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Application of Adaptive Neuro Fuzzy Inference System (Anfis) in River Kaduna Discharge Forecasting

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Abstract: The study and understanding of the amount of water that would be discharged by a stream in the future is of crucial importance to the water resources development, planning and management of any area. This is so because, stream flow data are very important for many areas of water engineering. The data used for this research include the monthly rainfall data for Kaduna town, Zaria and Jos, temperature data for Kaduna town, relative humidity for Kaduna town and the stage height data for the studied river and the discharge data. All the data used span the period 1975-2004 (30 years). These parameters are non-linear, stochastic (random) and uncertain in nature. Adaptive Neuro-Fuzzy based Inference System (ANFIS), an integrated system, comprising of Fuzzy Logic and Neural Network was used to model the discharge forecast, because it can address and solve problems related to non-linearity, randomness and uncertainty of data. The ANFIS-based model developed uses 70% of data for training and 30% for checking; subsequently validation data of the variables were used to predict the discharge and test the model developed. From the analysis carried out on the ANFIS-based model; Root Mean Square Error (RMSE) found to be 107.62. The analysis shows high level of accuracy with regards to the ANFIS-based model developed in forecasting the river discharge especially with a correlation (r) value of 86%.

Keywords: ANFIS, river discharge, RMSE

INTRODUCTION

River discharge known by several terms such as streamflow, or runoff and catchment yield, represents the excess of precipitation over evapotranspiration loses when allowance has been made for infiltration and surface detention.. It is expressed as the flow rate of the river at the collecting or measuring point in litres per second or cubic meters per second (cumecs), or as equivalent depths over the catchment area, measured in milliliters per day, month or year Ayoade (1988). One of the major areas of research interest in water resources management is forecasting the future flows in streams. The study and understanding of the amount of water that would be discharged by a stream in the future is of crucial importance to the water resources development, planning and management of any area. This is so because, it affects directly the design and operations of many water resources structures (Kisi, 2004, 2005).

Three major problems resulted in a great setback for water resources harnessing for effective planning and development in Nigeria inspite of its vast water resources endowment. First among these problems is the non-availability of consistent streamflow data of Nigerian rivers with less than 30% of its rivers gauged. For example, there are about 1058 river gauges all over Nigeria with only about 300 still having 10 years of continuous river flow data. In addition to these, the gauges are meant not solely for water supply management purposes, but also for the inland waterways and for irrigation (Oguntoyinbo, 1979). Secondly, is the vandalization of available manual (though obsolete) gauging equipment in few rivers in Nigeria and finally, is the prohibitive cost of gauging equipment. Apart from these, general knowledge about variation of river flows are often invalidated by the short time or unavailability of consistent and unreliable discharge data Ward (1968) and Jagtap (1995). It has also been established that these contributed noticeably to the inability to plan and manage the water resources assiduously (Nemec and Schaake, 1982; Cohen, 1987; Arnell *et al*., 1990; Lettenmaier and Gan, 1990; Saelthun *et al*., 1990; Vehvilainen and Lohvansuu, 1991; Krasovskaia and Gottschalk, 1993; Krasovskaia *et al*., 1993; Wateren-de-Hoog, 1993; Samuel, 1993).

In hydrological studies various methods or techniques has been used for streamflow prediction or forecasting as found in the literature, but they can all be categorized, following Ward (1975), as empirical methods, statistical methods, analytical methods and modeling methods. Similarly, whichever of these methods is chosen will depend on a number of factors including the purpose of the prediction or forecasting, the available data as well as the size and other characteristics of the basin Ward

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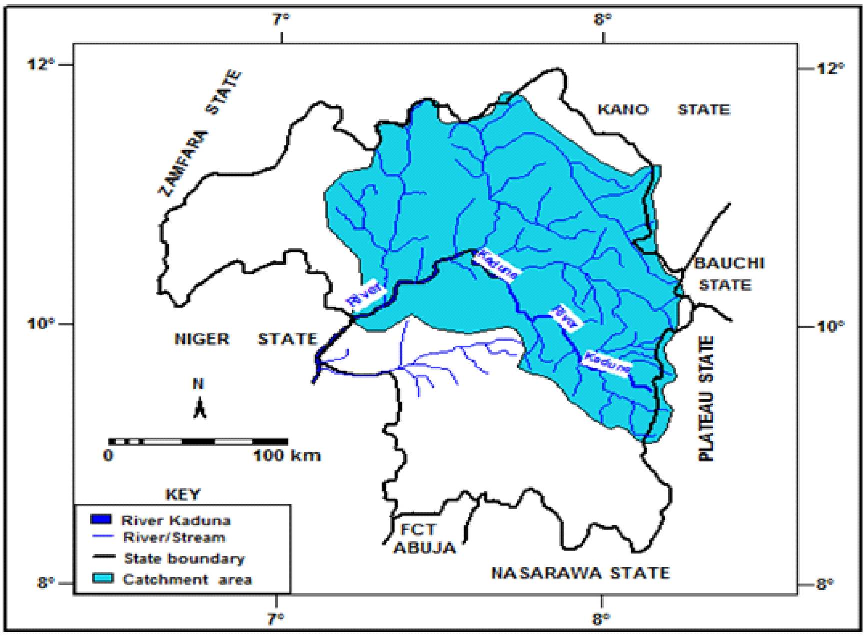

Fig 1 : The drainage basin of review Kaduna Modified from Drainage Map of Kaduna state

(1975). Most of these methods are based on the statistical analysis of flow data which were measured in the past and many of them offer very complex or too demanding tools for practical cases. Among them all, the most well employed method is regression analysis of the observed data until recent. Regression of the observed data in a nearby river can give important information on the behavior of the targeted river. Unfortunately, the hydrological and topographical conditions of the two basins should be similar to each other Kilinc *et al*. (2000).

Consequently, researchers have attempted the use of models in hydrological forecasting studies. For example, Srikanthan and McMahon (1983) in their study on Stochastic Simulation of daily rainfall for twelve Australian Stations using the Transition Probability Matrix (TPM) method (Allen and Haan, 1975), Modified Transition Probability (TPG) method (Carey and Haan, 1978) and a two part model (A two-state first-order; a two-state second-order Markov chain Model (Jones *et al*., 1972). From the observations, it was concluded that the TPM model was more suitable than the other models for generating the Australian daily rainfalls. However, a major problem is that it does not preserve maximum daily rainfalls. Another method of late being used for the flow prediction of rivers is the Adaptive Neuro-Fuzzy Inference System (ANFIS) introduced by Jang (1993). The ANFIS is well suited for dealing with ill-defined and uncertain systems as it finds application in imaging, statistical phenomenon, watershed, control and soft-computing such as hyper-spectral image, rainfall, ground water vulnerability, system identification, control design, fault diagnosis, genetic algorithms and rough sets as highlighted by Qiu (2008) Mu'azu (2006). Dixon (2000), Ojala (1995) and Mitra and Hayashi (2000). However, to the best of the author's knowledge, none of the above model has been used either directly or indirectly for the prediction of the future flow of River Kaduna at any time.

The ANFIS is a neuro-fuzzy system, which uses a feed-forward network to search for fuzzy decision rules that perform well on a given task. Using a given input/output data set, ANFIS creates a fuzzy inference system whose membership function parameters are adjusted using a back-propagation algorithm alone or combination of a back-propagation algorithm with a least mean squares (LMS) method (hybrid learning). This allows the fuzzy systems to learn from the data being modeled. ANFIS provides a method for the fuzzy modeling procedure to learn information from the data set, followed by creation of the membership function parameters that best performs the given task Antonio, (1997) and Mitra and Hayashi (2000). The ANFIS can simulate and analyze the mapping relation between the input and output data through a learning algorithm to optimize the parameters of a given Fuzzy Inference System (FIS). The aim of this research is the the application of ANFIS as a powerful features of fuzzy inference system model in River Kaduna discharge forecasting (1975-2004).

The study area: This study is focused on River Kaduna which takes its source from Sherri Hill in Plateau State. River Kaduna flows north-west towards the Kaduna metropolis and thereafter takes a south west direction turn at Mureji. River Kaduna covers a total distance of 540 km from source to mouth (using a topographical map of Kaduna on a scale of 1:500,000) (Folorunsho, 2004). The drainage basin for this study is approximately 21,065 $km^{2.}$ Kaduna State occupying a central position in the Northern geographical region of Nigeria lies within the Northern Guinea Savannah Zone of Nigeria with an absolute location of latitude 9º30′N and latitude 11º45′N; longitude 7ºE and longitude 8º30′E. It occupies a total land mass of 2,896,000 km^2 and it is bordered by Katsina and Kano States to the north;

Bauchi State to the east; Plateau State to the south-east; F.C.T. to the south; Niger State to the south-west and Zamfara state to the north-west (Fig. 1).

The climatic conditions of the study area is tropical continental (A_W) characterized by a well defined wet and dry season climate, strong seasonality in rainfall and temperature distributions (Koppen, 1928). This is influenced by the motion of two opposite air masses over the study area; the tropical maritime air mass ($_mT$) and the tropical continental air mass ($_CT$). These air masses have contrasting moisture and temperature characteristics. When the former, which originate over the Gulf of Guinea, prevails over the study area, it brings in the rainy season. While the later, which originates from the Sahara desert, brings in the dry season with cold, dry and dusty air that occasionally limits visibility and reduces solar radiation bringing in harmathan conditions in the study area Iguisi (1996).

The rainfall condition is determined by the position of the Inter Tropical Discontinuity (ITD) that separates the two prevailing air masses. The position of the ITD fluctuates approximately from latitude 5º north in January to about 22º north in mid August. The dry season usually starts around the month of November and lasts for about 7 months, which are usually dry and cold. The rainy season in the study area is short and usually lasts from May to last October. The mean annual rainfall can be as high as 2000 mm in wet years and as low as 500 mm in drought years, but with a long term average of 1000 mm Kowal and Adeoye (1973), Sola and Adeniran (2009), Iguisi (1996) and Folorunsho (2004).

MATERIALS AND METHODS

The Adaptive Neuro-Fuzzy based Inference System (ANFIS) was applied to model River Kaduna discharge in the River Kaduna basin using rainfall, temperature, relative humidity and stage height from 1975-2004 as the input variables. A total of (178) months data with (112) months used for the training data while (47) months data used as the checking and the last (9) months was used as validation data.

Table 1: The ANFIS-based modeling criterion

S/N	Custom ANFIS	Variables
1	Membership function type	Generalized bell membership function
2	Number of membership functions	Three (3)
3	Learning algorithm	Hybrid learning algorithms
4	Epoch size	Seven (7)
5	Data size	Data per week
6	Sugeno type-system	First order
7	Output type	Linear
8	Hybrid learning algorithms	Gradient descent and least square estimate

Project (2011)

Development of ANFIS-based forecasting model: The criterion chosen for development of the ANFIS model as shown in Table 1 were based on the selection of the following:

- Membership Function Type
- Number of Membership Functions
- Learning Algorithm
- Epoch Size
- Data Size

The modeling criterion adopted is to effectively tune the membership functions so as to minimize the output error measure and maximize performance index (Jang, 1993).

The Adaptive Neuro-Fuzzy Inference Systems (ANFIS) toolbox employed is the MATLAB ® V7.9.0.529 (R2009b). The model was developed using the following procedures at the ANFIS Graphical User Interface |(GUI|):

- Obtaining training data
- Data sizing
- Data partitioning
- Loading the data sets

Examination of the reliability of the ANFIS-based model: The development of a model serves as an end to a mean, yet the performance of such model is measured by the reliability of the forecasted output. One of the major tests of reliability of a good model is that the training set performance and that of the test set are fairly similar. The key indicator of such model is the performance of the model when subjected to the standard procedural and statistical tests such as the correlation coefficient *(R)* value , Root Mean Square Error (RMSE) value, Accuracy and Confidence Intervals (Mu'azu, 2006; Garba, 2011).

For the ANFIS-Based model, using the MATLAB toolbox, the forecasted outputs are evaluated using the command line shown below:

- Calling the ANFIS Editor with the name 'Ngbell' using the command anfisedit ('Ngbell')

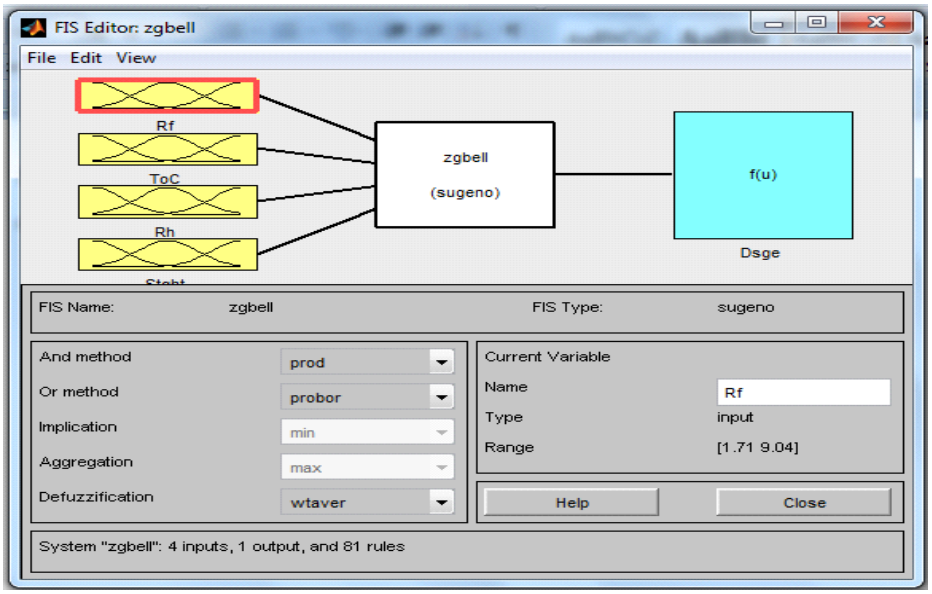

Fig. 2: Showing dialog box for the FIS editor

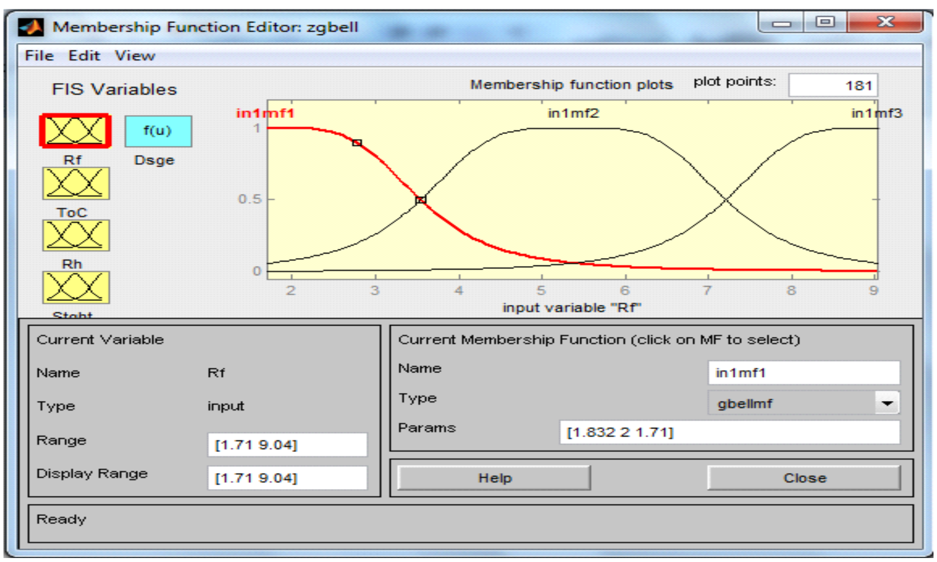

Fig. 3: Showing the dialog box for the membership function editor

- Read the model using the next command:A = readfis ('model name')
- Evaluate the output using the command: aa = evalfis ([input1, input2, input3, input4], a)

From the above command line, the forecasted output discharge values were obtained and thus fit in to the specified procedural and statistical measures defined. In order to achieve this, procedural and statistical measures such as the Root Mean Square Error and the Correlation Coefficient statistics using the Microsoft Excel Statistical Package will be employed. The Root Mean Square Error is the measurement of the models performance during the training phase. It is the square root of the average squared error between the target and the corresponding predicted output and this is calculated using Eq. (1) and (2) as shown:

$$RMSE = \sqrt{MSE} \quad 1$$

while the MSE is given by the equation

$$MSE = \sum_{i=0}^{n} (\textit{Actual output} - \textit{predicted output}) \quad 2$$

The *R* value and *RMS* error indicate how "close" one data series is to another-in our case, the data series are the

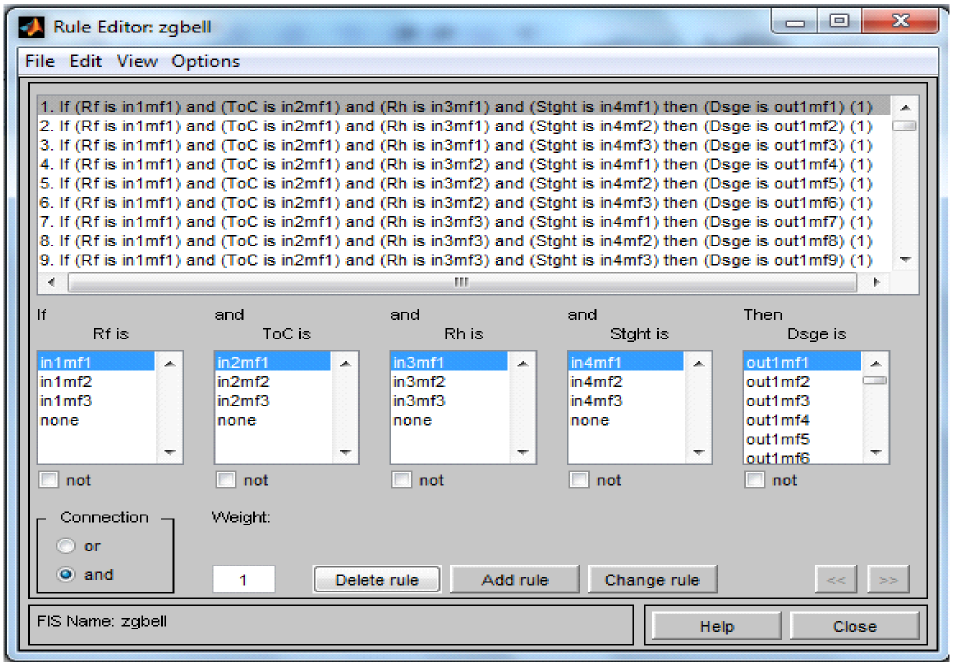

Fig. 4: Showing the dialog box for the rule editor

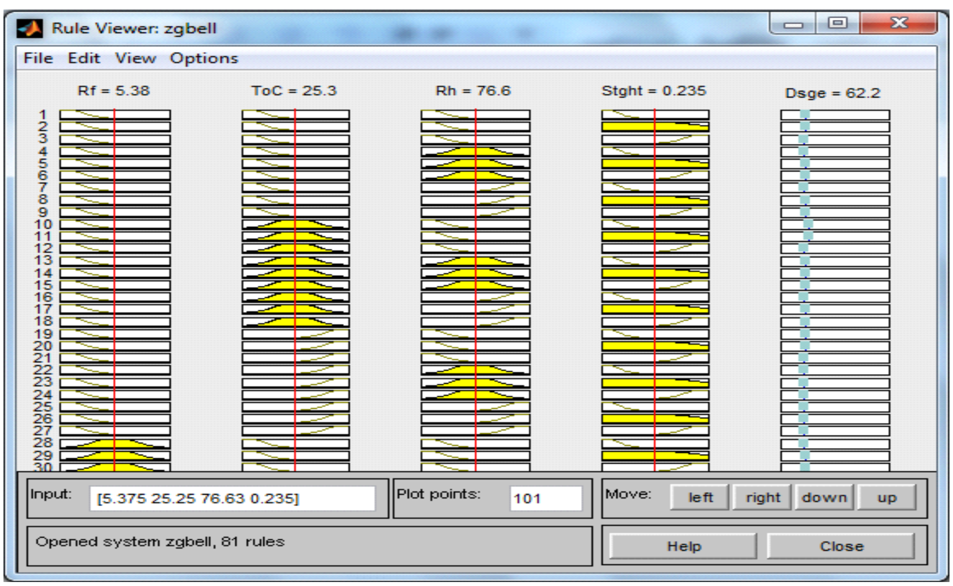

Fig. 5: Showing the dialog box for the rule viewer editor

Target (actual) output values and the corresponding *predicted* output values generated by the model. Smaller *RMS* error values are better.

Similarly, Pearson Correlation Coefficient (r) is a measure of linear relationship of two variables and it ranges from -1.0 + 1.0. Where the r-value is -1.0, it is an indication of a perfect but negative correlation; 0 implies absence of correlation, while +1.0 is an indication of a positive and perfect correlation. Thus, using Eq. (3):

$$r = \frac{\sum_{i=1}^{n}(A-\bar{A})(F-\bar{F})}{\sqrt{\sum_{i=1}^{n}(A-\bar{A})^2 \sum_{i=1}^{n}(F-\bar{F})}^{2}} \quad 3$$

where, r is the correlation coefficient, A is the actual output, A is the mean of the actual output and F is the forecasted output and F is the mean of the forecasted output.

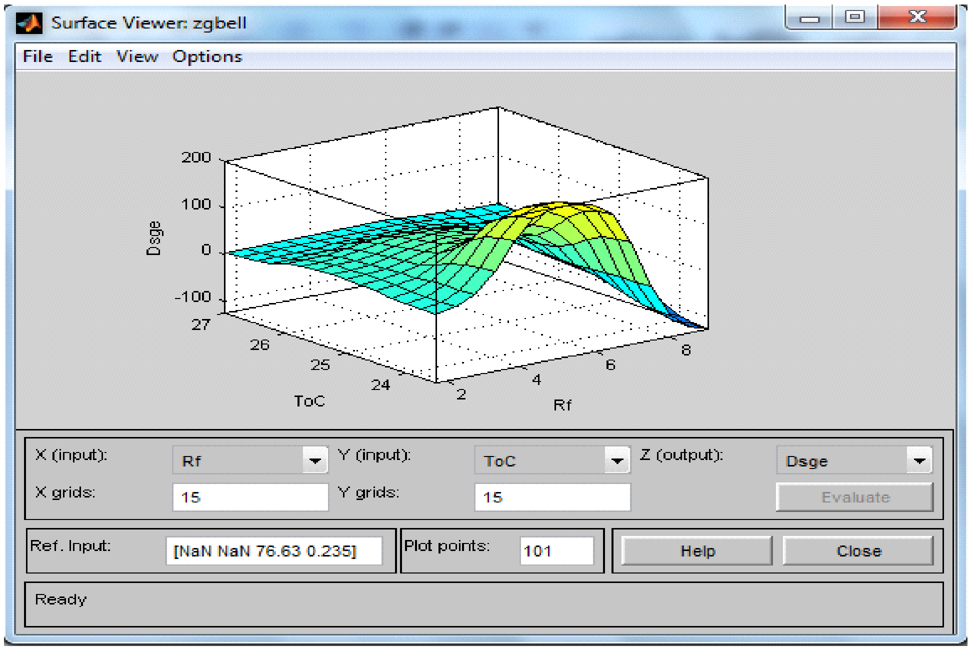

Fig. 6: Showing the dialog box for the surface viewer editor

Validation of the model: From the model developed, the performance of the model is validated by considering its performance in terms of the actual and predicted outputs. This will be achieved by a simple plot of the actual and forecasted outputs by the two models developed.

RESULTS AND DISCUSSION

Development of ANFIS-based forecasting model: The input and output data used in this research work were obtained from the Hydrology Department, Kaduna State Water Board Headquarters, Kaduna and the Nigerian Meteorological Agency, Oshodi, Lagos. The data period covers January 1975 to December 2004. A total of (178) months data with (112) months used for the training data while (47) months data used as the checking and the last (9) months was used as validation data. In order to have a large training and checking data set for the ANFIS-based model, the (178) months data was divided into seven months group (Apr-Oct in each set), resulting into (24) pair of months. This increases the data partitions and learning speed, reduces the possibility of over-fitting of the model and removes imbalances in the number of columns and rows.

Furthermore, the data was partitioned into two groups for the neuro-fuzzy model (training and checking data). The monthly data made up of 178 months was partition into seven-seven month's data resulting into 24 sets of data. The first 16 set of the data was used for training the model while 8 sets were used for checking the model under the ANFIS. The division of the data was generated using the MATLAB m-files spreadsheet. The first four (4) columns in every set represent the input variables while the last column represents the output. The set of input variables are monthly rainfall, temperature, relative humidity and stage height values while discharge is the output.

The ANFIS-based model is trained by loading the training data sets containing the 16 weeks into the ANFIS Editor graphical user interface (GUI) from the MATLAB workspace. The data set loaded is an array with the data arranged as column vectors and the output data in the last column. The loaded data gives room for the model to generate an inference system (Fahimifard *et al.*, 2009) (Fig. 2-6):

- Fuzzy Inference System (FIS) Editor- The dialog box for the FIS editor is as shown in Fig. 2.
- Membership Function Editor
- The dialog box for the membership function editor is as shown in Fig. 3.
- Rule Editor-The Rule Editor dialog box is as shown in Fig. 4.
- Rule Viewer-The Rule Viewer dialog boxis as shown in Fig. 5.
- Surface Viewer-The Surface Viewer dialog box is as shown in Fig. 6.

Examination of the ANFIS-based model reliability and validation: Having completed all the procedures shown

Table 2: Showing the actual and forecasted output discharge values

S. No.	Actual discharge	ANFIS discharge
1.	115.69	88.85
2.	423.48	582.08
3.	781.39	620.01
4.	4.12	4.08
5.	57.26	66.88
6.	301.06	106.88
7.	423.48	382.58
8.	655.85	554.36
9.	161.85	414.77
10.	11.58	33.01

Project (2011)

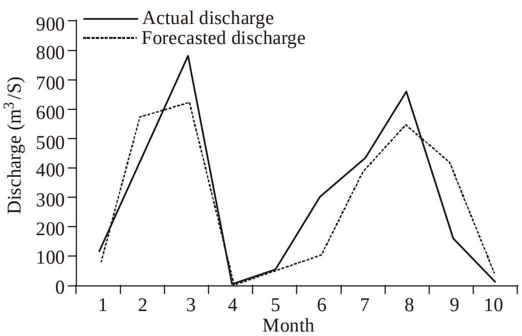

Fig. 7: Showing the actual discharge and the ANFIS predicted output

by the Graphical User Interface (GUI) in Fig. 2-6 for the development of the ANFIS-based model as discussed earlier, it is imperative to examine the reliability of this model. In order to achieve this, procedural and statistical measures were used. From the above command line, the forecasted output discharge values in Table 2 were obtained.

However, the results shown in Table 1 were analyzed in order to check the accuracy of the model. The statistical measures that were employed for these analyses are the Root Mean Square Error (RMSE) and the Pearson Correlation Coefficient using the Microsoft Excel Statistical Package. However, the MSE was obtained using Eq. (1)-(3) and the results from the RMSE are shown below:

Thus, MSE = 115809.20/10 = 11580.92
Then RMSE= 11580.92 ^ 0.5 = 170.62
Hence, the Root Mean Square Error is 107.62

From the analysis, it was observed that the squared error value for the ANFIS-based model using the generalized bell membership function is 115809.20 and the root mean square error is 107.62.

Similarly, the performance of the ANFIS-based model in its ability to predict the River Kaduna discharge was tested. This was carried out by comparing the actual discharge output and the ANFIS-based model output as shown in Table 2 and the result is shown in Fig. 7. From Fig. 7 and the statistical analysis carried out, it becomes clearer the ANFIS-based model developed has been able to learn the trend of the River Kaduna discharge pattern creditably. However, to be able to validate the reliability of the model, it is important to further subject it to other statistical analysis.

This is because any unscientific assumption can have serious and negative effects on policies based on the model for predicting the River discharge. This can hamper any formidable and dependable achievement of sustainable water resources planning for the drainage basin in study. Thus, the Pearson Correlation Coefficient (*r*) was employed. Using the Pearson Correlation Statistics in the Microsoft Excel programme, the *r-value* of +0.869156 was obtained.

From the r-value obtained, it is conspicuously evident that given all the assumption on the data, the ANFIS-based model will be appropriate for forecasting River Kaduna discharge for any immediate or future water resources planning, development and management.

CONCLUSION

The sustainable development of any region is of paramount importance to the planning, development and management of its water resource. As such, developing a model to effectively predict the river discharge is quite apt. In this research work, ANFIS-based model was developed to forecast the discharge of River Kaduna depending on available variables (rainfall, temperature, relative humidity and stage height). The ANFIS-Based Model was developed in the MATLAB® V7.9.0.529 (R2009b) environment.

Hence based on the results obtained from this research, it can be concluded that the ANFIS based model is a better modeling tools for predicting river discharge considering the strong, high and positive Correlation Coefficient the model displayed. The discharge data used in developing the model is a universally standard discharge data, which implies that model developed can be applied to other rivers anywhere in Nigeria or abroad, especially for policy formulators in water resources planning, development and management as long as the input data are available.

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