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A comparative study of artificial intelligence and conventional techniques for rainfall-runoff modeling

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■ **ABSTRACT :** The essential for accurate modeling of the rainfall–runoff process has grown rapidly in the past decades. However, considering the high stochastic property of the process, many models are still being developed in order to define such a complex phenomenon. In this study, two AI-based models which are reliable in capturing the periodicity features of the process are introduced for river rainfall–runoff modeling. In the first model, the ANN model, an ANN is used to five different type training algorithms namely momentum, Quickprop, Delta-Bar-Delta, Conjugate Gradient and Levenberg Marquardt. In the second model, ANFIS model trained used to two different type membership function (MFs) *viz.,* Gaussian and generalized bell and conventional techniques was used multiple linear regression (MLR). The artificial intelligence performed better than the conventional techniques for rainfall-runoff modelling of study area. The ANFIS models performing the best results, ANN models gives the satisfactory results and MLR model having poor result in runoff prediction for Arpa River basin. Also gamma test (GT) was used for identifying the best input combination of input variables.

■ **KEY WORDS :** Artificial neural network, Adaptive neural-fuzzy inference system, Multiple linear regression, Gamma test

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The effective flood management is always of great apprehension in the field of hydrology and water resources engineering. The damaging effects of floods are seen in various parts of the country recently, in particular extreme floods situations are discovered in Indian states like the Tamil Naidu, Jammu and Kashmir, Uttarakhand, Orissa and Bihar. Attention to the need for more effective flood management is must while the occurrence of floods cannot be prevented. Among a variability of measures for moderating the magnitudes of floods, river flow forecasting, a non-structural measurement in the short term is of great importance where as in the medium and long term, it is essential for reservoir operation and water resources management. However, the damage due to floods is tending to increase with an advance of flood plain zones and even river beds. An artificial neural network was presently being used in different fields such as finance, medicine and a wide range of engineering applications. The startup period of studying ANN application in hydrology occurred throughout the 1990s. The study discussed as the first paper on neural network application in hydrologic modeling by Daniell (1991). Since then, the application of ANN in hydrology and water resources modelling has involved a lot of consideration (Lorrai and Sechi, 1995; Dawson and Wilby, 1998 and Jain and Shrivastav, 1999). Different types of ANNs have been used in hydrological modeling like radial basis function (RBF) (Moradkhani *et al.*, 2004; Partal, 2009 and Lin and Wu, 2011), Bayesian neural networks (Khan and Coulibaly, 2006 and Jiang *et al.*, 2012), Self-Organizing Maps (SOM) (Srinivasulu and Jain, 2006 and Toth, 2009) and feed-forward multilayer perception also known as multilayer perceptron (MLP). Rajurkar *et al.* (2004) applied ANN to model daily flows during monsoon flood events for a large catchment of India and found high accuracy in modeling. Shamseldin *et al.* (2010) compared the performance of three neural network structures multilayer perceptron neural network (MLPNN), the simple multilayer perceptron neural network (SNN) and the radial basis function neural network (RBFNN). These neural networks were used to combine the simulated discharges provided by the four selected rainfall-runoff models. Shrivastav *et al.* (2014) compared feed-forward networks efficiencies of the back-propagation (BP), conjugate gradient (CG) and Levenberg-Marquardt (L-M) training algorithms for improving the computed performances and 72 models were prepared to select the best model.

In the past few decades ANNs and ANFIS methods have widely used in a wide range of engineering applications including hydrology such as for rainfall-runoff modeling, groundwater modeling and river flow forecasting (Kisi, 2015). There are many comparative studies and application of ANN and ANFIS in field of hydrology and water resource (Kisi *et al.*, 2013; Folorunsho *et al.*, 2014; He *et al.*, 2014 and Shafaei and Kisi, 2016). The objectives of the study presented in this paper are to (a) investigate the artificial intelligence techniques and conceptual techniques for modeling the complex rainfall–runoff process, (b) evaluate the investigated learning algorithms methods available for training the ANN rainfall–runoff models, and (c) investigate the suitable inputs variable for study area.

■ METHODOLOGY

Study area:

The daily rainfall and runoff data during the period from 2001-2007 for Arpa river were recorded from Ghatora station of Central Water Commission (CWC) and the data were obtained from Divisional office of CWC Raipur, Chhattisgarh, India. The Ghatora station of Arpa river is located in Bilaspur district of the Chhattisgarh state in India at latitude of 22 33'29.16'' N and longitude of 82 6'41.20'' E and having elevation of 246 m from mean sea level (MSL). The drainage area of Arpa river is approximately 3035 km^2. The location of study area is shown in Fig. A. The seven years data set are divided into two phases, first phase is training and second is testing. The models are trained using the five years data from June 1, 2001 to September 30, 2005, and the testing of the models was done using the two years data from June 1, 2006 to September 30, 2007 for validation of developed models.

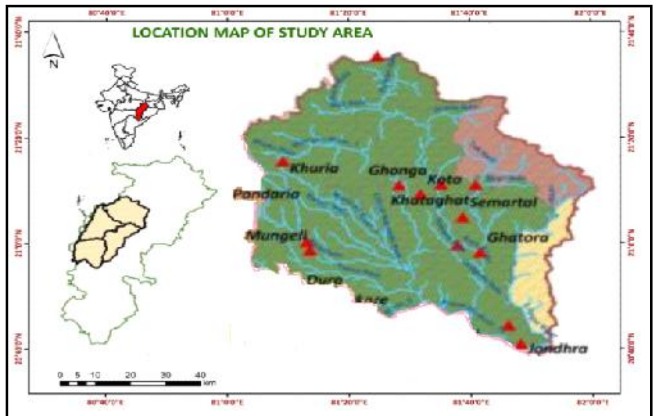

Fig. A : Location of study area

Artificial neural network (ANN):

Neural network is simple mathematical technique designed to accomplish a variety of tasks. Neural network uses a set of processing elements equivalent to neurons in the brain. These nodes are interconnected in network and learn from the experience just as people do. Neural network can be configured in various arrangements to perform a range of tasks including pattern recognition, data mining, classification, and process modeling. Artificial neural network is a network of consistent neurons (nodes), which are the important unit of ANN. The neuron is capable to accept and convey signals from one neuron to another neuron. The basic concept of neuron model is a binary threshold processing unit is presented by McCulloch and Pitts (1943).

ANFIS architecture:

One of the most popular integrated systems is adaptive neuro-fuzzy inference system (ANFIS) which has shown promising results in modelling nonlinear time series. In ANFIS, Takagi-Sugeno type fuzzy inference system is used. The output of each rule can be a linear combination of input variables plus a constant term. The final output is the weighted average of each rule's output.

Multiple linear regressions (MLR):

Regression model is another highly recognized method for hydrological prediction. A regression model that involves more than one independent variable is called multiple linear regression model (MLR). It is a linear relationship between inputs and output. Regression analysis studies the correlation between dependent and independent variables.Multiple linear regressions are the extended forms of simple linear regressions applied to the case of multiple explanatory variables. The purpose of MLR is to explain as much as possible of the variation observed in the response variableleaving as little variation as possible to unexplained "noise" (Helsel and Hirsch, 2002).

Model development:

Five different types of ANN and two ANFIS models have been developed and are represented in Table A that differ in the manner of the training algorithms employed to ûrst classify the input–output data into three categories before developing separate feed-forward MLP type ANN models trained using back propagation algorithm (BPA) and ANFIS model trained using two deferent type membership function namely Gaussian and Generalized bell.

Model input selection:

Also GT was used for identifying the best input combination of input variables. Different combinations of input variables were explored to assess their influence on the runoff simulation. Gamma test predicts the minimum achievable modeling error before the modeling. Suppose 'n' is the variables influencing on occurrence of a phenomenon; 2^n-1 meaningful combination would be established from the input variables.To determine the best input combination in modeling, various combinations of input parameters were assessed using GT so as to identify the most appropriate combination among the remained variables to predict the runoff discharge. Some of these combinations along with Gamma values are shown in Table 2. The results showed, the best input combination of the variable is when using Rt, Rt-1, Rt-2, Qt-1. The Small value of gamma indicates that the data with provided combination might possibly provide better results in modeling.

Model performance :

Root mean square error (RMSE) :

$$\mathbf{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}(\mathbf{Q_0} - \mathbf{Q_p})^2}{\mathbf{n}}} \qquad (1)$$

where, Q_o is i^{th} observed values of daily runoff, Q_p

Table A : Details of various types of the learning algorithms

Model	Algorithm / MFs	Learning rule description
ANN-1	Momentum	Gradient and Weight Change (Momentum)
ANN-2	Conjugate Gradient	Second Order method for Gradient
ANN-3	Levenberg Marquardt	Improved Second Order method for Gradient
ANN-4	Delta Bar Delta	Adaptive Step Sizes for Gradient plus Momentum
ANN-5	Quickprop	Gradient and Rate of Change of Gradient
ANFIS-1	Gaussian	
ANFIS-2	Generalized bell	

Table B : Determination of the best combination

Different combinations	Mask	Gamma	SE	V_{ratio}
R_t, R_{t-1}, R_{t-2},Q_{t-1},Q_{t-2}, Q_{t-3}	111001110	0.03768	0.009554	0.15075
R_t, R_{t-1}, R_{t-2}, Q_{t-1},Q_{t-2}	111001100	0.02987	0.005873	0.11949
R_t, R_{t-1}, R_{t-2}, Q_{t-1},	111001000	0.02419	0.003244	0.11357
R_t, R_{t-1}, Q_{t-1}	110001000	0.03298	0.011821	0.13194
R_t, R_{t-1}, Q_{t-1}, Q_{t-2}, Q_{t-3}	110001110	0.03478	0.009667	0.13915
R_t, R_{t-1}, Q_{t-2}, Q_{t-3}	110000110	0.03049	0.007098	0.12196

is predicted values of daily runoff and n is the number of observations.

Correlation co-efficient (r) :

$$r = \left[\frac{\sum_{i=1}^{n} \{(Q_O - \overline{Q}_O)(Q_p - \overline{Q}_p)\}}{\sqrt{\sum_{i=1}^{n} (Q_O - \overline{Q}_O)^2} \sqrt{\sum_{i=1}^{n} (Q_p - \overline{Q}_p)^2}} \right] \qquad (2)$$

where $\overline{Q}_O$ is average of the observed daily runoff series and $\overline{Q}_p$ is average of predicted daily runoff series.g statistical criteria are also applied.

Co-efficient of efficiency (CE) :

$$CE = 1 - \frac{\sum_{i=1}^{n} (Q_O - Q_p)^2}{\sum_{i=1}^{n} (Q_O - \overline{Q}_O)^2} \qquad (3)$$

RESULTS AND DISCUSSION

The results obtained from the present investigation as well as relevant discussion have been summarized under following heads :

ANN and ANFIS model results:

The results in terms of various performance statistics from all the ANN and ANFIS models are presented in Table 1. Analyzing the results during training, it can be observed that the ANN model trained using Momentum learning algorithm (ANN-1 model) performed the worst while the performances of the ANN models trained using Conjugate Gradient, Levenberg Marquardt,Delta-Bar-Delta and Quickprop (ANN-2, ANN-3, ANN-4 and ANN-5 models, respectively) were comparable. The ANN-2 model obtained the best RMSE, r and CE statistics of 18.70, 0.93 and 0.90, respectively; similarly the ANN-3 model obtained the best RMSE, r and CE statistics of 11.98, 0.97 and 0.96, respectively; ANN-4 model obtained the best RMSE, r and CE statistics of 17.10, 0.93 and 0.92, respectively and ANN-5 model obtained the best RMSE, r and CE statistics of 19.22, 0.92 and 0.92, respectively during the testing period. Analyzing the results during testing, it can be observed that the ANN model trained using Levenberg Marquardt learning algorithm the best outperformed all other models. The ANN-3 model obtained the best statistics results

Table 1 : Statistical performance evaluation measures from various ANN model

Model	Networks	Training			Testing		
		RMSE	r	CE	RMSE	R	CE
ANN-1	4-15-1	43.94	0.85	0.79	19.94	0.89	0.89
ANN-2	4-16-1	31.10	0.93	0.89	18.70	0.93	0.90
ANN-3	4-4-1	20.46	0.97	0.95	11.98	0.97	0.96
ANN-4	4-11-1	24.41	0.93	0.93	17.10	0.93	0.92
ANN-5	4-13-1	36.06	0.90	0.85	19.22	0.92	0.92
ANFIS-1	Gauss(5)	18.12	0.97	0.96	10.04	0.98	0.97
ANFIS-2	Bell(4)	19.43	0.97	0.95	11.57	0.97	0.96

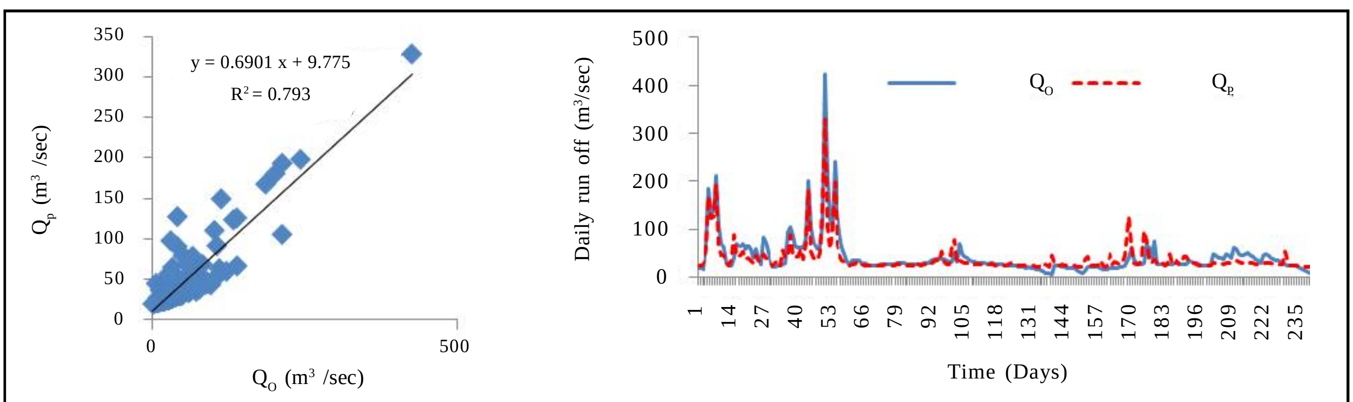

Fig. 1 : **Comparison of observed (Q_o) and predicted (Q_p) daily runoff and their corresponding scatter plot during testing period for ANN-1 model**

during testing period. Thus, it can be said that when the overall performance is considered, the ANN model trained using Levenberg Marquardt learning algorithm performed the best, the ANN model trained using Momentum learning algorithm performed the worst, and the performance of the ANN model developed using Conjugate Gradient, Delta-Bar-Delta and Quickprop learning algorithms was moderate. The qualitative performance was evaluated by visual observation Fig. 1 to 5. Similarly ANFIS-1 model trained using Gaussian MFs and ANFIS-2 model trained using generalized bell MFs. Analyzing the results from the Table 1. It can say that ANFIS-1 model having the best statistical result during training and testing period in compared to ANFIS-2 model. The qualitative performance was evaluated by visual observation Fig. 6 and 7.

MLR model result:

The results of the MLR model were obtained the best RMSE, r and CE statistics of 26.66, 0.80 and 0.85, respectively during the testing period. The qualitative performance of developed model was judged by observed and predicted daily runoff graph and scatter plots as shown in Fig. 8. The runoff graph shows that the MLR Model under predict both during high and low runoff indicating that MLR models have high deviation between observed and predicted daily runoff. It was also found that MLR model was having high accuracy during low flow.

Some researchers have reported that the ANN rainfall–runoff models trained using popular BPA do not perform well in predicting low magnitude de flows (Srinivasulu and Jain, 2006). In order to compare the performances of ANN models namely ANN-1, ANN-2, ANN-2, ANN-3, ANN-4, ANN-5, ANFIS models *viz.*, ANFIS-1 and ANFIS-2 and MLR model. For this, selected error statistics (RMSE, r and CE) were calculated from different models for the data

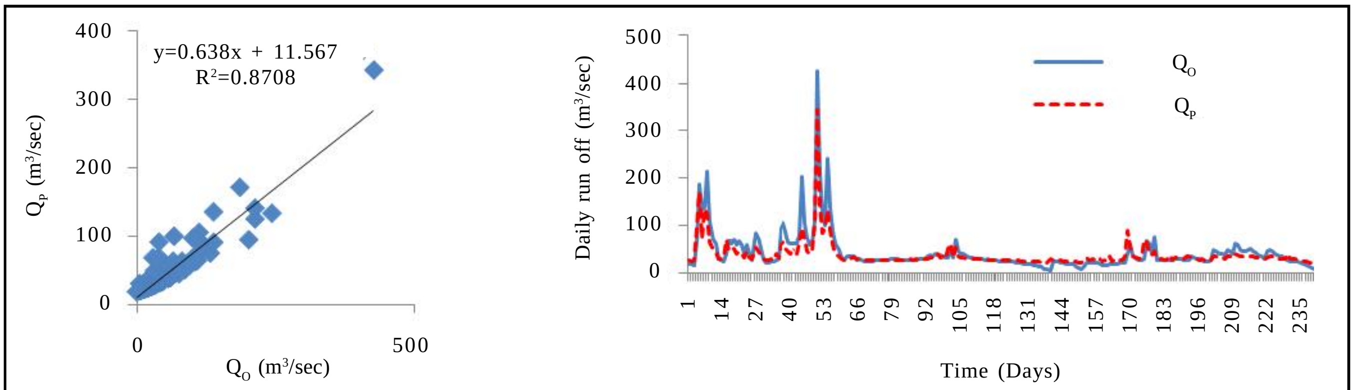

Fig. 2 : Comparison of observed (Q_o) and predicted (Q_p) daily runoff and their corresponding scatter plot during testing period for ANN-2 model

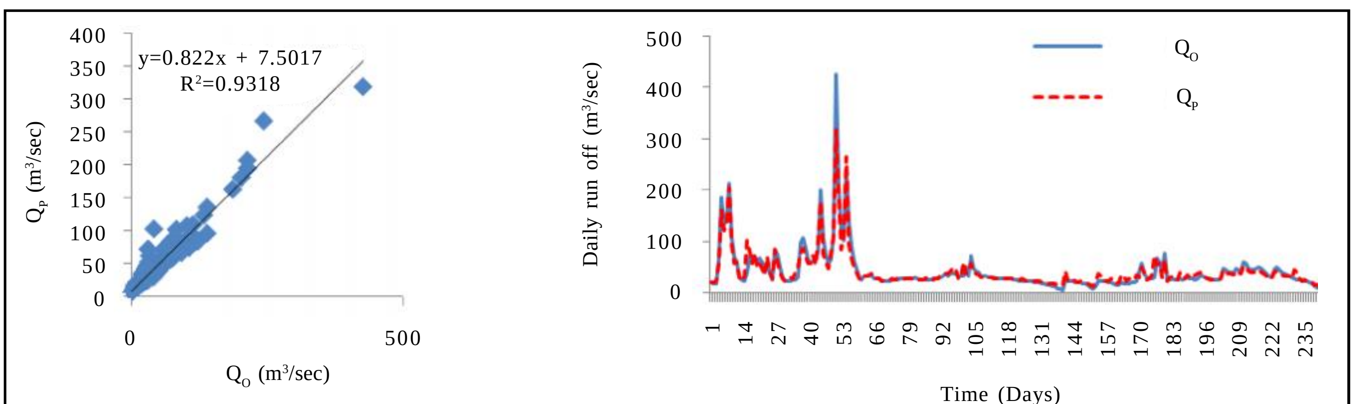

Fig. 3 : Comparison of observed (Q_o) and predicted (Q_p) daily runoff and their corresponding scatter plot during testing period for ANN-3 model

corresponding to low and high magnitudes of flow.It can be noted from Table 2 that during training the ANN-3 model having best values of statistics RMSE, r and CE of 16.57, 0.85 and 0.86 for low magnitude flows. But during testing period ANFIS-1 model with values of statistics RMSE, r and CE of 9.14, 0.94 and 0.96 for low

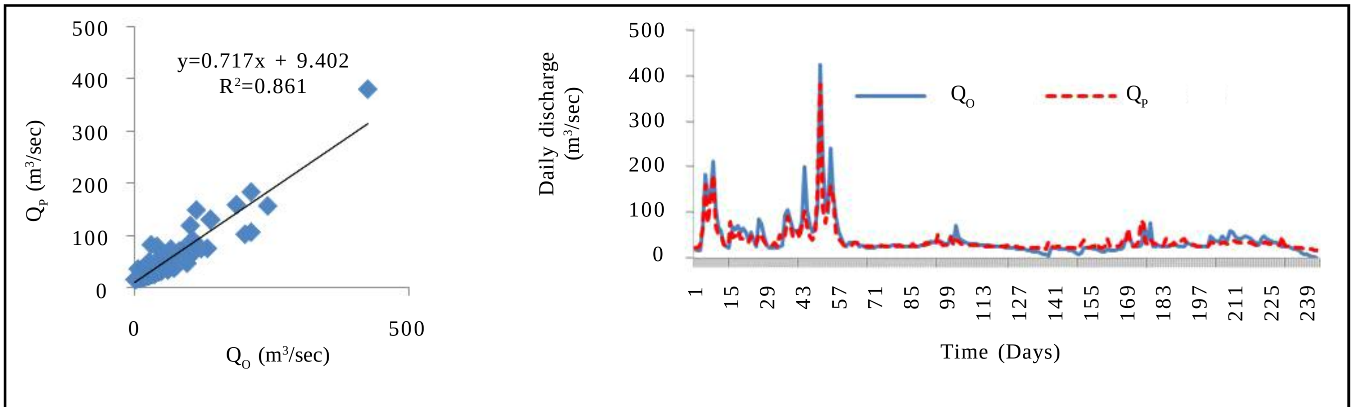

Fig. 4 : **Comparison of observed (Q_o) and predicted (Q_p) daily runoff and their corresponding scatter plot during testing period for ANN-4 model**

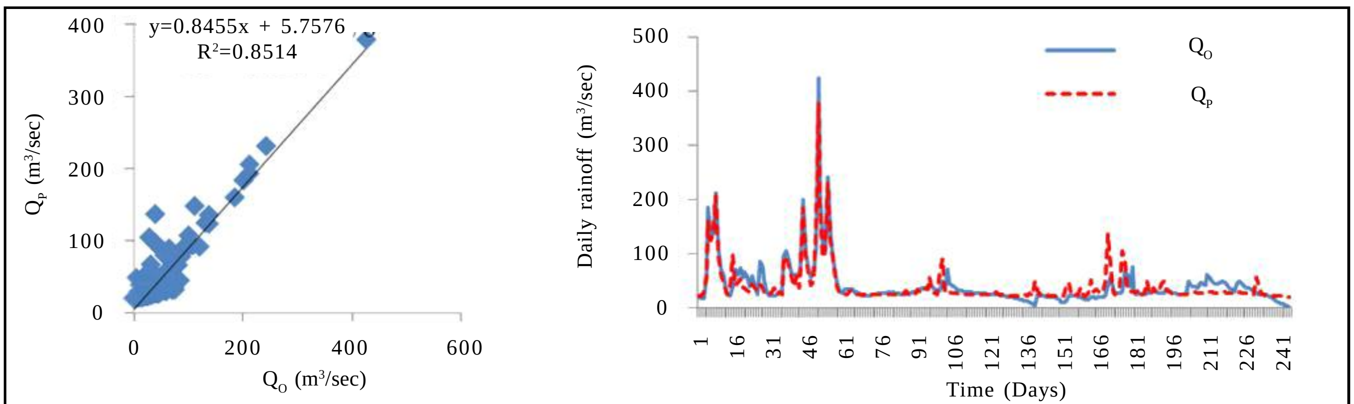

Fig. 5 : **Comparison of observed (Q_o) and predicted (Q_p) daily runoff and their corresponding scatter plot during testing period for ANN-5 model**

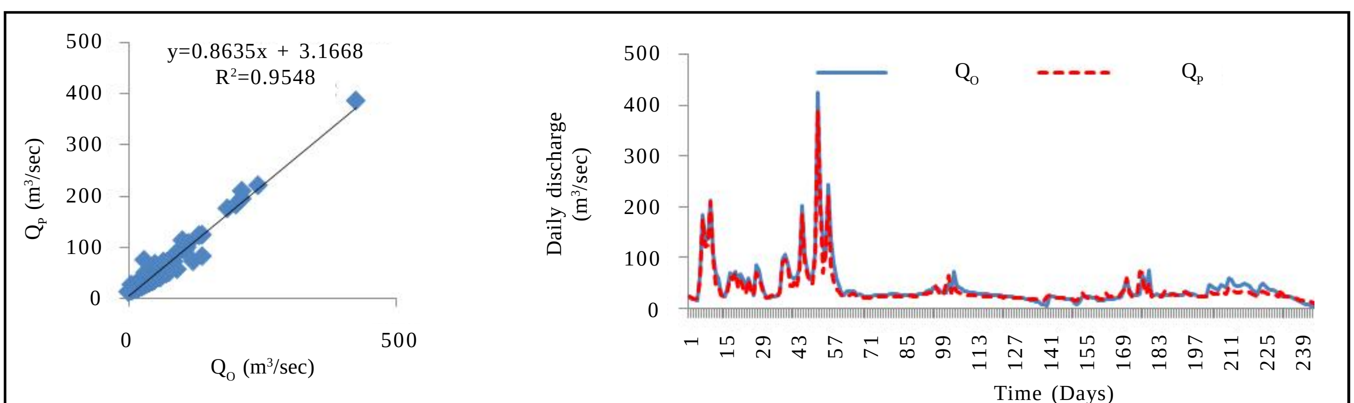

Fig. 6 : **Comparison of observed (Qo) and predicted (Qp) daily runoff and their corresponding scatter plot during testing period for ANFIS-1 model**

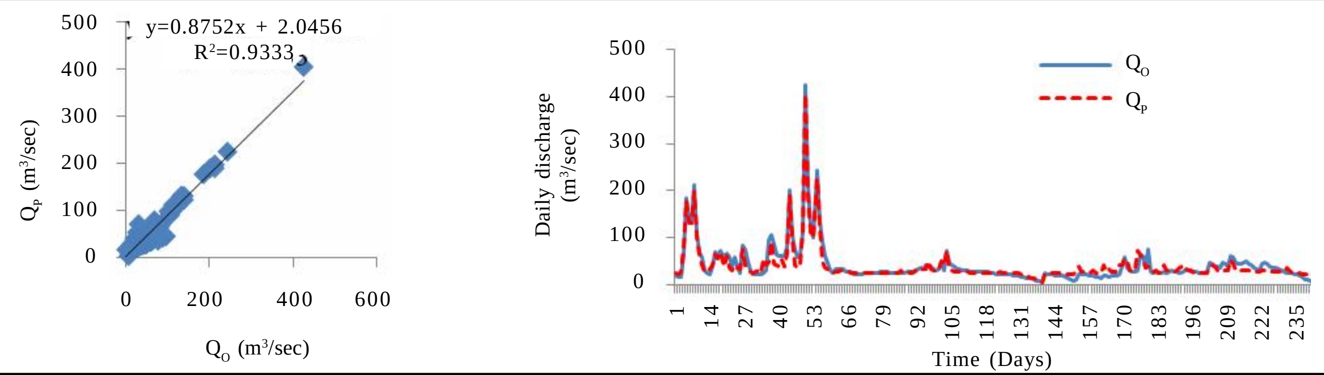

Fig. 7 : Comparison of observed (Qo) and predicted (Qp) daily runoff and their corresponding scatter plot during testing period for ANFIS-2 model

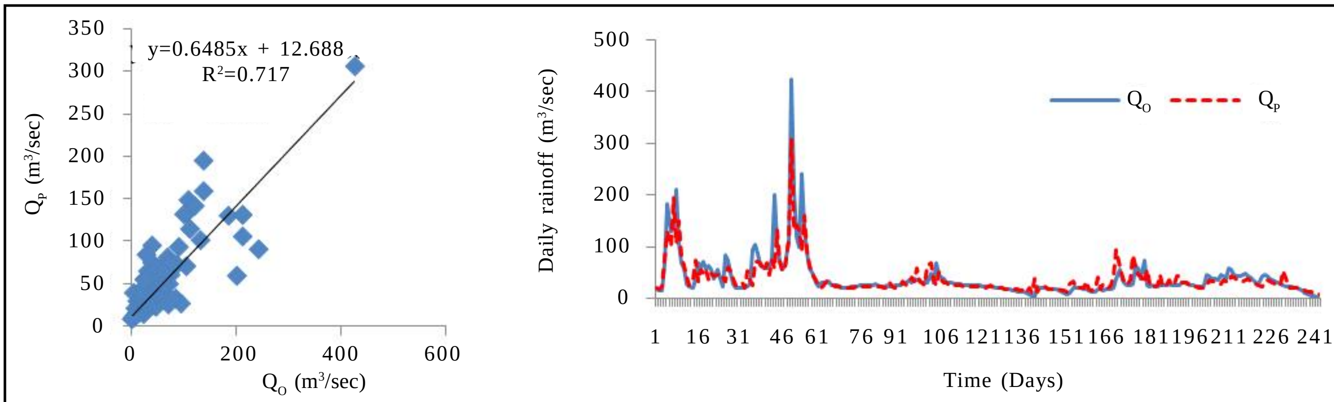

Fig. 8 : Comparison of observed (Q_o) and predicted (Q_p) daily runoff and their corresponding scatter plot during testing period for MLR model

Table 2 : Statistical results for low and high magnitude flows

Model	Training			Testing		
	RMSE	R	CE	RMSE	R	CE
Low magnitude flows						
ANN-1	27.54	0.66	0.61	17.47	0.68	0.87
ANN-2	22.49	0.72	0.74	13.39	0.85	0.90
ANN-3	16.57	0.85	0.86	09.54	0.92	0.95
ANN-4	18.34	0.82	0.83	13.4	0.84	0.91
ANN-5	27.84	0.64	0.61	15.96	0.76	0.88
ANFIS-1	52.01	0.82	0.87	09.14	0.94	0.96
ANFIS-2	51.58	0.81	0.86	10.51	0.93	0.95
MLR	32.12	0.63	0.59	20.15	0.72	0.81
High magnitude flows						
ANN-1	179.61	0.78	0.82	63.39	0.89	0.94
ANN-2	115.52	0.92	0.92	84.10	0.92	0.89
ANN-3	65.39	0.98	0.98	35.31	0.96	0.98
ANN-4	84.58	0.96	0.96	71.55	0.94	0.92
ANN-5	128.08	0.90	0.92	23.50	0.99	0.99
ANFIS-1	61.27	0.98	0.98	31.29	0.97	0.98
ANFIS-2	54.12	0.98	0.98	20.14	0.99	0.99
MLR	192.21	0.66	0.78	91.41	0.68	0.79

magnitude flows. It was concluded that ANFIS-1 model trained using Gaussian MFs having best performing results during low magnitude flow. Similarly during high magnitude flow the ANFIS-2 model was found best results of statistics of RMSE, r and CE of 20.14, 0.99 and 0.99, respectively during testing period.After the analyzing the results both during training and testing, it was found that ANFIS-1 model having best performance in low magnitude flow, but during high magnitude flow the ANFIS-2 model was found to be the best performing results. Improvements in the r and CE statistics also can be noted from Table 2 for all magnitude flows during both training and testing data sets by the ANFIS models having the best result in compared to ANN and MLR models.

Summary and conclusion :

In presents study was found that comparison results of the available learning algorithms include momentum, Quickprop, Delta-Bar-Delta, Conjugate Gradient and Levenberg Marquardt for training of the ANN rainfall-runoff models. It found Levenberg Marquardt algorithms was the best training algorithm of ANN model for study area. Gamma test (GT) is one of the non-linear modelling tools whereby an appropriate combination from input parameters can be investigated for modelling. A wide variety of standard statistical performance evaluation measures were employed to evaluate the performances of various ANN, ANFIS and MLR models developed.

The findings of the study reported in this study suggest that the Momentum learning algorithm is not suitable in training the ANN rainfall–runoff models. The Levenberg Marquardt learning algorithm trained ANN rainfall–runoff models were found to represent the complex, dynamic, non-linear, and fragmented rainfall-runoff process in a much better manner. The predictive capability of the Levenberg Marquardt learning algorithm trained ANN rainfall-runoff models were found to be much superior to those trained using all learning algorithm. The artificial intelligence performed better than the conventional techniques for rainfall-runoff modelling of study area. The ANFIS models performing the best results, ANN models gives the satisfactory results and MLR model having poor result in runoff prediction for Arpa river basin. Many researchers have reported that the ANN rainfall-runoff models trained using the Delta-Bar-Delta learning algorithms are not efficient in learning the complex rainfall–runoff relationships during low flow events. This study is able to demonstrate that this problem can be easily overcome by the ANN rainfall-runoff models trained using the Levenberg Marquardt learning algorithm. It is advantageous to perform an error analysis of the results for varying magnitudes of flows (such as low, and high) in order to properly examine the robustness and predictive capability of the ANN models. Further, the performances of various ANN models need to be evaluated using a wide variety of standard statistical performance evaluation measures rather than relying on a few global error statistics, such as correlation co-efficient and efficiency, normally employed that are similar in nature to the global error minimized at the output layerof an ANN model.

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