

Artificial Neural Network Modeling of Rainfall in Ilorin, Kwara State, Nigeria.

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Abstract

Accurate information about rainfall is essential for the management of water resources, disaster prevention, and agricultural production. On a worldwide scale, numerous attempts have been made to predict behavioural pattern using various techniques. This paper is aimed at developing a real time Artificial Neural Network based rainfall forecasting model for Ilorin, Nigeria using observed rainfall records. This ANN model is designed to run a real time task in which the input to the model is a consecutive data of the rainfall. The neural network was trained with sixty years (1952–2011) total monthly historical rainfall data. The trained network yielded 76% and 87% of good forecast for the training and testing data set respectively. The correlation coefficient of 0.88 was obtained which showed that the network is fit to be used for the subsequent quantitative prediction of rainfall in Ilorin.

Keywords

Rainfall model, ANN, training algorithms, connection weights, coefficient of correlation.

1. Introduction

Rainfall is a natural climatic phenomenon whose prediction is challenging and demanding as the world continues to witness an ever changing climate conditions. Its forecast plays an important role in water resource management and therefore, it is of particular relevance to agricultural sector, which contributes significantly to the economy of any nation. Rainfall is one of the most complex and difficult

elements of the hydrological cycle to understand and model due to the tremendous range of variation over a wide range of scales both in space and time (French et al., 1992). The complexity of the atmospheric processes that generate rainfall makes quantitative forecasting of rainfall an extremely difficult task (Hung et al, 2008). Generally, rainfall has strong influence on the operation of dams and reservoirs, sewer systems, traffic and other human activities. As a result, 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). Many computational methods of modeling have been proposed in an attempt to predict rainfall accurately (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. Black box models normally contain no physically-based input and output transfer functions. It is therefore considered to be purely empirical models. Artificial Neural Network (ANN) which is one of the artificial intelligent techniques is a typical black box model. The development of this model has recently become an important alternative tool to conventional methods such as regression methods in modeling of non linear functions.

ANN was first developed in the 1940s and the development has experienced a renaissance in iterative auto-associable neural networks (Hung et al, 2008). In recent decades, various commercially available algorithms such as MATLAB, NuExpert, NeuNet, Easy NN, ALYUDA-Forecaster, etc have been developed to overcome a number of limitations in the early networks. This makes the practical applications of ANN more appreciable in the field of hydrology. The operation is based upon the neural structure of the human brain. An ANN provides the user 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, ANN could learn and generalize from examples to produce meaningful solution even when the input data contain errors or is 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 function optimization. Training of the network with the relevant data enable

the network with the ability of making predictions based on any input it encounters (Kumarasiri and Sonnadara, 2006). Based on the structure of the learning algorithm of neural networks, various neural network models have been studied 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.

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; and Karim, 2009); precipitation prediction (Kevin, 2008; and Khaing and Thinn, 2008); rainfall modeling (Sunyoung et al, 1998; Hung et al, 2008; and Somvanshi et al, 2006); and simulation of daily temperature (Ricardo and Jean, 1999). According to Khaing and Thinn (2008), among the forty eight (48) studies conducted using ANN between 1988 and 1994, Adya and Collopy (1998) found that neural network models produced superior predictions. The results obtained showed that 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.

2. Materials and Method

2.1 Study Area

The study area, Ilorin, is the capital city of Kwara State, Nigeria. It is located at Latitude 8° 24'N and 8° 36'N and Longitude 4° 10'E and 4° 36'E as shown in Figure 1. It has an approximate area of about 32,500Km² (Fadeyi et al, 2009). It is situated in the North central of Nigeria at about 302km North of Lagos and 475km south of Abuja (FCT). The climate of Ilorin is characterized by both wet and dry seasons. The mean monthly temperatures are very high varying from 25°C to 28.9°C (Ajadi et al, 2011). The diurnal range of temperature is high in the area. The rainfall in Ilorin city exhibits greater variability both temporarily and spatially. The total annual rainfall in the area is about 1200mm (Olaniran, 2002). The diurnal regime of moderate rain in the area shows clear nighttime rainfall maximum. Relative humidity

at Ilorin in the wet season is between 75 and 80% while in the dry season, it is about 65% (Ajadi et al, 2011).

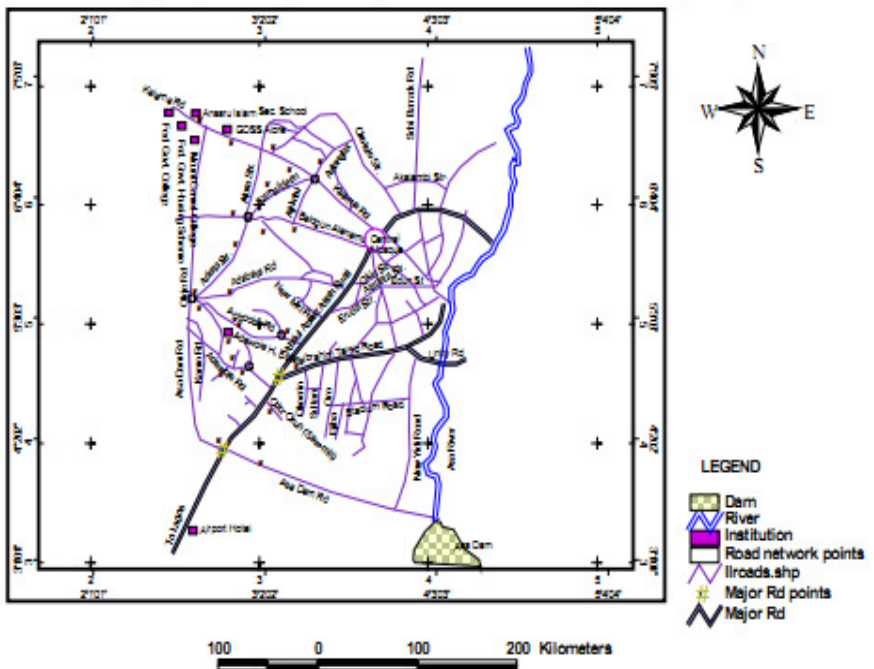


Figure 1 Location map showing the Ilorin metropolis (Ajadi et al, 2011).

2.2 ANN model

An ANN is a highly interconnected network of many simple processing units called neurons, which are analogous to the biological neurons in the human brain (Andy et al, 2004; Hung et al, 2008; Kumarasiri and Sonnadara, 2006; and Luk et al, 2001). 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.

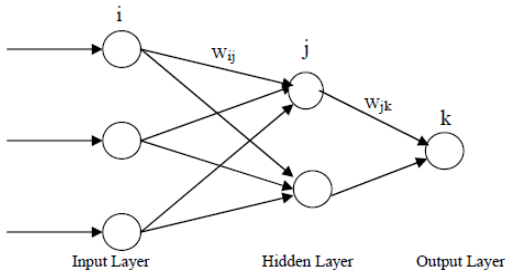


Figure 2 Typical ANN topology

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 k , (dependent variables) which produces output information, is called an output layer. There exists between the output and input layers the hidden layers 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} . Somvanshi et al (2006) recommended the use of one hidden layer in preliminary studies. Having more than one hidden layer will definitely increase the number of parameters to be estimated. This may slow down the training process without reasonably improving the efficiency of the network.

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. MLP maintains high level of research interest due to its ability 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-sigmoid function as shown in Equation 1. This function map any input to a finite output range usually between 0 and 1 or -1 and 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 two; prior to the model building: the training and validation sets. A set is used for training and the other is 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 root-mean-square error (RMSE), mean square error (MSE), Mean Absolute Percent Error (MAPE) and the coefficient of correlation (CORR) to examine the model performance (Somvanshi et al, 2006; Khaing and Thinn, 2008; Hung et al, 2008; and Karim, 2009).

$$y_i = \frac{1}{1 + e^{-x_i}} \quad (1)$$

Where y_i = model output, x_i = model input, e = exponential function

2.3 ANN training algorithms

The training of the network 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). There are basically two types of training mechanisms: supervised and unsupervised training. A supervised training algorithm also known as back propagation training algorithms requires an external teacher to guide the training process. The goal of supervised training is to minimize the error at the output layer by searching for a set of connection strengths that cause the ANN to produce outputs that are equal to or closer to the targets (Shiru and McCann, 2011 and Karim, 2009). A supervised training mechanism is normally adopted in most of the engineering applications. An unsupervised training algorithm called self-organizing neural network is used when the training set lacks target output values (Shiru and McCann, 2011). The most famous self-organizing neural network 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.

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

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. The main steps involved in the training are as illustrated below:

- (i) initialize network weight value, usually using small numbers obtained from random number generator;
- (ii) carry out forward propagation of the first input vector through the whole network. i.e. input signals multiplied by corresponding synaptic weights and then summed at each node. This is further transformed by an activation function in Equation 1 and sent to the output node;
- (iii) compute the error by comparing the model output with the target (observed) data;
- (iv) back-propagate the error information through the network;
- (v) update the weights and
- (vi) repeat the previous steps for several iterations until the error is within an acceptable range.

The above procedures are as summarized in the flow chart shown in Figure 3.

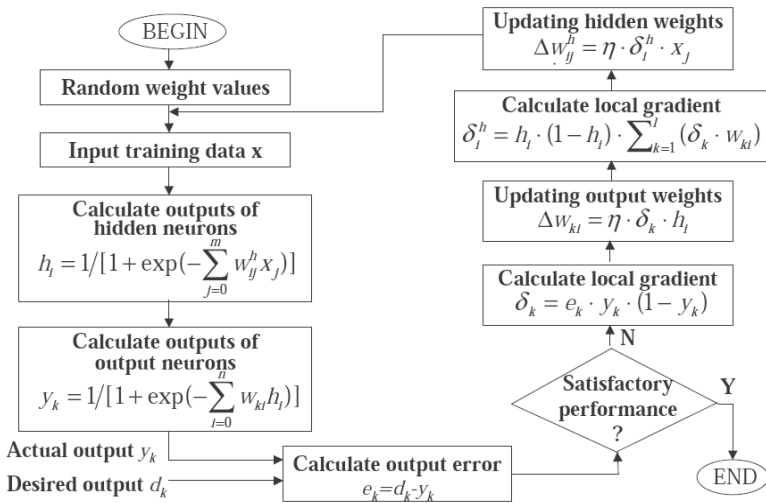


Figure 3 Flow chart for the training process (Shiru and McCann, 2011)

In this study, the model is trained using the data format of the form in Equation 3. After the network is adequately trained as demonstrated in Figure 2, it has to be tested for its ability to produce accurate outputs.

$$\mathbf{X}_t = f(\mathbf{X}_{t-1}, t-2, t-3, \dots, \mathbf{X}_{t-n}) \quad (3)$$

where x_t = rainfall data at the present time, x_{t-1} = subsequent rainfall data series.

3.0 Data analysis

The most common problem that a modern data analyst encounters is the extraction of meaningful conclusions about a complicated system using data from a single measured parameter. For this study, rainfall data for Ilorin, the study area, was collected for a period of sixty

years (1952–2011) from Nigerian Metrological Agency (NiMET) in Ilorin. The total monthly rainfall values from several successive observations are computed and fed into the neural network. The network training of the rainfall data was automated in ALYUDA forecaster software with total of seven hundred and twenty (720) rainfall data. According to the early stopping method, the data were split into two (2) sets: training and validation set. The training set was used to train the network whereas the validation set was used to monitor or test the network performance at regular stages of the training. During the training, weights of input and hidden layer nodes were adjusted by checking the training and testing stage performances of neural network as automated in ALYUDA forecaster. 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 coefficient of determination and the mean square error were as the performance criteria for the testing stage.

4.0 Discussion of results

ALYUDA forecaster was used in this study for the training of the network. This 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 ‘ALYUDA forecaster XL’ environment automatically generated best network structure. This topology produced 76% and 87% of good forecast in the training and testing data set respectively. The correlation coefficient obtained for the training in neural network was 0.88. The performance report of the network generated a scatter plot of the network forecasted rainfall against the actual rainfall values which are shown in Figure 4. This Figure showed that there is a linear relationship between the actual and forecasted rainfall values.

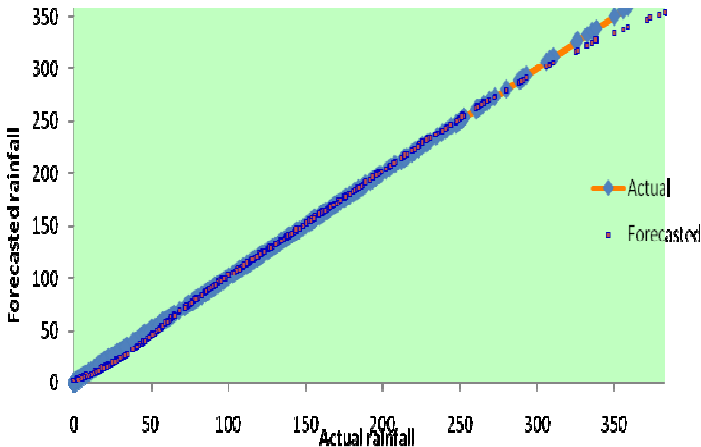


Figure 4 Scatter plot of forecasted and actual rainfall data

5.0 Conclusion

Rainfall is one of the key entities of hydrological cycle that strongly influence the operation of dams and reservoirs, flood control, drought mitigation, operation of sewer systems, agricultural practice, traffic conditions and other human activities. As a result, accurate modelling of rainfall plays an important role in the management of water resources. The modelling of rainfall data of Ilorin using ANN, automated in ALYUDA Forecaster showed that ANN is a good method of optimization, since error observed in the comparison of actual and model output is minimal. The neural network summary yielded 76% of good forecasts for rainfall in Ilorin with correlation coefficient of 0.88. This showed that the trained network is reliable and fit to be used for the subsequent quantitative prediction of rainfall. It can therefore be concluded that forecasting using ANN is a very versatile tool in water resources management modelling.

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