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ARTIFICIAL NEURAL NETWORK AND DYNAMIC PROGRAMMING IN OPTIMIZATION OF FORECASTED RESERVOIR INFLOW

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ABSTRACT

In the study, simulation model is developed for the prediction of daily inflow into Dadin-Kowa Reservoir (River Gongola) in Northern Nigeria. In the study, the 1991-2001 records of observed and forecasted daily rainfall amounts are used as predictors and the reservoir daily inflow as predicted targets for Multilayer Perceptron Artificial Neural Networks (MLP-ANNs). With a learning rate of 0.01 and momentum coefficient of 0.85, the MLP-ANN model is developed using 1 input node, 7 hidden nodes, 1000 training epoches and 24 adjustable parameters. Error measures such as the Mean Absolute Error (MAE), the Mean Squared Relative Error (MSRE) and the Coefficient of Determination (R^2) are employed to evaluate the performance of the developed model for data calibration (1991-1998), verification (1991-2001) and validation (2010-2011). The result revealed: MAE={0.7156, 0.6717, 1.046} x 10^{-5}; MSRE = {1.4984, 1.5087, 1.1478 }x 10^{-7}; and R = {0.9957,0.9958,0.9688}. Furthermore, dynamic model is developed based on observed and simulated daily reservoir inflow to obtain optimal allocation policy to irrigation, industrial and domestic user sectors for each month of the year. The research reveals that only the months with prolonged dry spells have optimal returns to the user sectors while the months with records of rainfall could not produce optimized returns in the model. Therefore, the application of the results will lead to saving ₦175, 298,126 annually in the dam provision of water to the region.

KEYWORDS: Developed Model; Multilayered Artificial Neural Network; Prediction; Daily Inflow; Dadin-Kowa Reservoir; Optimal, Water Resources; Allocation; Semi-Arid Regions.

INTRODUCTION

Dadin-Kowa dam was commissioned in 1988 for irrigation, domestic water supply and flood control (Ibeje et al., 2012). Over the years, it has become very difficult to determine the area of cultivable land in each year because there is no prior information of available reservoir inflow. Sometimes the water needs of the cultivable area would be more than the available water in the reservoir. This has often resulted in the reduction of the cultivable area which in turn reduced the amount of agricultural produce. At other times, especially in wet years, the cultivable area would be limited. This resulted in evacuation of some water from the reservoir through the dam outlets. It is therefore very important to forecast the reservoir inflow in order to determine the optimal cultivable area which the reservoir supplies water. Dadin-kowa reservoir has lost large amount of water many times in the recent years. Excess rainfall during rainy season can fill the reservoir and make it to overflow at the end of rainy season. By forecasting the reservoir inflow, the excess water in rainy season could be used to generate hydropower energy before overflowing the dam.

The use of Artificial Neural Network (ANN) techniques in water resources and stream flow prediction is relatively new and has been reported by French et al., (1992); Zurada (1992); Hall and Minns (1993); Zealand et al., (1999); Abrahart et al., (1998); Zhu and Fugita (1994); Hsu et al (1993); Minns (1998) and Salazar et al., (1998), among others. ANN have a structure where nonlinear function are present and the parameter identification are based on techniques which search for global maximum in the space of feasible parameter values, and hence can represent the nonlinear effects present in the rainfall-runoff processes. An important advantage of ANN compared to classical stochastic models is that they do not require variables to be stationary and normally distributed (Burke, 1991). Non-stationary effects present in global phenomena, in morphological changes in rivers and other can be captured by the inner structure of ANN (Dandy and Mainer, 1996). Furthermore, ANNs are relatively stable with respect to noise in the data and have a food generalization potential to represent input-output relationships (Zealand et al., 1999). When combined with optimization methods, prediction techniques like ANN, serve management purposes much better.

"Water allocation is a means of dividing up available water resources among multiple users, with an aim of balancing the competing needs for water among all the users" (Australian Department of Agriculture, 2008). Allocation allows limited resources to be shared. In the case of water, allocation is currently made on the basis of whether the resources being assessed is currently in surface storage (surface water) or subsurface (groundwater). Water allocation is based on an estimate of sustainable yield of a defined resource, derived from an understanding of storage capacity, degree of replenishment and the impacts of extraction. Dynamic programming model, the technique of optimization of resources allocation was utilized in solving water allocation problem in this research. Allocation of water to the various user sectors namely irrigation, domestic and industrial water often resulted to conflicts in the chosen case study. This becomes more pronounced in months of dry spell. Thus, the objective of the study is to develop rainfall-inflow simulation model using Artificial Neural Network (ANN) which will be used to determine the optimal water allocations to each water demand sector that maximizes the total returns from all the demand sectors-irrigation, domestic and industrial water supply.

The Study Area

The study area is the Dadin-Kowa reservoir. This is located at the narrow section of the Gongola River in the present Gombe sate, Nigeria (see Figure 1). Dadin-kowa town is located between latitudes 10 to 10^o 20^o N and longitudes 11^o01^oE and 11^o19^oE (Figure 1) it shares common boundary with Akko L.G.A in the south and west, Yamatu-Deda to the East and Kwami to the North. It occupies an area of about $45km^2$ (Dadin-kowa L.G.A., 1999). The climate of Dadin-kowa is characterized by a dry season of six months, alternating with a six months rainy season. As in other part of Nigerian savanna, the precipitation distribution is mainly triggered by a seasonal shift of the inter-tropical Convergence Zone (ITCZ). For the years 1977 to 1995, the mean annual precipitation is 835mm and the mean annual temperature is about 26^oC whereas relative humidity has same pattern being 94% in August and dropping to less than 10% during the harmattan period (Dadin-kowa L.G.A., 1999). The relief of the town ranges between 650m in the western part to 370m in the eastern parts. Dadin-Kowa Dam is a multipurpose dam which impounds a large reservoir of water from Gongola River. It has a storage capacity of 1.77 billion cubic meters for irrigation to $950km^2$ (Ibeje, et al, 2012). Its flood spillway has a capacity of $1.111m^3/s$.

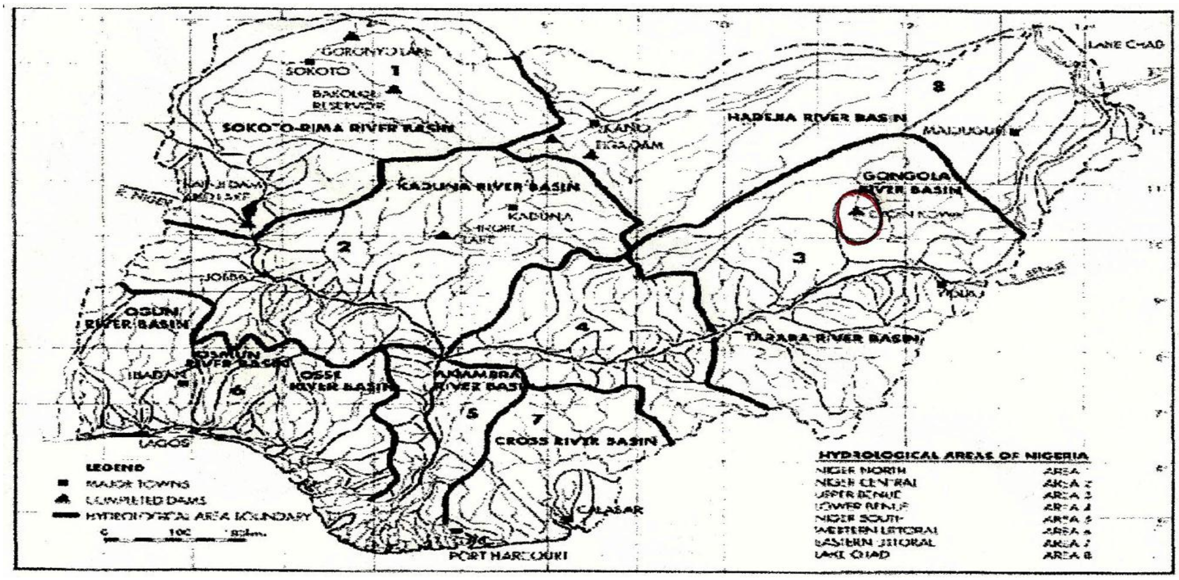

Figure 1: Hydrological Map of Nigeria Showing the Location of Dandi Kowa Reservoir.

Dadin-kowa dam construction was the Nigerian federal government project. The construction commenced in 1981 and was completed in 1987. The dam is a multipurpose project designed to serve among other uses, irrigation, industrial and domestic supply and flood control. Downstream of the River is located a rice farm that is irrigated by a canal from the dam (Ibeje et al., 2012). According to the farm manager, the farm is a 70Ha land and returns an annual yield of 8.5MT/Ha. The farm is allotted to small farmers cooperatives who pay agreed amount of money to the dam authorities for the water used in irrigation. More than 50 farmers are cultivating on the farmland. There is also a major conduit from the river intake that pumps water to a water treatment plant from where the water is sent to Gombe town for industrial and domestic uses. The water is toll free.

Rainfall-Inflow Simulation Modelling

In simulation context, MLP-ANN training consists of providing input-output examples to the network, and minimizing the objective function (i.e. error function) using either a first order or a second order optimization method. This so-called supervised training can be formulated as one of minimizing as function of the weight, the sum of the nonlinear least squares between the observed and the predicted outputs, defined by:

$$E = \frac{1}{2}\sum_{p=1}^{n}\sum_{k=1}^{m}\left(y_{pk} - \hat{y}_{pk}\right)^2 \qquad (1)$$

Where n is the number of patterns (observations) and m the total output units, y represents the observed response ("target output") and $\hat{y}$ the model response ("predicted output"). In the case of one output unit (m = 1) reduces to

$$E = \frac{1}{2}\sum_{p=1}^{n}(y_p - \hat{y}_p)^2 \quad (2)$$

Which is the usual function that is minimized in least squares regression. In the BP training, minimization of E is attempted using the steepest descent method and computing the gradient of the error function by applying the chain rule on the hidden layers of the MLP-ANN (Rumelhart et al., 1986). Consider a typical multi layer MLP-ANN whose hidden layer contains M neurons. The network is based on the following equations:

$$net_{pj} = \sum_{i=1}^{N} W_{ji} x_{pi} + W_{jo} \quad (3)$$

$$g(net_{pj}) = \frac{1}{1 + e^{-net_{pj}}} \quad (4)$$

Where net_{pj} is the weighted inputs into the jth hidden unit, N the total number of input nodes, W_{ji} the weight from input unit i to the hidden unit j, x_{pi} a value of the ith input for pattern p, W_{jo} the threshold (or bias) for neuron j, and $g(net_{pj})$ the jth neuron's activation function assuming that g() is the sigmoid function. Note that the input units do not perform operation on the information but simply pass it onto the hidden node. The output unit receives a net input of

$$net_{pj} = \sum_{j=1}^{M} W_{kj}\, g(net_{pj}) + W_{ko} \quad (5)$$

$$\hat{y}_{pk} = g(net_{pk}) \quad (6)$$

Where M is the number of hidden units, W_{kj} represents the weight connecting the hidden node j to the output k, W_{ko} is the threshold value for neuron k, and $\hat{y}_{pk}$the kth's predicted output. Recall that the ultimate goal of the network training is to find the set of weights W_{ji} connecting the input units i to the hidden units j and W_{kj} connecting the hidden units j to output k, that minimize the objective function (Eq. (6)). Since Eq. (6) is not an explicit function of the weight in the hidden layer, the first partial derivates of E are evaluated with respect to the weights using the chain rule, and the weights are moved in the steepest-descent direction. This can be represented mathematically as

$$\Delta W_{kj} = -\eta \frac{\partial E}{\partial W_{kj}} \quad (7)$$

Where η is the learning rate which simply scales the step size. The usual approach in BP training consists in choosing η according to the relation $0 < \eta < 1$. From Eq. (7), it is straightforward that BP can suffer from the inherent slowness and the local search nature of first order optimization method. However, BP remains the most widely used supervised training method for MLP-ANN because of the available remedies to its drawbacks. In all, second order nonlinear optimization techniques are usually faster and more reliable than any BP variant (Masters, 1995). Therefore, LMBP for MLP-ANN was used for data training. The LMBP uses the approximate Hessian matrix (second derivatives of E) in the weight update procedure as follows:

$$\Delta W_{kj} = -[H + \mu I]^{-1} J^T r \quad (8)$$

Where r is the residual error vector, μ a variable small scalar which controls the learning process, J = ∇E is the Jacobian matrix, and H = J ^{T} denotes the approximate Hessian matrix usually written as $\nabla^2 E = 2J^T J$. In practice, LMBP is faster and finds better optima for a variety of problems than do the other usually methods (Hagan and Menhaj, 1994).

Design of MLP-ANN Architecture

The number of predictors and predicands specified the number of neurons in the input and output layers respectively. An experiment with trial-and-error measure, recommended as the best strategy by Shamseldin (1997) is used to determine the number of neurons in the hidden layer. In general, the architecture of multi-layer MLP-ANN can have many layers where a layer represents a set of parallel processing units (nodes). The three-layer FNN used in this study contains only one intermediate (hidden) layer. MLP-ANN can have more than one hidden layer; however theoretical works have shown that a single hidden layer is sufficient for ANNs to approximate any complex nonlinear function (Cybenko, 1989; Horinik et al., 1989). Indeed many experimental results seem to confirm that one hidden layer may be enough for most forecasting problems (Zhang et al., 1988; Coulibaly et al., 1999). Therefore, in the study, one hidden layer FNN is used. It is the hidden layer nodes that allow the network to detect and capture the relevant pattern(s) in the data, and to perform complex nonlinear mapping between the input and the output variables. The sole role of the input layer of nodes is to relay the external inputs to the neurons of the hidden layer. Hence, the number of input nodes corresponds to the number of input variables. The outputs of the hidden layer are passed to the last (or output) layer which provides the final output of the network

Performance Assessment of Rainfall-Inflow Simulation Model

Commonly used error measures, therefore, were employed in this study to make the evaluation of the forecasts. They are coefficient of efficiency (CE), the mean absolute error (MAE), the squared relative error (MSRE) and the coefficient of determination (R^2), respectively defined as follows:

$$\text{MAE} = \frac{\sum_{i=1}^{n} /Q_i - \hat{Q}_i/}{n} \quad (9)$$

$$\text{MSRE} = \frac{\sum_{i=1}^{n} \frac{(Q_i - \hat{Q}_i)^2}{Q_i^2}}{n} \quad (10)$$

$$R^2 = \left[\frac{\sum_{i=1}^{n} (Q_i - \bar{Q})(\hat{Q}_i - \tilde{Q})}{\sqrt{\sum_{i=1}^{n} (Q_i - \bar{Q})^2 (\hat{Q}_i - \tilde{Q})^2}} \right]^2 \quad (11)$$

Where Q_i is the observed discharge, $\hat{Q}_i$ is the simulated discharge, $\bar{Q}$ is the mean of the observed discharges, $\tilde{Q}$ is the mean of the simulated discharges and n is the length of the observed/simulated series.

The MAE, which ranges from 0 to + ∞, is used to measure how close forecasts are to the eventual outcomes. Theoretically, a coefficient of zero (MAE = 0) means the best model with a perfect performance. The MSRE, which ranges from 0 to + ∞, can provide a balanced evaluation of the goodness of fit of the model as it is more sensitive to the larger relative errors caused by the low value and the best coefficient will be zero (MSRE = 0). The $R^{2,}$ which ranges from 0 to 1, is a statistical measure of how well the regression line close to the observed data and coefficient of one (R^2=1) indicates that the regression line perfectly fits the observed data.

Inflow Optimization Modelling

The main data used for the analysis were provided by the Upper Benue River Development Authority, Gombe State, Nigeria. They include information for the period 1991-2001 daily conduit outflow, daily canal outflow, price of water and total daily discharge. The cash benefits resulting from the use of water for basic house needs such as drinking water, water for cooking, cleaning, laundry, lawn care are referred to as domestic returns. On the other hand, cash returns basically due to allocation of water for various industrial purposes like product processing, cooling of machines, washing of plants and other diverse industrial applications are classified as industrial returns. The allocations from the dam are jointly pumped as town water supply; no separate meters were available to measure allocations to industries and the industries do not have water meters. Thus, industrial and domestic returns were lumped together in the model. The monthly industrial and domestic returns were lumped together in the model. The monthly industrial and domestic returns were computed as the product of the price of water, total monthly conduit discharge and the number of days in which the conduit was open in that month. This procedure was repeated for eleven years records of each month. Mathematically,

$$R_1(X_1) = s \times p \times n \tag{12}$$

Where s = Total monthly conduit flow in cubic meters per second (m^3/s), p = price of water in Naira per cubic meter (₦/m^3) and n = number of days the canal was on in a given month. As stated earlier, the dam allocates water to an irrigation site downstream of the Gongola River. The cash returns resulting from the use of water irrigation may not necessarily mean the monthly farm yield. This is because the farm yield is a composite unit resulting from more than just water as the farm input. Hence, the returns were computed as the product of the canal discharge, the price of water and the number of days in which the canal was left open in that month. This computation was repeated for eleven years record of the month considered. Mathematically,

$$R_2(X_2) = s \times p \times n \tag{13}$$

Where c = Total monthly canal discharge in cubic meters per second (m^3/s), p = price of water in Naira per cubic meter (₦/m^3) and n = number of days the canal was open in a given month.

Formulation of Inflow Optimization Model

A consideration of the model formulation for the month of January was first made. Then, the same approach was applied to the other months. However, the constraints for each of the months are different. The constraints for the other months are shown in Table1. For all the months the objective functions and the state variables are the same.

Stage 1: State variable: S_1, X_2, X^*_2 where S_1 = Amount of resource (water) available for allotment to agriculture, X_2 = Amount of resource (water) allocated to agriculture and X^*_2 = Allotment to agriculture that results in F^*_1 (s_1).

Objective Function: The objective is to maximize the return due to allocation of s_1.

Mathematically: $F^*1(S_1) = \mathrm{Max}[R_1(X_1)]$ (14)

Constraints: $0 \leq X_1 \leq S_1$; $0 \leq S_1 \leq 2{,}659{,}651{,}200 m^3$

Model: $F^*1(S_1) = \mathrm{Max}[R_2(X_{21})]$ (15)

$0 \leq X_2 \leq S_1$ $\qquad$ $0 \leq_{s1} \leq 2{,}659{,}651{,}200 m^3$

Stage 2: State variable: S_2, X_1, $(S_1\text{-}X_2)$, X^*_1 where S_2 = Amount of resource (water) available for allocation to agriculture, industrial and domestic uses; X_1 = Amount of resource allocated to industrial and domestic use, $(S_1\text{-}X_2)$ = Amount of resource available for allocation at stage 1 and X^*_1 = Allocation to industrial and domestic use that results in $F^*_2(S_2)$.

Objective function: $F^*2(S_2) = \mathrm{Max}[R_1(X_1) + F^*1(S_1) - X_2]$ (16)

Constraints: $0 \leq X_2 \leq S_1$; $0 \leq S_2 \leq 2{,}287{,}353{,}600 m^3$

Model: $$F^*2(S_2) = \mathrm{Max}[R_1(X_1) + F^*1(S_1) - X_2] \quad (17)$$

$0 \leq X_2 \leq S_1$ $\quad 0 \leq X_1 \leq 2{,}287{,}353{,}600 m^3$

Assumptions

(i) The price of water was assumed to be constant over the years as 1Kobo/m^3. This assumption though not practical was made because water is free of charge in Gombe state.

(ii) Conduit and canal outflows represent allocations to industrial and domestic; agricultural sectors.

(iii) No losses occurred in the allocations to the various user sectors.

(iv) Flow duration in a day was assumed to be 24 hours.

The constraints as well as the results of the parameters estimations are then inputted into TORA software. The dynamic programming calculations were performed using TORA software. This is a computer program capable of performing calculations in dynamic and linear programming (fig 4 and fig 5).

Results of Rainfall-Inflow Simulation Modeling

Tables 2, 3 and 4 show the R^2 (coefficient of determination) tests for the analysis to determine the number of input nodes, hidden nodes and the training epochs for MLP network trained using back propagation algorithm (MLP-BP). The results in table 2 were produced by assigning hidden node for the neural networks model and the number of input nodes was varied to identify the best input node required by the neural network. It is clear that the best R^2 tests were produced with one input node, i.e. when only the last inflow lag is used. By assigning input node to one and changing the number of hidden nodes, the results in table 3 were obtained. The results indicated that the best number of hidden nodes for MLP-BP is 7. The analysis to find the adequate training epochs was carried out and the results are shown in table 4. The results suggested that the adequate training epoch is 1000 for MLP-BP. In order to test the generalization properties of the neural networks models, R^2 tests for multi-step-ahead (MSA) forecasting of the inflow were calculated. The neural network models were trained using the following structure:

MLP-BP: input node = 1, Hidden Nodes = 7, Training Epochs = 1000

Table 1: Major Constraints in Optimization for Each Month.

Month	Stage of programming	Constraints (m^3)
January	2	$0 \le s_1 \le 2{,}659{,}651{,}200$
	1	$0 \le s_1 \le 2{,}287{,}353{,}600$
February	2	$0 \le s_1 \le 1{,}782{,}950{,}400$
	1	$0 \le s_1 \le 1{,}782{,}950{,}400$
March	2	$0 \le s_1 \le 1{,}628{,}467{,}200$
	1	$0 \le s_1 \le 1{,}628{,}467{,}200$
April	2	$0 \le s_2 \le 982{,}022{,}400$
	1	$0 \le s_1 \le 982{,}022{,}400$
May	2	$0 \le s_2 \le 3{,}152{,}653{,}200$
	1	$0 \le s_1 \le 3{,}153{,}563{,}200$
June	2	$0 \le s_2 \le 3{,}983{,}904{,}000$
	1	$0 \le s_1 \le 3{,}983{,}904{,}000$
July	2	$0 \le s_2 \le 5{,}244{,}307{,}200$
	1	$0 \le s_1 \le 5{,}244{,}307{,}200$
August	2	$0 \le s_2 \le 429{,}481{,}440$
	1	$0 \le s_1 \le 429{,}481{,}440$
September	2	$0 \le s_2 \le 679{,}752{,}000$
	1	$0 \le s_1 \le 679{,}752{,}000$
October	2	$0 \le s_2 \le 3.346272 \times 10^{10}$
	1	$0 \le s_1 \le 3.346272 \times 10^{10}$
November	2	$0 \le s_2 \le 1.061424 \times 10^{10}$
	1	$0 \le s_1 \le 1.061424 \times 10^{10}$
December	2	$0 \le s_2 \le 8{,}991{,}388{,}800$
	1	$0 \le s_1 \le 8{,}991{,}388{,}800$

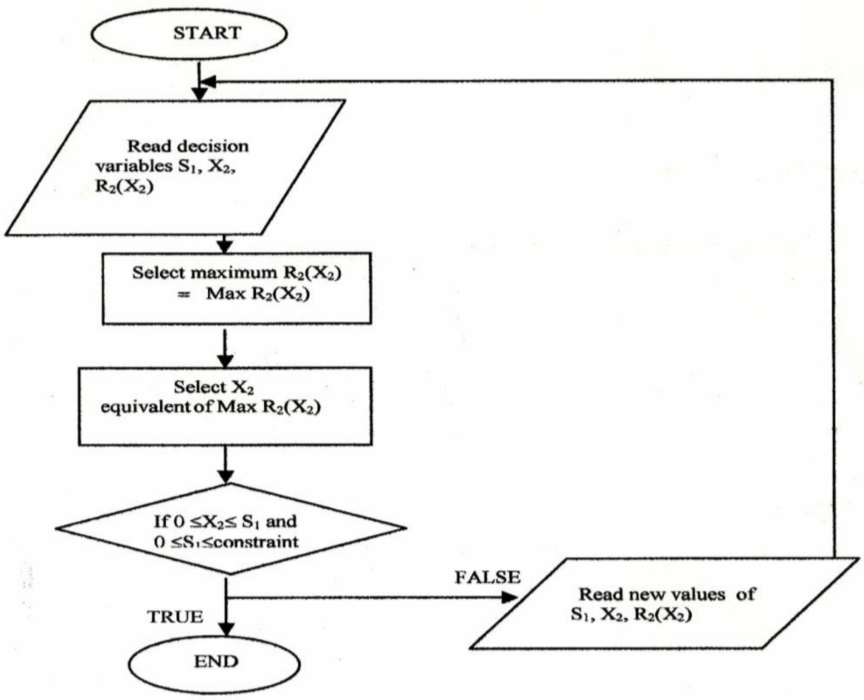

Figure 4: The Algorithm of the Stage 1 Flowchart of the TORA Software Dynamic Programming Calculations.

R^2 tests for lead-time from 1-day up to 6-day of the inflow were calculated over both the training and independent data sets as shown in table 5. The results for training data set indicate that MLP-BP gave good R^2 tests up to 4-day, 5-day and 6-day lead-time respectively, where their R^2 test values are about 0.8. The results for independent set in table 4 showed that MLP-BP gave good R^2 tests up to 4-day, 5-day and 6-day ahead, respectively.

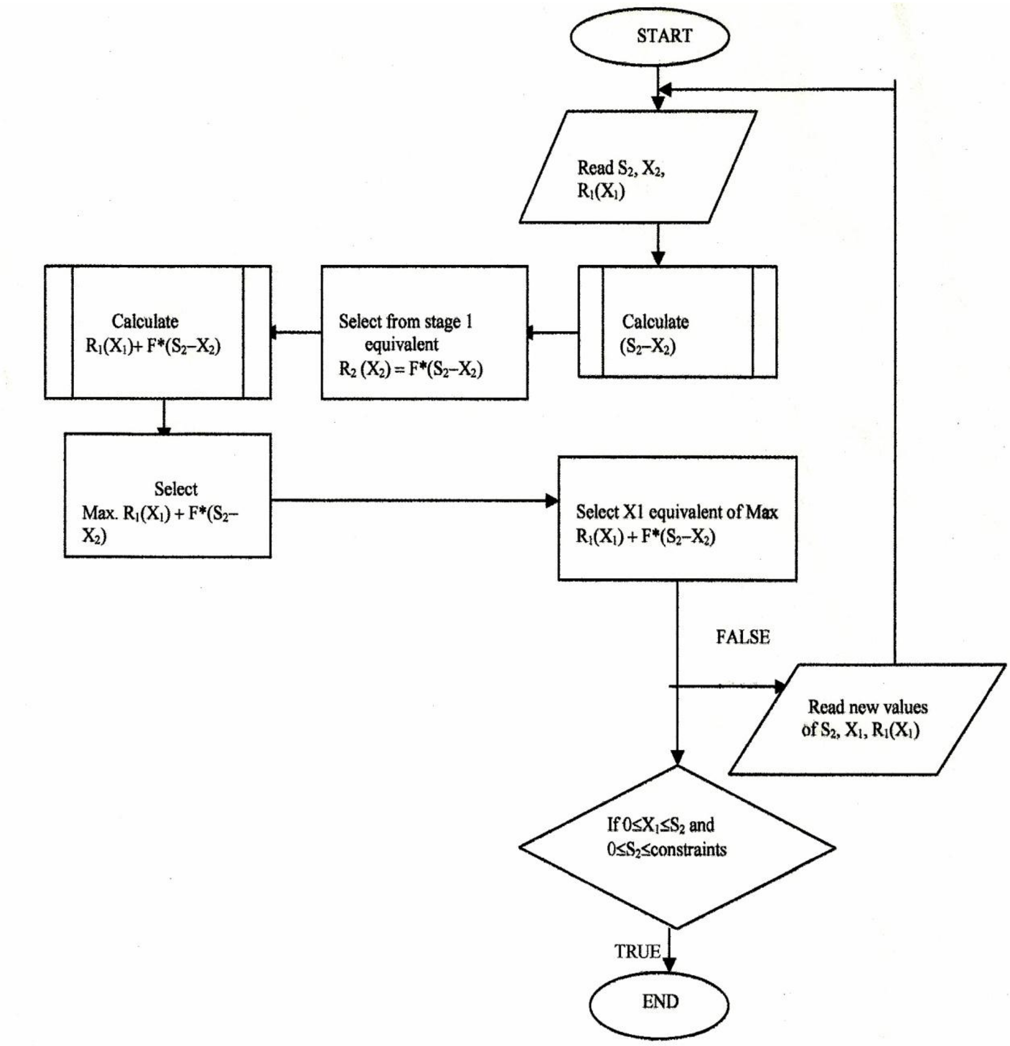

Figure 5: The Algorithm of the Stage 2 Flowchart of the TORA Software Dynamic Programming Calculations.

Table 2: Variation of R^2 Tests with Different Input Nodes.

No. of input nodes	MLP-BP
1	0.9290
2	0.3927
3	-0.3635
4	-0.4949
5	-0.4949

Table 3: Variation of R^2 Tests with Different Hidden Nodes.

No. of hidden nodes	MLP-BP
1	-1.5959
2	0.8946
3	0.9290
4	0.9536
5	0.9521
6	0.9508
7	0.9570
8	0.9543
9	0.9507
10	0.9296
11	-
12	-
13	-
14	
15	-
20	-

Table 4: Variation of R2 Tests with the Number of Training Epochs.

No. of epoch	MLP-BP
1	-0.6300
2	-0.6278
3	-0.6233
4	-0.6129
5	-0.5847
6	-0.5123
7	-0.3538
8	-0.1210
9	0.0854
10	0.2498
12	0.5184
14	0.7317
16	0.8567
18	0.8996
20	0.9242
100	0.9570
1000	0.9706
1500	-
2000	-
3000	-

Table 5: R^2 Tests Calculated over both the Training and Independent Data Sets.

Lead-time (days)	Training data set	Independent data set
	MLP-BP	MLP-BP
1	0.9888	0.9706
2	0.9771	0.9342
3	0.9491	0.8899
4	0.9098	0.7955
5	0.8672	0.7232
6	0.8138	0.6311

Results of Model Performance Assessment

Table 6: Model Error Measures for the Calibration, the Validation and Verification Data sets.

Q_R/ MLP-BP-ANN: 1-7-1/0.9957			
Data	**R**	**MAE×10^{-5}**	**MSRE×10^{-7}**
Calibration (1991-1998)	0.9957	0.7156	1.4984
Validation (2010-2011)	0.9946	1.1046	1.4035
Verification 1999-2001	0.9688	1.1478	1.1478

Satisfactory forecasting is obtained in this study since the R^2 is sufficiently high and close to 1, and the MSRE is adequately low and approximates to 0. The measures MAE of calibration and validation are far less than the relevant mean value of the observed data. The high score of R^2 indicate that all the models present the “best” performance according to the standard given by Dawson et al. (2007). The statistic result of error measures of the validation are as much as that of the calibration and both of them are encouraging. This outcome implies that the training procedures are successful without “overtraining” or “local minimum” and the proposed models have powerful generalization abilities for out-of-sample forecasting.

Results of Inflow Optimization Modelling

The water allotted to the industrial and domestic sector (town water supply) should be varied within the lower limits of demand especially on days of prolonged rainfall. This is because the energy utilized in pumping the water to the treatment plant as well as the cost of treatment is not justified by the reckless use of the water by the consumers. This is because alternative sources such as rainwater harvesting are available during such days. This recommendation should be followed religiously mainly in the months of July, September, October and December where no optimal returns were observed in the model for industrial and domestic water allocation. The following allocation policies as shown in the table 10 are recommended for adoption for the management of the Dadin-Kowa dam project. It is strongly recommended that the respective total monthly allocations should never fall below the values presented in the table above. The dam authority is advised to use any of the months of April, May or June for maintenance of the dam facility. This is suggested based on the revelations of the research that no amount of allocations in any of these months would attract any optimal benefit to the water users in any of the demand sectors.

CONCLUSION

In this work, Multilayer Perceptron Back Propagation Artificial Neural Network (MLP-BP-ANN) models were developed for forecasting daily inflow values into Dadin-Kowa reservoir. The experimental results indicate that these models can extend the forecasting lead-times with a satisfactory goodness of fit. As regards the accuracy, the model provided good

Table 7: Summary of the Results for Agricultural returns.

Month	Model Returns (₦)	Real Returns (₦)	Net Savings due to model (₦)
January (1991-2001)	4,313,088	2,239,486	2,073,602
February (1991-2001)	5,612,544	2,806,272	2,806,272
March (1991-2001)	6,642,432	6,220,000	422,432
April (1991-20010	*	*	*
May (1991-2001)	*	*	*
June (1991-2001)	*	*	*
July (1991-2001)	6,642,432	6,220,000	422,432
August (1991-2001)	6,642,432	1,555,200	5,087,232
September (1991-2001)	6,220,800	5,812,993	407,800
October (1991-2001)	7,776,000	6,642,432	1,133,568
November (1991-2001)	6,220,880	1,555,200	4,665,680
December (1991-2001)	*	*	*
Total			**17,019,018**

*No optimal yield was achieved

Accuracy for short time horizon forecast which however decreased when longer time horizons were considered and this was particularly true for the rising phase of the flood wave where a systematic underestimation was observed. This temporal limit is coherent with that detected by other authors using similar data-driven models applied to basins with similar extension to that considered in this study (e.g. Campolo et al., 1999, 2003; See and Openshaw, 1999; Solomatine and Dulal, 2003), and this limit is certainly due to the fact that no information or forecast of rainfall is considered available within the time spell ahead with respect to the instant when the forecast is performed. When the simulated inflow were applied in dynamic modelling for optimal reservoir release policy, the following inferences were remarkable. According to the model, optimal returns for various allocations of water: including agricultural; industrial and domestic uses are readily attained in the first three months of the year: January, February and March. Also similar success was recorded in the first months of August and November.

Table 8: Summary of Results for Industrial and Domestic Returns.

Month	**Model Returns (~~N~~)**	**Real Returns (~~N~~)**	**Net Savings due to model (~~N~~)**
January (1991-2001)	22,873,536	19,954,080	2,919,456
February(1991-2001)	12,458,000	7,499,520	4,958,480
March (1991-2001)	749,928,000	662,320,640	4,958,480
April (1991-2001)	3,392,062	3,392,064	-2
May (1991-2001)	6,722,784	6,722,000	784
June (1991-2001)	33,410,000	33,410,782	-782
July (1991-2001)	*	*	*
August (1991-2001)	270,920,160	207,847,648	63,072,512
September(1991-2001)	*	*	*
October (1991-2001)	*	*	*
November (1991-2001)	101,088,000	98,366,400	2,721,600
December (1991-2001)	*	*	*
Total			**158,279,408**

* No optimal yield was achieved

It could be inferred that optimization of returns to water allocation is possible only in the months that have long dry spells, i.e. unavailability of rainfall. September, October; represents periods of partial dry spells, optimal returns were recorded only in the agricultural sector through the use of the model. Thus, partial dry spell favors optimal returns for agriculture. However, the months of April, May, June, and December were the zero optimization months as none of the allocation sectors yielded optimal returns for the total unit of water allocated. The model and the real scenario replicated each other in these months. Therefore periods of rainfall do not require any optimization of water allocation based on the above judgments. The functional reservoir volume that supported all allocation policy was observed to be $1.5877557 \times 10^{10} m^3$ whereas the actual Live storage Capacity of the $1.77 \times 10^{10} m^3$. Application of the result will lead to saving ~~N~~175, 298,426 annually in the dam. Thus, a total of N175, 298,426 will saved in the dam annually by using the model.

Table 10: Recommended Optimal Allocation of Water.

Month	Recommended total monthly water allocations for optimal returns to all sectors (m^3)	Number of days in the month	Recommended average daily water allocations for optimal returns to all sectors (m^3/s)
January	2,659,651,200	31	993
February	1,782,950,400	29	712
March	873,043,200	31	326
April	982,022,400*	30	975
May	3,152,563,200*	31	1,177
June	3,983,904,000*	30	1,537
July	1,238,976	31	0.5
August	1.6×10^{10}	31	5,974
September	1.6×10^{10}	30	6,173
October	3.3×10^{10}	31	12,321
November	9,562,272,000*	30	3,793
December	3,562,272,000*	31	1330

*: Current allocation policy which is the average 11-year record for the month.

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