ANNALS OF FACULTY ENGINEERING HUNEDOARA
– INTERNATIONAL JOURNAL OF ENGINEERING
Tome X (Year 2012) – FASCICULE 3 (ISSN 1584 – 2673)

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APPLICATION OF ARTIFICIAL NEURAL NETWORK MODEL TO THE MANAGEMENT OF HYDROPOWER RESERVOIRS ALONG RIVER NIGER, NIGERIA

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ABSTRACT: *Reservoirs are constructed major to accommodate unregulated excess random water flows in the periods of high inflows for use in low-flow periods. In most cases, these reservoirs are meant to perform multiple functions. As a result of high variability of annual rainfall and conflicting demand for water resources, the study of operation and management of reservoir systems has assumed great significance. The achievement of multi-objective nature of the reservoir anchored mainly on the volume of water present at a particular period of time. Thus, management of hydropower reservoirs along river Niger was carried out by forecasting its future storage using Artificial Neural Network (ANN) model. This helps in planning on how it can be fully optimized for hydropower generation, domestic and industrial uses, irrigation and other uses. The networks were trained with monthly historical data of Jebba and Kainji hydropower reservoirs' inflow, outflow (release), storage and the evaporation loses. The trained networks yielded 95% and 97% of good forecast of training and testing set for Jebba, and 69% and 75% respectively for Kainji reservoir. The correlation coefficients of 0.64 and 0.79 were obtained for Jebba and Kainji reservoirs respectively.*
KEYWORDS: Hydropower variables, ANN Model, Network, Forecasting, Reservoir operation and management

INTRODUCTION

Reservoirs are built to accommodate unregulated excess random flows. This excess water is stored in reservoir in the periods of high inflows for use in low-flow periods. In the storage process, unregulated inflows are transformed by the reservoir into three kinds of outflows as highlighted by Campos (2010): the yield or regulated outflows, to supply societal water demand; evaporation losses from the reservoir surface; and the spill that represents the portion of unregulated inflow that remains unregulated as outflow. The management of the water resources is crucial since it directly affect the design and operation of many hydrological and hydraulic structures. At the planning of the construction of a dam, optimization modeling is very important in determining the optimum size of the reservoir. This procedure is called the operation study of a dam. The main data series used are monthly total inflow, evaporation losses and the amount of water that is planned to be taken from the reservoir called monthly demand (or Release). This may be used for domestic, industrial, irrigation or hydropower generation purposes. In operational study, the reservoir is assumed to be full of water at the beginning; this means the planner should assign a value of reservoir size. Salami and Sule (2012) developed optimal water management model for hydropower system on river Niger in Nigeria. The analysis revealed that an optimal energy of 5995.60 GWH can be generated, which is about 41% higher than the average energy generation of 4261.12 GWH obtained from the historical records at the power plants. The study also revealed that flood wall with the crown level at 76.50m (a.m.s.l) would be sufficient to prevent flooding downstream of Jebba dam.

The operation study is a trial and error method to check if the reservoir size assigned by the planner is sufficient or not (Cigizoglu and Kilinc, 2005). In recent years, data driven modelling is emerging. These data serves as a source of information for the development of model and to build a rule to simulate the operation of hydrological systems. Thus, artificial intelligence tools such as genetic algorithms, artificial neural network and fuzzy logic are increasingly used as soft computing techniques to solve modelling issues. The main advantage of these techniques lies in handling noisy data, addressing non-linear and dynamic systems (Swingler, 1996). These tools are equally useful when it is difficult to explain the physical relationships that exist within the data as well as the ability to self-train (Ogwueleka and Ogwueleka, 2009, and, Cigizoglu and Kilinc, 2005). Of recent, there is a significant advancement in the application of Artificial Neural Network (ANN) in modelling, especially in the field of hydrology and hydraulic engineering. In this study, the goal is to develop an ANN model to estimate or predict the future reservoir storage. In application of ANN model, the first step is the preparation of the training and testing. Having known the inter-dependence of the parameters, then, the structure of an ANN model will be constructed. This defines the number of hidden layers and neurons in each layer and selection of transformation function's type. The historic storage volume of reservoir is a discrete *variable (i.e. decision variable) and inflow, evaporation losses and the optimum release of the reservoir are state variables and formed the input data of the model.*

Proper management of hydropower reservoirs along river Niger i.e. Jebba and Kainji reservoirs can be achieved by forecasting their future storage from historical data of reservoir inflow, outflow (release) and the evaporation loses. The achievement of multi-objective nature of these reservoirs anchored majorly on the volume of water (reservoir storage) present at a particular period of time. Prediction of future reservoir storage using ANN model goes a long way in planning on how it can be fully optimized for hydropower generation, domestic and industrial uses, irrigation and other uses. Through the adequate forecasting, the following can also be achieved;

- *Optimization of reservoir volume for abstracting sufficient amount of water for hydropower generation, domestic and industrial water uses, irrigation etc*
- *Control of flood of the downstream reaches of Jebba and Kainji hydropower dams that might affect infrastructural developments, Bacita sugar-cane field and other agricultural activities.*
- *Evaluating reservoir capacities of Jebba and Kainji hydropower dams.*
- *Analyze operating policy to take account of the future water demand increase.*

In achieving this, series of computer programs have been written by many researchers to ease the applicability of ANN in modeling. To mention but few are; Neuro-solution, Alyuda Forecaster, Easy Neural Network Plus, NueNet Plus, MATLAB toolbox, SPSS etc. In this study, Alyuda Forecaster XL was used as a neural network forecasting tool because of its embedded support for Microsoft Excel.

DESCRIPTION OF STUDY AREA

The Niger River is the third longest river in Africa after the Nile and Congo/Zaire Rivers. It has a total length of about 4200 km with a theoretical area of about 2 million sq km. This area has reduced to an active catchments area of just about 1,500,000 sq km thus excluding Algeria which is among the 10 countries covered by the Niger River basin. Other countries are Benin, Burkina Faso, Cameroon, Chad, guinea, Ivory Coast, Mali, Niger, and Nigeria. Figure 1 present the course of River Niger and locations of dams at Kainji and Jebba in Nigeria. Niger River is usually subdivided into upper, the middle and the lower Niger, along with its tributaries forms the most important water resources of the Sahel region of West Africa. A series of dams have been constructed in the Niger basin for irrigation, domestic & industrial water supply and hydroelectric power generation. Notable among these dams especially in lower Niger are the Kainji and Jebba hydropower dams. The study area is however restricted to the Jebba and Kainji hydropower dams in which Jebba dam is located about 100km downstream of Kainji and on latitude $9^{o}06^{1}$N and longitude $4^{o}50^{1}$E. The important characteristics for the two reservoirs are presented in Table 1. The flow of river Niger downstream of Jebba dam is governed by the operations of the Kanji and Jebba hydroelectric schemes and runoff from the catchments (Sule et al, 2009). Reservoir releases from Kainji hydropower dam constitutes the major inflow into Jebba H.P dam since it lies directly under it.

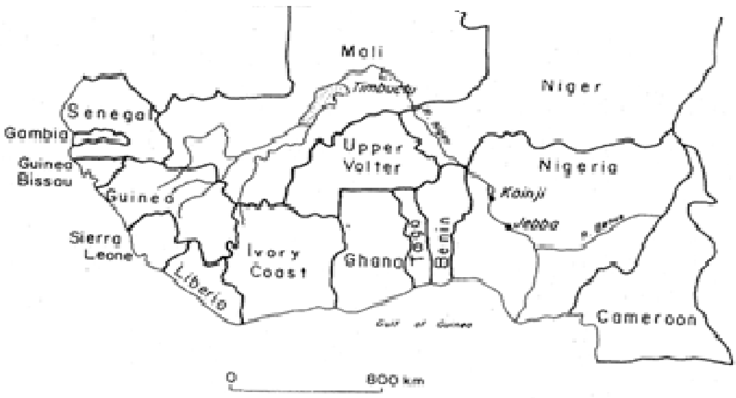

Figure 1. Map showing the course of River Niger and location of dams at Kainji and Jebba

Table 1. Basic Data on the Hydropower System

	Kainji	Jebba
First year of operation	1968	1984
Installed capacity (MW)	760	560
Design power plant factor	0.86	0.70
No. of generators	8	6
Reservoir flood storage capacity (Mm^3)	15,000	4,000
Reservoir flood level (m)	143.50	103.55
Maximum operating reservoir elevation (m.a.s.l)	141.83	103.00
Minimum operating reservoir elevation (m.a.s.l)	132.00	99.00
Maximum storage (Mm^3)(active storage capacity)	12,000	3,880
Minimum storage (Mm^3)(Dead storage capacity)	3,000	2880

Source: Power Holdings Company of Nigeria (PHCN) 2010

RESERVOIR MANAGEMENT

Reservoirs are built usually to serve multiple purposes such as irrigation, municipal and industrial water supply, hydropower generation, navigation and flood control among others. As a result of high variability of annual rainfall and conflicting demands on scarce water resources, the study and operation *of reservoir systems through adequate management has assumed great significance to meet the short and long-term requirements. One of the ways of improving the efficiency of water management is increasing the efficiency of the utilization of reservoirs. Hence, it is necessary to study the system and determine optimal reservoir operation guides for each scheme (Bosona and Gebresenbet, 2010). Determination of the size of the structure is mainly based on the statistical data of the natural events (majorly precipitation and evaporation losses) that will affect the structure. For reservoir management purposes several methods are used but all are based on the continuity equation given in Equation 1.*

$$S_{(t+1)} = S_t + Q_t - E_t - R_t \qquad (1)$$

where: $S_{(t+1)}$ = Present reservoir storage; S_t = Previous reservoir storage; t = Time increment (generally selected as one month), Q_t = inflow to the reservoir at present time, E_t = evaporation losses at present time, R_t = release /demand taken from the reservoir at present time.

ARTIFICIAL NEURAL NETWORK (ANN)

Artificial neural networks (ANN) are black box models that are used for forecasting and estimating purposes in many different areas of the science and engineering. An ANN in the context of statistical analysis is an alternative to or in addition to multiple regressions which is an information processing paradigm that is inspired by the way biological nervous systems, such as the brain, process information (Andy et al, 2004). The key element of this paradigm is the novel structure of the information processing system. Its computing system composed of a large number of highly interconnected processing elements (neurons) working together to solve a specific problem. ANNs, like people, learn by example (Juan and Julian, 2006). An ANN model is designed for specific applications which include data classification through a learning process, extracting patterns and detecting trends that are too complex to be noticed and deriving meanings from complicated or imprecise data. Learning in biological systems involves adjustment to the synaptic connections that exist between the neurons (Richard, 1987). The same occurs in ANN in which neurons (units) receive inputs from single or multiple sources and produces output in accordance with a predetermined nonlinear function called activation function. A neural network model is created by interconnecting many of these neurons in a known configuration. Haykin (1994) identified the following areas of application of ANN model; pattern matching (adaptive learning), optimization, data compression, self-organization and function optimization. The different methods of ANN model are Feed-Forward Back-Propagation Neural Networks (FFNN), Radial Basis Neural Networks (RBNN) and Recurrent Neural Networks (RNN). There have been a number of reported hydrological and hydraulic studies in which ANN model have been used to address. Doğan et al (2009) applied ANN for forecasting of daily stream-flow, Modarres (2008) used ANN to model rainfall-runoff process, rainfall forecasting model by Kin et al (2009). Omid and saeed (2005) worked on evaluation of ANN in optimization models of hydropower reservoir operation.

ESSENTIAL FEATURES OF ARTIFICIAL NEURAL NETWORK

The three essential features of a neural network are network topology, the computational functions of its elements, and the training of a network. Network topology refers to the number and organization of the computing units, the type of connections between neurons and the direction of flow of information in the network. The number of nodes in the input layer is the number of independent variables while that of output nodes corresponds to the number of variables to be predicted. A simple ANN of N-input nodes, L-Hidden nodes and one Output node O architecture of N-L-O is as shown in Figure 2.

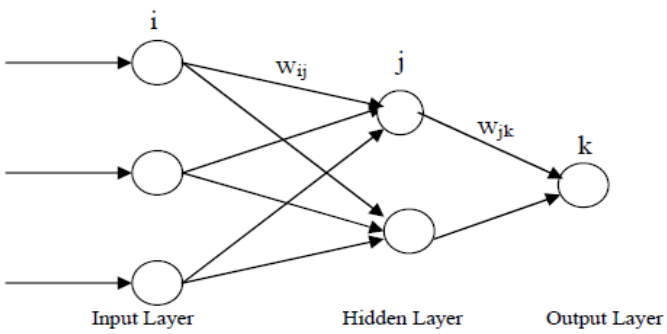

Figure 2: Typical Neural Network Computational Structure

The number of hidden layers and nodes used within the hidden layer vary according to the complexity of the task the network must perform. Kristen and Lee (2003) observed that there is no rigorous rule that determine the optimum configuration of a neural network to solve a specific problem. The computational function is another feature of the neural network which consists of the operations of the individual neurons and the way they are connected. Individual neurons calculate an output using the sum of inputs and an activation function. These nodes specifically perform the following functions as outlined by Kristen and Lee (2003):

1. *Signals are received from other neurons [X_0, X_1, X_2]*
2. *The signals are multiplied by their corresponding weights [W_0X_0, W_1X_1, W_2X_2]*
3. *The weighted signals are summed [$Sum=W_0X_0+W_1X_1+W_2X_2$]*
4. *The calculated sum is transformed by an activation function [f(Sum)]*

5. The transformed sum is sent to other neurons [Repeats 1-4 above]

The input into a node or neuron is either the direct input from a source exterior to the network or the weighted sum of the outputs from nodes in the layer above. Thus, the input into a node can be expressed by

$$\text{Net input } i = \sum_{j}^{n} W_{ij} \text{ x Output } j + \mu i \qquad (2)$$

where W_{ij} are the weights connecting node j to node i and μ is threshold function.

Activation function which may be linear or nonlinear is a crucial feature of neural nets. It limits the neuron's output to a range, usually between 0 and 1 or -1 and 1. Sigmoid or logistic functions are the most common activation functions and is written as

$$f(x) = \frac{1}{1+e^{-x}} \qquad (3)$$

where x is input/output of the network depending on the location within the network.

Training or learning is another feature of ANN model where optimal connection weights are determined by minimizing an objective function. Once the network layout and computational characteristics of the network are established, the network's adaptive learning strategy must be determined (Kristen and Lee, 2003). The learning process is when network weights change in response to a training data set. ANNs learn in two ways: supervised and unsupervised learning. Supervised training is used when the data set contains target output values associated with each input in the data set. The network compares the values it generated with the target values and minimizes the errors by discovering the driving features in the data and adjusting the weights. The most common algorithm used for adjusting the weights in supervised training is called back-propagation. This is used to find weights in multilayer feed-forward networks. The back-propagation algorithm is commonly used model for neural networks. The errors resulting from the comparison of the actual and target output values are propagated backward through the network, and the weight values are adjusted to minimize error. As long as the network continues to generate values closer to the validation values, training continues. The training simulation process ends when the error fall within a selected range of accuracy. In neural networks, the performance criterion is the minimization of squared error. Therefore, the total system error is expressed as follows:

$$E = \sum_{p,i} \left(t_{ip} - y_{ip}\right)^2 \qquad (4)$$

where E is error; i is indexes units of output; p indexes of the input-output pairs to be learned; t_{ip} refers to the desired output, and y_{ip} is the network's calculated output. The process begins with a set of arbitrarily chosen weights, W_o. Figure 3 shows the flow chart for the training process of the network.

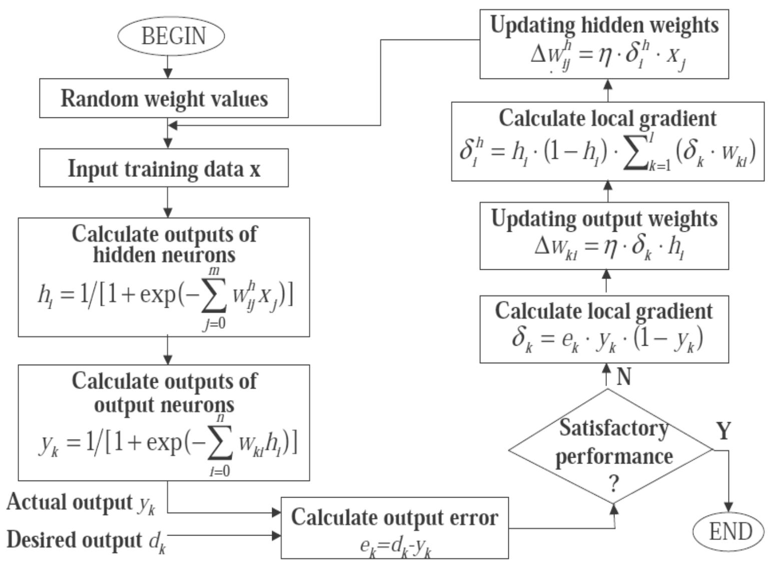

Figure 3: Flow Chart for the Training of the Network

MATERIAL AND METHOD. STATISTICAL ANALYSIS OF HYDROPOWER VARIABLES AT JEBBA AND KAINJI RESERVOIRS

Total monthly reservoir inflow (Mm^3), turbine release (Mm^3), evaporation losses (Mm^3) and storage (Mm^3) data were collected for a period twenty six years (1984 – 2010) for Jebba reservoir and forty years (1970 -2010) for Kainji reservoir. The total monthly data for each of the variables for Jebba and Kainji hydropower reservoirs are 312 and 480 respectively. Summary of the statistical analysis of the data is presented in Table 2.

Table 2: Statistics of Data for Jebba (1984-2010) and Kainji (1970-2010) Reservoirs

	Reservoir Inflow (Mm^3)		Turbine release (Mm^3)		Evaporation Loss (Mm^3)		Reservoir Storage (Mm^3)	
	Jebba	Kainji	Jebba	Kainji	Jebba	Kainji	Jebba	Kainji
Mean	2711.06	2504.35	2612.62	1881.96	18.74	141.54	3604.39	8063.30
Min	1012.44	24.36	956.45	513.91	10.00	26.78	2774.00	1579.00
Max	9738.67	7944.48	8680.70	3871.20	30.00	297.30	3911.00	12173.00
St dev	1330.69	1887.84	1001.34	580.10	5.00	65.80	167.67	2881.69
Skew	2.61	0.28	2.04	0.41	0.55	0.30	-0.63	-0.20

APPLICATION OF ANN MODEL TO JEBBA AND KAINJI RESERVOIRS MANAGEMENT

The data were splitted into three (3) sets: training, validation and testing set. The training set was used to train the network whereas the validation set was used to monitor or test the network performance at regular stages during the training. The training stopped when the error on the validation set reached the minimum. Finally, the performance of the network was evaluated on the test data set which had not been involved in the training process. In this study, the neural network was trained in Alyuda forecaster XL with 306 and 474 data of each of inflow, turbine release, and evaporation losses respectively for Jebba and Kainji reservoirs been the independent parameters (as input layers) and reservoir storage were used been the dependent variable (as output layer). The weights of input layer and hidden layer node are adjusted by checking the training and testing stage performances of neural networks. The determination coefficient and the mean square error are the performance criterion for the testing stage. In testing the performance of this model after the training, set of six (6) data of reservoir inflow, turbine release and evaporation losses that were not involved in the training of the network were used to forecast the future reservoir storage. The network's forecasted reservoir storage values were then compared with the measured storage values and the result is presented in Table 3.

Table 3: Comparison of ANN Forecasted with Measured Reservoir Storage (Mm^3).

S/No	Actual reservoir Storage		ANN forecasted reservoir Storage		Absolute Error		% Error	
	Jebba	Kainji	Jebba	Kainji	Jebba	Kainji	Jebba	Kainji
1	3418.00	4986.40	3500.57	5187.85	82.57	201.45	2.40	4.04
2	3623.00	4251.20	3610.40	4395.88	12.60	144.68	0.40	3.40
3	3585.00	6951.60	3651.30	7398.41	66.30	446.81	1.90	6.43
4	3266.00	8342.80	3357.52	8747.83	91.52	405.03	2.80	4.85
5	3615.00	8628.60	3577.52	9089.75	37.48	461.15	1.00	5.34
6	3653.00	9854.10	3713.95	10446.14	60.95	592.04	1.60	6.01

DISCUSSION OF RESULTS

Application of ANN model to Jebba hydropower reservoir inflow, outflow/release, evaporation losses and storage in 'Alyuda forecaster XL' environment generated a network structure (No. of input, hidden and output layers) of 3: 15: 1. This topology produced 95% and 97% of good forecast of reservoir storage in the training and testing set respectively. Similarly, ANN model for Kainji reservoir generated a network structure of 3: 22: 1 with 69% and 75% of good forecast in the training and testing set respectively. The correlation coefficients obtained for Jebba and Kainji hydropower reservoirs were 0.64 and 0.79 respectively. The comparison between ANN forecasted and actual reservoir storage data that were not used in training showed that the forecasts done were closer with a maximum error of 2.8% for Jebba and 6.4% for Kainji hydropower dams. This showed that the networks are fit to be used for subsequent prediction of reservoir storage. The relationship between the ANN forecasted and actual reservoir storage for Jebba and Kainji reservoir are presented in Figures 4 and 5 respectively.

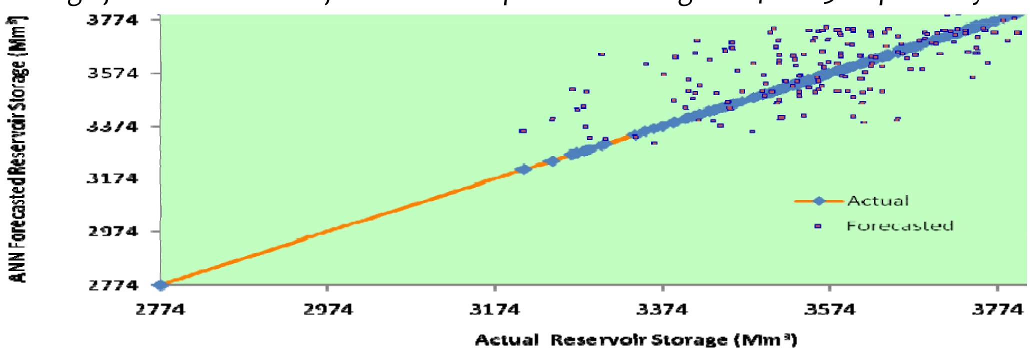

Figure 4: ANN Forecasted and Actual Reservoir Storage for Jebba Hydropower dam

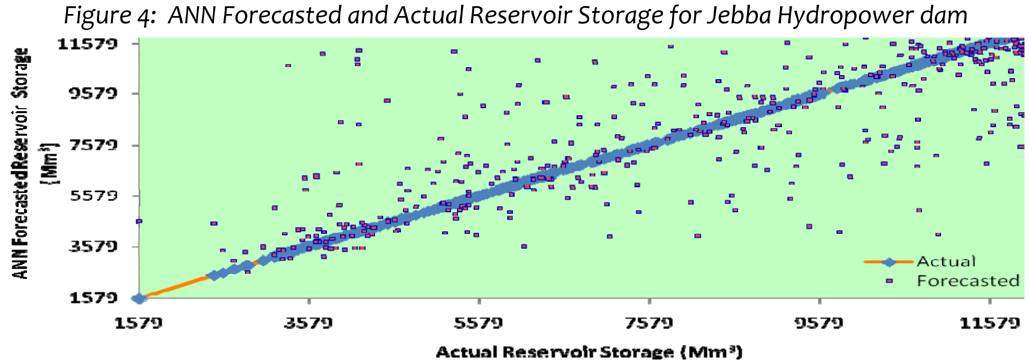

Figure 5: ANN Forecast and Actual Reservoir Storage for Kainji Hydropower dam

CONCLUSION AND RECOMMENDATION

Management of Jebba and Kainji hydropower reservoirs by forecasting their respective future storage at any given time helps in planning and optimizing the multi-objective uses of the reservoir. Having predicted future storage values, an operating policy can be formulated as regards to the quantity of water will be available for domestic & industrial uses, irrigation and hydropower generation. Neural network summary yielded 95% and 69% of good forecasts for Jebba and Kainji hydropower dams with respective correlation coefficients of 0.64 and 0.79. This showed that the networks are reliable for forecasting. It can therefore be concluded and recommended that forecasting using ANN is very versatile tool in reservoir management modeling.

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