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Prediction of annual runoff using Artificial Neural Network and Regression approaches

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सार – बाढ़ और सूखा जैसी चरम घटनाओं के प्रबन्धन तथा जल भंड़ारण और निकासी कार्यों के अनुकूलतम डिजाइन के लिए प्रायः अपवाह का पूर्वानुमान करना महत्वपूर्ण है। अपवाह के पूर्वानुमान के लिए वर्षा अपवाह (आर. आर.) मॉडलों को बहुत प्रभावशाली और व्यावहारिक माध्यम माना जाता है। आर. आर. माडुलन के लिए प्रसंभाव्य, संकल्नात्मक, निर्धारणात्मक, ब्लैक बॉक्स इत्यादि जैसे मॉडल आसानी से उपलब्ध है। इस शोध पत्र में बेतवा और चम्बल के क्षेत्रों के लिए अपवाह के पूर्वानुमान हेतु कृत्रिम तंत्रिका संजाल (ए. एन. एन.) और समाश्रयण (आर. ई. जी.) विधि के उपयोग का अध्ययन किया गया है। अपवाह पूर्वानुमान हेतु ए. एन. एन. और आर. ई. जी. निष्पादन का आकलन करने के लिए मॉडल दक्षता, सहसंबंध गुणांक, वर्ग माध्य मूल त्रुटि और वर्ग माध्य निरपेक्ष त्रुटि जैसे मॉडल निष्पादन सूचकों का उपयोग किया गया है। अध्ययन किए जाने वाले आँकड़ों हेतु ए. एन. एन. और आर. ई. जी. से पूर्वानुमान में सटीकता का पता लगाने के लिए सांख्यिकीय प्राचलों का प्रयोग किया गया है। इस अध्ययन से यह पता चला है कि बेतवा और चम्बल क्षेत्रों के लिए अपवाह पूर्वानुमान हेतु कृत्रिम तंत्रिका संजाल उचित है।

ABSTRACT. Prediction of runoff is often important for optimal design of water storage and drainage works and management of extreme events like floods and droughts. Rainfall-runoff (RR) models are considered to be most effective and expedient tool for runoff prediction. Number of models like stochastic, conceptual, deterministic, black-box, etc. is commonly available for RR modelling. This paper details a study involving the use of Artificial Neural Network (ANN) and Regression (REG) approaches for prediction of runoff for Betwa and Chambal regions. Model performance indicators such as model efficiency, correlation coefficient, root mean square error and root mean absolute error are used to evaluate the performance of ANN and REG for runoff prediction. Statistical parameters are employed to find the accuracy in prediction by ANN and REG for the data under study. The paper presents that ANN approach is found to be suitable for prediction of runoff for Betwa and Chambal regions.

Key words – Artificial neural network, Performance indicators, Rainfall, Regression, Runoff.

1. Introduction

Importance of runoff prediction is increasing day-by-day because of increasing population and economic activity in flood plains and along major rivers. Rainfall-runoff models (RR) are considered to be most effective and expedient tool for runoff prediction. RR models are very much useful in many water resources applications such as flood control, drought management, optimal reservoir operation involving multiple objectives such as irrigation, hydropower generation and water supply. RR models are also used in design of various hydraulic structures such as dams, bridges, culverts, barrages, etc. RR models can broadly be divided into two categories. The first category of RR model is based on the law of physics and is commonly known as deterministic or conceptual model. The second category of RR model is of the black box type, which does not account for the underlying physics (Cigizoglu, 2003, Jain *et al*., 2009). From the recent past studies, it has been understood that large-scale atmospheric circulations significantly influence the temporal structure of a hydrologic time series. However, it is scientifically and mathematically challenging to use such signals for the prediction of basin-scale hydrological variables (ISO 5168, 1978). In addition, the hydrometeorological systems are quite complex and very difficult to model, as the mechanism behind the hydrological cycle is spread over large area and

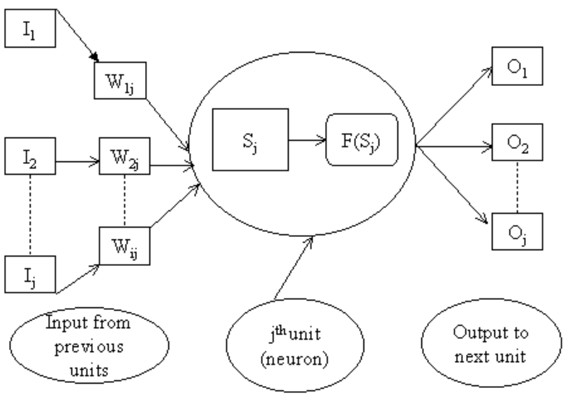

Fig. 1. Structure of Artificial Neural Network

the physics behind all the atmospheric processes is not completely understood. Hence, the advanced techniques to understand the process are being investigated and also found to be more efficient as compared to the traditional modelling approaches based upon statistical concepts. In view of the above, Artificial Neural Network (ANN) has been proposed as effective tool for modelling and forecasting studies in recent times.

ANN modelling procedures adapt to complexity of input-output patterns and accuracy goes on increasing as more and more data become available. Fig. 1 gives the architecture of ANN that consists of input layer, hidden layer, and output layer. In turn, these layers have a certain number of neurons or units, so the units are also called input units, hidden units and output units. From ANN structure, it can be easily understood that input units receive data from external sources to the network and send them to the hidden units, in turn, the hidden units send and receive data only from other units in the network, and the output units receive and produce data generated by the network, which goes out of the system. In this process, a typical problem is to estimate the output as a function of the input. This unknown function may be approximated by a superposition of certain activation functions such as tangent, sigmoid, polynomial, and sinusoid in ANN. A common threshold function used in ANN is the sigmoid function f(S) expressed by Eqn. (1), which provides an output in the range of $0 < f(S) < 1$.

$$f(S) = \left[1 + \exp\left(-S_j\right)\right]^{-1} \text{ and } S_j = \sum_{j=1}^{M} I_j W_{ij} + O_j, \quad i=1,2,3,\ldots..N \qquad (1)$$

The sigmoid function is chosen for mathematical convenience because it resembles a hard-limiting step function for extremely large positive and negative values of the incoming signal and also gives sufficient information about the response of the processing unit to inputs that are close to the threshold value. Furthermore, the sigmoid function has a simple derivative that makes the subsequent implementation of the learning algorithm much easier. In the present study, ANN is employed for prediction of runoff for Betwa and Chambal regions, and the results are compared with regression (REG) approach for the selection of best suitable method for RR modelling.

2. Methodology

2.1. *ANN Approach*:

Number of training algorithms such as Back Propagation Network (BPN), Cascade Correlation Network (CCN), Conjugate Gradient Network (CGN), Genetic Network (GN), etc is commonly used in ANN. The objective in any training algorithm of ANN is to reduce the global error between the predicted and targeted outputs. From the recent studies on ANN, it may be observed that number of researchers have applied different networks for prediction of runoff for various regions (Imrie *et al*., 2000; Thirumalaiah and Deo, 2000; Tokar and Markus, 2000; Rajurkar *et al*., 2004). Carriere *et al.* (1996) developed a virtual runoff hydrograph system that employed a recurrent BPN to generate a runoff hydrograph. Shamseldin *et al.* (1997) applied CGN to train feed forward network using daily average rainfall and runoff data from six catchments from different climatic conditions around the world. Thirumalaiah and Deo (2000) studied the application of CCN and BPN to real-time forecasting of hourly flood runoff and daily river stage for major river basins in India. Jain and Srinivasulu (2004) expressed that ANN model trained with GN was able to overcome the problems associated with the modelling of low-magnitude flows. Sarangi *et al.* (2005) developed ANN and regression models using watershed scale geomorphologic parameters to predict surface runoff and sediment losses of St. Espirit watershed (Canada) and found that ANN model performed better than the regression model. Jothiprakash *et al.* (2006) expressed that stream flow prediction with ANN model was more satisfactorily than the HEC-4 model in case of multi-site stream flow generation. Wang *et al.* (2007) studied three-layer feed forward time delay neural network combined with a GN to predict runoff level of Linsham Watershed, China. See *et al.* (2008) applied graphical and statistical methods to visualize hidden neuron behaviour in a trained neural network rainfall-runoff model developed for the river Ouse catchment in northern England. Kote and Jothiprakash (2009) studied the application of time lagged recurrent networks (TLRN) with different memory structures and found that TLRN is suitable for predicting monthly seasonal reservoir flows. From the research studies, it is noticed that there is a general agreement in applying BPN for RR modelling though different networks are commonly available for runoff prediction. Therefore, BPN is applied for prediction of runoff for the data under study.

Gradient descent is the most popular algorithm and used for the training of BPN (Kaltech, 2008). Each input unit of the training data set is passed through the network from the input layer to output layer. The network output is compared with the desired target output and output error (E) is computed using Eqn. (2). This error is propagated backward through the network to each neuron, and the connection weights are adjusted based on Eqn. (3).

$$\mathrm{E} = \frac{1}{2}\sum_{i=1}^{N}\left(Q_i - Q_i^*\right)^2 \tag{2}$$

$$\Delta W_{ij}(N) = -\varepsilon\frac{\partial E}{\partial W_{ij}} + \alpha\Delta W_{ij}(N-1) \tag{3}$$

In BPN, momentum factor (α) is used to speed up training in very flat regions of the error surface to prevent oscillations in the weights and learning rate (ε) is used to increase the chance of avoiding the training process being trapped in local minima instead of global minima.

2.2. *Regression Approach*

Regression approach is one of the statistical tools and commonly used for RR modeling (Jain and Indurthy, 2003). The general form of the multiple linear regression for RR modelling is expressed by Q_{i+1} = f(R_i, R_{i-1}, Q_i; Constant). The parameters are determined by method of least squares and further used in runoff prediction for the regions under study.

2.3. *Model performance*

Chen and Adams (2006) expressed that the performance of ANN and REG models could be analyzed using model performance indicators such as model efficiency, correlation coefficient, root mean square error and root mean absolute error, and are expressed by:

$$\text{Model Efficiency (MEF)} = 1 - \frac{\sum_{i=1}^{N}\left(Q_i - Q_i^*\right)^2}{\sum_{i=1}^{N}\left(Q_i - \overline{Q}\right)^2} \tag{4}$$

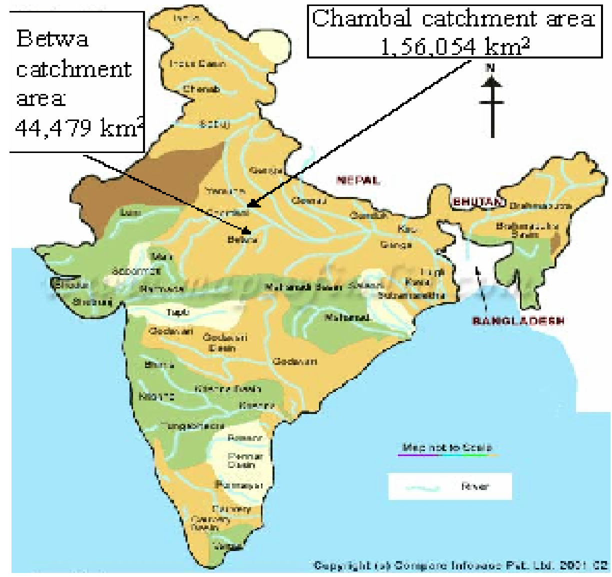

Fig. 2. Index map of study area

Correlation Coefficient (CC)

$$= \frac{\sum_{i=1}^{N}\left(Q_i - \overline{Q}\right)\left(Q_i^* - \overline{Q^*}\right)}{\sqrt{\left(\sum_{i=1}^{N}\left(Q_i - \overline{Q}\right)^2\right)\left(\sum_{i=1}^{N}\left(Q_i^* - \overline{Q^*}\right)^2\right)}} \tag{5}$$

Root Mean Square Error (RMSE)

$$= \left((1/N)\sum_{i=1}^{N}\left(Q_i - Q_i^*\right)^2\right)^{0.5} \tag{6}$$

Root Mean Absolute Error (RMAE)

$$= \left((1/N)\sum_{i=1}^{N}\left|Q_i - Q_i^*\right|\right)^{0.5} \tag{7}$$

2.4. *Data used*

Due to non-availability of daily data, annual rainfall and runoff recorded at Betwa and Chambal regions for the period 1901-2000 was used. Fig. 2 shows the index map of the study area. The data for the period 1901-1980 has been used for training (calibration), data for the period 1981-90 has been used for testing (validation) and data for the period 1991-2000 has been used for cross-validation. For the present study, the recorded rainfall at i^{th} and $(i\text{-}1)^{\text{th}}$

TABLE 1

Comparison on ANN architecture using performance indicators with combinations of hidden units and epochs used in training for Betwa region

Architecture	Epochs used	RMSE	RMAE	CC
3-6-1	1,000	30.68	7.50	0.86
3-7-1	2,500	29.55	6.48	0.89
3-8-1	5,000	29.39	6.32	0.91
3-9-1	7,500	28.36	5.28	0.94
3-10-1	10,000	25.18	4.34	0.98

TABLE 2

Comparison on ANN architecture using performance indicators with combinations of hidden units and epochs used in training for Chambal region

Architecture	Epochs used	RMSE	RMAE	CC
3-11-1	2,500	6.75	3.50	0.79
3-12-1	5,000	6.28	3.48	0.83
3-13-1	7,500	5.96	2.32	0.89
3-14-1	10,000	5.35	2.28	0.92
3-15-1	12,500	4.95	1.71	0.99

years (R_i and R_{i-1}), runoff at i^{th} year (Q_i) were considered as input units, and predicted runoff in one-year advance (Q_{i+1}) obtained from ANN and REG approaches were considered as output unit.

3. Results and discussions

3.1. *Prediction of runoff using ANN*

By considering the nature of sigmoid function adopted in ANN, the training data set values were normalized between 0 and 1 by Eqn. (8) and passed into the network (Sudheer *et al*., 2008). After the completion of training, the output values were in normalized format due to the output range of sigmoid function. These values were denormalized to provide the results in original domain.

$$N(V_i) = \frac{V_i - \mathrm{Min}(V_i)}{\mathrm{Max}(V_i) - \mathrm{Min}(V_i)} \tag{8}$$

ANN was trained using different combinations of parameters to determine the topology of the network for the present study. The model parameters $\alpha = 0.08$ and

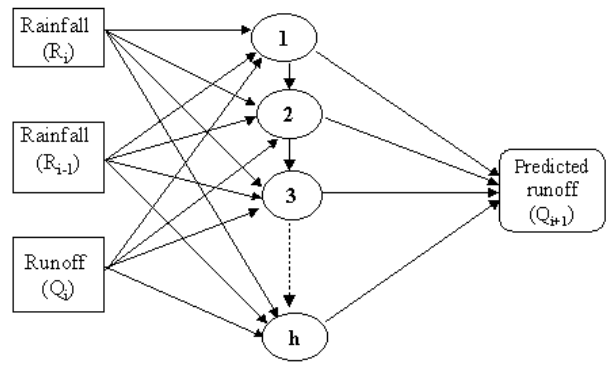

Fig. 3. ANN architecture of Betwa and Chambal

ε = 0.012 were adopted in optimizing the ANN architecture of Betwa. Similarly, the parameters α = 0.09 and ε = 0.015 were used to obtain optimum ANN architecture of Chambal. Tables 1 and 2 give the results of a study on comparative performance of ANN architecture with different combination of number of hidden units in hidden layer and number of epochs that have been used for training the network for both the regions under study.

From Table 1, it may be noted that one hidden layer with ten hidden units gives the best result for Betwa on the basis of performance indicators whereas the input neurons without the process of transmitting into a hidden layer have a large error. Also, from Table 2, it may be noted that a hidden layer with fifteen hidden units shows the best result for Chambal. Although good performance was found in the BPN prediction model for all five cases in which the RMSE is small, it is observed that as the number of hidden unit increases, it leads to more complex operations for BPN, which gives result in a phenomenon of over learning. Fig. 3 gives the optimized ANN architecture used for prediction of runoff for Betwa and Chambal. In Fig. 3, 'h' indicates the number of hidden units (10 for Betwa and 15 for Chambal) used in hidden layer for optimizing the network.

With the help of ANN architectures along with the model parameters obtained during training, runoff at the validation and cross-validation periods were predicted for both the regions.

3.2. *Prediction of runoff using REG*

By using recorded annual RR of training data sets, multiple linear regression equations for Betwa and Chambal regions were formulated and are:

$$Q_{i+1}^{*} = 0.087R_i + 0.102R_{i-1} + 0.422Q_i - 248.702 \tag{9}$$

TABLE 3

Performance indicators of ANN model for Betwa and Chambal regions

Performance indicators	Betwa			Chambal		
	TRG	VAL	CVL	TRG	VAL	CVL
MEF	0.960	0.914	0.980	0.983	0.966	0.960
CC	0.981	0.966	0.993	0.994	0.986	0.983
RMSE	25.177	31.124	23.727	4.945	2.002	2.108
RMAE	4.336	4.820	3.986	1.712	1.310	1.379

(TRG: Training; VAL: Validation; CVL: Cross-validation)

TABLE 4

Performance indicators of REG model for Betwa and Chambal regions

Performance indicators	Betwa			Chambal		
	TRG	VAL	CVL	TRG	VAL	CVL
MEF	0.906	0.716	0.930	0.974	0.842	0.940
CC	0.956	0.904	0.980	0.987	0.931	0.978
RMSE	38.863	58.239	29.922	6.081	4.290	2.542
RMAE	5.544	6.901	4.316	2.129	1.876	1.440

TABLE 5

Statistical parameters of observed and predicted runoff using ANN and REG for Betwa

Statistical parameters	OBS			ANN			REG		
	TRG	VAL	CVL	TRG	VAL	CVL	TRG	VAL	CVL
Mean	258.2	357.7	427.7	263.3	370.9	437.9	269.6	389.1	402.1
Std. Dev.	126.6	109.3	188.3	123.3	106.4	189.2	120.1	84.1	163.9
Skewness	0.727	0.879	0.702	0.733	0.727	0.765	0.583	0.989	0.478
Kurtosis	0.155	1.243	-0.352	0.118	0.533	0.053	0.291	0.326	-0.943

TABLE 6

Statistical parameters of observed and predicted runoff using ANN and REG for Chambal

Statistical parameters	OBS			ANN			REG		
	TRG	VAL	CVL	TRG	VAL	CVL	TRG	VAL	CVL
Mean	62.4	23.8	29.6	64.5	23.4	28.6	62.6	22.2	29.3
Std. Dev.	37.7	10.4	10.8	39.0	10.4	11.1	37.5	9.3	11.7
Skewness	0.097	0.439	0.439	0.051	0.322	0.128	0.087	0.015	0.303
Kurtosis	-1.270	-1.102	-1.102	-1.334	-1.222	-2.028	-.284	-0.647	-1.164

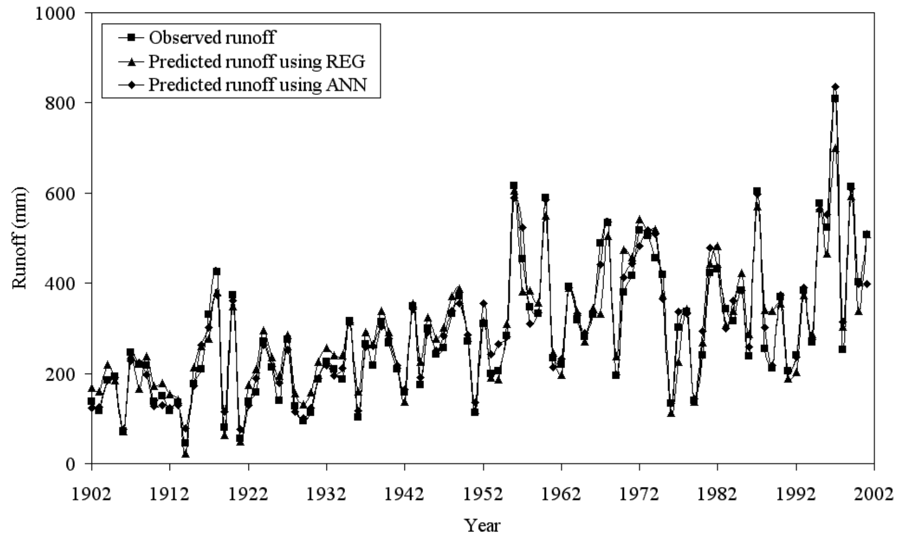

Fig. 4. Plot of observed and predicted runoff using ANN and REG approaches; Betwa

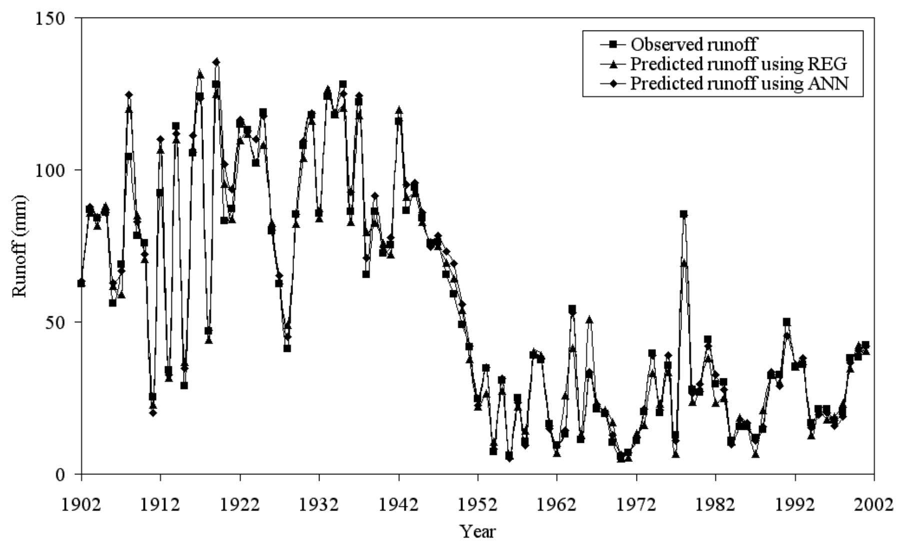

Fig. 5. Plot of observed and predicted runoff using ANN and REG approaches; Chambal

$$Q_{i+1}{}^{*} = 0.022R_i + 0.035R_{i-1} + 0.840Q_i - 20.405 \tag{10}$$

The equations were further used for prediction of runoff in one-year advance (Q_{i+1}) for both the regions. The performance of ANN and REG models were analyzed using performance indicators that are computed from Eqns. (4-7) for both the regions under study and are given in Tables 3 and 4 respectively.

3.3. *Discussions*

On the basis of performance indicators given in Table 3, it is noted that ANN model shows good performance on runoff prediction at cross-validation period for Betwa region while at testing period for Chambal. From Table 4, it is noted that the performance indicators on predicted runoff by REG at cross-validation period shows good results for both the regions under study. Also, from Tables 3 and 4, it can be noticed that

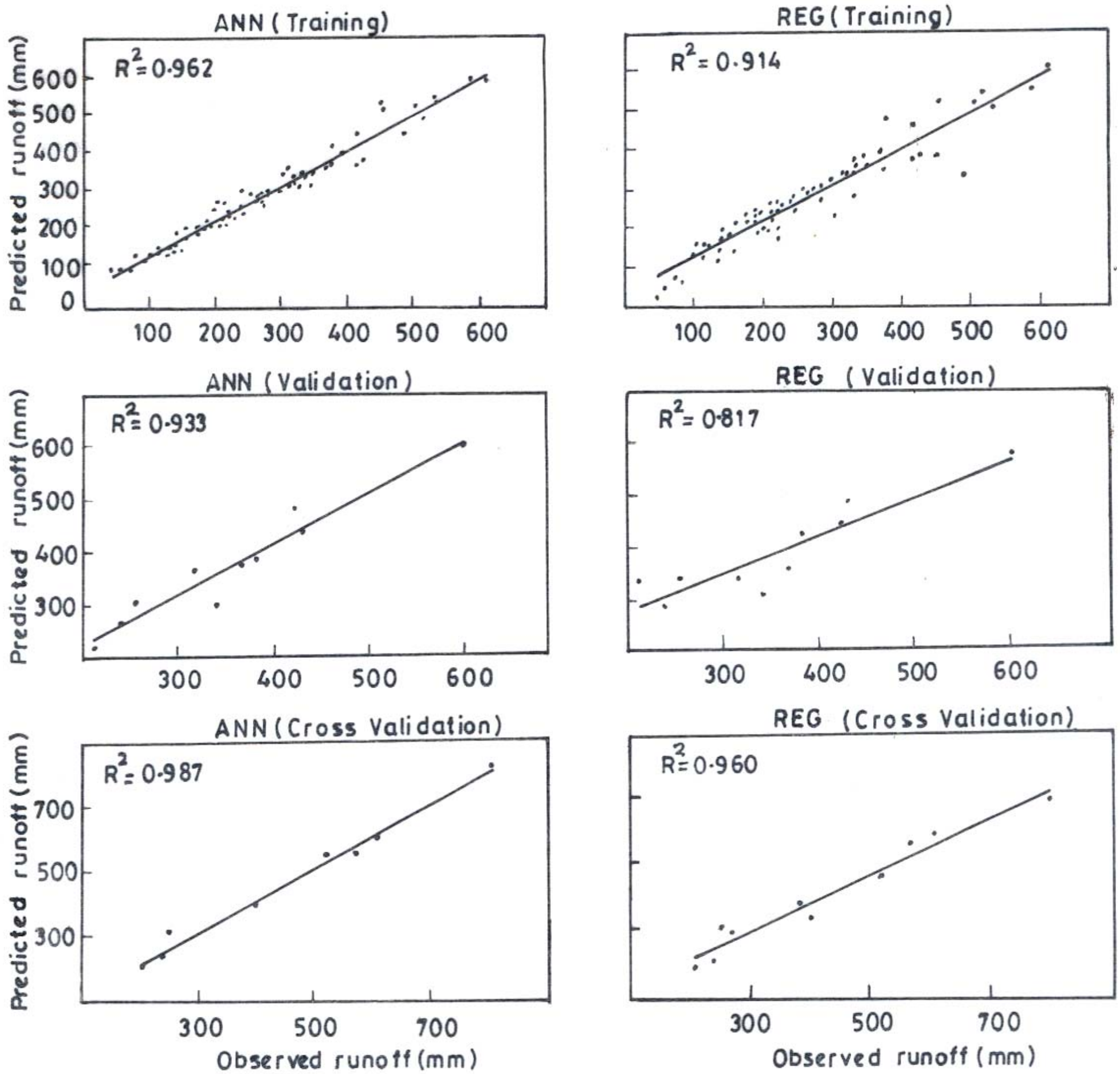

Fig. 6. Scatter plot of observed and predicted runoff by ANN and REG approaches for Betwa region

the predicted runoff using ANN is comparatively better than the values given by REG for both the regions at validation and cross-validation periods, which were supported by model performance indicators such as EFF, CC, RMSE and RMAE. Figs. 4 and 5 give the plot of observed and predicted runoff using ANN and REG approaches for Betwa and Chambal regions. The statistical parameters such as mean, standard deviation, skewness and kurtosis for the observed and predicted runoff using ANN and REG were computed and are given in Tables 5 and 6.

From Tables 5 and 6, it is noticed that the average predicted runoff by ANN with reference to average observed runoff varied from about 2% to 4% for Betwa and Chambal regions. Also, from Tables 5 and 6, it is

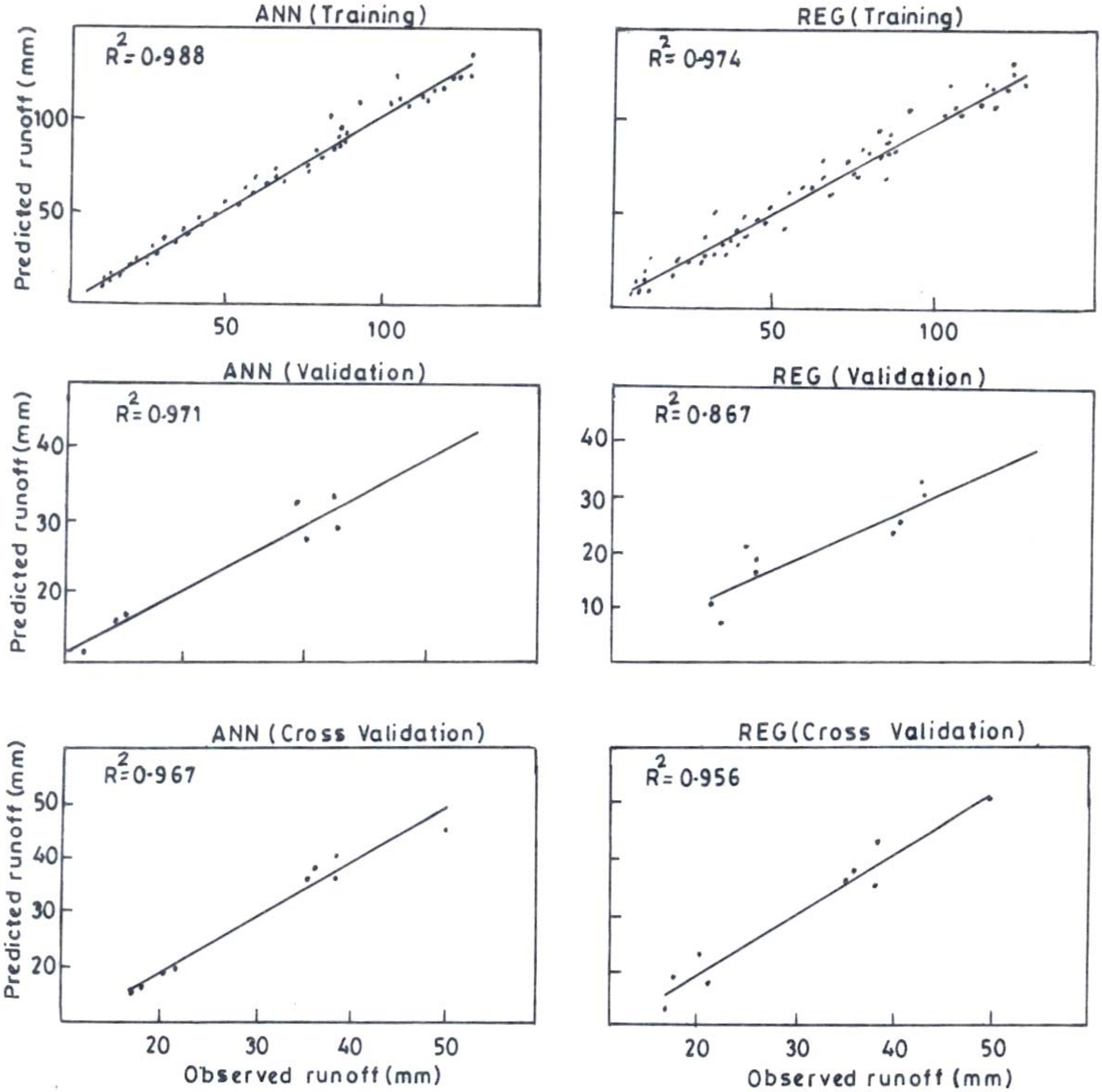

Fig. 7. Scatter plot of observed and predicted runoff by ANN and REG approaches for Chambal region

noticed that the average predicted runoff by REG with reference to observed runoff varied from about 5% to 9% for Betwa while 1% to 7% for Chambal. From these values, it can be argued that the percentage of uncertainty in runoff prediction using ANN and REG are within the acceptable tolerance limit of ±10% as given by USGS (2004). Figs. 6 and 7 give the scatter plot of observed and predicted runoff by ANN and REG approaches for Betwa and Chambal regions respectively. From Figs. 6 and 7, it can be seen that there is a good line of agreement between the observed and forecasted runoff using ANN during training, validation and cross-validation periods for both the regions. Similarly, from Figs. 6 and 7, it can be seen that there is some deviation in line of agreement between the observed and predicted runoff using REG at validation and cross validation periods though there is a good line of agreement between the observed and predicted values at training for the regions under study. From the scatter plots of observed and predicted runoff, it is noted that the coefficient of determination (R^2) given by ANN and REG approaches varied from 0.817 to 0.987 for Betwa while 0.867 to 0.988 for Chambal. These results showed that there is generally good correlation between the observed and predicted runoff by ANN and REG though two approaches are different. From the values of model performance indicators and statistical parameters, ANN is found to be suitable approach and suggested for prediction of runoff for both the regions under study.

4. Conclusions

The study estimates the model efficiency at cross-validation period using ANN and REG approaches for Betwa to be 98% and 93% respectively. The study also estimates the model efficiency given by ANN and REG for Chambal as 96% and 94% respectively. It is found from the study that the percentage of deviation on average predicted runoff by ANN and REG approaches with reference to average observed runoff varied from about 2% to 5% at training, 4% to 9% at validation and 3% to 6% at cross-validation for Betwa while 1% to 4% at training, 2% to 7% at validation and 1% to 4% at cross-validation for Chambal. These results indicate that the percentage of uncertainty in runoff prediction using ANN and REG approaches are within the acceptable tolerance limit of ±10%. The study compares superiority of ANN over REG approach for prediction of runoff in one-year advance through model performance indicators and statistical parameters. From the results of the data analysis, it is suggested that ANN could be used for prediction of runoff for both the regions considered in the study.

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Abbreviations

A and B	=	Regression coefficients
I_j	=	Input unit of j^{th} layer
M	=	Number of neurons (units) of hidden layer
Min (V_i)	=	Minimum value of the series of rainfall/ runoff for i^{th} year
Max(V_i)	=	Maximum value of the series of rainfall/ runoff for i^{th} year
N	=	Number of observations
$N(V_i)$	=	Normalized value of rainfall/ runoff for i^{th} year
O_j	=	Bias unit of j^{th} layer
Q_i	=	Observed runoff for i^{th} year
$\overline{Q}$	=	Mean of observed runoff
Q_i^*	=	Predicted runoff of i^{th} year
Q_{i+1}^*	=	Predicted runoff of $(i+1)^{th}$ year
$\overline{Q^*}$	=	Mean of predicted runoff
R^2	=	Coefficient of determination
R_i	=	Observed rainfall for i^{th} year
V_i	=	Observed value of rainfall/ runoff for i^{th} year
S_j	=	Characteristic function
W_{ij}	=	Synaptic weights between input and hidden layers
$\Delta W_{ij}(N)$	=	Weight increments between i^{th} and j^{th} units during N epoch
$\Delta W_{ij}(N-1)$	=	Weight increments between i^{th} and j^{th} units during N-1 epoch