International Journal of Engineering Research and General Science Volume 3, Issue 5, September-October, 2015
ISSN 2091-2730

Neural Network Based Model for Forecasting Reservoir Storage for Hydropower Dam Operation

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Key words: Neural Network, Forecasting, Reservoir operation, reservoir storage, hydrological variables.

Abstract- Reservoirs are constructed to accommodate unregulated excess random water flows in the periods of high flows for use in low-flow periods. In most cases, these reservoirs are meant to perform multiple objectives. As a result of high variability of annual rainfall and conflicting demand for water resources, the study of reservoir operation requires accurate forecasting of available water in the reservoir, which helps in planning and management of multi-objective reservoirs. This paper therefore, presents the operation of hydropower reservoirs in Nigeria by forecasting their future storage using Neural Network (NN) model. The networks were created and trained with monthly historical data such as reservoir inflow, turbine releases, reservoir storage and evaporation losses for Jebba, Kainji and Shiroro hydropower dams. The trained networks yielded 95% & 97% of goodness of fit respectively for training and testing of data at Jebba, 69% &75% at Kainji and 98% & 97% at Shiroro. The correlation coefficients between the forecast and observed reservoir storage of 0.64, 0.79 and 0.84 were obtained for Jebba, Kainji and Shiroro reservoirs respectively. The values of correlation coefficient suggested that the model fairly fit the variables and can subsequently be used for prediction of reservoir storage for operational performance.

1. 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 spillage. At the planning stage of a dam development, optimization modeling is very important in determining the optimum size of the reservoir. This procedure is called the operation study of a dam. The variables required for this study are inflow, evaporation losses and the amount of water planned to be taken from the reservoir (demand or release). This demand may be used for domestic, industrial, irrigation or hydropower generation purposes. This implies that improvement in reservoir operation can lead to large benefits (Bosona and Gebresenbet, 2010). Different operational models have been developed and applied to evaluate alternative plans for solving water management problems. The selection of an appropriate model for the derivation of reservoir operating guide curves is difficult and there is need for further improvement (Jothiprakash and Ganesan, 2006). The choice of techniques usually depends on the reservoir specific system characteristics, data availability, the objectives specified and the constraints imposed (Bosona and Gebresenbet, 2010). Salami and Sule (2012) developed optimal water management model for hydropower (HP) system on River Niger in Nigeria. The analysis found 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 found that flood wall with the crown level at 76.50m above mean sea level (a.m.s.l) would be sufficient to prevent flooding downstream of Jebba dam. Abdulkadir *et al.* (2013) modeled reservoir variables of two hydropower dams along the River Niger (Kainji and Jebba dams) in Nigeria for energy generation using multilayer perceptron neural network. The reservoir variables considered were inflow, storage, reservoir elevation, turbine release, net generating head, plant use coefficient, tail race level and evaporation losses. It was found that the networks are reliable for modeling energy generation as a function of reservoir variables for future energy prediction.

The operation of the three major HP reservoirs namely Jebba, Kainji and Shiroro in Nigeria was studied by forecasting their future storage from historical data of reservoir inflow, outflow (release) and the evaporation loses. The multi-objective nature of these reservoirs anchored majorly on the volume of water (reservoir storage) present at a particular period of time (Abdulkadir *et al.*, 2012a), hence through the adequate forecasting, the following can 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 the three hydropower dams that might affect infrastructural developments and agricultural activities.
- Evaluation of reservoir capacities of three hydropower dams.

Recently, data driven models are emerging. The data serve as source of information for the development of model and to build rules 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; 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 (Abdulkadir *et al.*, 2013). In this study, the goal is to develop an ANN model to predict the future reservoir storage for the three hydropower dams in Nigeria.

2 Materials and Method

2.1 Description of Study Area

River Niger 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 catchment 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. It includes two deltas: an inland delta in central Mali and a coastal delta along the Gulf of Guinea. The coastal delta is the largest in Africa, spanning nearly 190 km (120 mi). 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 and industrial water supply and hydroelectric power generation. Notable among these dams especially in lower Niger are the Kainji and Jebba while Shiroro HP dam is located along River Kaduna which is one of the tributaries of River Niger. The study area is however restricted to the Jebba, Kainji and Shiroro hydropower dams in which Jebba dam is located about 100km downstream of Kainji and on latitude $9^0 06^1$N and longitude $4^0 50^1$E. Shiroro dam on latitude $9^0 58^1$N and longitude $6^0 5^1$E located along River Kaduna originated from North West of Jos and flow through Kaduna and Shiroro George and discharged into River Niger. Fig. 1.1 is the map of Nigeria showing hydrological areas with hydropower location outlined while Fig. 1.2 shows location of the three Hydropower dams with floodplain hatched. The important characteristics for the three reservoirs are presented in Tab. 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 HP dam constitute the major inflow into Jebba HP dam since it lies directly under it.

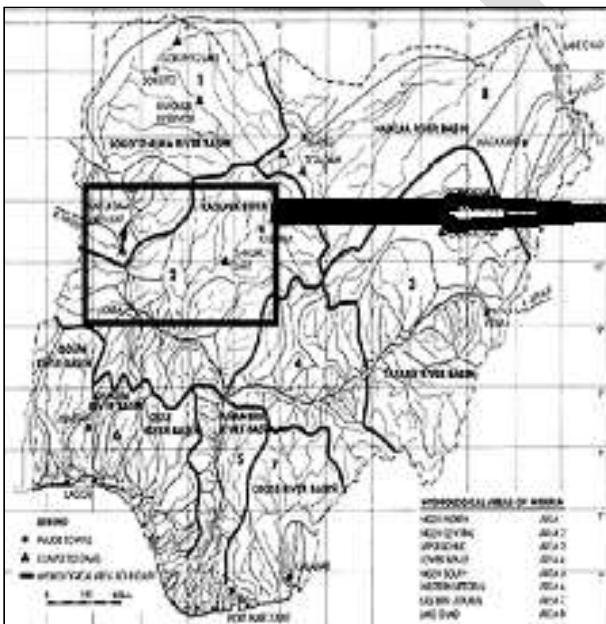

Figure 1.1 Map of Nigeria showing hydrological areas with hydropower location outlined

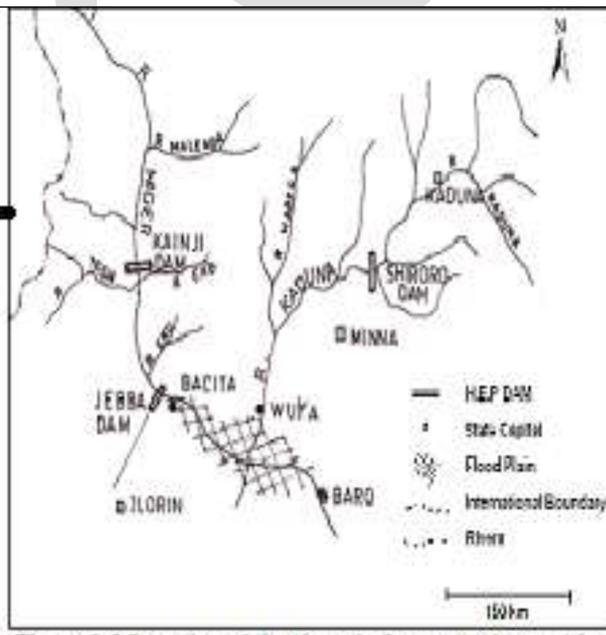

Figure 1.2 Location of the three hydropower dams with flood plain hatched

Tab. 1: *Basic Data of the Hydropower Reservoirs in Nigeria*

Parameters	Kainji	Jebba	Shiroro
First year of operation	1968	1984	1990
Installed capacity (MW)	760	560	600
Design power plant factor	0.86	0.70	0.8
No. of generators	8	6	4

Reservoir surface area (km^2)	1,250	270	312
Reservoir flood storage capacity (Mm^3)	15,000	4,000	7,000
Reservoir flood level (m)	143.50	103.55	385.00
Maximum operating reservoir elevation (m.a.s.l)	141.83	103.00	382.00
Minimum operating reservoir elevation (m.a.s.l)	132.00	99.00	342.00
Maximum storage (Mm^3)(active storage capacity)	12,000	3,880	6,500

Source: Power Holding Company of Nigeria (PHCN), 2012

2.2 Artificial Neural Network

Artificial neural networks (ANN) are black box models used for forecasting and estimating purposes in many different areas of the science and engineering (Abdulkadir *et al.*, 2013). 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; Hung *et al.*, 2008; Abdulkadir *et al.*, 2012b). 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. There have been a number of reported hydrological and hydraulic studies in which ANN model have been used to address. Dogan *et al.* (2009) applied ANN for forecasting of daily stream-flow, Modarres (2008) used ANN to model rainfall-runoff process and rainfall forecasting model was done using ANN by Kin *et al.* (2009) and Abdulkadir *et al.* (2012b). Omid and saeed (2005) also worked on evaluation of ANN in optimization models of hydropower reservoir operation.

The three essential features of a neural network are network topology, the computational functions of its elements and the training of the network. Network topology is 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 model is characterized by a network of three layers of processing units: p-input nodes, q-hidden nodes and r-Output nodes which are connected to one and other as shown in Fig. 2.

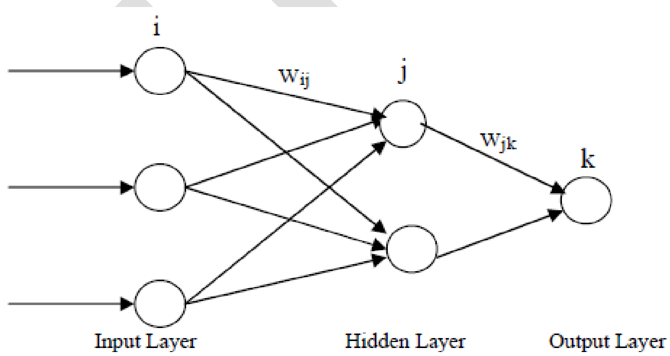

Fig. 2: *Typical Neural Network Computational Structure*

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. The first layer ***i***, (independent variables) that receives input information, is called an input layer. The last layer ***k***, (dependent variables) which produces output information, is called an output layer. There exists between the output and input layers the hidden layer ***j***. There can be one or more hidden layers with many nodes. Information is transmitted through the connections between nodes in different layers with the aid of connection weights w_{ij} and w_{jk}. Somvanshi *et al.* (2006) recommended the use of one hidden layer in preliminary studies. Having more than one hidden layers will definitely increase the number of parameters to be estimated. This may slow down the training process without reasonably improving the efficiency of the network.

Various ANN models approaches have been proposed for modeling since its inception. Multilayer perceptron (MLP) otherwise known as feed forward back propagation (FFBP), radial basis function (RBF), time-delay neural network (TDNN) and partial recurrent neural network (PRNN). The first two are the most widely used model. MLP maintains high level of research interest due to its ability to map any function to arbitrary degree of accuracy (Modarres, 2008) and amount to 80% of practical applications in field of engineering and science (Kin *et al.*, 2009). It is composed of multiple simple processing nodes, or neurons, assembled in several different layers. Each node computes a linear combination of weighted inputs (including a bias terms) from the links feeding into it (Ricardo and Jean, 1999). The summed value (net input) is transformed using a non-linear function called log-sigmold function as shown in Equation 1. This function maps any input to a finite output range usually between 0 and 1 or -1 and 1. Then, the output obtained serves as an input to other nodes. In modeling of hydrological variables, a set of variables is divided into three prior to the model building: the training, testing and validation sets. A set is used for training and the other is used to evaluate the accuracy of the model derived from the training set. In validation phase, the model output is compared with the actual output using statistical measurements such as root-mean-square error (RMSE), mean square error (MSE), Mean Absolute Percent Error (MAPE) and the coefficient of correlation (CORR) to examine the model performance (Somvanshi *et al.*, 2006; Khaing and Thinn, 2008; Hung *et al.*, 2008; Karim, 2009).

$$y_{i}= \frac{1}{1+e^{-x_i}} \qquad (1)$$

Where y_i = model output, x_i = model input, e = exponential function

2.3 ANN training algorithms

The training of the network is aimed at determining the main control parameters of ANN called weights. The processes of estimating these parameters are known as training where optimal connection weights are determined by minimizing an objective function (Somvanshi *et al.*, 2006). There are basically two types of training mechanisms: supervised and unsupervised training. A supervised training algorithm also known as back propagation training algorithms requires an external teacher to guide the training process. The goal of supervised training is to minimize the error at the output layer by searching for a set of connection strengths that cause the ANN to produce outputs that are equal to or closer to the targets (Shiru and McCann, 2011 and Karim, 2009). A supervised training mechanism is normally adopted in most of the engineering applications. An unsupervised training algorithm called self-organizing neural network is used when the training set lacks target output values (Shiru and McCann, 2011). The most famous self-organizing neural network is the Kohonen's Self-Organizing Map (SOM) classifier, which divides the input-output space into a desired number of classes (Karim, 2009). In supervised training, the network compares the generated values with the target values. The error resulting from the comparison is propagated backward through the network, and the weights are adjusted to minimize this error. The procedure continues until network generates value of error closer to the validation value. Thus, the performance criterion is the minimization of square error and this is expressed in Equation 2.

$$\boldsymbol{error} = \sum_{p,i}(t_{ip} - y_{ip})^2 \qquad (2)$$

Where i indexes unit of output, p indexes the input – output pairs to be learned. t_{ip} = desired output, y_{ip} = learned (network) output.

The standard training algorithm used in most hydrological applications is the back-propagation algorithm (Abdulkadir *et al.*, 2012a). The full mathematical derivation of this can be found in several neural networks textbooks. The main steps involved in the training are as illustrated below:

(i) initialize network weight value, usually using small numbers obtained from random number generator;
(ii) carry out forward propagation of the first input vector through the whole network. i.e. input signals multiplied by corresponding synaptic weights and then summed at each node. This is further transformed by an activation function in Equation 1 and sent to the output node;
(iii) compute the error by comparing the model output with the target (observed) data;
(iv) back-propagate the error information through the network;
(v) update the weights and
(vi) repeat the previous steps for several iterations until the error is within an acceptable range.

2.4 Statistical Analysis of hydropower Reservoir Variables

Total monthly HP reservoir inflow (Mm^3), turbine release (Mm^3), evaporation losses (Mm^3) and storage (Mm^3) data were obtained from PHCN for a period twenty nine years (1984–2012) for Jebba reservoir, forty three years (1970-2012) for Kainji reservoir and twenty three years (1990– 2012) for Shiroro reservoir. The number of total monthly data for each of the variables for Jebba, Kainji and Shiroro HP reservoirs are 348, 516 and 276 respectively. Summary of the statistical analysis of the data such as mean, median, standard deviation, minimum, maximum and skewness is presented in Tab. 2.

Tab. 2: *Statistical Analysis of the HP Reservoir Variables*

	Reservoir Inflow (Mm^3)			Turbine Release (Mm^3)			Evaporation Loss (Mm^3)			Reservoir Storage (Mm^3)		
	Jebba	Kainji	Shiroro	Jebba	Kainji	Shiroro	Jebba	Kainji	Shiroro	Jebba	Kainji	Shiroro

Mean	2711.1	2504.4	289.9	2612.6	1882.0	274.1	18.7	141.5	374.9	3604.4	8063.3	11.2
Min	1012.4	24.4	9.9	956.5	513.9	20.8	10.0	26.8	355.3	2774.0	1579.0	3.0
Max	9738.7	7944.5	1752.5	8680.7	3871.2	792.5	30.0	297.3	423.8	3911.0	12173.0	25.2
St dev	1330.7	1887.8	364.6	1001.3	580.1	111.9	5.0	65.8	14.2	167.7	2881.7	5.3
Skew	2.6	0.3	1.5	2.0	0.4	0.7	0.6	0.3	1.9	-0.6	-0.2	0.4

2.5 Application of NN Model to HP Reservoir Variables

Series of computer programs have been written by many researchers to ease the applicability of ANN in modeling. Some are Neuro-solution, Alyuda Forecaster XL, EasyNN Plus, NueNet Plus, MATLAB toolbox, SPSS, etc. In applying 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.

The HP reservoir data for each of the stations were partitioned 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 errors 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 342, 510 and 270 data of each of inflow, turbine release, and evaporation losses respectively for Jebba, Kainji and Shiroro reservoirs being the independent parameters (as input layers) and reservoir storage were used, being the dependent variable (as output layer). The weights of input layer and hidden layer node are automatically adjusted by checking the training and testing stage performances of neural networks. The coefficient of correlation and the mean square error are the performance criterion for the testing stage. In testing the performance of these models after the training, set of six (6) data of reservoir inflow, turbine release and evaporation losses for each of the locations that were not involved in the training of the network were used to forecast the future reservoir storage. The network's forecasted result for reservoir storage values were then compared with the measured storage values that were not involved at all in the training and the result is presented in Tab. 3.

Tab. 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	Shiroro	Jebba	Kainji	Shiroro	Jebba	Kainji	Shiroro	Jebba	Kainji	Shiroro
1	3418	4986.4	355.4	3500.6	5187.9	339.5	82.6	201.5	15.9	2.4	4	4.49
2	3623	4251.2	416	3610.4	4395.9	399.9	12.6	144.7	16.1	0.4	3.4	3.88
3	3585	6951.6	378.6	3651.3	7398.4	398.6	66.3	446.8	-20.0	1.9	6.4	-5.28
4	3266	8342.8	381.8	3357.5	8747.8	357.6	91.5	405	24.2	2.8	4.9	6.35
5	3615	8628.6	381.8	3577.5	9089.8	366.3	37.5	461.2	15.5	1	5.3	4.06
6	3653	9854.1	379.5	3714	10446.1	369.4	61	592	10.1	1.6	6	2.66

The relationship between the ANN forecasted and actual reservoir storage for Jebba, Kainji and Shiroro reservoirs for all the data involved in the training exercise are presented in Fig. 3, 4 and 5 respectively.

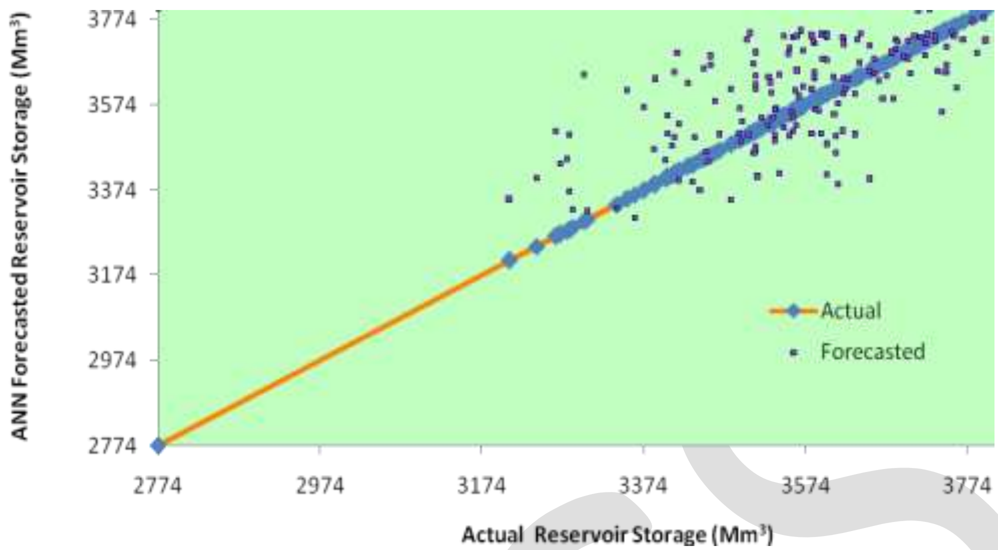

Fig. 3: *ANN Forecasted and Actual Reservoir Storage for Jebba HP dam*

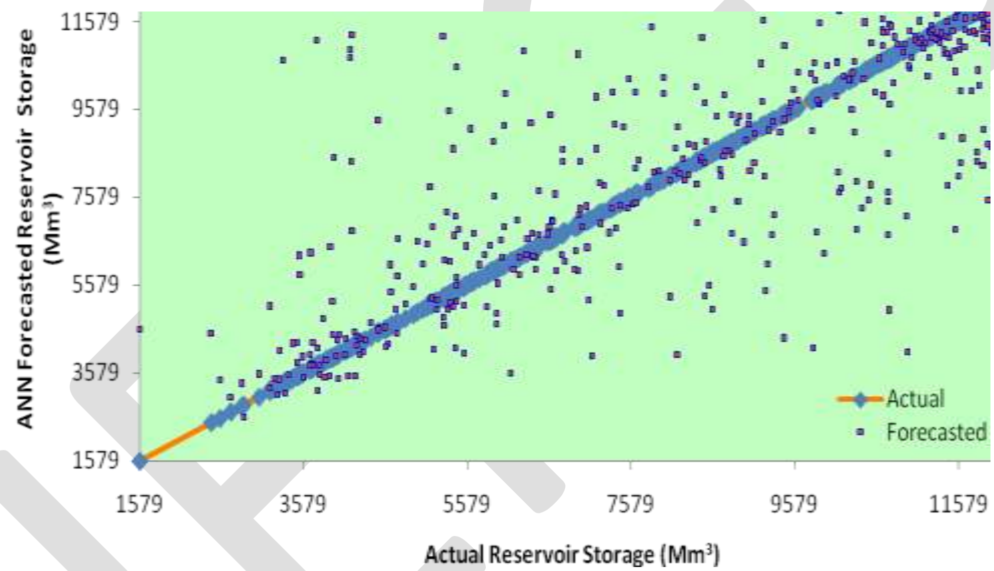

Fig. 4: *ANN Forecast and Actual Reservoir Storage for Kainji HP dam*

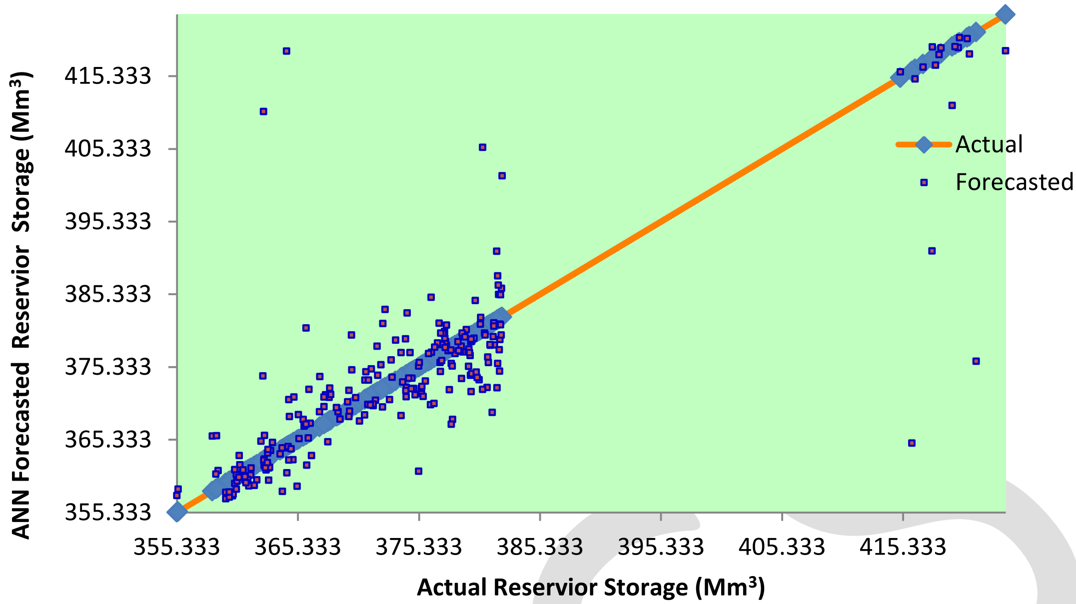

Fig. 5: *ANN Forecast and Actual Reservoir Storage for Shiroro HP dam*

3. Results and Discussion

The historical monthly data such as inflow, turbine releases, evaporation loss and reservoir storage at Jebba, Kainji and Shiroro hydropower reservoirs were statistically analyzed. Statistical parameters such as mean, median, standard deviation, minimum, maximum and skewness were estimated for each variable as presented in Tab. 2. Application of NN model to Jebba hydropower reservoir inflow, turbine releases, evaporation losses and storage generated a network structure (Number of neurons in input, hidden and output layers) of 3:15:1. This topology having one hidden layer with 15 neurons produced 95% and 97% of good forecast of reservoir storage in the training and testing set respectively. Also the 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, while for Shiroro reservoir network structure was 3:11:1 with 98% and 97% of good forecast for training and testing set respectively. The correlation coefficients (CORR) between the forecast and observed storage obtained for Jebba, Kainji and Shiroro HP reservoirs were 0.64, 0.79 and 0.84 respectively. The percentage errors of estimate between ANN forecasted and actual reservoir storage data not used in the training exercise showed that the forecasts done were closer with a maximum error of 2.8% for Jebba, 6.4% for Kainji and Shiroro HP reservoirs. Literatures had shown that CORR and MAPE are some of the tools to examine the model performance (Somvanshi *et al.*, 2006; Khaing and Thinn, 2008; Hung *et al.*, 2008; Karim, 2009; Abdulkadir *et al*, 2012a,b). The closeness of the values of CORR to one and MAPE to zero, the better the results. This showed that the networks are fit to be used for subsequent prediction of reservoir storage.

4. Conclusion and Recommendation

Operation of Jebba, Kainji and Shiroro hydropower reservoirs by forecasting their respective future storages would assists in planning and optimum management of multi-objective uses of the reservoirs. Having predicted future storage values, an operating policy can be formulated as regards to the quantity of water that will be available for domestic and industrial uses, irrigation and hydropower generation. Neural network analysis during training yielded 95%, 69% and 98% of good forecasts for Jebba, Kainji and Shiroro HP reservoirs, while during testing it yielded 97%, 75% and 97% respectively. Also, the respective correlation coefficient between forecast and observed storage are 0.64, 0.79 and 0.84. This showed that the networks are reliable for forecasting. It can therefore be concluded that forecasting using ANN is very versatile tool in reservoir management modeling.

It is recommended that other NN modeling approaches be employed and further studies are required to forecast the discharge/release from the HP reservoirs in order to model the flood regime and consequently control the effect on infrastructural developments and agricultural activities in the downstream reaches of the three hydropower reservoirs.

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