>');
         if usropt == 1
            netin=input('\n Enter ANN input file name>> ','s');
            net=load(netin);
         elseifusropt == 2
%%             Network Default Parameters. These can be edited.
            net = newff(x,y,7);
            net.trainParam.show = 1;
            net.trainParam.lr = 0.5;
            net.trainParam.epochs = 1000;
            net.trainParam.goal = 1e-3;
            net.trainParam.mc = 0.9;
         else
            break;
         end
%% TRAIN ANN
         usropt=1;
         while usropt ~= 0
            if usropt == 1
               [net,tr,out,err] = train(net,x,y);
               g=tr
            elseifusropt == 2
               netout=input('\n Enter ANN output structure file name>> ','s');
```

```
            save(netout,'net','tr')
          elseifusropt ~= 0
            fprintf('\n INVALID OPTION! PLEASE REENTER!');
          end
          usropt=input('\n Select one:\n  1) Continue\n  2) Save\n  0) Done\n >>');
        end
        fprintf('\n Exiting Training Mode:');
        clear 'x''y''net';
%% TEST ANN
      elseif option == 2
        fprintf('\n Running Testing Mode:');
        testin=input('\n Enter test data file name>> ','s');
        load(testin);
        x=x';
        y=y';
        netin=input('\n Enter ANN input file name>> ','s');
        load(netin,'net');
        [net,tr,out,err] = train(net,x,y);
        figure
        plot(err);
        title('Error/Input');
        net = revert(net);
        usropt=input('\n Save results?\n  1) Yes\n  2) No\n >>');
        if usropt == 1
          result=input('\n Enter ANN output results file name>> ','s');
          save(result,'net','out','err');
        end
        fprintf('\n Exiting Testing Mode:');
        clear 'x''y''net';
      end
    end
%% EXIT
end

fprintf('\n\n Exiting module NFPS:\n');
```

4.1 ANALYSIS OF RESULTS

A neural network structure defined with 7 inputs, 1 output and a seven pe hidden layer was built, trained and tested. The network structure is given in Attachment 7. The network was trained and tested on data presented via Attachment 8. The target mean-squared error (MSE) rate for training was .001. The network was able to exceed this threshold and training was halted once an error/pe of 7.69775e-005 was obtained. An excerpt of the training session is shown below.

TRAINLM, PERFORMANCE GOAL MET.

After training, the network was tested on the weather data and the following results were obtained.

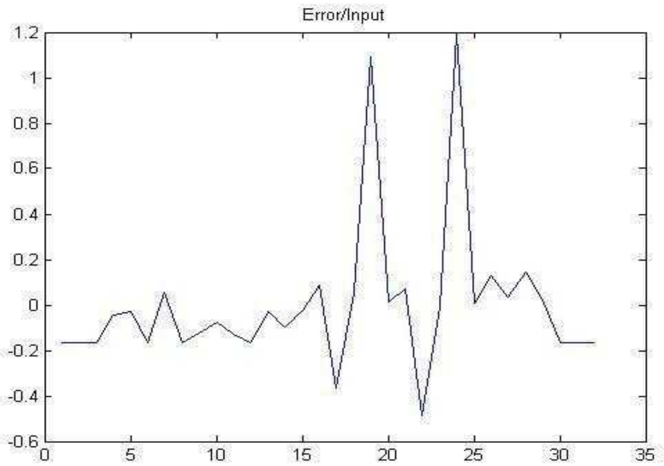

Figure 3: NFPS Testing Results

As shown above, 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.

5.0 CONCLUSION AND RECOMMENDATION

In this research, the justification for and implementation of a neural network structure to perform short-term rainfall prediction is presented. The goal here was to take the first step in validating this approach for what may blossom into a sophisticated early warning system to minimize the destruction and fatalities that have been suffered by people in the Port Harcourt, Rivers State region of Nigeria.

The results clearly validate the underlying artificial neural network foundation and should be used as motivation for continued research and development.

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