Inflow Prediction for Proposed Halele Warebessa Cascaded Reservoirs in Omo Ghibe Basin using Artificial Neural Networks

M. Sc in (Hydraulic and Hydropower Engineering)

Terefe Adugna Assefa (M Sc)
Water supply and Environmental Engineering
Arba Minch, Ethiopia

Bogale G/Mariam (Ph D)
Hydraulic and water resources engineering
Arba Minch, Ethiopia
P.O.BOX 21

Abstract **- An effective reservoir inflow forecasting enables the reservoir operators to get the accurate information for decision making in planning, operating and measuring effective management of the reservoirs. The prime aim of this study is used to develop the best ANN model using historical data to predict a real Halele Warebessa reservoir inflow, one day ahead and one month ahead based on different techniques of Neural Network. The best input scenario employs the current areal rainfall (Rt), anterior rainfalls Rt-1, Rt-2 and anteceded inflows Qt-2, Qt-1. A total of twenty years historical data (1989-2008) of daily and monthly areal rainfall and inflow of the catchment is used for Halele and Warebessa reservoir respectively to train and validate networks. Three types of Neural Network Architectures i.e. Multilayer Perceptron (MLP), Radial Basis Function (RBF) and General Feed Forward (GFF) are employed in study. The number of hidden neurons and Epochs is fixed by trial and error till there is no further improvement on the desired output. The optimum Artificial Neural Network with 5 inputs, 2 neurons in hidden layer and one output is selected. To evaluate the accuracy of the proposed model, the RMSE, MAE, R^2 and NSE are employed and the value proves that MLP is a superior model to GFF and RBF. Finally, MLP network is trained and conveyed to determine inflow to reservoir prediction at R^2 = 0.99 and 0.79, NSE = 0.98 and 0.96, RMSE = 0.0033 and 0.267, for calibration and R^2= 0.99 and 0.79, NSE= 0.82 and 0.73, RMSE=0.0018 and 4160.9, MAE = 0.0319 and 34.93 validation respectively for Halele and Warebessa by using data subjected to early stopping approach. The overall results reveal that Multilayer perceptron is demonstrating good result for both daily and monthly reservoir inflow predicting of Halele and Warebessa respectively.**

Keywords— Artificial Neural Network, Inflow prediction, Reservoir inflow, Halele and Warebessa

I. INTRODUCTION

Water management activities, particularly hydropower, play a great role in the development by enhancing the positive contribution of water and controlling its negative impacts (Xie, 2001). The identification of suitable models for forecasting daily inflows to hydropower reservoirs is an essential pre-requisite for the effective reservoir management and scheduling (Jorge et al.2012). And, the need for intelligent and efficient water resource management has become more urgent than ever (Jain et al. 1999). One of the main difficulties in real-life reservoir management is the lack of accurate prediction of reservoir inflow and future water demand (Fourcade and Quentin , 1994). According to Shentsis and Ben-zvi (1999) real-time forecasting of reservoir inflow volume is a very essential tool for reservoir management, however, an accurate and reliable inflow forecast is usually difficult to obtain, particularly for a long lead time (Varawoot Vudhivanich, 2006).

will depend principally on development of its hydropower resources (EEPCO, 2000). In addition to this, the future plan of Ethiopia also includes, exporting energy to neighboring countries. So as to fulfill this, more hydropower plants are expected to be developed. Whether it is an existing or newly proposed water reservoir for multipurpose or single purpose hydropower plant, an optimal operation of reservoir plays an important role in efficient water resources utilization. In practice, the reservoir net inflow is computed based upon the application of the water balance equation to the reservoir system; this makes the direct and reliable measurement of this variable difficult.

There are many models which have been adopted and applied to perform reservoir forecasting models for hydrological systems. Namely exponential smoothing models (Mentzer and Cox, 1984), Autoregressive-moving average (ARMA) models (Maier and Dandy, 1996), linear regression models and neural approaches(Pulido-Calvo et al., 2007), combined feed forward CNN, fuzzy logic and genetic algorithm (Pulido-Calvo and Gutierrez-Estrada, 2009) and Artificial Neural Networks (ANN). The ANN models used in reservoir inflow predicting includes, Artificial Neural Networks (ANNs), genetic algorithms, fuzzy theory (Yu and Yang, 2000; Nayak et al., 2004), and chaos theory (Abarbanel, 1996). ANN (Zealand et al., 1999; Coulibaly et al.,2000; Sajikumar and Thandaveswara, 1999; Imrie et al., 2000; Tokar and Johnson, 1999; Campolo et al., 2003; Kişi, 2007) is among the popular ones. Different end-user objectives will lead to different requirements on the performance of flow forecasting.

This study focuses on, the applicability of ANN to predict inflow to Halele Warebessa reservoir one day a head and one month ahead respectively by using historical data of areal rainfall and observed inflow of the catchment is investigated. Among the ANN built the Multilayer perceptron (MLP), General Feed Forward (GFF) and Radial Basis Function (RBF) are adopted in this study and their performance are compared to each other. Therefore, the required model performance is determined by simulating the benefits (in terms of electricity generated) obtained from the forecasting with varying lead times and accuracies. Synthesized flow forecasting series served as input into an optimization model to simulate the benefits.

Artificial neural networks (ANN) are a new and promising computing technique in the area of artificial intelligence (Jain et al., 1999). They are capable of recognizing hidden patterns in the data and have no requirement of understanding of hydrologic processes. Additional advantages of ANNs include data error tolerance, lack of any exogenous input and high adaptability (Thirumalaiah and Deo, 2000). All these features make ANNs suitable for reservoir inflow prediction for Halele Warebessa reservoir. Further, many previous studies of reservoir inflow were carried out of a monthly scale but very few have been done on a daily scale. Daily inflow prediction is necessary for real-time operation of reservoirs systems because it allows reservoir managers to adjust operation policy based on a finer scale. Hence, the strategic management of reservoir system calls for real-time daily reservoir inflow forecasting. Such important work has not been done for Halele Warebessa reservoirs, therefore, this study attempts to integrate reservoir inflow forecasting with optimum reservoir operation planning system.

Research questions are:

1. Can the reliability of hydropower generation be improved by considering the inflow predicted?
2. Would the Artificial Neural network model show good correlation in inflow prediction with historically observed?

The objectives were:

The prime objective of this study is to predict inflow into the reservoirs and develop a methodology to apply inflow forecasting models

Specific objectives:

1. To generate inflow time series through prediction, that could be used for developing the optimal rules/policies
2. To develop models using historical inflow data, area rainfall data and combination of these two data to predict reservoir inflow one day ahead and one month ahead
3. Compare the adopted models in order to determine the best models in terms of forecasting accuracy, efficiency of model development and adaptability for future predictions.

A. Significance of the study

As inflow is a stochastic variable, it leads to a high degree of uncertainty concerning future hydropower production capacity; hence the optimum operation of a hydropower system can be greatly improved if reliable inflow predicting and optimal reservoir operation policy can be available. Inflow forecasting of Halele Warebessa reservoir will therefore enable to give the optimum benefit of power production for poorly regulated systems.

Study Area

The Omo-Gibe River Basin covers an area of about 79,000km^2 and is situated in the south-west of Ethiopia, between 4°00'N & 9°22'N latitude and between 34°44'E & 38°24'E longitude. Halele and Warebessa is one of the Omo Ghibe sub-basin which covers draining area of about 6126Km^2 and 566 km2 respectively and its UTM coordinates are 8^{0}17' N and 37^{0}2' E on upper Ghibe river. Annual average rainfall varies over the project catchment from a maximum approaching 1800 mm in the south to around 1200 mm in the north. 75 to 80% of the annual rainfall occurs between May to September (EEPCO, 2000) which refers 'Kiremt' season.

To determine the overall discharge at Halele Warebessa dam site, streamflow data is transferred from Ghibe near Baco and Tunjo confluence to Halele and Warebessa respectively by using the area ratio methods. The recommended guide lines for area ratio method to assess the available dependable flow for the potential assessment purpose (Douglas et al.2005):

$$\left[\mathbf{Qungauged} = \left(\frac{\mathbf{Aungauged}}{\mathbf{Agauged}}\right)^{\mathbf{n}} * \mathbf{Qgauged}\right]$$ ------(**Error! No text of specified style in document.**-1)

Where: Qungauged = discharge at site of interest
Aungauged = drainage area at the site of interest
Agauged = drainage area at the gauging site
n- Varies between 0.6 and 1.2

If the Aungauged is within 20% of the Agauged $(0.8 \le \frac{Aungauged}{Agauged} \le 1.2)$ then n =1 to be used, the estimate discharge at the site will be within 10 % of the actual discharge (Awlabachew, 2000). Before using the Area ratio method its accuracy was tested using the instantaneous discharge data at station with Legasama which are both flowing to the Ghibe River on the same stream line and their correlation is shown in Figure 4. The drainage area at the Halele Dam site (Aungauged = 2977.84 Km2) is 2.001 time that of the Ghibe near Baco station (A gauged 1488.24Km2). However, in this particular study exponent for the drainage-area ratio method of 0.75 is used after testing that the accuracy of the area ratio method with simple linear regression and the flow series at Ghibe near Baco is transferred to dam site and used for inflow forecasting to the reservoir using equation 4.2.

$$[\mathbf{QatHal} = (\mathbf{1.68} * \mathbf{Qat\ Ghibe\ near\ Baco})]$$ .... (**Error! No text of specified style in document.**-2)

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 5 Issue 10, October-2016

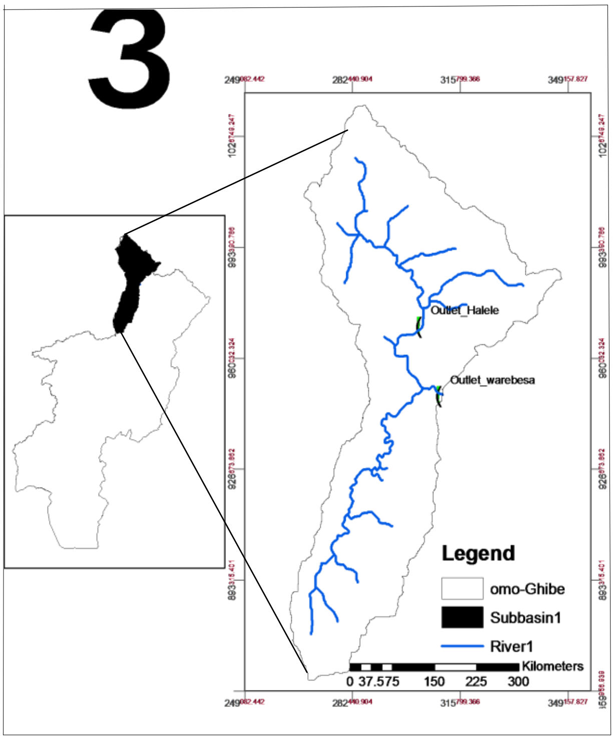


Figure 1 Locations of Halele Warebessa Sub-basin

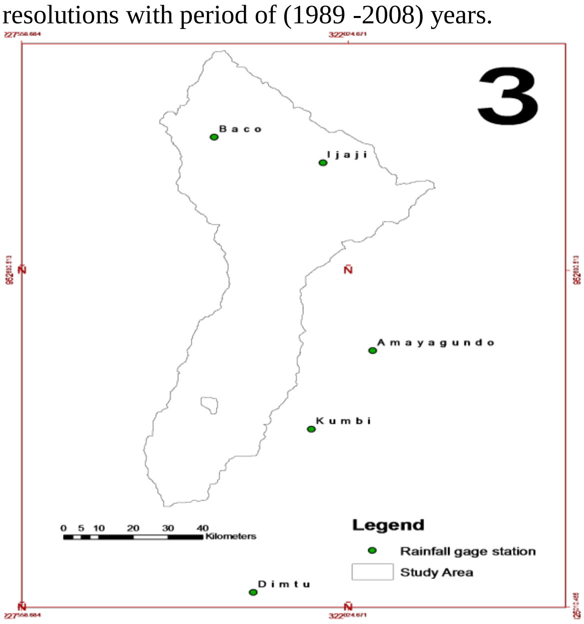
MATERIALS AND METHODS

Hydrological Data

Observed hydrological data series of three gauging stations; Ghibe near Baco, and Legasama near Tebe, gauge stations are available in the Halele basin, Whereas Tunjo River station is located at the Warebessa Basin, as Legasama is only with 11 years' data and hence not used for analysis, but used to fill missed data in Ghibe near Baco station. Therefore, two gauging stations- Ghibe near Baco and Tunjo near the confluence have been used for this study.

Rainfall Data

The precipitation data used in this study are obtained from 5 meteorological stations are shown in (Figure 2.5) and it is daily resolutions with period of (1989 -2008) years.



Analysis of Rainfall data

In order to select the representative rainfall stations for the analysis of areal precipitation on the reservoir at the dam site of Halele Warebessa and filling of rainfall data, the following tests have been carried out: - Rough screening of data, Plotting the data, test for Outlier, test for Absence of trend, the F-Test for Stability of Variance, the t-Test for Stability of Mean and the double mass curve.

Hydrological parameters selection for Models

Hydrological parameters are primarily used for hydrological prediction and for understanding hydrological processes. Since in and around Halele Warebessa basin, most metrological stations covering wide range of topographical variations are only temperature and rainfall are available records, areal rainfall and flow are identified as suitable predictor for this study using Neuron solution version 6.0.

$$Q_{t+x} = f\,(Q_{t-n}, R_{t-n})$$

In which Q_{t+x} is future flow (at x times steps in the future), Qt-n is antecedent flow (at t, t-1, t-2, t-n time steps), R_{t-n} is antecedent areal rain fall (at t, t-2, t-n time steps). When using upstream station information as inputs to the Neural Network model, the average travel time is used to lag the inputs. To investigate the worth of forecasting also, a lead time needs to be considered, time of concentration for the catchment draining to the project site is used to estimate the feasible lead time using Kirpich's modified formula.

Tc = 0.02L0.8 S-0.4…………… (**Error! No text of specified style in document.**-3)

Where, Tc= time of concentration in minute, L = length of the catchment along the longest river channel in meter, S = is the overall catchment slope

To calculate the time concentration of Halele and Warebessa reservoirs, the longest flow line and its slope has been calculated using HECGeoHMS with help of Arc GIS 9.3 and as a result forecast lead time is suitably identified.

Neural Network Model

Artificial neural network (ANN) is highly distributed interconnections of adaptive nonlinear processing elements (PEs). When implemented in digital hardware, the PE is a simple sum of products followed by a non-linearity (Regulwar, 2011). An artificial neural network is nothing but a collection of interconnected PEs. Artificial neural networks are biologically inspired; that is the development of ANNs is inspired by a desire to understand the human brain and emulate its functioning. The idea of artificial neural network was proposed by Mc. Cullock and Pitts in 1943. ANNs have a highly interconnected structure and consist of large number of simple processing elements called neurons, which are arranged in different layers in the network: input layer, output layer and one or more hidden middle layers.

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 5 Issue 10, October-2016

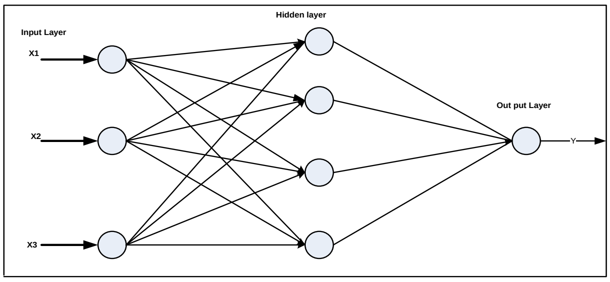


Figure 2 Three-layer Artificial Neural Network used for flow prediction

The nodes receive input either from the initial inputs or from the interconnections. Error back propagation involves two phases: a feed forward phase in which the external input information at the input nodes are propagated forward to compute the output information signal at the output unit, and a backward phase in which modifications to the connection strengths are made based on the differences between the computed and observed information signals at the output units. The main objective of the back propagation training is to adjust the weights of the network to minimize the sum of squared errors of the network, which approximates the model outputs to the target values. An optimal ANN structure might be considered as the one that yields a minimum model error, while retaining a simple and compact structure (Vemuri and Rogers, 1994). A trial and error procedure is often used to determine an optimal ANN architecture (Maier and Dandy, 1996).

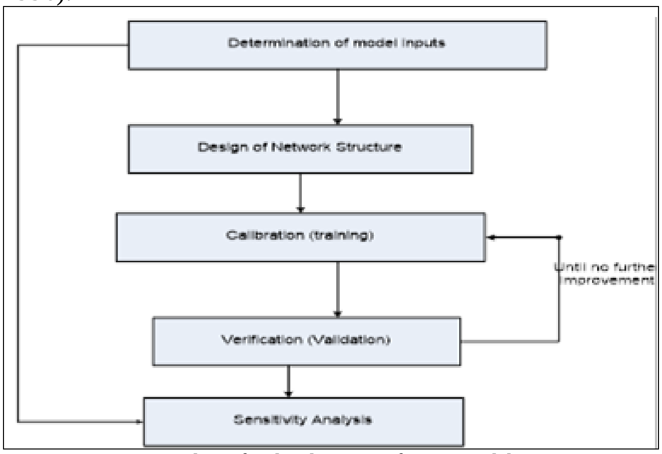


Figure 3 Procedures for development of ANN models

Training of the neural network is accomplished by providing inputs to the model, computing the output, and adjusting the interconnection weights until the desired output is reached within the smallest model error. There are supervised and unsupervised training in which supervised training both inputs and output are provided, while in unsupervised training, the network is provided inputs only. In our case supervised learning or training was used. validation is carried out to understand how a network is able to respond to training set and to a new set to which the network has not found. The performance of a network is usually evaluated by some parameters, such as, RMSE (Root Mean Square Error); R (Correlation Coefficient), MAE (Mean Absolute Error), MINAE and MAXAE (minimum and maximum Absolute Error).

In this study, the built of Artificial Neural Network(ANN) multilayer preceptor, General feed forward and radial basis function are employed. These models were developed using the 1st thirteen years of areal rainfall and observed inflow data (1989-2002) period for calibration, while the remaining seven years of these of data (2002-2008) period were used for validation. The two anteceded inflows Qt-2, Qt-1, current Rt and anterior rainfalls Rt-1, Rt-2 was used as inputs to predict current reservoir inflow Qt as desired output.

Table 1 Input neural network models based on trial and error

Input parameters(Predicants)	Number of inputs	Network developed
Qt-2,Qt-1,Rt,Rt-1,Rt-2	5	5-1-1, 5-2-1
Qt-2,Qt-1,Rt-1,Rt-2	4	4-1-1, 4-2-1
Qt-1,Rt-1,Rt-2	3	3-1-1, 3-2-1
Qt-2,Qt-1	2	2-1-1, 2-2-1

II. RESULTS AND DISCUSSION

Inflow Analysis

In order to fill the missed observed flow data of Ghibe near Baco the correlation coefficient conducted with Legasama near tibe shows, R2 = 0.89 in (Figure 5-1) which reflects good relationship. The monthly flow series at Ghibe near Baco is transferred to Halele dam site and used for inflow forecasting to reservoir. The anteceded inflows Qt-2, Qt-1, and current areal rainfall (Rt), anterior rainfalls (Rt-2, Rt-1) were used as inputs, and current inflow was used as output. The results of figure 5-2 rainfall-runoff daily data reveals that in most of the days when there is a rainfall there is also run off except for few days due to unknown reason they are not proportional.

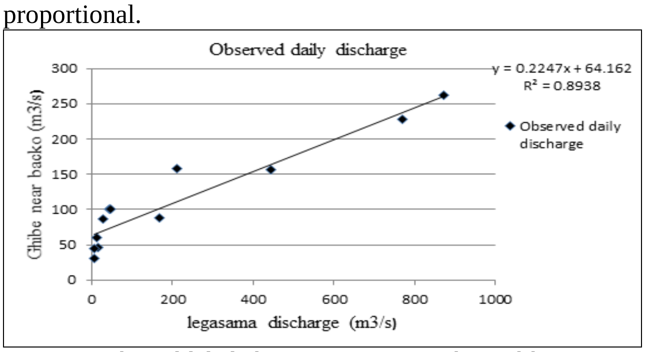


Figure 4 Observed daily discharge at Legasama near Tibe Vs Ghibe near Baco

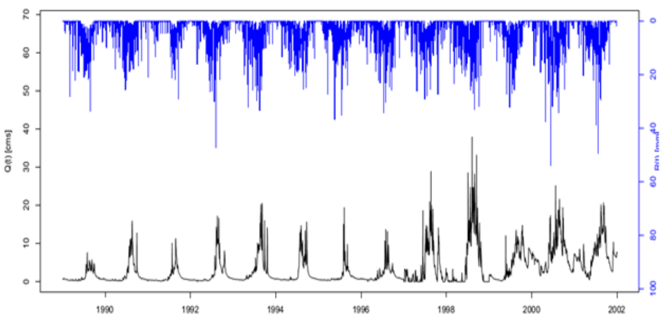


Figure 5 Daily reservoir inflow and areal rainfall for training

Published by :
http://www.ijert.org

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 5 Issue 10, October-2016

RAINFALL DATA QUALITY ASSESSED

In the rough screening of data, the completeness of the data is verified and the observer's arithmetic is checked when computing totals. Thus, the recorded rainfall looks good for all years (1989-2008) at all stations. A time series plots of the yearly rainfall totals (1989- 2008) for Kumbi meteorological station is shown for illustration (Figure 5-2). From the plot, no appreciable outlier is observed in the Kumbi rainfall station records and also in the rest station used in this study. Plots for the other meteorological stations used in this study are given were also done.

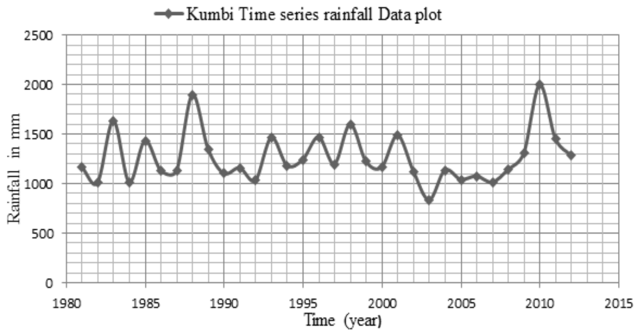


Figure 6 Kumbi time series rainfall data plot

To verify absence of trend in rainfall observed data at station used in this study (Amaya gundo, kumbi, Dimtu, Baco and Ijaji), trend test was done. From the t-distribution table the critical values of 't', at the 5-percent level of significance, for 31 - 2 = 29 degrees of freedom is: t {28,2.5%} = -2.045, and t {28,97.5%} = 2.045. Checking result in (Table 2) clearly shows that the condition is satisfied and thus, there is no trend for Amaya gundo rainfall station. Similarly, all the data from the selected stations are checked for absence of trend using the same method.

Table 2 illustration for trend test of rainfall time-series data

Amaya Gundo station							
Year	RF	x(i)	Y(ranked)	Kxi	Kyi	Di	Di^2
1981	1233	1	887.1	1	31	-30	900
1982	1195.5	2	944.3	2	28	-26	676
1983	1227.8	3	1027.7	3	11	-8	64
1984	1437.85	4	1039.5	4	13	-9	81
1985	1113.15	5	1049	5	30	-25	625
1986	1193.5	6	1066.8	6	14	-8	64
1987	1129	7	1082.4	7	27	-20	400
1988	1547.8	8	1102.4	8	20	-12	144
1989	1456.05	9	1113.15	9	5	4	16
1990	1384.3	10	1113.3	10	22	-12	144
1991	1027.7	11	1129	11	7	4	16
1992	1280	12	1193.5	12	6	6	36
1993	1039.5	13	1195.5	13	2	11	121
1994	1066.8	14	1224.9	14	23	-9	81
1995	1409.9	15	1227.4	15	21	-6	36
1996	1314.6	16	1227.8	16	3	13	169
1997	1580.5	17	1233	17	1	16	256
1998	1335.2	18	1251.6	18	29	-11	121
1999	1452.5	19	1280	19	12	7	49
2000	1102.4	20	1314.6	20	16	4	16
2001	1227.4	21	1328.1	21	26	-5	25
2002	1113.3	22	1333.3	22	25	-3	9
2003	1224.9	23	1335.2	23	18	5	25
2004	1355.9	24	1355.9	24	24	0	0
2005	1333.3	25	1384.3	25	10	15	225
2006	1328.1	26	1409.9	26	15	11	121
2007	1082.4	27	1437.85	27	4	23	529
2008	944.3	28	1452.5	28	19	9	81
2009	1251.6	29	1456.05	29	9	20	400
2010	1049	30	1547.8	30	8	22	484
2011	887.1	31	1580.5	31	17	14	196
	N	31				sum(Di^2)	6110
	V	29				R_{sp}	-0.41
						t_t	**-2.0053**
From t-distribution table;							
t(28,2.5%)= -2.045 and t(28,97.5%)= 2.045							
Since, -2.045 < -2.01 < 2.045			⇒	**NO trend**			

Then, Stationarity of time series, absolute consistency and homogeneity of the data had been verified employing F-test for stability variance and t-test for stability of mean for all rainfall station of the study. And, the kumbi rainfall time series result in (

Table 3) show the station was stationary, homogeneity and consistency. Similarly, analysis was done for the rest stations.

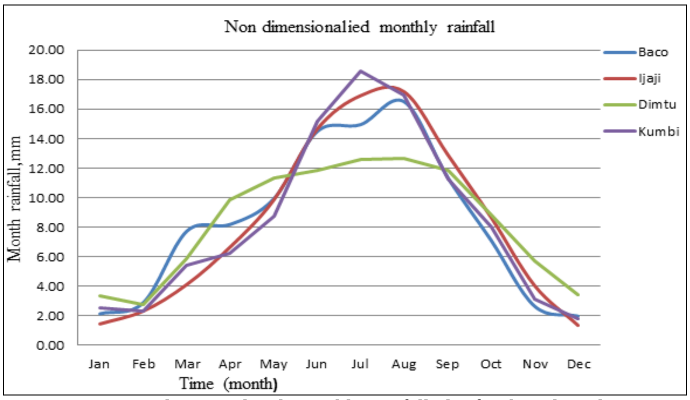


Figure 7 Non-denationalized Monthly rainfall plot for the selected stations

In addition to F test and t-test, double mass analysis was used to verify the consistency and homogeneity of the data. The result shown in () reflects the homogeneous nature of the stations in the study area as all station almost have similar rainfall pattern, whereas the maximum rainfall falls between May to October.

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 5 Issue 10, October-2016

Table 3 Time series Rainfall Stationary Test at Kumbi Station

Time-series Rainfall data Stationary Test at Kumbi Station					
Sub-set I(1981-1996)			Sub-Set II (1997-2012)		
Year	Xi	Xi²	Year	Xi	Xi²
1981	1166	1359556	1997	1196.1	1430655
1982	1008.9	1017879	1998	1600.7	2562240
1983	1633.2	2667342	1999	1222.9	1495484
1984	1010.6	1021312	2000	1165	1357225
1985	1433.6	2055209	2001	1488.7	2216228
1986	1131.3	1279840	2002	1123.8	1262926
1987	1127.8	1271933	2003	831.6	691558.6
1988	1897.2	3599368	2004	1134.5	1287090
1989	1348.7	1818992	2005	1040.7	1083056
1990	1101.6	1213523	2006	1074	1153476
1991	1157.1	1338880	2007	1012.7	1025561
1992	1032.2	1065437	2008	1139.2	1297777
1993	1464.1	2143589	2009	1307	1708249
1994	1181	1394761	2010	2000.4	4001600
1995	1241.7	1541819	2011	1454	2114116
1996	1470.6	2162664	2012	1280.9	1640705
Total	**20405.6**	**26952104**		**20072.2**	**26327948**
N	16			16	
Xmean	1275.35			1254.513	
s	240.8067			1280.9	
s2	57987.86			1640704	
Ft	**0.035343**				
tt	0.063951				
v1	15				
v2	15				
v	30				
From F-& t-distribution tables;					
F(15,15,2.5%)= -2.92 and F(15,15,97.5%)= 2.92 i.e., -2.92 < 0.0353< 2.92			**⇒ Variance is stable**		
t(30,2.5%)= -2.042 and t(30,97.5%)= 2.042 i.e., -2.042 < 0.0640 < 2.042			**⇒ Mean is stable**		

The double mass curve plot technique is used to adjust rainfall records to take accounts of non-rainfall records to take accounts of non-representative factors, as shown in the (Figure 8) employing all the selected stations have shown relative consistency and no need for correction

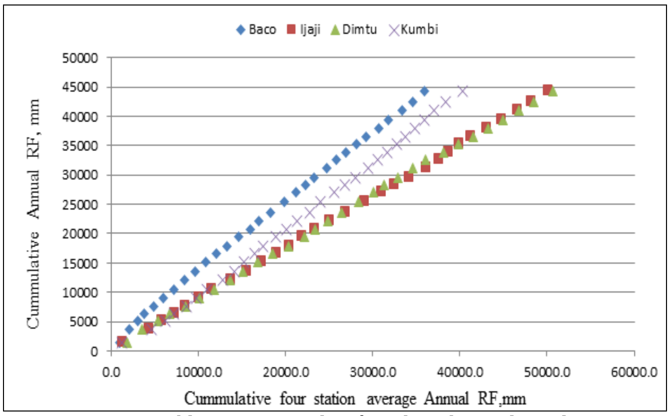


Figure 8 Double mass curve plots for selected metrological station

Using the kripht's f formula in equation 4.1 longest flow line and minimum slope catchment was investigated for the catchment draining to both Halele and Warebessa reservoirs, as a result, the time concentration runoff joining the Halele and Warebessa dam site is 10.01hr and 17.31hr, respectively. Hence, one day ahead forecast lead time is considered appropriately.

ANNs Model results

Table 4 Represents the prediction performance of different models for Halele reservoir

Model	Multilayer Preceptor		Radial basis Function		General Feed Forward	
	Training	Validation	Training	Validation	Training	Validation
NSE	**0.980115**	**0.82784**	0.979931	0724776	0.89043	0.6897
MSE	**0.0033083**	**0.001827**	2.570332	4160.889	0.601281	4173.86
NMSE	**0.0002222**	**0.000149**	0.172647	0.6032745	0.000156	0.60515
MAE	**0.04131461**	**0.031886**	0.423729	34.92562	0.653880	35.541
R	**0.9998898**	**0.88940**	0.99976	0.8971068	0.9992	0.83968

Based upon statistical measures of performance indicator of Neural Network model, however, the General Feed Forward and the Radial Basis Function show a good result in inflow forecasting of Halele and Warebessa reservoirs; the Multilayer perceptron are found to be the superior one in both training and validation as shown clearly in (Table **1**Table 4 and Table **5**).

Table 5 Represents the prediction performance of different models for Warebessa reservoir

Model	Multilayer Preceptor		Radial Basis Function		General Feed Forward	
	Training	Validation	Training	Validation	Training	Validation
NSE	**0.969931**	**0.734776**	0.890115	0.603275	0.8505	0.7123
MSE	**0.266769**	**4160.8895**	76.74161	4998.9084	0.6012810	4173.86
NMSE	**6.91E-05**	**0.6032750**	0.019885	0.724776	0.0001558	0.60515
MAE	**0.423720**	**34.925624**	6.7319353	45.436912	0.65387996	35.541
R	**0.999988**	**0.8971068**	0.990376	0.88940	0.9992	0.83968

From
Table **6** the model 5-2-1(5 input, 2 neurons in hidden layers and one output) demonstrates that the network associated with minimum value of MSE, MAE, NMSE and also it certifies highest value of NSE and R for both calibration and validation; see also Table 1 for input parameter structure. Therefore, Multilayer perceptron (MLP) model with network structure of 5-2-1 is adopted, as the final model for inflow prediction in this study. The model achieved acquired 99% and 89 % accuracy for training and validation after trial and error with two hidden layer and sigmoid transfer function. This selected ANN model is subjected to further improvement, and the early stopping approach has been employed for the training process to avoid over fitting problem.

Table 6 Performance of training and validation for selected ANN model

model	Training			Validation		
	MSE	MAE	NMSE	MSE	MAE	NMSE
5-2-1	**0.267**	**0.423**	**6.9E-05**	**4160.9**	**34.93**	**0.603**
4-2-1	1.087	0.551	0.0028	4187.3	35.96	0.607
3-2-1	1.057	0.96	0.004	4185.4	36.78	0.780

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 5 Issue 10, October-2016

The numbers of neurons of hidden layer in (Figure 9 andFigure **10**) show how average mean square errors were getting closer to optimal with varying the processing elements(PEs). The results of these figures also reveal that as the number of Epoch increases, the error in data set for validation will decrease. It could be seen from these figures that 2 hidden neuron layers of 5 processing elements is a good indication of forecasting performance of network with smaller error. And, the network is trained under early approach and converged at average MSE = 0.2 for training and 0.018 for validation.

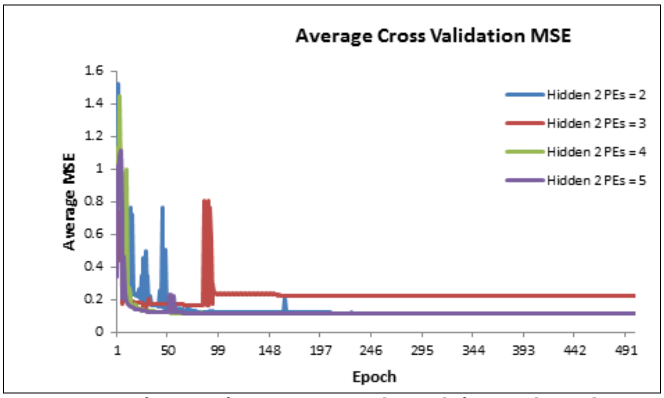


Figure 9 Verification of average MSE with Epoch for Warebessa during validation in 2 hidden layer

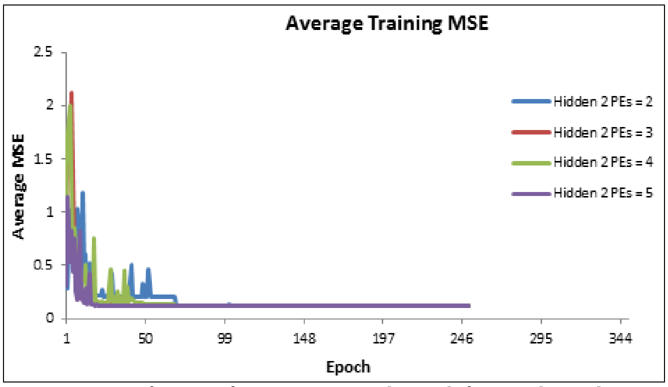


Figure 10 Verification of average MSE with Epoch for Warebessa during training in 2 hidden layer

The network forecasted using training and validation data set with the accuracy of shown in
Table **6** implies, the optimum Artificial Neural Network with 5 inputs, 2 neurons in hidden layer and one output is the best to forecast reservoir inflow in this study. Comparison between the observed (desired output(Qt)) and ANN forecasted a daily (Qt output) and a monthly inflow head to Halele and Warebessa respectively for training and validation data set is shown in Figure 11 and Figure **12** respectively. It can be seen from these figures that, the agreement between observed and forecasted data employing very attractive results.

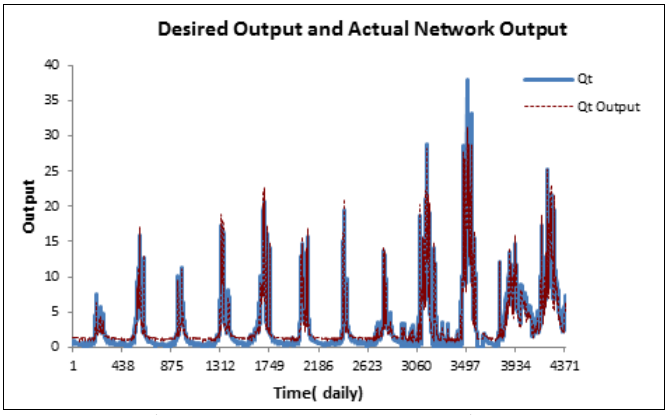


Figure 11 performance by MLP model in training for Halele reservoir

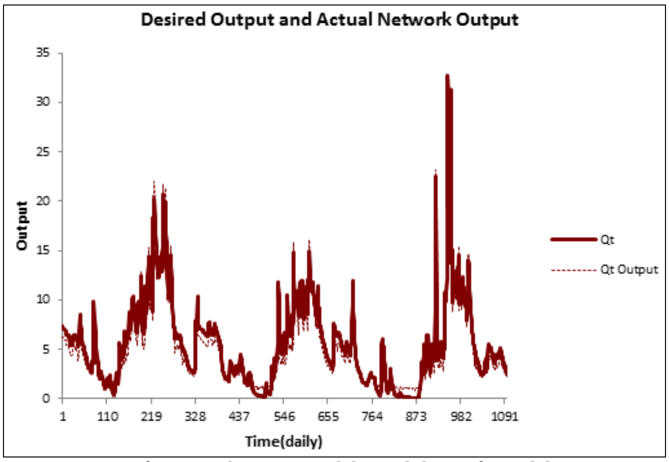


Figure 12 Performance by MLP model in validation for Halele reservoir

It is another confirmation that with standard deviation boundaries of +1 and -1, the average minimum MSE is getting converted to minimum optimal error with five process elements as shown in (Figure 13) than the rest processing elements. As a result, the five point elements with 2 hidden layers are selected as the best number of processing elements for the network.

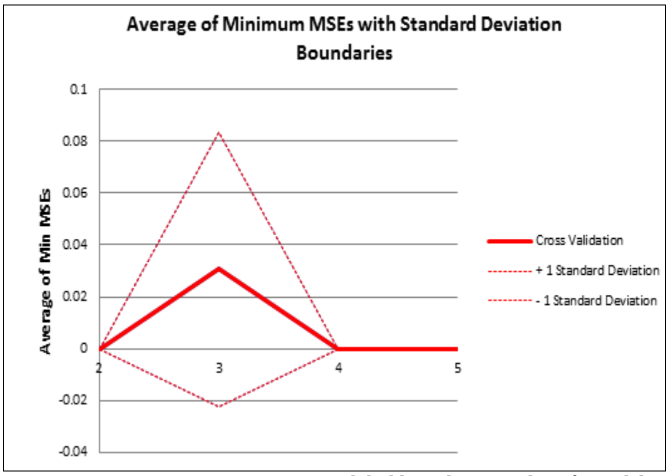


Figure 13 Average minimum MSEs with hidden 2 layers and PE for Halele

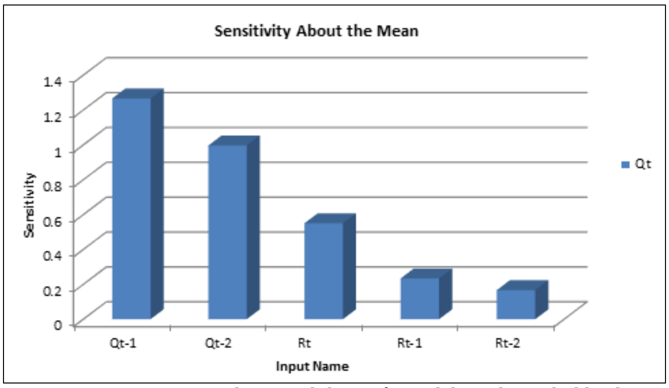


Figure 14 Sensitivity test during validation for Halele with two hidden layer

The result of the sensitivity analysis indicated that the inputs with one-day lag time are more sensitive to variation than two-day lag time both in reservoir inflow and areal rainfall in providing the forecast value than the other input parameters is shown in (Figure 14) for Halele. The result of the sensitivity analysis indicates that the inputs with one-day lag time(Qt-1) mean is also more sensitive to make variation other than input parameters (Qt-2, Rt, Rt-1, Rt-2) in providing the forecast value as shown in Figure 15 and for Halele reservoir during validation.

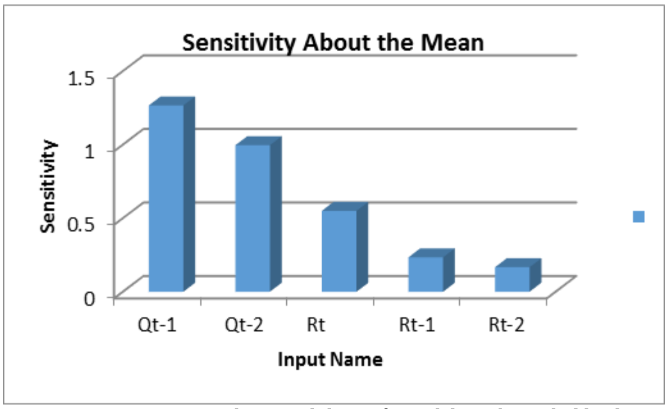


Figure 15 Sensitivity test during validation for Halele with two hidden layer

III. CONCLUSION AND RECOMMENDATION

Conclusion

The aim of the study of this thesis is to develop a model and apply a methodology to determine the real inflow prediction for proposed Halele Warebessa reservoir by using ANN model. Inflow data is transferred from Ghibe Near Baco and the combination of Tunjo Confluence and Ghibe station to Halele and Warebessa dam site and areal rainfall of the Catchments draining to the dam site during the period of 1989- 2008 are used for training, validation and testing of the ANN models.

The positive potential of successfully using Artificial Neural Networks for daily and monthly reservoir inflow is presented in this study. The determination of models inputs is the primary importance for model development and achieved forecasting accuracy. A good understanding of hydrological processes helps in selecting proper inputs, which in turn allows ANNs to build the best possible input/output mapping. In this study, using inflow or Areal rainfall data alone to predict current inflow does not lead to good mapping, as evidenced by high model errors. Using both Areal rainfall and inflow data as input allowed network to build a better mapping between input/output and improved forecasting accuracy. The two anteceded inflows Qt-2, Qt-1, current rainfall (Rt) and anterior rainfalls Rt-1, Rt-2 are used as input where current inflow was used as output.

Three types of Neural Network Architectures I.e. Multilayer perceptron (MLP), Radial Basis Function (RBF) and General Feed Forward (GFF) has been employed. The prediction of performance of the network examined between the desired out and predicted output values. The evaluation and performance of the models is conducted by the Mean squared error (MSE), MAE, R2, and the Nash- Sutcliffe correlation coefficient (NSE) for both training and validation as its accuracy subjecting to early stopping approach.

The evaluation and performance of the model reveals that Multilayer perceptron has shown great improvement compared to General Feed forward and Radial Basis Function techniques in modeling. Also results GFF and RBF model application are very encouraging both for training and validation of reservoir inflow data employed.

The optimum Artificial Neural Network (MLP) with 5 inputs, 2 neurons in hidden layer and one output is selected with minimum error and best forecasted value. Sensitivity test analyses are used in conjunction with judgment to rank and isolate the important factor of each of the input to model performance. The result of sensitivity study shows that one-day inflow (Qt-1) is the most influencing factor on the output result than other input parameters. Hence, this study has been provided a general reservoir inflow forecasted for one day and one-month lead time with appropriate forecasting model structure of ANN for Halele and Warebessa reservoir respectively.

IV. RECOMMENDATIONS

- Since hydrological and meteorological data are fundamental inputs for the reservoir inflow forecasting and operational planning, efforts should be made to improve the stations network in the future.
- This study considered by hydrological and metrological data for inflow to reservoir and estimation power production pattern using data driven models. However, it is recommended to conduct the physical data based models with more forecasting parameters and to compare with historical catchment responses. Using additional parameters such as temperature, soil moisture, sunshine and infiltration my help to get better predicting result.
- ANNs do not provide any mathematical expression for physical process they model. These drawbacks need to be taken into consideration when choosing appropriate prediction method.

  As the model development is based on a trial and error procedure fixing the network architecture is time consuming

ACKNOWLEDGMENT

Special thanks goes to Arba Minch university who allows me to attend the programme by covering all expenses during the course and thesis work.

REFERANCES

[1]. Xie, Ming. (2001, July). Prediction of Daily Net inflows for management of Reservoir Systems. A thesis submitted to Faculty of Graduate Studies and Research, in partial fulfillment of requirements of for degree of Masters of Science.

[2]. Jorge O. Pierini, Eduardo A. Gómez & Luciano Telesca. (2012). Prediction of water flows in Colorado River. Argentina: Latin American Journal of Aquatic Research.

[3]. Jain, S.K., Das, A., and Srivastava, D.K. (1999). Application of ANN for Reservoir inflow prediction & operation. Journal of water Resources planning and management, ASCE, 263-271.

[4]. Fourcade and Quentin (1994). Balancing Reservoir management and water conservation application and irrigation. NATO ASI series E Applied sciences, 275, 455-464.

[5]. Shentsis and Ben-Zvi. (1999, October). Within season Updating of seasonal forecasting of Lake kinneret inflow. Journal of Hydrologic Engineering, 4, 381-385.

[6]. Varawoot Vudhivanich, S. T. (2006). Application of Artificial Networks for reservoir inflow forecasting. journal of natural Science, 1.

[7]. EEPCO. (2000). Feasibility Study of Halele Warebessa Stage I Hydropower Project CSA,

[8]. Mentzer, J.T., Cox, J.E., 1984. Familiarity, application, and performance of sales forecasting techniques. J. Forecast. 3, 27–36.

[9]. Maier, H.R., and Dandy, G.C. (1996). The use Artificial Neural Networks for the prediction of water quality parameters. Water Resources Research, 67.

[10]. Pulido-Calvo, I., Montesinos, P., Roldán, J., Ruiz-Navarro, F., 2007. Linear regressions and neural approaches to water demand forecasting in irrigation districts with telemetry systems. Biosystems. Eng. 97, 283–293.

[11]. Nayak, P.C., Sudheer, K.P., Rangan, D.M., Ramasastri, K.S., 2004. A neuro-fuzzy computing technique for modeling hydrological time series. J. Hydrology 291, 52–66.

[12]. Pulido-Calvo, I., Gutierrez-Estrada, J.C., 2009. Improved irrigation water demand forecasting using a soft-computing hybrid model. Biosystems. Eng. 102, 202–218.

[13]. Yu, P.-S., Yang, T.-C., 2000. Fuzzy multi-objective function for rainfall-runoff model calibration. J. Hydrology 238, 1–14.

[14]. Abarbanel, H.D., 1996. Introduction, in: Analysis of Observed Chaotic Data. Springer, pp. 1–12.

[15]. Zealand, C.M., Burn, D.H., Simonovic, S.P., 1999. Short term streamflow forecasting using artificial neural networks. J. Hydrol. 214, 32–48.

[16]. Coulibaly, P., Anctil, F., Bobee, B., 2000. Daily reservoir inflow forecasting using artificial neural networks with stopped training approach. J. Hydrol. 230, 244–257.

[17]. Sajikumar, N., Thandaveswara, B.S., 1999. A non-linear rainfall–runoff model using an artificial neural network. J. Hydrol. 216, 32–55.

[18]. Abarbanel, H.D., 1996. Introduction, in: Analysis of Observed Chaotic Data. Springer, pp. 1–12

[19]. Sajikumar, N., Thandaveswara, B.S., 1999. A non-linear rainfall–runoff model using an artificial neural network. J. Hydrol. 216, 32–55.

[20]. Imrie, C.E., Durucan, S., Korre, A., 2000. River flow prediction using artificial neural networks: generalization beyond the calibration range. J. Hydrology 233, 138–153.

[21]. Tokar, A.S., Johnson, P.A., 1999. Rainfall-runoff modeling using artificial neural networks. J. Hydrol. Eng. 4, 232–239

[22]. Campolo, M., Soldati, A., Andreussi, P., 2003. Artificial neural network approach to flood forecasting in the River Arno. Hydrol. Sci. J. 48, 381–398.

[23]. Kişi, Ö., 2007. Streamflow forecasting using different artificial neural network algorithms. J. Hydrol. Eng. 12, 532–539.

[24]. Jain, S.K., Das, A., Srivastava, D.K., 1999. Application of ANN for reservoir inflow prediction and operation. J. Water Resour. Plan. Manag. 125, 263–271

[25]. Thirumalaiah, K., Deo, M.C., 2000. Hydrological forecasting using neural networks. J. Hydrol. Eng. 5, 180–189.

[26]. Awlabachew, S. B. (2000). Investigation of Water Resources Aimed at Multi-Objective development with respect to limited Data: The case study of Abaya -Chamo Basin, Ethiopia, Ph.D. thesis, TU Dresden.

[27]. Regulwar, D. G. (October 2011). Inflow prediction by different Neural Network Architectures International. Journal of Earth Sciences and Engineering, 225-230.

[28]. Ndirika, V.I.O., 1993. Development and performance evaluation of a millet thresher. Journal of Agricultural Technology, 1(1): 2-10.

[29]. Pande, S., R. Bandyopadhyay, M. Blümmel, J. Narayana Rao, D. Thomas, S.S. Navi, 2003. Disease management factors influencing yield and quality of sorghum and groundnut crop residues. Field Crops Res. 84(1-2): 89-103.

[30]. Raji, A.O. and D.I. Akaaimo, 2005. Development and evaluation of a threshing machine for Prosopis Africana seed. Journal of Applied Science, Engineering and Technology, 5(1 and 2): 56-62.

[31]. Sajikumar and Thandaveswara (1999), A time delay Artificial Neural Network for flow routing in river system approach.

[32]. Sharma, V., L. Das, R.C. Pradhan, S.N. Naik, N. Bhatnagar and R.S. Kureel, 2010. Physical properties of Tung seed: An industrial oil yielding crop. Industrial Crops and Products (In Press).

[33]. Shirgley. J.E., 1980. Engineering design, 4th edition, McGraw-Hill Coy, NY.

[34]. Awlabachew, S. B. (2000). Investigation of Water Resources Aimed at Multi-Objective development with respect to limited Data: The case study of Abaya -Chamo Basin, Ethiopia, Ph.D. thesis, TU Dresden.

[35]. Govindaraju, Maier and Dandy. (2000). Application of artificial neural networks for flood warning systems.