Received: 28 September 2017 | Revised: 5 November 2018 | Accepted: 13 November 2018

DOI: 10.1002/rra.3391

RESEARCH ARTICLE

WILEY

Comparing ANN and ARIMA model in predicting the discharge of River Opeki from 2010 to 2020

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Abstract

Many attempts have been made in the recent past to model and forecast streamflow using various techniques with the use of time series techniques proving to be the most common. Time series analysis plays an important role in hydrological research. Traditionally, the class of autoregressive moving average techniques models has been the statistical method most widely used for modelling water discharge, but it has been shown to be deficient in representing nonlinear dynamics inherent in the transformation of runoff data. In contrast, the relatively newly improved and efficient soft computing technique artificial neural networks has the capability to approximate virtually any continuous function up to an arbitrary degree of accuracy, which is not otherwise true of other conventional hydrological techniques. This technique corresponds to human neurological system, which consists of a series of basic computing elements called neurons, which are interconnected together to form networks. The aim of the study is to compare the artificial neural network and autoregressive integrated moving average to model River Opeki discharge (1982–2010) and to use the best predictor to forecast the discharge of the river from 2010 to 2020. The performance of the two models was subjected to statistical test based on correlation coefficient (r) and the root-mean-square error. The result showed that autoregressive integrated moving average performs better considering the level of root-mean-square error and higher correlation coefficient.

KEYWORDS

ANN, ARIMA, discharge, hydrological, River Opeki

1 | INTRODUCTION

Surface water is very important, and it is a dominant source of water in the supply system. It is fundamental to many sectors including agriculture, power generation, and fisheries. The rate of flow (discharge) of surface water in many cases affects its optimal use either through the provision of hydropower, pipe-borne water supply, and flood design structures. With the increasing demand for water resources worldwide, uncertainty in estimating water availability, predicting flood stages and areas of inundation, predicting areas of low flows, and hydrological drought, prediction of discharge becomes extremely important for effective mitigation and management of floods, droughts, environmental flows, water demand by different sectors, maintaining reservoir levels, and managing natural disasters (Maher & Eyre, 2012).

Precipitation, a major factor affecting the discharge characteristics in a particular catchment area is periodical. As a result of periodicity, river discharge also becomes periodical in most cases (Livina et al. 2003). Due to the issue of periodicity, many attempts have been made in the recent past to model and forecast streamflow using various techniques with the use of time series (TS) proving to be the most common (Gorman & Toman, 1966; Salas, Deulleur, Yevjevich, & Lane, 1980; Galeati, 1990). Forecast of streamflow is defined as the prediction of the amount of water discharged on a specific waterway or a river during a certain period of time. A classical methodology for carrying out this prediction is presented by Bowerman and O'Connell (1993), where TS of data was used. A TS is a sequence of observations of a variable collected, observed, and recorded at regular time intervals. TS analysis plays an important role in hydrological research studies, which are handled by mathematical models to predict new records and identify trends. In recent times, mathematical models have taken over most of the important tasks in problem solving in hydrology (Borgonovo, Lu, Plischke, Rakovec, & Hill, 2017; Zhang, He, Li, Wang, & Wang, 2017; Fonesca, Santos, & Santos, 2018; Martin & McCutcheon, 2018 and Kavetski, 2018). In TS analysis, it is assumed that the data consist of a systematic pattern with a set of identifiable components and random noise (error). The TS patterns can be described in terms of two basic classes of components: trend and seasonality. In streamflow forecasting, TS models are used to describe the stochastic structure of the time sequence of streamflow and precipitation values measured over time.

The autoregressive integrated moving averages (ARIMA) has been quite popular for modelling discharge and rainfall data due to the ease in its development and implementation (Somvanshi et al., 2006), but it is deficient in representing nonlinear dynamics inherent in the transformation of runoff data (Chowdhary, Jha, & Chowdary, 2010). In contrast, the relatively new and efficient computer technique popularly known as the artificial neural networks (ANNs) has the capability to approximate virtually any continuous function up to an arbitrary degree of accuracy, which is not otherwise true of other conventional hydrological techniques such as ARIMA (Hornik, Stinchcombe, & White, 1989). The ANN technique is similar to the human neurological system, which consists of a series of basic computing elements called neurons, which are interconnected together to form networks (McClelland, Rumelhart, & Hinton, 1986). The parallel distributed processing architecture of ANN has proved to be a very powerful computational tool, which is now being used in several fields to model dynamic processes including rainfall (Cigizoglu, 2002; Singh & Chowdhury, 1986; Somvanshi et al., 2006), stream flow (Zealand, Bum, & Simonovic, 1999; Campolo, Soldati, & Andreuss, 1999; Abrahart & See, 2000), groundwater management (Rogers & Dowla, 1994), water quality simulation (Maier & Dandy, 1996; Maier & Dandy, 1999), and rainfall-runoff (Hsu, Gupta, & Sorooshian, 1995; Shamseldin, 1997). More detailed discussion regarding the application of ANN in hydrology can be referred to in a special technical report (ASCE, 2000). ARIMA and ANN modelling have been successfully applied in other literatures (Galeati, 1990, Maier & Dandy, 2000, Mohammadi, Eslami, & Dardashti, 2005, Hung, Babel, Weesakul, & Tripathi, 2008, Rani & Govardhan, 2013, Abdulkadir, Salami, & Kareem, 2012). The aim of this research was to forecast the discharge of River Opeki from 2010 to 2020. To achieve this aim, modelling of the River Opeki discharge from 1982 to 2010 was undertaken using ANN and ARIMA techniques and the better predictor of the two was used to forecast the river discharge. River discharge forecasting is useful for environmental management applications especially with regard to the sustainable development of irrigation practices, hydroelectricity generation, and water supply for both domestic and industrial uses.

2 | STUDY AREA

2.1 | Location

The River Opeki catchment is located in Oyo State, a major tributary of River Ogun. It lies between longitudes 3°15′ and 3°30′E and latitudes 7°20′ and 7°54′N (Figure 1). Located on the river is an earth dam with a capacity of 2.6 million cubic metres. The dam is meant to act as a source of water supply for Igbo-Ora and its environs. It lies entirely within one climatic environment and a consistent geological environment of the Basement Complex of southwestern Nigeria. Hence, it can provide insights into the nature of groundwater recharge. The attraction of the catchment for the study of discharge is enhanced by the fact that a gauging station exists on the River channel.

2.2 | Climate

The River Opeki catchment is within the humid tropical climate with distinct wet and dry seasons. The climate is influenced by the Inter-Tropical Convergence Zone (ITCZ) separating the subtropical continental air mass over the Sahara and the equatorial air mass over the Atlantic Ocean. The ITCZ moves northward beyond the basin to latitude 20°N in the rainy season and southwards to the Lagos Lagoon in the dry season. The wet season, which is usually double peaked, starts in April and lasts till November. February and March are the hottest months of the year with temperatures ranging from 32 to 37°C.

2.3 | Vegetation

The area lies within the savanna environment although the southern half lies within the fringes of the forest zone of southwestern Nigeria. The two major vegetation zones identified on the watershed are the high forest vegetation in the north and central parts and the swamp/mangrove forests that cover the southern coastal and floodplains next to the lagoon. Its vegetation consists of tall grasses in addition to trees with long tap roots, which ensure access to water during the dry season when the water table drops and the grasses wither and die. However, along the water course darker and denser vegetation occur throughout the year. The population is mainly rural, and the dominant land use is arable agriculture in the wet season. The crops are mainly maize, cassava, and yams.

2.4 | Physical characteristics

Generally, the channel width of River Opeki is between 60 and 80 m wide. The drainage pattern of the river is heavily controlled by the rock types of the Basement complex; the flow is controlled by foliation and joints especially on the more resistant rock resulting into a dendrite river pattern. The basin geology of the River Opeki is mainly gneisses and minor occurrence of the Older Granites. In the upper half of the basin there are migmatized undifferentiated biotites and biotite-hornblend gneisses with intercalated amphibolites. In the lower half of the catchment, the schists, amphibolites, pegmatites,

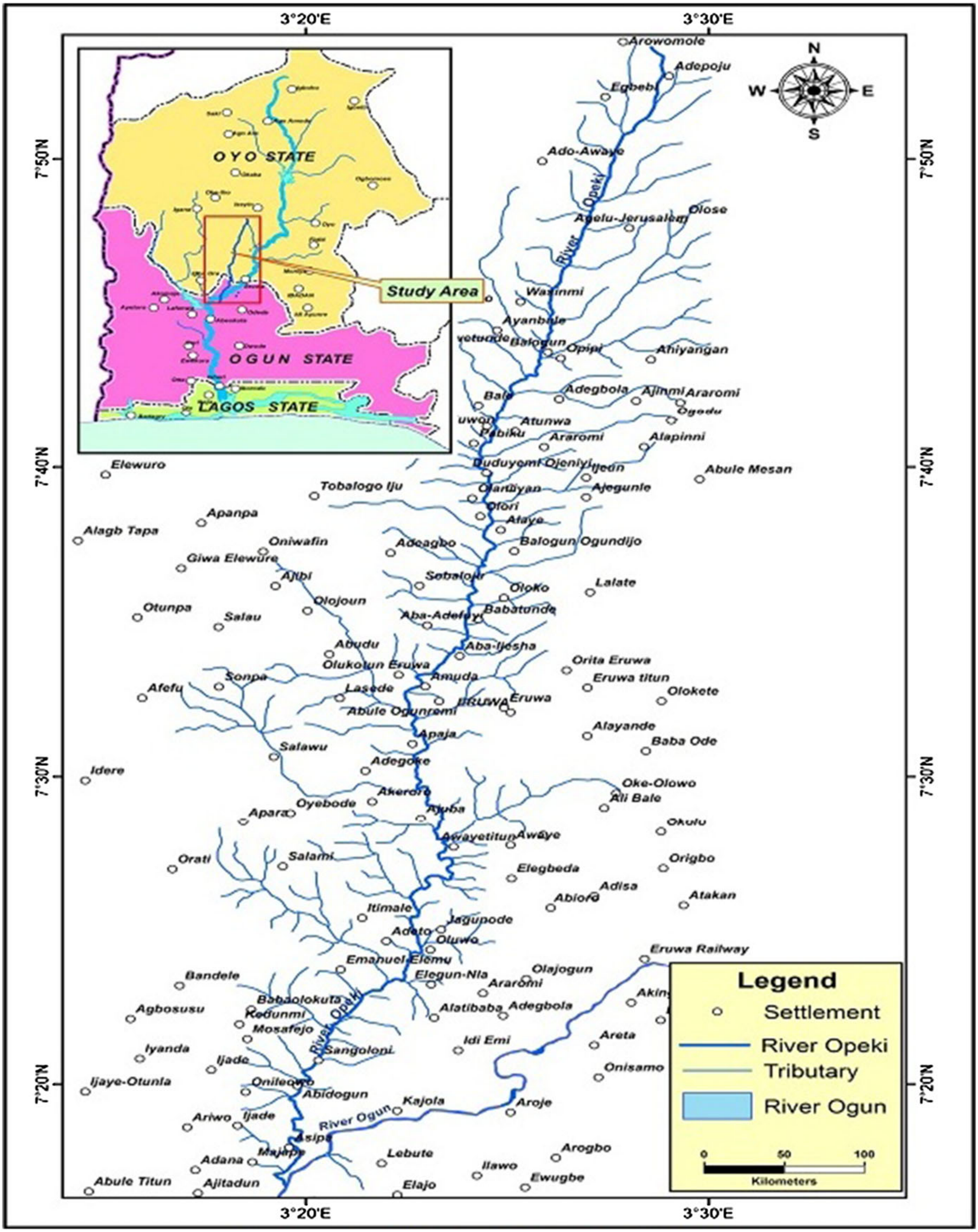


FIGURE 1 Map of study area [Colour figure can be viewed at wileyonlinelibrary.com]

and coarse porphyritic biotite and biotite-muscovite granite occur (Jones and Hockey, 1964). The catchment rises to an altitude of about 460 m above sea level in the northern part of the basin around Awaiye and slopes southwards to about 135 m above sea level at Abidogun at the mouth of the catchment. The axial length of the basin is about 73 km, and its form factor and basin circularity ratio are 0.2 and 0.8, respectively, indicating a long and narrow basin (Horton, 1932).

2.5 | Methodology

2.5.1 | Type and data source

The data used in the research comprised monthly discharge of River Opeki. The data were obtained from the Ogun-Oshun River basin Development Authority, Abeokuta, Ogun state (OORBDA) from 1982 to 2010 (28 years). However, there exists missing years within the period of study; hence, they were not included into the modelling because they were few and not continuous. Therefore, they would not affect the expected outcome.

2.6 | Data preparation

2.6.1 | ARIMA model

An ARIMA model is a combination of *p*,*d*,*q* model, AR (*p*) refers to order of the autoregressive component, I (*d*) integrated refers to degree of differencing involved, and MA (*q*) refers to the order of the moving average component. AR is based on the assumption that each value of the TS depends only on the weighed sum of the product of the previous values and the regression coefficient plus residual. An autoregressive model can be considered as a (*p*) order autoregressive model. It refers to previous (lagged) values of the dependent variable. MA is based on finding the mean for a specified set of values and then using it to forecast the next periods; MA (moving average) refers to lagged error terms (i.e., residuals) created by the model. It is represented by (*q*). Elements in the series can also be affected by past errors (or random shock) that cannot be accounted for by the autoregressive component. The general ARIMA *p*,*d*,*q* model can be expressed as

$$\begin{aligned}&[1 - \varphi 1(B) - \varphi 2(B)2 - \ldots - \varphi p(B)p]^{*}Xt \\ &= c + [1 - \theta 1(B) - \theta 2(B)2 - \ldots - \theta p(B)p]^{*}et\end{aligned} \tag{1}$$

or in a general form

$$\varphi 1(B)Xt = c + \theta 1(B)et\ldots \tag{2}$$

where φi refers to *i*th term autoregressive parameter, θi refers to *i*th term moving average parameter, *c* means constant, *e* means error at time *t*, *Bp* refers to *p*th order backward shift operator, and *Xt* refers to TS value at time *t*.

The first step in modelling is to determine if the TS is stationary (Figure 2) and if there is any significant seasonality in the TS. One of the assumptions of an ARIMA model is that the TS has to be stationary; if there is seasonality, the discharge data have to undergo seasonal differencing to make the series stationary; the data should also have a constant variance; and to satisfy stationary in variance the data also have to undergo log transformation to make the variance constant (Figure 2). In the model identification phase, the main tools that were used are plots of series of correlograms, which are the autocorrelation function (ACF) and the partial autocorrelation function (PACF; Baunso, 1998; Box & Jenkins, 1970). The ACF and the PACF are the most important elements of TS analysis and forecasting. The ACF measures the amount of linear dependence between observations in a TS, whereas the PACF plot helps to determine how many autoregressive terms are necessary to reveal the time lag characteristics. The AIC (Akaike Information Criterion) was used for the purpose of selecting an optimal model fit to a given data. The model that gives the minimum AIC was selected as a parsimonious model (Akaike, 1973, 1974; McQuarine & Tsai, 1998; Yaya & Fashae, 2014).

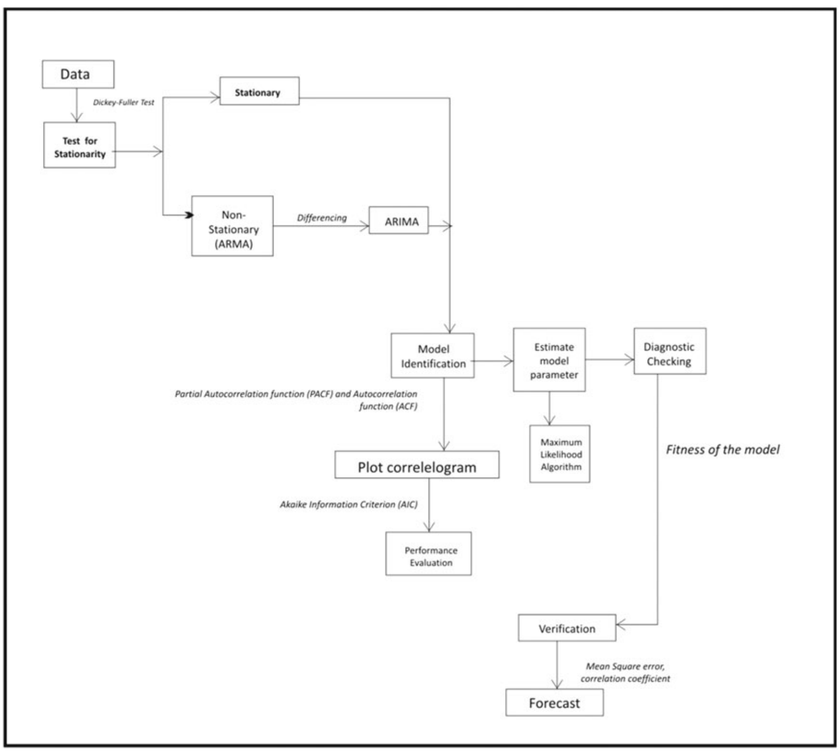


FIGURE 2 Schematic diagram of the methodology used in autoregressive integrated moving average modelling of the river discharge

2.6.2 | The ANN model

Neural networks emulate the human brain computational capacity by distributing computations to relatively simple processing units called neurons. The neurons are grouped in layers, and adjacent layers are interconnected through synaptic links (weights). Three different layer types can be distinguished: input layer, which connects the input information; output layer, which produces the final output; and one or more hidden layers, acting as intermediate computational layers between input and output Somvanshi et al. (2006). The input values are multiplied by the first interconnection weights, then the products are summed with a neuron-specific parameter called bias, which is used to scale the sum of products into a useful range and become inputs to the hidden layer nodes, which apply a nonlinear activation function (usually a sigmoid unit) to the above sum producing an hidden node output. These outputs are processed in the same way through the subsequent hidden layers (if existing) or through the output layer, generating the network output.

To model the discharge of River Opeki using ANN, the following basic steps were considered: collection of the data, data preprocessing, network building, training, and testing the performance of model. The modelling of the discharge of River Opeki using the ANN involves the preparation of the discharge data from 1982 to 2010 followed by training, testing, and lastly, validation. Past studies have proven that a three-layer ANN model with one hidden layer is sufficient to handle any nonlinear data. In this study the multilayer perceptron otherwise known as feed forward back propagation technique was adopted, the most widespread neural network structure. This ANN is fed in a forward direction from the input to the output, then the network was configured; discharge data from 1982 to 2009 were used for calibrating the model, whereas discharge data of 2010 were used for validation. The data required for the ANN model calibration are normally larger than the one required for model validation and forecasting (Salami, Mohammed, & Olukanni, 2015). In the third procedure, which is network building, the number of hidden layers, neurons in each layer, training function, and training algorithm were specified before applying the model (Salami et al., 2015). The training process involved the adjustment of the weights in each node using a specified error value in order to make the actual outputs (predicted) close to the target (measured) outputs of the network (Salami et al., 2015). The training period is normally longer than the validation and testing periods (Chen, Duan, Cai, & Liu, 2011). Discharge data of the River Opeki from 1982 to 2009 were used for training, whereas discharge data for 2010 were used to evaluate the accuracy of the model derived from the training set. At the forecasting stage, the estimated parameters were tested for their validity using the root-mean-square error (RMSE) and correlation coefficient (*r*). Specifically, the monthly discharge data sets of all the input variables were loaded for the ANN model development. The transfer function used was the Tangent Sigmoid (tansig) and the iteration (epoch) was 100. All the data sets were used for training the algorithm, testing, and validation. The input was 1, hidden neurons were 10, output was 1, and the lowest AIC value was 243.6. To choose the best model, the AIC was used as proposed by Akaike (1974). The model with the lowest AIC value was considered the best model for forecasting.

2.7 | Data analysis

EView 7 and MATLAB software was used for ARIMA and ANN modelling respectively. To achieve the aim of the study, a TS graph was plotted to show the trend in the discharge from 1982 to 2010 from where it was possible to describe the trend in discharge of the River Opeki. ARIMA and ANN model were then used to model the discharge of River Opeki from 1982 to 2010. Finally, ARIMA and ANN were compared with determine the best model.

3 | RESULT AND DISCUSSION

3.1 | Results of the ARIMA model for River Opeki (1982–2010)

The monthly discharge data show that there is a seasonal cycle within the series (Figure 3). Plots of ACF and PACF of the original data (Figure 4) show that the discharge data are not stationary; it also presents an attenuating sine wave pattern that reflects the random periodicity of the data and possibly indicates the need of seasonal differencing.

Both the ACF and PACF (Figure 4) input TS for ARIMA is required to be stationary and should have a constant mean, variance, and autocorrelation with respect to time, but the monthly discharge TS exhibits a yearly periodicity, but it could satisfy stationarity in variance by log transformation so as to make the variance constant (Figure 5).

The mean of the discharge data was also made stationary by differencing the original data in order to fit an ARIMA model. However, if differenced transformation is applied only once to a series, that means data have been *first differenced* (D = 1). The monthly discharge data of River Opeki required having a first seasonal differencing of the original data in order to have a stationary series. Then, the ACF and PACF for the differenced series were tested to check stationary (Figure 6).

To determine the best fitted model of the observed flows, the ordinate of ACF and PACFs was used at the important lag value of 12, which means that the ACFs have significant values at lags that are multiples of 12 (Figure 7).

The peak on the graph of the PACF at lag 12 suggests seasonal MA terms (Mehrdad, Mehrdad, Hossein, Hossein, & Mohammad, 2012). After Bartlett's transformation (α = 0.5) was applied to the data,

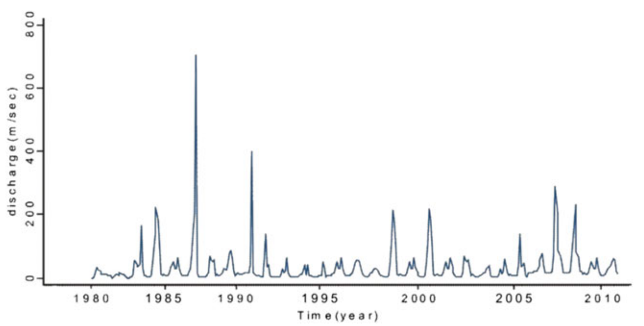


FIGURE 3 Time graph of original discharge data [Colour figure can be viewed at wileyonlinelibrary.com]

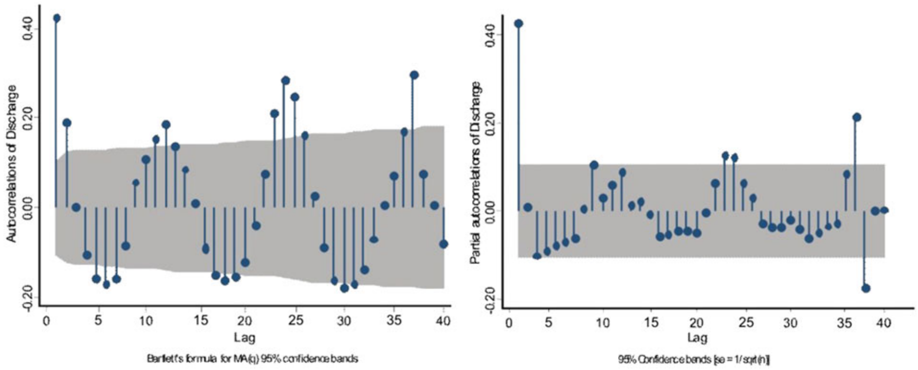


FIGURE 4 Autocorrelation and partial autocorrelation functions of monthly discharge [Colour figure can be viewed at wileyonlinelibrary.com]

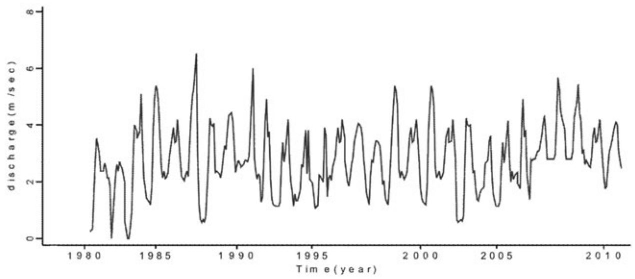


FIGURE 5 Log transformation of the discharge data of River Opeki

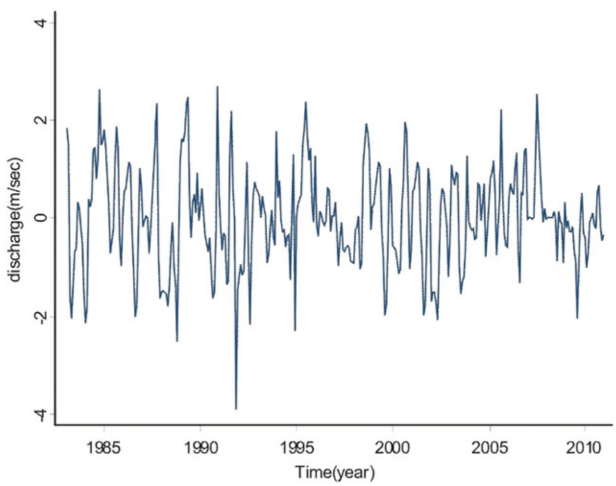


FIGURE 6 Seasonal differenced series of discharge data [Colour figure can be viewed at wileyonlinelibrary.com]

an ARIMA model of (p,0,q) × (P,1,Q)^{12} was identified for the seasonally differenced series. The suitability of the model was tested using AIC (Salas, Tabios, & Bartolini, 1985). The minimum AIC value (1.73) was selected. Hence, according to the AIC results, autoregressive moving average techniques (ARMA; 1, 12) becomes the most appropriate model.

3.2 | Results of the ANN model for River Opeki (1982–2010)

3.2.1 | Trend of the discharge of River Opeki (1982–2010)

There has been a discharge fluctuation on the River Opeki over the study period. For instance, the highest discharge received in the study area was in November 1987 with a value of 705 m^3/s. The

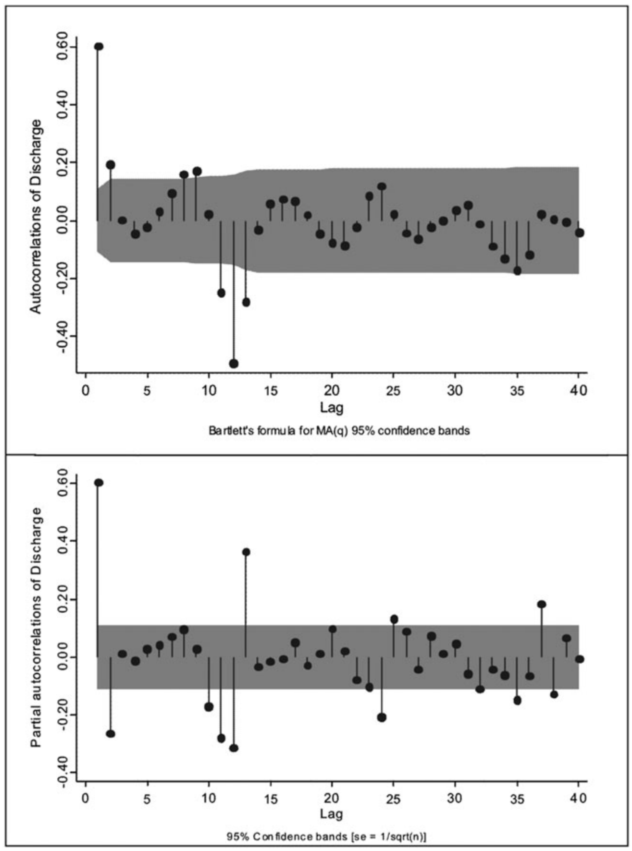
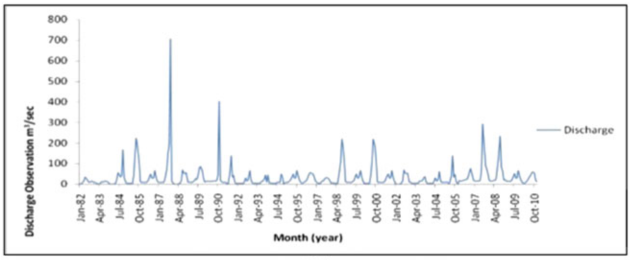
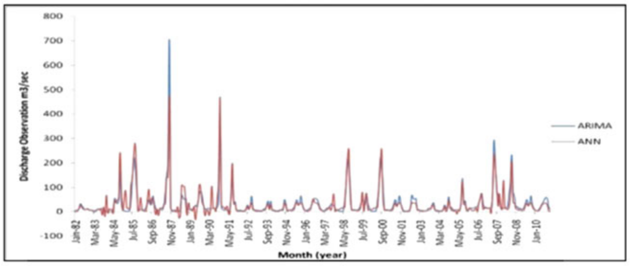


FIGURE 7 Autocorrelation and partial autocorrelation functions of monthly discharge taken after log and differencing

River Opeki also experienced a high level of discharge during November 1990 with a discharge value of 403 m^3/s, since this time the river has never experienced such a high volume of discharge (Figure 8). August 1998 and 2000 experienced similar discharges with values of 216 and 262 m^3/s, respectively. It was also observed that in July 2007 there was another rise in the discharge experienced with a value of 290.6 m^3/s (Figure 9). The variations in the discharge experienced by the river are determined by climatic factors particularly precipitation and the physical characteristics of the drainage basin. The latter includes land use, type of soil, type of vegetation, area, shape, elevation slope, orientation, type of drainage network, extent of indirect drainage, and artificial drainage (Wisler & Brater, 1959; Fetter, 1988; Ufoegbune, Yusuf, Eniola, & Awomeso, 2011; Olusola & Fashae, 2017; Fashae & Olusola, 2017).



(a)



(b)

FIGURE 8 (a) Monthly trend of discharge of River Opeki (1982–2010). (b) autoregressive integrated moving average (ARIMA) and artificial neural network (ANN)–predicted discharge (1982–2010). [Colour figure can be viewed at wileyonlinelibrary.com]

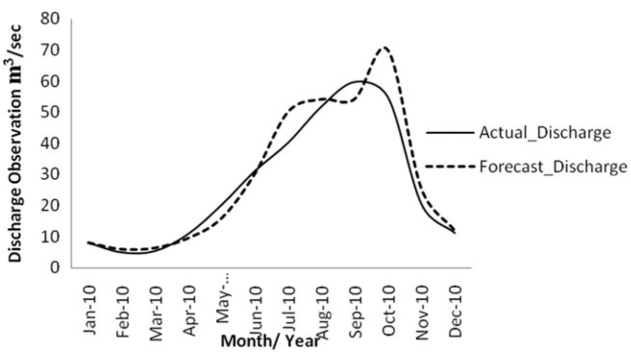


FIGURE 9 The observed and predicted discharge of autoregressive integrated moving average model for 2010

The effect of rainfall has great influence on the discharge level of a river, and the variation in the seasonal distribution of rainfall on the river is attributed to the ITCZ. According to Livina et al. (2003) the fluctuations in river flow are high for large river flow and small for low river flow. The low flows experienced in the river during some months can also result from groundwater level at that period, and the flow at a particular time is a function of previous flows during the period, which may be represented by an autoregressive dependence structure. The high flows during the wet seasons are formed mainly by heavy rainfall and therefore may be represented by a moving average scheme (Salas et al. 1985).

3.2.2 | Forecast analysis of the discharge using the ARIMA and ANN model

The transformed discharge data were used to model the discharge of the River Opeki. The predicted discharge of ARIMA from 1982 to 2010 was compared with ANN (Figure 8b). The ANN result shows that during October 1987 the discharge is 473.4 m^3/s, whereas the ARIMA result is 705.7 m^3/s (Figure 8b); it was also observed that both ARIMA and ANN models have the same discharge values in March 1988 and September 2000 with a discharge value of 260 m^3/s. In July 2007 ARIMA predicted the discharge of 298 m^3/s, whereas ANN-predicted discharge is 250 m^3/s.

3.2.3 | Short-term prediction of ARIMA and ANN model for 2010 (observed)

The performance of ARIMA and ANN model was assessed by using the models to predict the discharge of 2010 and comparing the predicted discharge with the observed discharge. The graph of ARIMA and the observed data was plotted (Figure 9).

ANN and the observed data for 2010 were plotted on the same graph (Figure 10). The performance of the two models (ARIMA and ANN) was subjected to statistical test, the correlation coefficient (*r*), and the RMSE of the actual; and the forecasted data were used for comparison. The correlation coefficient (*r*) for ARIMA is 0.97 with a RMSE of 0.57, whereas ANN revealed a correlation coefficient of 0.93 and a RMSE of 15.06 (Table 1).

The result indicates that the ARIMA model appeared to display better performance compared with the ANN model. ARIMA showed a better performance than the ANN model when the RMSE was compared on a short-term basis. ANN had a higher RMSE value (15.06) than the ARIMA model (0.57), making the ARIMA model prediction better and more reliable.

Although the two models are different in structure and algorithm, they are essentially using the same information based on the monthly discharge to forecast future discharge values. The performance of the ANN model may be better if there were more information such as meteorological parameters (Hung et al., 2008); some other studies have also shown that for forecasting of discharge, the ARIMA is better (Juan et al., 2008), whereas studies involved with reservoir

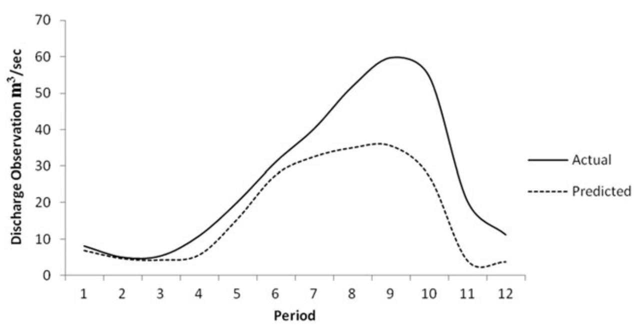


FIGURE 10 The observed and predicted discharge of artificial neural network model for 2010

TABLE 1 Observed and predicted discharge for both models for 2010

Technique	RMSE	*r*
ANN (feed forward back propagation)	15.06	0.93
ARIMA (1,12,12)	0.57	0.97

Note. ANN, artificial neural network; ARIMA, autoregressive integrated moving average.

and large datasets have indicated ANN models to be better (Abdulkadir et al., 2012; Mehrdad et al., 2012).

4 | CONCLUSION

This study has shown that river discharges can best modelled using the ARIMA technique. The result from the study has revealed that the ARIMA model performs better compared with the ANN model especially when there is limited information on other parameters (such as meteorological). The location of the river Opeki has strong implications on the economic, social, and environment. Therefore, modelling the river discharge in the light of existing poor infrastructures across major river basins in Nigeria and other parts of Africa is an added advantage.

Possibilities in modelling river discharges as presented in this study include efficient irrigation practice for arable farming, precision agriculture especially in sub-Saharan Africa, flood early warning designs, integrated hydroelectricity generation, effective water supply in the light of conjunctive uses, and promotion of healthy river systems.

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How to cite this article: Fashae OA, Olusola AO, Ndubuisi I, Udomboso CG. Comparing ANN and ARIMA model in predicting the discharge of River Opeki from 2010 to 2020. *River Res Applic*. 2018;1–9. https://doi.org/10.1002/rra.3391