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To,

Dear **Swagatika Biswal, Dr. Bandita Naik, and Dr. K. K. Khatua**

Subject: (a) Acceptance of Research Paper for ORAL Presentation
(b) Submission of Registration Fee for its publication in Proceedings

Ref.: Paper No. 444 (RAINFALL RUNOFF STUDIES OF BRAHMANI RIVER BASIN USING)

It is my pleasure to inform you that your above referred research paper has been accepted for ORAL PRESENTATION in the very prestigious International Conference HYDRO-2018-INTERNATIONAL.

You are requested to kindly make online payment of Registration Fee for at least one Author and Co-authors attending the Conference and send the duly filled Registration Form by 25th October 2018. **The research papers are likely to be published in the Proceedings (Springer) only after the receipt of registration fee from the author.** E-poster Template is attached too.

Looking forward to see you in HYDRO 2018 International at NIT Patna.

With kind regards,

(PROF. (DR.) RAMAKAR JHA)

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RAINFALL RUNOFF STUDIES OF BRAHMANI RIVER BASIEN USING ANN

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Abstract

Rainfall-runoff is a very complicated process due to its nonlinear and multidimensional dynamics, hence it difficult to model. There are various methods for time series based on the model to rainfall and runoff. In the present study, Feed-Forward Back Propagation & Auto-Regressive Integrated Moving Average models are applied to predict monthly runoff in Brahmani River of the three stations Jaraikela, Jenapur, and Tiliga. ANN with different transfer function like *TANSIG* and *PURELIN* is used to find runoff prediction in these areas. Different statistical error analysis is done, to known the better transfer function. From the observation, it was concluded that transfer function is given the better result than *PURELIN*. The predicted runoff found by *TANSIG* transfer function was again compared with ARIMA model. From the statistical error analysis, it was observed that ANN was given the better result than ARIMA method.

Keywords: tansig, purelin, ann, arima, feed forward back propagation

1. INTRODUCTION

Many natural resources available on the earth, water is one of them most important natural resources. Without water life cannot be imagine on the earth surface. 71% of the Earth's surface is water- covered, and the oceans hold about 96.5% of all Earth's water. Water also exists in the air as water vapors, in rivers and lakes, in icecaps and glaciers, in the ground as soil moisture and in aquifers (Ref water.usgs.gov). But the problem is that water is not available at proper place at proper time. Water is not constant. It always moves on one place to another place. Water of the different catchment area always changes from one state to another under the effect of solar radiation. Water surface converted to vapor by evaporation due to solar heat radiation. The vapor goes too continuously atmosphere, then it contain due to sudden fall of temp & pressure by this process clouds will be formed then precipitation occurs. Some vapors converted into ice at peak of the mountain. These Ices again melt in summer duration & flow as river to meet the sea or ocean. These processes of evaporation, precipitation & melting of Ice go on continuously like an endless chain thus balance is maintain in atmosphere. This phenomenon is known as hydrology cycle. Rainfall is the major component of hydrology cycle & runoff is the primary sources of this cycle. Rain fall – runoff relationship is one of the most complicated hydrologic phenomena to comprehend due to the tremendous spatial and temporal variability of watershed characteristics and precipitation patterns, and the number of variables involved in the modeling of the physical processes. Since the 1930s, numerious rainfall- runoff models have been developed to forecast stream flow (A. Sezin Tokar et.al 1999). The ANN models are powerful prediction tool for the relationship between rainfall and runoff. The rain fall runoff relationship is highly non linear, multidimensional, time dependence and spatial varying parameter.

Y. B. Dibike et al. (2001) Two type of ANN network MLP & RBF were using to investigate for downstream flow fore casting in the Apure river basin (Venezula). Those networks were compared with conceptual rainfall-runoff model and were found which one given better for this river flow forecasting. . Rajurkar et al. (2002) stated that a linear MISO model coupled with the ANN was provided a better represented of the rainfall- runoff relationship in such large size catchment compared with linear &non linear MISO models. The presented model provided systematic runoff estimation. Wilby et al. (2003) provided neural network solution to develop for daily discharge series simulated by conceptual rainfall-runoff model, observed daily precipitation total & evaporation rates of the test river basin in south England. Correlation analysis suggests that hidden nodes in the NN correspond to dominant processes within the conceptual model. Rajurkar et al. (2004) modeling daily flows during flood event using ANN. The study uses data from two large size catchments in India and five other catchments used earlier by the World Metrological Organization (WMO) for inter comparisons of the operational hydrological models. ANN proves to be very much useful modeling the rainfall-runoff relationship in the non- updating mode. Yen-Ming Chiang et al. (2004) provided a systematic comparison of two basic types of Neural Network of Static & dynamic method used in Lan-Yang-River of Taiwan. V. K. Somvanshi et al. (2006) was predicting rainfall based past observation using ANN and ARIMA technique. Muhammed aqil et al. (2007) was suggested that recurrent & feed forward network with Levenberg-Marquardt are able to forecast of the catchment flow in advanced with reasonable prediction accuracy Vahid Nourani et al. (2009) Recently ANN as a nonlinear- extrapolator is extensively used by hydrologist for rainfall-runoff modeling as well as other field of hydrology. The model was predicted both short & long term runoff discharges of using multi-scale series of rainfall & runoff data as the ANN input layer. Ghumman et al. (2012) compared ANN model with a mathematical conceptual model. An ANN model is an important alternative to a conceptual models & it was used when the range of collected data set is short and data is of low standard. Ghose et al. (2013) predict runoff used Non-Linear Multiple Regression (NLMR) & Adaptive Neuro-Fuzzy Inference system (ANFIS). Mohammad Valipur et al. (2013) observed that ARIMA model had a less error comparing with the ARMA model of Dez dam reservoir in 12 past months. Elsafi. 2014 used ANN model to forecast flooding along the river Nile. This work was provided baseline information toward the establishment of a flood warning system certain section of the river. Farajzaden et al. (2014) was observed that estimated values of monthly rainfall through FFNN were close to ARIMA model of Urima lake basin. In this paper correlation of rainfall-runoff, prediction of runoff using precipitation, mean temperature, solar, wind, humidity and discharge.ANN with different transfer function used to predict runoff and analyzed with mean absolute deviation, mean square error and root mean square error. Comparing the validation phase of runoff predicted by ANN and ARIMA model use statistical error analysis.

2. STUDY AREA

Brahmani River is the second largest river in Odisha after Mahanadi. Location of Brahmani river basin and study area is shown in Figure 1 and 2 respectively. It is a major seasonal river in the Odisha state of Eastern India. The Brahmani is formed by the confluence of the South Koel River and Sankh River near at the Vedvyas, Panposh in Odisha. The latitude 22°14′45″N and longitude 84°47′02″ E are the geo coordinate of river. At about 480 kilometers long, its constituent rivers are included its length extends to about 799km, of which 541 km are in Odisha. It has a catchment area of about 39,033 square kilometers in Odisha alone. Brahmani river basin has 9 hydro-observation stations. In present study discuss about 3 gauging stations, Jenapur, Jaraikela and Tiliga. These stations belongs districts are Jajpur, Sundargarh and Simdega (Jharkhand). Jaraikela and Tiliga located on the tributary river Koel and Sankh. The Sankh River and south Koel River is two major tributary river of Brahmani river basins. The Sankh River and South Koel River has originated Ranchi district of state Jharkhand. The latitude of the south koel river 23°20′N and longitude 85°12′E. The Sankh river latitude 23°14′N and longitude 84°16′E geo coordinate of the river. The total length of the Sankh River is 240 km. The gauging stations Jenapur, Jaraikela and Tiliga drainage area are respectively 33955, 9160 and 3160 sqkm.

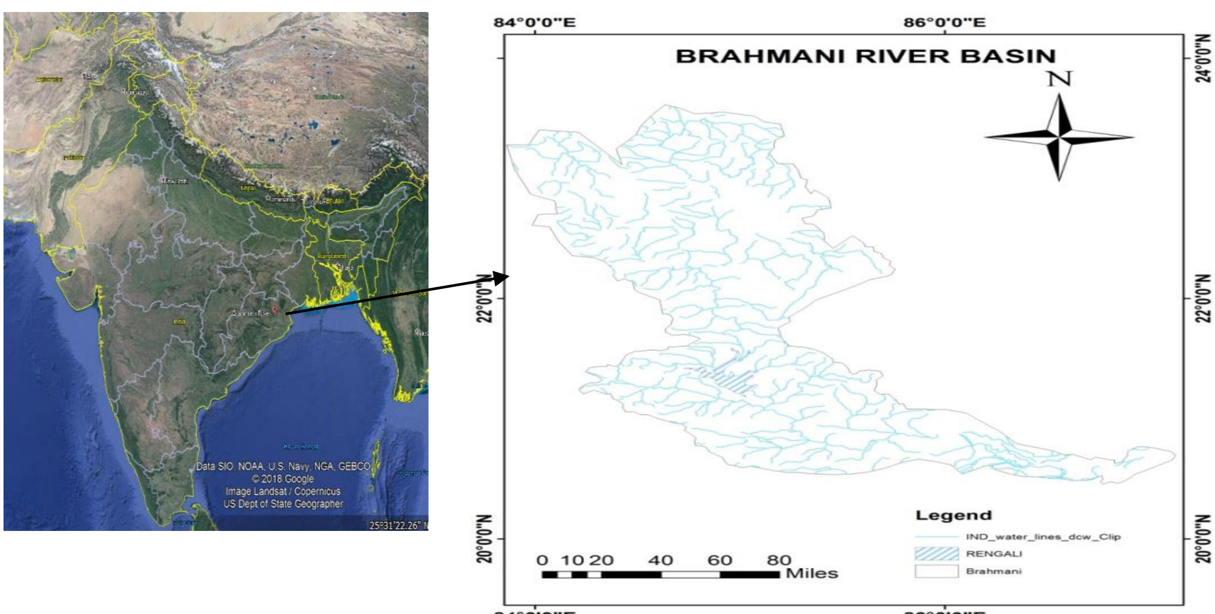


Figure 1. Location of Brahmani river basin

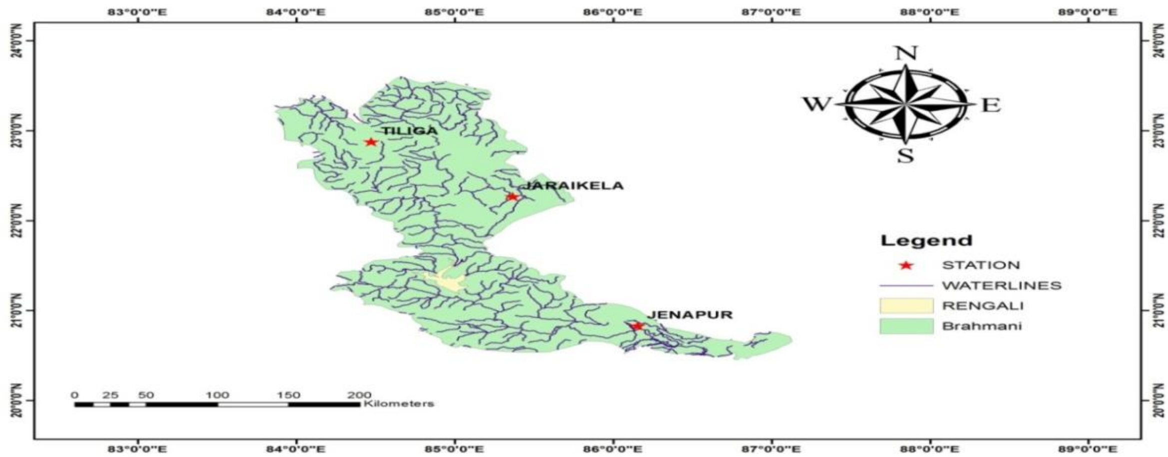


Figure 2. Location of study area

3. METHODOLOGY

3.1 Feed forward back propagation neural network

In this study feed forward back propagation neural network is propagated in one direction from input layer to output layer. The MLP networks can more than one hidden layer. The feed forward network that has interconnected nodes arranged into three layer input layer, hidden layer and output layer. In this study five number input layer, one output layer and 10 hidden layers are used in multilayer feed forward back propagation algorithm to predict river basin runoff. Five input variables, temperature, solar, wind, humidity and precipitation. The input nodes pass on the input signal values to the nodes depending on the connection weight between the input nodes & hidden nodes. Connection between weight and hidden nodes are inter connection link between the successive layer each neuron in a certain layer is connected to every single neuron to the next layer and adjustable connection weight. This network have used for training purpose Levenberg-Marquardt back propagation (LMBP) algorithm because this technique is more effective than conventional gradient techniques.

$$X_{K+1} = [X_K - J^T J + \mu I]^{-1} J^T e \qquad \text{Equation (1)}$$

Where X is the indicate the weight of under neural network and μ scalar control the learning process. J is the Jacobian matrix; 'e' is the vector of network.

In this present study two type of transfer function have to be used Tansig and Purelin.The tansig transfer function, hyperbolic tangent (tanh) is a symmetric s-shaped (sigmoid) function whose put lies in the range [-1, 1] with the identify function the activation neuron is passed on directly as the output of the neuron & output lies in the range [∞.-∞].Purelin is the linear function values between [-1,1].Function of linear activation function is f(x) =x.

3.2 Auto Regressive Integrated Moving Average (ARIMA)

Time series model such as Auto Regressive Intigrated Moving Average (ARIMA) are widely used for hydrological time series forecasting. They are basically linear model assuming the data the data are stationary and have limited ability to capability non stationarities & non-liearities in hydrologic data. It has basically three parts moving average and differencing process.In general auto regressive(AR) moving average (MA),auto regressive moving average (ARMA) & auto regressive integrated moving average (ARIMA) model are applied to time series .Therefore, when the process is non-stationary series before conducting a modeling process .In an ARIMA model the futher value of a variable is supposed to be a linear combination of past values and past errors which can be expressed as in the eq (2)

$$Yt= \theta_0 + \emptyset_1 y_{t-1} + \emptyset_2 y_{t-1} + \cdots\cdots\cdots + \emptyset y_{t-p} + \cdots\cdots\cdots +$$
$$\epsilon_t - \theta_1 \epsilon_{t-1} - \theta_2 \epsilon_{t-2} - \cdots\cdots \qquad - \theta_q \epsilon_{t-q} \cdots\cdots$$

Equation (2)

Where $\theta_{j,}\emptyset_J$ are coefficients ,Y_t is the actual value at time *'t'*

P and *q* are the Auto regressive and moving average coefficients.

3.3 Evaluation criteria

The model is to obtained both statistical and graphical criteria. Statistical model criteria consist mean absolute deviation, mean square error and root mean square error.

Where MAD = $\sum_{i=1}^{n}[Q_i - \hat{Q}_i]$ Equation 3

MSE = $\sum_{i=1}^{n}[Q_i - \hat{Q}_i]^2$ Equation 4

RMSE= $\frac{\sqrt{\sum_{i=1}^{n}[Q_i - \hat{Q}_i]^2}}{n}$ Equation 5

The above equation Q_i is the observed value. $\hat{Q}_i$ is the predicted value and 'n' is the total number of observed sample.

3.4 ANN model development for prediction runoff

ANN model use in three station Jaraikela, Jenapur and Tiliga for runoff modelling using MLP feed forward back propagation network. Solar, wind, temperature,humidity and precipitations are taken into input parameter and discharge is taken output parameter. Monthly weather data are collected from 1990 to 2014 are collected from `http://swat.tamu.edu for each station. Out of 295 sample data 70% are use for training phase, 15% use for testing phase & 15% use for validation phase. For training phase minimize error, testing and validation phase properly training. The weather data set in the present study input variables as well as target variable are first normalised for the activation function using the equation.

$$\bar{x} = \frac{x - x_{\min}}{x_{\max} - x_{\min}}$$

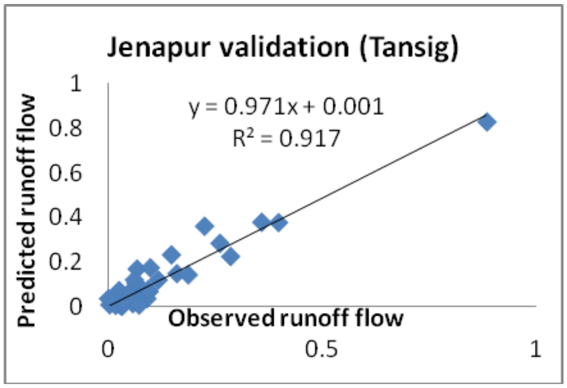
Where $\bar{x}$ is the standardized value of the input, x_{min} and x_{max} are respectively the minimum & maximum of the actual values in all observation & x is the original data set The main reason of the standardizing the data matrix is input variables have measured in different unit, recasting then in dimensionless unit.The graphical performance indicator give better result when the data pair are closing to 45° line and good super position between the desired and calculated flow values in the training ,testing and validation. The activation function changed in second layer because hidden layer to represent the output layer.

4. RESULT AND DISCUSSION

The validation phase 15% data should be used.The main aim of the validation phase using twotype of transfer function Tansig and Purelin properly trained, after trained validation phase, stastical error calculation is done for knowing which transfer function is given better perfermance.Table 1, Table 2 and Table 3 shows the statistical error ananlysis of three station using different activation function.

Table1. Comparision stastical analysis is done of using two transfer function of ANN at Jenapur of validation phase.

	Stastical analysis	TANSIG	PURELIN
JENAPUR	MAD	0.033	0.032
	MSE	0.001	0.003
	RMSE	0.043	0.565
	R^2	0.917	0.866



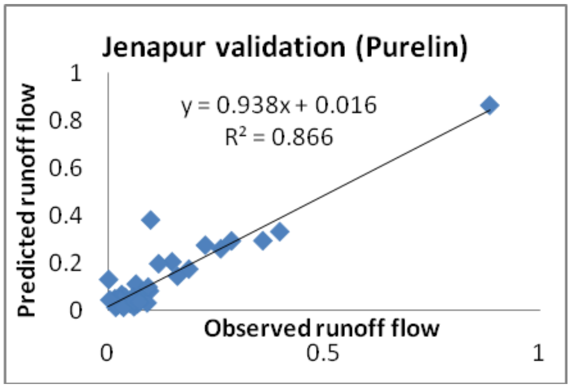
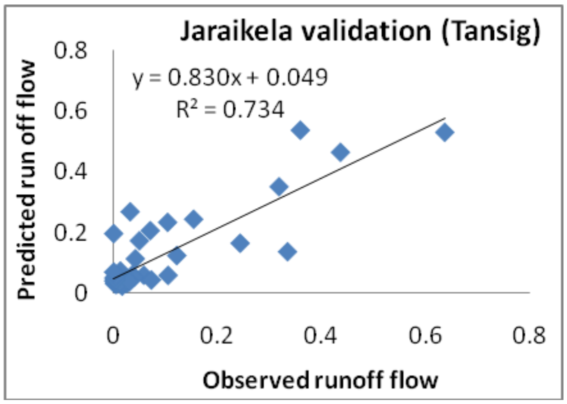


Figure 3 Cofficient of determination graph of using Tansig and Purelin transfer function at Jenapur.

Table 2. Comparision stastical analysis is done of using two transfer function of ANN at Jaraikela of validation phase.

JARAIKEL	Stastical analysis	TANSIG	PURELIN
	MAD	0.056	0.045
	MSE	0.006	0.006
	RMSE	0.080	0.088
	R^2	0.734	0.681



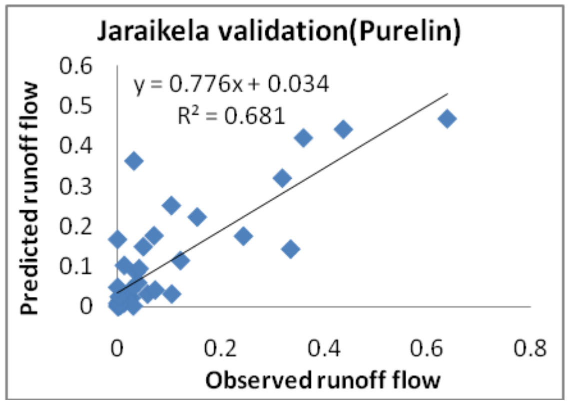


Figure 4 Cofficient of determination graph of using Tansig and Purelin transfer function at Jaraikela.

Table 3. Comparision stastical analysis is done of using two transfer function of ANN at Tiliga of validation phase.

TILIGA	Stastical analysis	TANSIG	PURELIN
	MAD	0.034	0,034
	MSE	0.003	0.004
	RMSE	0.058	0.065
	R^2	0.920	0.915

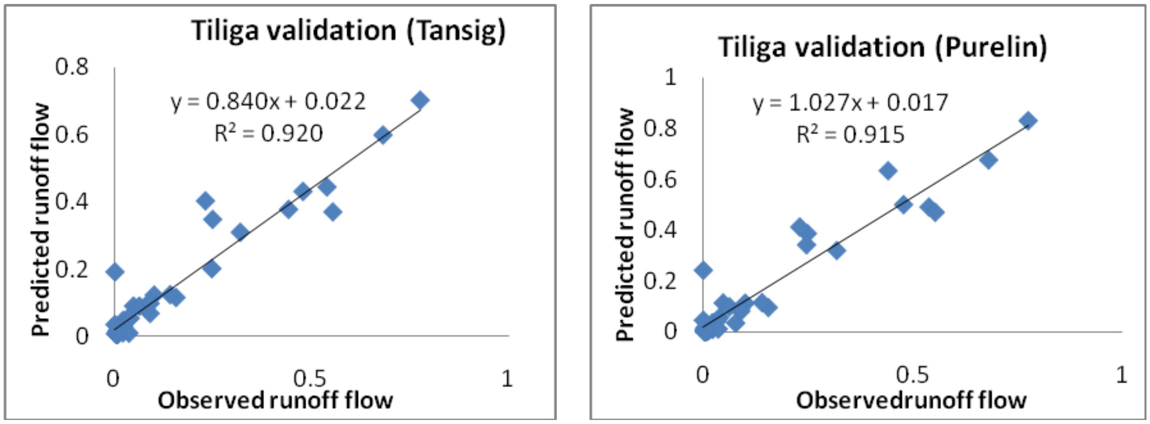


Figure 5 Cofficient of determination graph of using Tansig and Purelin transfer function at Tiliga.

The performance measure of ANN models in terms of numerical computation are MAD, MSE, RMSE and R^2 shown in Table-1, Table-2 and Table-3. On the above table it is observed that Tansig function is given better result according to Purelin.

4.1 Comparison graph of ANN model and ARIMA model

The predicted runoff by used ARIMA method and it is again comparing with the best transfer function of ANN found by the observation as shown in Figure-7, Figure-8 and Figure-9. Performance evaluation statistics ANN and Time series model at different station.

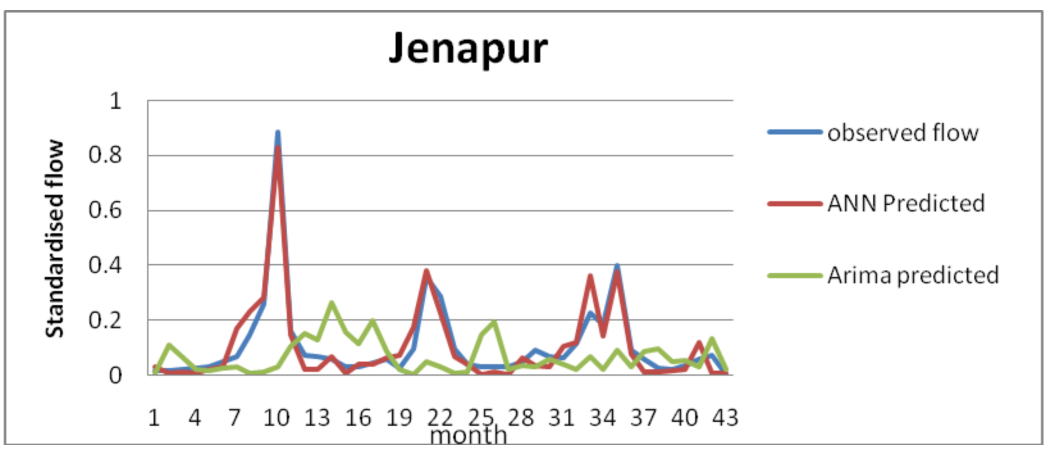


Figure 6. Comparison graph of ANN and ARIMA predicted flow of Jenapur

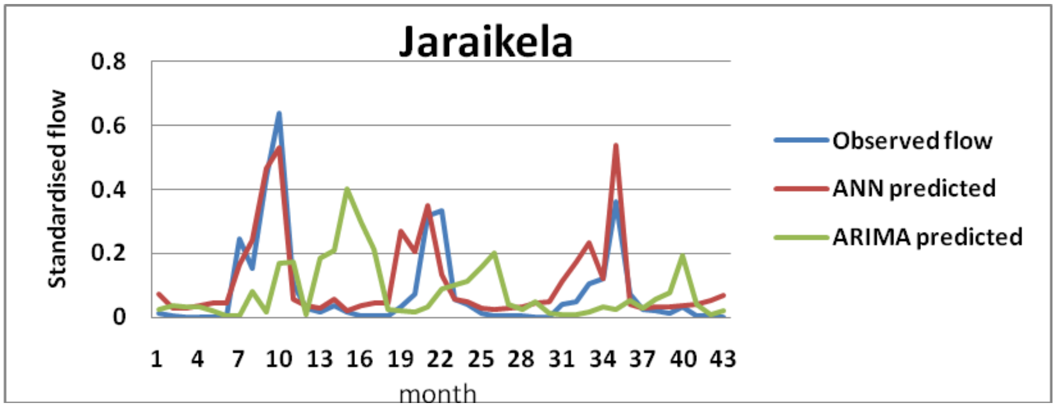


Figure 7 .Comparison graph of ANN and ARIMA predicted flow of Jaraikel

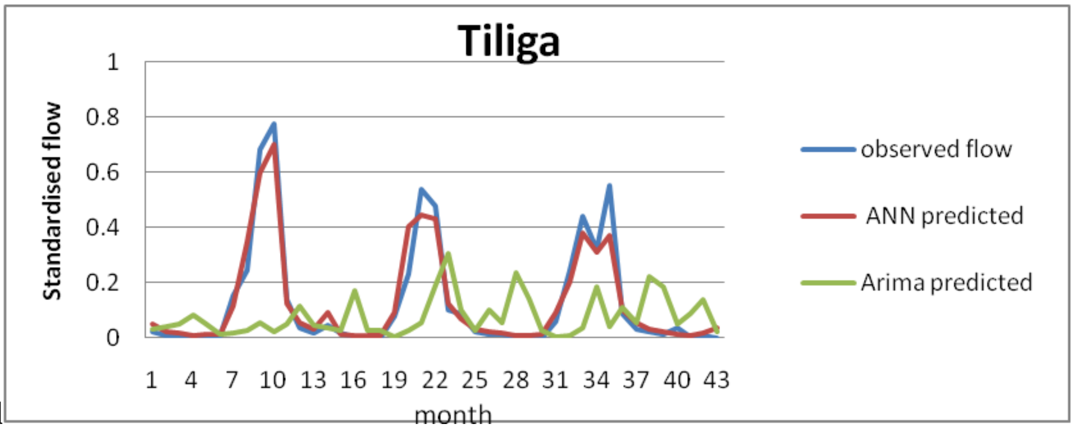


Figure 9. Comparison graph of ANN and ARIMA predicted flow of Tiliga

Table 4. Comparison statically analysis ANN and Time series model at different Gauging stations.

STATIONS	TECHNIQUES	MAD	MSE	RMSE
Jenapur	ARIMA	0.104	0.030	0.175
	ANN	0.033	0.001	0.043
Jaraikela	ARIMA	0.110	0.027	0.166
	ANN	0.053	0.005	0.005
Tiliga	ARIMA	0.142	0.050	0.224
	ANN	0.030	0.002	0.051

The performance measure of ANN and ARIMA models in terms of numerical computations are shown in table 4.The table indicates that the ANN model outperforms the ARIMA model. The MAD error for model data set of Jenapur, Jaraikela, and Tiliga for ARIMA model is 0.104, 0.110

and 0.142 while the same error measure is considerably lower at 0.033, 0.053 and 0.030 in ANN method. The other performance measures such as MSE at, Jenapur, Jaraikela and Tiliga for ARIMA models are 0.030, 0.027 and 0.050 but in same error measure is considerably lower at 0.001, 0.005 and 0.002 in ANN. The RMSE values of, Jenapur, Jaraikela and Tiliga in ANN models are 0.043, 0.005 and 0.051which are lower than 0.175, 0.166 and 0.224. On the basis error calculation of MAD, MSE and RMSE the ANN model is more appropriate than ARIMA model. In our study observed that ANN model should be appropriate prediction tool for predicts rainfall according to ARIMA model

5. CONCLUSION

Highly nonlinear multidimensional natural recorded parameter of rainfall-runoff studies using ANN and ARIMA techniques. 2010 December to 2014 July recorded data solar, wind humidity, temperature, precipitation and runoff data was used for validation model or predict runoff. ARIMA method use runoff data of past observation as input to neural network. For present analysis uses 5 types of past observation data and one output data that is runoff which was used to ANN. On this study concluded that ANN model is used to an appropriate model for prediction runoff, than performance of ARIMA model.

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