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Application of Artificial Neural Network (ANN) for the Modelling and Prediction of Ikpoba River Flow Data

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Abstract

This study focuses on evaluating the effectiveness of artificial neural network (ANN), specifically employing the Levenberg Marquardt Back Propagation algorithm, for streamflow prediction in Ikpoba River, Benin City. Hydrological data from September 2022 to March 2023, along with historical data (2010-2015), were used to establish a cubic polynomial relationship between gage height and river discharge. The ANN model, with 10 hidden neurons, demonstrated a strong performance with a mean square error of 0.000303, surpassing the target error of 0.01. The study highlights the significance of accurate streamflow prediction models, especially in mitigating floods and optimizing reservoir management.

1.0. Introduction

Adequate scientific evidence exists now to show that the global climate is changing [1, 2]The three prominent signals of climate change, namely; increase in global average temperature, rise in sea levels, and change in precipitation patterns have culminated into regional-scale hydrologic change resulting in extremes of floods, droughts and other related phenomenon such as; water availability, water demand, water quality, salinity intrusion in coastal aquifers and groundwater recharge [3, 4]. Increase in atmospheric temperature, for example, is likely to have a direct impact on river runoff, water demands of crops and vegetation including; the indirect impacts on all other hydrological processes of interest [5]. Similarly, a change in the regional precipitation pattern may have a direct impact on the magnitude and frequency of flood, including droughts and water availability [6, 7].

River flow forecasting is one of the most important components of hydrological processes in water resource management [8, 9]. Accurate estimations for both short- and long-term forecasts of river flow can be used in several water engineering problems such as designing flood protection works for urban areas and agricultural land and optimizing the allocation of water for different sectors such as agriculture, municipalities, hydropower generation, while ensuring that environmental flows are maintained [10, 11]. The identification of highly accurate and reliable river flow models for future river flow is an important precondition for successful planning and management of water resources.

Lack of adequate streamflow data have continued to pose a serious challenge to Hydrologist and Water Resources Engineers in dealing with the issues of flooding and hydroelectric power generation especially in developing nations. In addition, many engineering projects require the information regarding the accurate and reliable streamflow prediction model for both short term and long term predictions. These kinds of information are of great important in planning, design and management of hydraulic structures such as; dams, spillways, culverts and water resources management such as; allocation of water for different sectors like agricultural, municipalities and hydropower generation, while ensuring that environmental flows are maintained.

Most available time series analysis considers linear relationships between variables. However, in the real world, temporal variations in data are difficult to analyze and predict since they do not show simple regularities [12,13,14]. The use of non-linear models such as Artificial Neural Networks (ANN), which are capable of modelling complex non-linear problems, can be suitable for real world temporal data [15, 16]. Neural networks procedure is considered data driven as opposed to model driven procedures. This is due to its dependence on the available data [16,17].

Artificial neural networks (ANNs) belong to a class of models, where difference or differential equation are used to identify a direct mapping between inputs and outputs without detailed consideration of the internal structure of the physical processes [18,19]. An ANN is a system inspired by the operation of biological neurons with the purpose of learning a certain system. The construction of an ANN is achieved by providing a stimulus to the neuronal model, calculating the output, and adjusting the weights until the desired output is achieved. An entry is submitted to the ANN along with a desired target, a defined response for the output (when this is the case, the training is regarded as supervised). In this case, wind speed, temperature and evaporation become the entry data while rainfall is the target data. An error field is built based on the difference between the desired response and the output of the system. The error information is used as feedback for the system, which adjusts its parameters in a systematic way; in other words, the back propagation error algorithm is used to train the network. According to [20,21,22], the back propagation architecture is the most popular, most effective, and easiest-to-learn model for complex, multilayered networks. This network is used more than all others combined. This algorithm has a first phase with a functional propagation signal (feed forward) and a second phase with the back propagation of the error (back propagation).

2.0. Methodology

2.1 Description of study area

Ikpoba River is situated within the rainforest belt of Edo State, southern Nigeria. The river rises from the Ishan Plateau in the northern part and flowing in south westerly direction in a steeply incised valley and through sandy areas before passing through Benin City and joining the Ossiomo River. Edo State lies roughly between longitude 06^o 04'E and 06^o 43'E and latitude 05^{o}44' N and 07^{o}34' N. Edo State has a tropical climate characterized by two distinct seasons: the wet and dry seasons. The wet season occurs between April and October with a break in August, and an average rainfall ranging from 150 cm in the extreme north of the State to 250 cm in the south. The dry season lasts from November to April with a cold harmattan spell between December and January. The temperature averages about 25 °C (77 °F) in the rainy season and about 28 °C (82 °F) in the dry season. The climate is humid tropical in the southern part and sub-humid in the northern part . Ikpoba River is highly disturbed while passing through Benin City due to the high population density and the dependence on the stream. Victor and Dickson (1985) reported that in the upper reaches of the stream, it flows through a dense rainforest where surface run-off and organic matter from the surrounding vegetation contribute to organic input. At the outskirt of the city, riparian settlements are thinly populated, so that disturbance due to human activities is low and localized. The river is particularly important to the people of Benin City. One of the major dams in the Edo

State was constructed across the river in Okhoro Community. The name of the dam is Okhoro Dam. The dam was built mainly for water supply and was used by the then Bendel State Urban Water Board to supply pipe-borne water to some parts of Benin Metropolis. Downstream riparian communities depend on the river for water for various domestic purposes. Car washing companies are also attached to the river in Benin City. Industrial effluence and water from drainage channels are discharged into the river at various points. The study area map is presented in Figure 1.

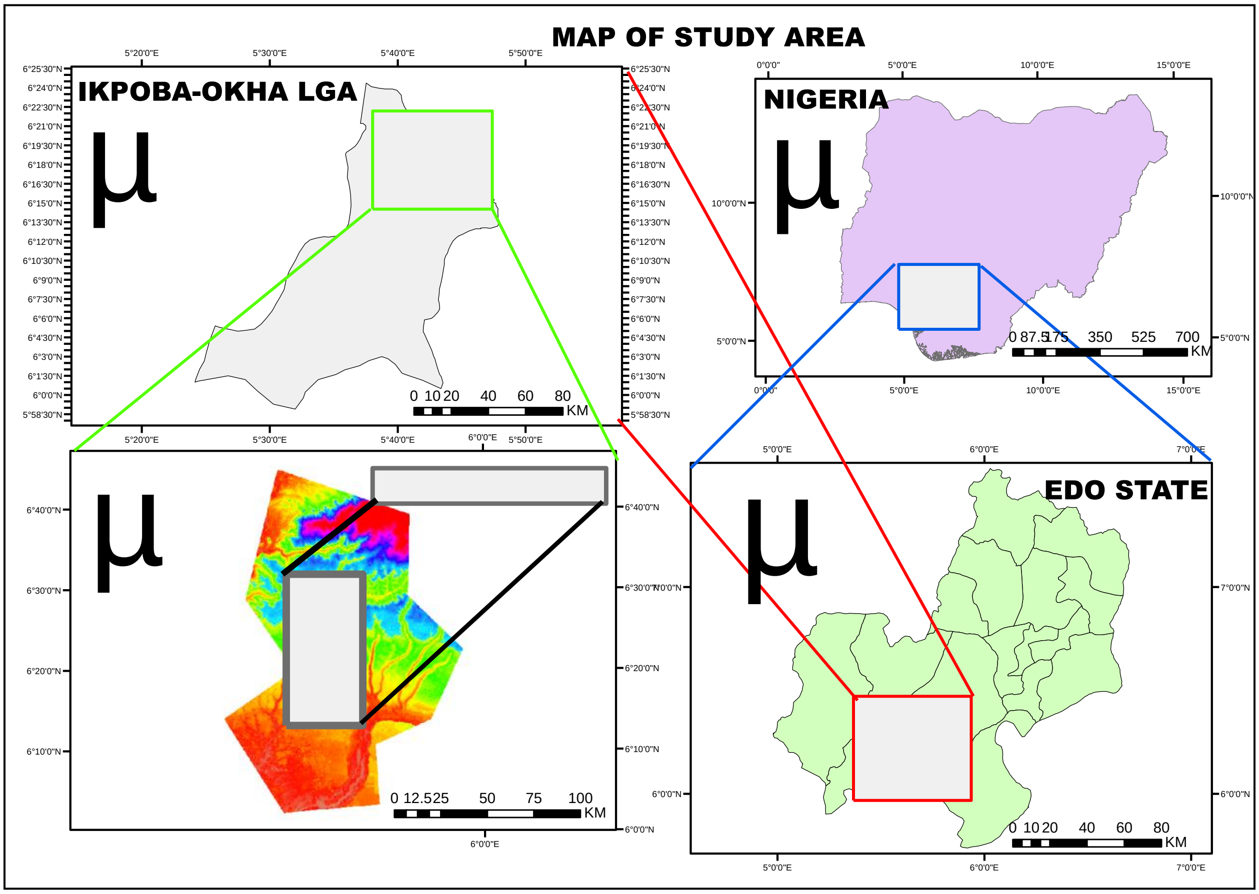

Figure 1: 3D map of the study area

2.2 Data Collection

Hydrological data, namely; gage height, pressure and temperature for Ikpoba River, Benin City Edo State were acquired using hydromet instrument at an interval of 15 minutes from September 2022 to March 2023. In addition, historical gage and discharge data (2010-2015) were extracted from the rating curve of Ikpoba River. Curve fitting analysis was applied to the data in order to determine the exact mathematical relationship between the gage height (m) and the river discharge (M^3/s). Using the goodness of fit statistics, namely; coefficient of correlation (r), Adjusted-R^2 value and standard error of estimate (SEE), the cubic polynomial relationship was selected as the best fit relationship between gage height and river discharge and was thereafter employed to determine the river discharge using the measured gage height from September 2022 to March 2023. To obtain the optimal network architecture that possesses the most accurate understanding of the input and output data, two factors were considered. First was the selection of the most accurate training algorithm and secondly, the number of hidden neurons.

2.3 Streamflow analysis using ANN

To train a network, large volume of data is required. In this study, 14,521 rows of data subdivided into 4 columns (pressure, temperature, gage height and discharge) were used. To apply neural network, 60% of the data was employed to train a network, 25% of the data was used to validate the network while the remaining 15% was used to test the performance of the network. The neural network modelling and prediction was done with the aid of a neural network modelling tool (MATLAB 10.1). The basic steps involved in the application of the network are as follows:

i. Normalization of the data
ii. Selection of optimum training algorithm or learning rule
iii. Selection of optimum number of hidden neurons
iv. Training of the network
v. Network validation
vi. Network testing and prediction

To avoid the problem of weight variation which can subsequently affect the efficiency of the training process, the input and output data were first normalized to obtain a value of between 0.1 and 1.0 using the normalization equation proposed by [19]as follows;

$$x_i = \frac{x - x_{\min}}{x_{\max} - x_{\min}} + 0.1 \tag{1}$$

Where

x_i = normalized value of the input and output data

x_{min} and x_{max} = the minimum and maximum value of the input and output data

Input and output data training resulting in the design of network architecture is of paramount importance in the application of neural network to data modeling and prediction. To obtain the optimal network architecture that possesses the most accurate understanding of the input and output data, two major factors were considered. First is the selection of the most accurate training algorithm and secondly, the number of hidden neurons. Based on this consideration, different training algorithm and hidden neurons were tested to determine the best training algorithm and accurate number of hidden neurons that will produce the most accurate network architecture. Selectivity was based on the coefficient of determination (r^2) and the mean square error value (MSE) [20].

To train the network, 3 runs of 1000 epochs, each with a precision rate of 0.00001 and a learning rate of 0.05 was used. In addition, cross validation data representing about 25% of the total input data was introduced to monitor the progress of training and prevent the network from memorizing the input data instead of leaning which is a common problem associated with overtraining. The progress of the training was monitored using the mean square error (MSE) graph for training and cross validation. To test the efficiency of the trained network, 15% of the input data was introduced to the network to generate the predicted streamflow. To test the reliability of the network and acertain the prediction accuracy, a reliability plot of output using the predicted streamflow as the vertical axis and the observed streamflow as the horizontal axis was obtained with the aid of

Microsoft Excel Spreadsheet. Reliability of the network was then evaluated using the value of the coefficient of determination (r^2) between the predicted and the observed streamflow.

3.0 Results and Discussion

3.1 Preliminary Analysis of Data

The dataset contains 14521 rows of data subdivided into 4 columns (pressure, temperature, gage height and discharge). Searching through the dataset, no null value, empty space, or mistyped data was found. As observed in Table 1, the univariate analysis showed the spread of each column data distribution starting with the mean value and the standard deviation of each data, the range of the distribution starting from the minimum value to the maximum value; and the most common value in the 25%, 50% and 75% data distribution quartile.

Table 1: Univariate analysis of the dataset

	pressure	temperature	gage height	discharge
count	14521.000000	14521.000000	14521.000000	14521.000000
mean	12.936317	25.333209	17.304057	5481.070123
std	0.185619	0.914314	0.437838	240.396598
min	12.669000	21.780000	2.706000	14.658000
25%	12.798000	25.023000	17.219000	5379.175000
50%	12.872000	25.477000	17.374000	5547.794000
75%	13.041000	25.920000	17.445000	5626.447000
max	13.654000	27.123000	17.544000	5736.980000

As observed in Table 1, each column distribution had a mean value approximately similar to the most common value in the 50% data distribution quartile. For example, the data distribution under the label “pressure” had a mean value of 12.936317 and the most common value in the 50% data distribution of 12.872000, which is approximately 12.9 for both. Similarly, column labelled “temperature” had approximately similar value of 25.00, “gage height” had 17.30, and “discharge” had 5500.00. This indicates the centralized positioning of the mean value on the data distribution curve. Also, the minimum value of 12.669000 on the label “pressure” in terms of range was close to 12.798000, the most common data in its 25% distribution quartile. This information represents a closely packed data distribution and similar pattern can be observed in the data column labelled “temperature”. However, the data column labelled “gage height” and “discharge” had minimum values farther away in terms of range from their most common data in their 25% distribution quartile. This indicates the presence of outliers in such data columns. To get a better view on the data distributions, the visualization plots presented in Figures 2 and 3 were employed.

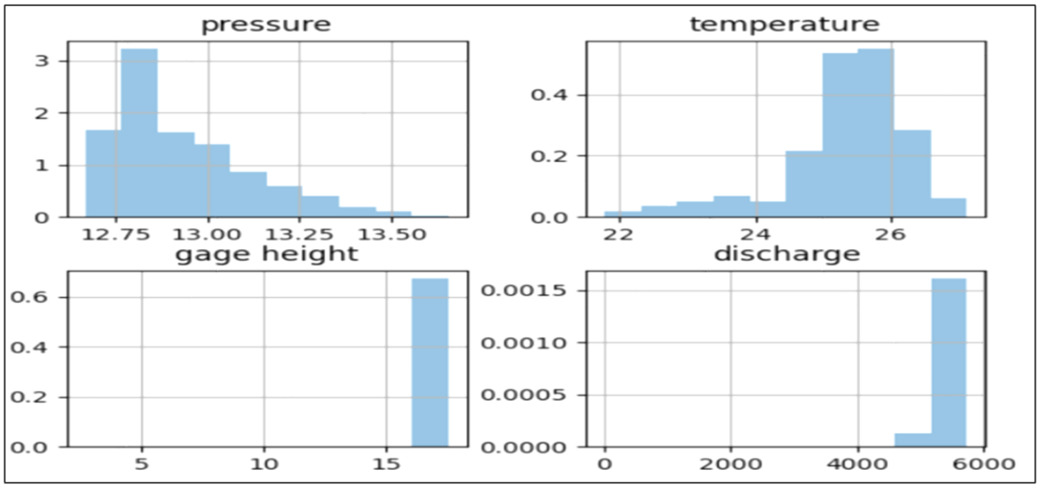

Figure 2: Histogram plot of the dataset

The histogram plot showed a left and right skewed distribution of each data column distribution respectively.

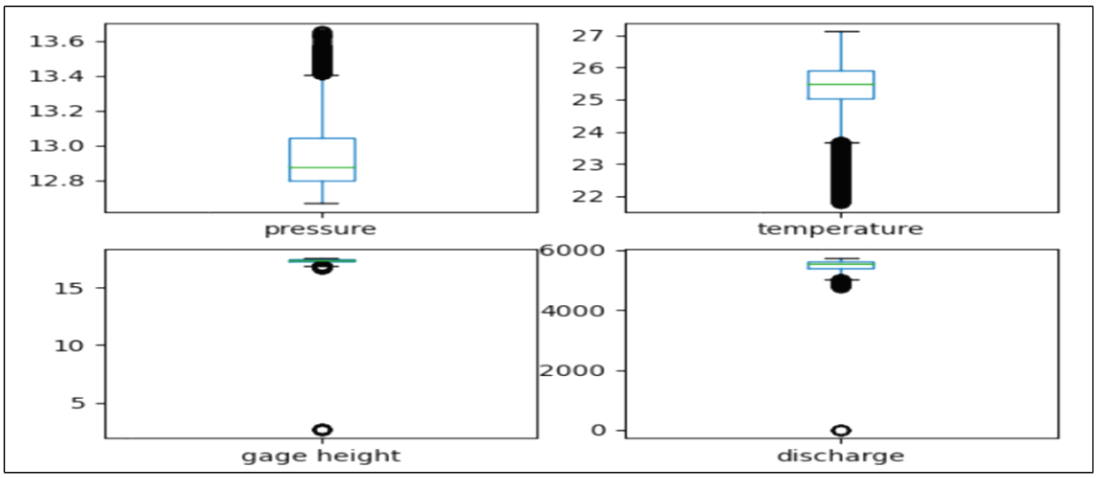

Figure 3: Box and Whisker plot of the dataset

The box and whisker plot confirmed the closely packed data distribution of columns labelled “pressure” and “temperature” at the upper and lower limits respectively. However, data columns labelled “gage height” and “discharge” have some outlying data farther away from the lower data limits. In terms of range, outliers present in the data column labelled “gage height” seem farther from its lower data limit compared to the other column data distributions.

To identify these outliers, present in the data column labelled “gage height”, Z standard score method was employed. The Z standard score is the number of standard deviations by which the value of a raw score is above or below the mean value of the observed data distribution. Consequently, lower and upper limit of 3; standard deviation away from the mean, to capture at least a 99.73% data distribution of the “gage height” was set, and a total of 11 outliers were identified and removed from the dataset. The resulting visualization plot after the removal of outliers is presented in Figure 3.

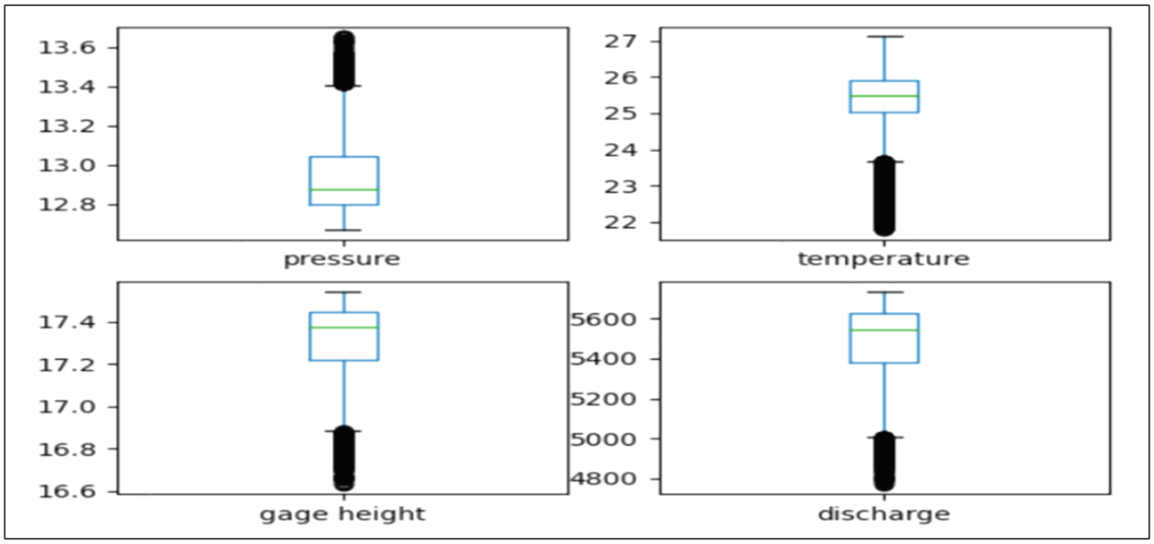

Figure 4: Box and Whisker plot of the dataset after outlier removal

3.2 ANN Model Developments

Table 2 shows the performance of the different training algorithm tested.

Table 2: Selection of optimum training algorithm for ANN

S/No	Training Algorithm (Learning Rule)	Training MSE	Cross Validation MSE	R-Square (r^2)
1	Gradient information (Step)	0.06766	0.06021	0.766
2	Gradient and weight change (Momentum)	0.05844	0.06601	0.709
3	Gradient and rate of change of gradient (Quick prop)	0.04478	0.03832	0.702
4	Adaptive step sizes for gradient plus momentum (Delta Bar Delta)	0.04221	0.00546	0.788
5	Second order method for gradient (Conjugate gradient)	0.05032	0.08037	0.637
6	Improved second order method for gradient (Levenberg Marquardt)	0.00013*	0.00018*	0.951*

Result of Table 2 revealed that improved second order method of gradient also known as Levenberg Marquardt Back Propagation training algorithm was the best learning rule and was adopted in designing the network architecture. To determine the exact numbers of hidden neuron, different numbers of hidden neurons were selected to create a trained network using Levenberg Marquardt Back Propagation training algorithm. Performance of the trained network was assessed using mean square error (MSE) and coefficient of determination r^2. The number of hidden neuron corresponding to the lowest MSE and the highest r^2 as presented in Table 3 was selected to design the network architecture.

Table 3: Selection of optimum number of hidden neurons for ANN

S/No	Number of Hidden Neurons	Training MSE	Cross Validation MSE	R-Square (r^2)
1	2	0.0145	0.0336	0.71
2	3	0.0267	0.0141	0.72
3	5	0.0108	0.0600	0.79
4	8	0.0277	0.0481	0.83
5	10	0.0012	0.0022	0.95

Based on the results of Tables 2 and 3, Levenberg Marquardt Back Propagation training algorithm having 10 hidden neurons in the input layer and output layer was used to train a network of 3 input processing elements, namely; pressure, temperature, gage height and 1 output processing element (Discharge). The input layer of the network uses the hyparbolic targent (tan-sigmoid) transfer function to calculate the layer output from the network input while the output layer uses the linear (purelin) transfer function. The number of hidden neuron was set at 10 neurons per layer and the network performance was monitored using the mean square error of regression (MSEREG). The network training diagram generated for the prediction of stream discharge using back propagation neural network is presented in Figure 5.

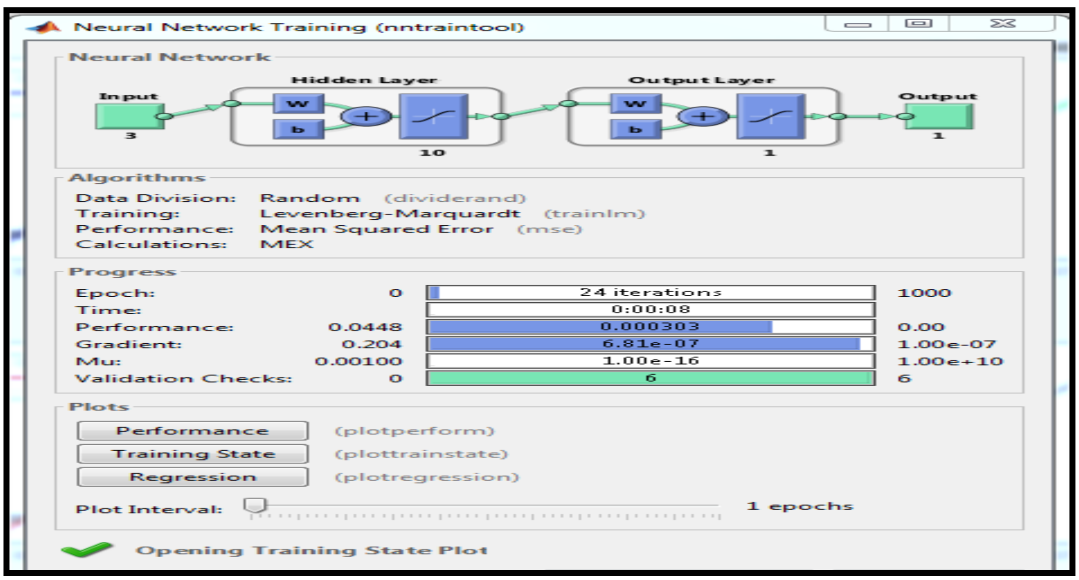

Figure 5: Network training diagram for predicting stream discharge

From the network training diagram of Figure 5, it was observed that the network performance was significantly good with a mean square error of 0.000303 which is far lesser than the set target error of 0.01. The maximum number of iteration needed for the network to reach this performance was observed to be 24 iterations which is also lesser than the initial 1000 epochs. The gradient function was calculated to be 6.81e-07 with a training gain (Mu) of 1.00e-16. Validation check of six (6) was recorded which is expected since the issue of wieght biased had been addressed via normalization of the raw data. The performance evaluation plot which shows the progress of training, validation and testing is presented in Figure 6.

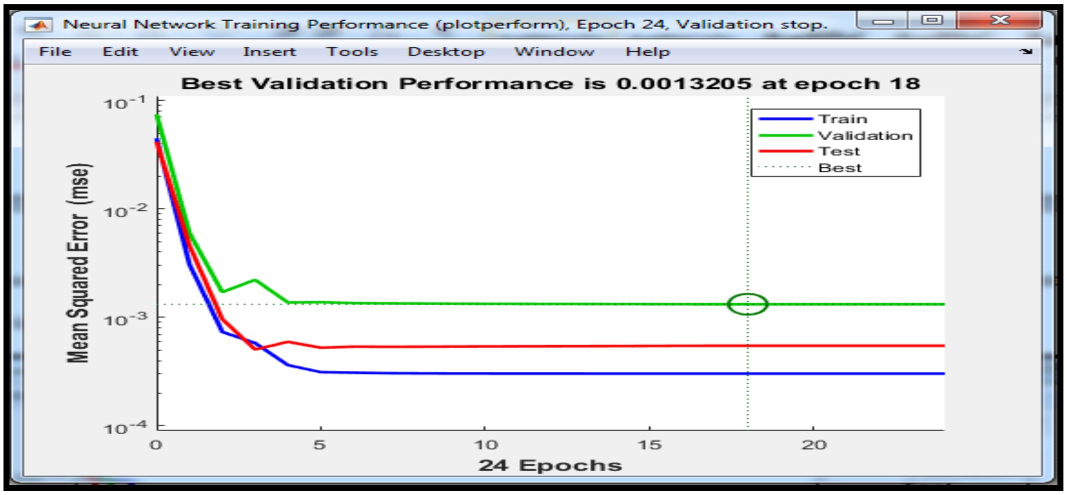

Figure 6: Performance curve of trained network for predicting stream discharge

The training curve (marked blue) shows the performance of the model on the training data during the training process. It should generally decrease over time, as the model learns to better fit the training data. If the training curve is not decreasing, it may indicate that the model is too simple or that the learning rate is too low. If the training curve decreases rapidly and eventually flattens out, it may indicate that the model is starting to overfit the training data. A gradual decrease of the training curve as observed in Figure 6 indicates a good fit of the ANN model. The validation curve (marked red) shows the performance of the model on the validation data during the training process. It is used to monitor the model's generalization ability, i.e., how well the model can generalize to new data. If the validation curve follows the training curve closely, it suggests that the model is not overfitting the training data. If the validation curve starts to flatten out or increase while the training curve continues to decrease, it may indicate that the model is overfitting the training data and that the hyper parameters should be adjusted. As observed in Figure 6 the validation curve follows the training curve closely which suggests that the model is not overfitting the training data. The testing curve shows the performance of the model on a separate testing dataset after the training is complete. It provides an estimate of the model's generalization ability to new data. If the testing curve follows the validation curve closely, it suggests that the model has good generalization performance. However, if the testing curve performs significantly worse than the validation curve; it may indicate that the validation dataset was not representative of the testing dataset or that the model was over fitted to the validation data. As observed in Figure 6 the testing curve follows the validation curve closely which suggests that the model is not over fitting the validation data.

From the performance plot of Figure 6, no evidence of over fitting was observed. In addition, similar trend was observed in the behaviour of the training, validation and testing curve which is expected since the raw data were normalized before use. Lower mean square error is a fundamental criterion used to determine the training accuracy of a network. An error value of 0.0013205 at epoch 18 is evidence of a network with strong capacity to predict the stream discharge. The training state, which shows the gradient function, the training gain (Mu) and the validation check, is presented in Figure 7.

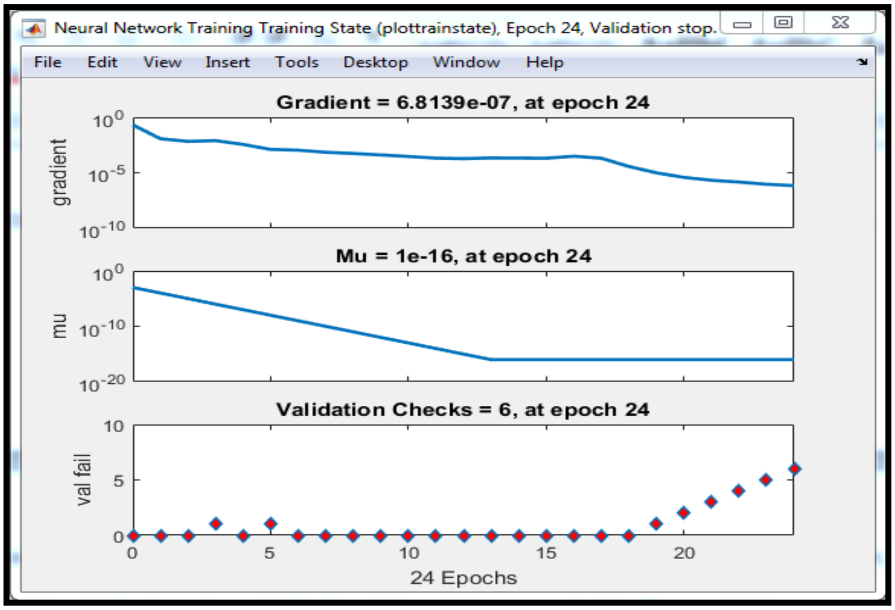

Figure 7: Neural network training state for predicting stream discharge

The gradient function in ANNs is used to calculate the rate of change of the error with respect to the weights and biases of the network. It is typically calculated using back-propagation, which involves propagating the error backwards through the network and updating the weights and biases to minimize the error. Back propagation is a method used in artificial neural networks to calculate the error contribution of each neuron after a batch of data training. Technically, the neural network calculates the gradient of the loss function to explain the error contributions of each of the selected neurons. Lower error is better. Computed gradient value of 9.607e-08 as observed in Figure 7 indicates that the error contributions of each selected neurons is very minimal. The training gain (Mu) is a parameter used in the Levenberg-Marquardt algorithm, which is a commonly used optimization algorithm for training ANNs. The training gain controls the balance between the Gauss-Newton approximation (which is efficient but can be inaccurate) and the gradient descent algorithm (which is slower but more accurate). Momentum gain (Mu) is the control parameter for the algorithm used to train the neural network. It is the training gains and its value must be less than one. Momentum gain of 1.0e-13 shows a network that is adequate and with high capacity to predict the stream discharge. The validation check curve in ANNs is a graph of the network's performance on a validation dataset as a function of the number of training epochs. It is used to monitor the network's performance during training and to detect overfitting (when the network becomes too specialized to the training data and performs poorly on new data).
The regression plot which shows the correlation between the independent variables (pressure, temperature and gage height) and the target variable (stream discharge) coupled with the progress of training, validation and testing is presented in Figure 8.

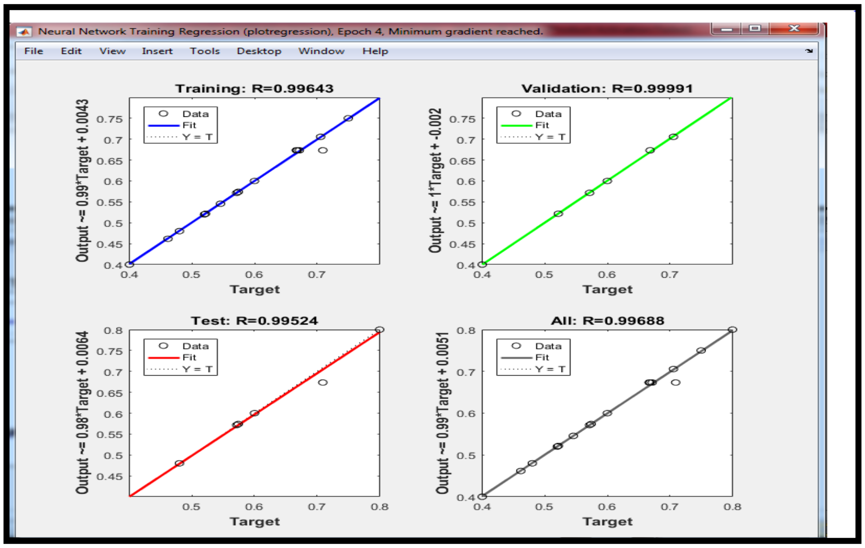

Figure 8: Regression plot showing the progress of training, validation and testing

The correlation coefficient is a statistical measure that quantifies the strength and direction of the relationship between two variables. In a regression plot, the correlation coefficient can be used to interpret the relationship between the predicted outputs and the actual outputs. The correlation coefficient, typically denoted by "r", ranges from -1 to +1. A value of -1 indicates a perfect negative correlation, where the predicted outputs decrease as the actual outputs increase. A value of +1 indicates a perfect positive correlation, where the predicted outputs increase as the actual outputs increase. A value of 0 indicates no correlation between the predicted and actual outputs. In general, a higher absolute value of the correlation coefficient indicates a stronger relationship between the predicted and actual outputs. However, the interpretation of the correlation coefficient can be influenced by a number of factors, such as the sample size and the range of the data. It is important to note that while the correlation coefficient can provide valuable insights into the relationship between the predicted and actual outputs, it is not a measure of the overall performance of the model. Other metrics, such as mean squared error or R-squared, should also be considered when evaluating the performance of an ANN regression model.

Based on the computed values of the correlation coefficient (R) as observed in Figure 8, it was concluded that the network has been adequately trained and can be employed to predict the stream discharge corresponding to a known pressure, temperature and gage height. To test the reliability of the trained network, the network was thereafter employed to predict its own value of stream discharge using the same set of input parameters (pressure, temperature and gage height) generated from the central composite design. Based on the observed and the predicted values, a regression plot of outputs was thereafter generated as presented in Figure 9.

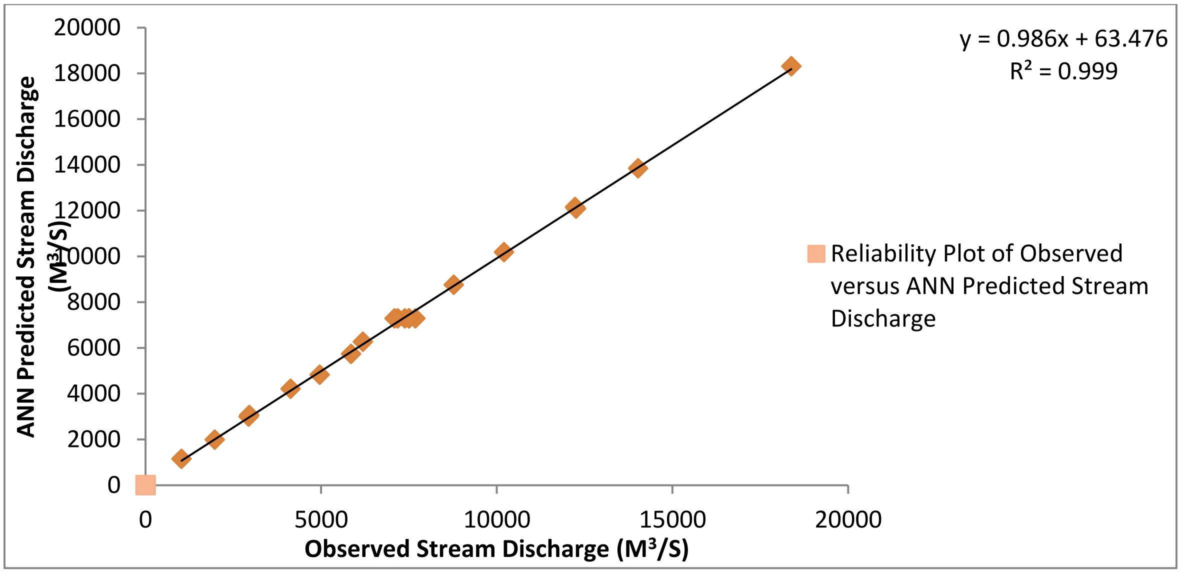

Figure 9: Regression plot of observed versus ANN predicted stream discharge

4.0. Conclusion

In conclusion, the performabce of the neural network (ANN) was assessed using a variety of matrics; the Mean Squared Error (MSE): MSE is a commonly used metric in regression problems. It measures the average of the squared differences between the predicted and actual values. A lower MSE indicates better performance. MSE value of 0.0013205 revealed a network with high performance. Coefficient of determination (R^2); R^2 measures the proportion of variance in the target variable that is explained by the model. It ranges from 0 to 1, with higher values indicating better performance. R^2 value of 0.999 as observed in Figure 9 shows a network that is strong enough to predict stream discharge.

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