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RADIAL BASIS FUNCTION ARTIFICIAL NEURAL NETWORK (RBFANN) MODEL FOR SIMULATING DAILY RUNOFF FROM THE HIMALAYAN WATERSHEDS

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ABSTRACT

In this paper, a Radial Basis Function Artificial Neural Network (RBFANN) model was developed based on k-means clustering algorithm to simulate the daily rainfall-runoff process in three Himalayan watersheds i.e., Naula, Chaukhutia, and Ramganga located in Uttarakhand State, India. Different network parameters such as learning rate in the function layer (ALR), learning rate in output layer (ALRG), and the number of iterations were optimized. The outcomes of the RBFANN model was evaluated by using statistical (i.e., root mean square error: RMSE, correlation coefficient: CC, and Nash-Sutcliffe efficiency: NSE) and hydrological (i.e., volumetric error: EV) indicators during calibration, cross-validation, and validation phases. The performance of the RBFANN model improved and stabilized within 500 iterations. The model was very sensitive to learning rate in the function layer (ALR), however, not in the output layer (ALRG). Overall results reveal a promising performance of the RBFANN model in simulating the daily runoff in the study catchments.

Keywords: *Artificial Neural Network (ANN), RBFANN, Himalayan watershed, Ramganga River*

INTRODUCTION

The long-term hydrologic simulation is useful in augmentation of hydrologic data, water resources planning, and watershed management (Mishra and Singh, 2003, 2004) Further, these models are often used as decision- making tools in describing the performance of a water resource system under climatic variations of rainfall and other aspects (Kottegoda et al., 2000). The rainfall–runoff models have been widely applied in hydrology and allied fields since they were first introduced in the late 1960s and early 1970s.

The existing model of rainfall-runoff can be broadly grouped into two main categories such as physically based models and data-driven models. The former attempts to represent the known physical process occurring in the rainfall-runoff transformation, however, the model calibration and implementation are complicated and time-consuming. For instance, the Sacramento Soil Moisture Accounting (SAC-SMA) model is defined by 22 parameters in addition to 12 parameters required by the potential evapotranspiration. The number of parameters required for water balance (Watbel) models can be much larger and can often exceed 50, or even 100, for larger basins with a large number of computational units (Markus and Baker 1994). The simplest conceptual rainfall-runoff model (SCRR) model has seven fitting coefficients and two storage elements (McCuen and Synder 1986). Despite their comprehensive structure, many of these models have not yet become standard tools in hydrological practice in developing countries of Asia as well as Africa. The reason is two-fold. First, most basins in these countries are un-gauged and there is little hydro-meteorological (generally rainfall and runoff) data available. Second, the major problem with the conceptual model is the lack of uniqueness in parameters obtained in calibration from the observed data (Spear. 1995, Wheater et al, 1993) which restricts their use in other catchments. The later, named as the black box type models, are developed to identify the connection between input and output, without considering the physical governing factors. The ANN based rainfall-runoff modeling is one of such black box approach that has been applied to several diverse hydrological problems and the results in each case have been very encouraging. ANNs have been applied in the hydrological study for rainfall-runoff modelling (French et al., 1992; Shamseldin, 1997; Anwala et al., 2000; Agarwal and Singh, 2004; Chiang et al., 2004; Lin and Chen, 2004; de Vos and Rientjes, 2005, Singh et al.; Malik et al., 2020); flood forecasting (Fernando and Jayawardena, 1998); groundwater modelling (Yang et al., 1997; Krishna et al., 2008); reservoir inflow forecasting (Coulibaly et al., 1998; Jain et al., 1999; Chaves and Kojiri, 2007), suspended sediment estimation (Agarwal et al., 2005; Raghuwanshi et al., 2006); evapotranspiration modelling (Kumar et al., 2002; Sudheer et al., 2003; Jain et al., 2008); and aquifer parameters determination (Rashid and Wong, 1992). Learning the relationship among input-output variables through nonlinear universal function approximation, robustness is some of the encouraging remarks of ANN models (ASCE, 2000a & b). Furthermore, the availability of hydro-climatic variables such as precipitation, air temperature, and streamflow data, and other data of sub-processes runoff generating mechanism might not be available everywhere in developing countries. In such situations, ANN models are the most efficient tool for runoff simulation and forecasting.

Mason et al. (1996) and, Fernando and Jayawardena (1998) found RBFANN to be more effective than the conventional BackPropagation ANN (BPANN) due to less time consuming and faster convergence. Lin and Chen (2004) simulated the rainfall-runoff process in the Fei-Tsui reservoir watershed in northern Taiwan using RBFANN

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with supervised learning and hybrid-learning, for setting up the number of hidden layer neurons. The fully supervised learning algorithm provided better training and accuracy than the network trained using the hybrid-learning algorithm. Comparatively, the RBFANN network required more hidden neurons but trained faster than the BPANN network. Kumar et al. (2005) fixed the structure of RBFANN networks using an appropriate training algorithm while simulating the rainfall-generated runoff, whereas BPANN networks required a long trial-and-error procedure to fix the optimal number of hidden nodes

Keeping in view of the capability of the ANN to mimic the complex non-linear processes from wide areas, an attempt has been made to develop an RBFANN model using a k-means clustering algorithm to simulate the rainfall-runoff process of three watersheds of the Ramganga river catchment located in the Himalayan region of Uttarakhand State of India. The computer program code was written in the FORTRAN environment with the objective that a user can alter the program for different conditions for testing various network behavior.

STUDY AREA

Three watersheds namely Naula, Chaukhutia, and Ramganga were used to develop an ANN-based rainfall-runoff model. Naula and Chaukhutia are sub-watershed of the Ramganga River catchment (Fig 1).

(a) Ramganga Watershed

The Ramganga river is a major tributary of Ganga and drains a catchment area of 3,134 km^2 (Fig. 1). Its catchment lies in the Sivalik ranges of the Himalaya and the valley is known as Patlei Dun. It emerges out of the hills at Kalagarh (District Almora of Uttarakhand) where a major multipurpose 127.5 m height earth and rock-fill type Dam is situated on Ramganga River. Its catchment lies between elevation 338 m and 3088 m above mean sea level, and it is considerably below the perpetual snow line of the Himalaya. The river traverses approximately 158 km before it meets the reservoir and then continues its journey in the downstream plains for 370 km before joining River Ganga at Farrukhabad. During its travel up to Ramganga dam, the river is joined by main tributaries: Gagas, Bino, Khatraun, Nair, Badangad, Mandal, Helgad, and Sona Nadi. About 50% of the drainage basin is covered with forest, 30% is under cultivation on terraced fields, and the remaining 20% is under settlements & others land use.

(b) Naula Watershed

Naula watershed comprises an upper hilly portion of the Ramganga catchment (Fig. 1), and hence it is a major sediment contributor in the reservoir. Naula watershed is geographically located between 29°44' N and 30°6'20" N latitudes and 79°6'15" E and 79°31'15" E longitudes in the Ranikhet Forest Sub-Division of Ramganga River catchment and having a drainage area of 1084 sq. km. The topography of the watershed is undulating and irregular with slopes varying from moderate to steep. The minimum and maximum elevations of the watershed are 790 m and 3088 m, respectively, above the mean sea level.

(c) Chaukhutia Watershed

This watershed has a drainage area of 572 sq. km is the most upstream sub-watershed of Ramganga reservoir catchment as well as the Nalua watershed (Fig. 1). Geographically, the entire boundary of the Chaukhutia

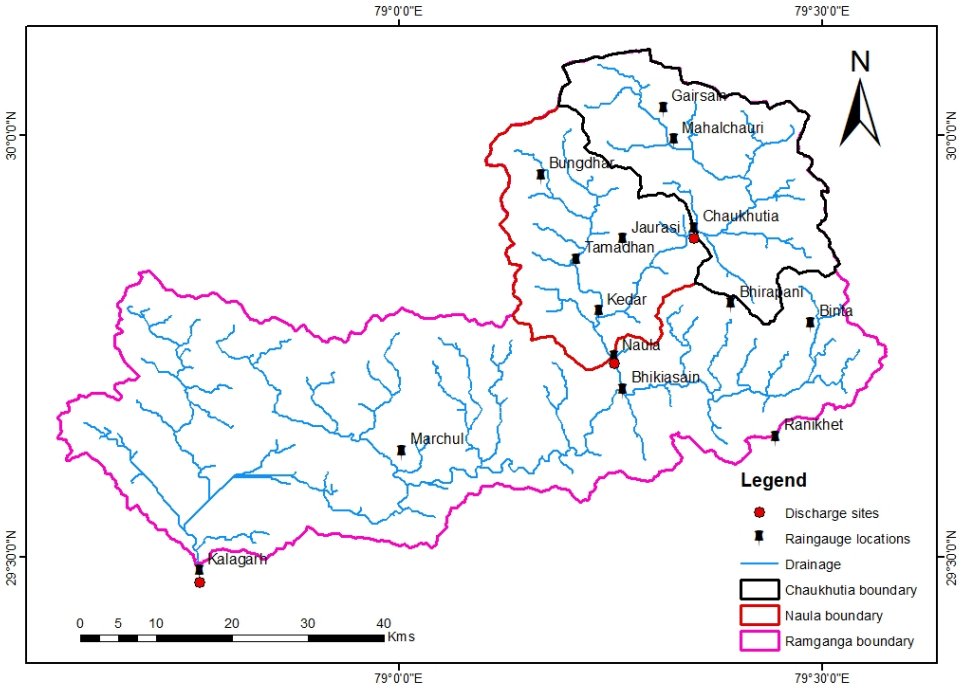


Fig. 1: Location map of study watersheds

Input layer (j) **Function layer (i)** **Output layer (k)**

watershed is situated between latitudes of 29^{0}46'35" and 30^{0}06'11" North and longitudes of 79^{0}11'23" and 79^{0}31'21" East. The maximum and minimum elevations within this watershed are 3088 m and 939 m above mean sea level, respectively. This watershed consists mostly of rolling and undulating topography having very steep irregular slopes.

DATA AVAILABILITY

The hydro-meteorological data of Naula and Chaukhutia watersheds were collected from the Divisional Forest Office (Soil Conservation) Ranikhet, Government of Uttarakhand, whereas, the Ramganga watershed data was collected from the Ramganga dam authority at Kalagarh. The rainfall is measured in the units of mm/day, and runoff is recorded in the unit of hectare-meter (ha-m). However, runoff data is converted into m^3/s and used for the development of ANN based rainfall-runoff model.

Fourteen years daily rainfall-runoff data for the monsoon season (June-September) from 1974 to 1987, 1974 to 1988 (data for the year 1984 was not available), and 1979 to 1992 were collected for Chaukhutia, Naula, and Ramganga watershed, respectively. Weighted rainfall for the study area was estimated using Thiessen polygons. Six raingauge stations located at Gairsen, Mehalchauri, Bungidhar, Chaukhutia, Bhirapani, and Binta installed in/outside of Chaukhutia watershed were used to calculate the weighted rainfall of the Chaukhutia watershed. For the Naula watershed, ten station data (Naula, Kedar, Tamadhanu, Jourasi, and six stations of Chaukhutia watershed) were used for the estimation of weighted rainfall. However, in addition to Naula watershed raingauge stations, data from four more stations installed at Ranikhet, Bhikiasen, Marchulla, and Kalagrah was used for estimation of weighted rainfall of Ramganaga watershed. Average weighted annual rainfall for Naula, Chaukhutia and Ramganga watershed was found to be 955 mm, 1076 mm and 1057 mm, respectively. With the help of weighted annual rainfall and runoff, runoff coefficients were calculated for each year of the monsoon. Average runoff coefficient for Naula, Chaukhutia and Ramganga watershed was found to be 0.61, 0.64 and 0.31, respectively. It indicates that Naula and Chaukhutia are the high runoff producing watersheds whereas the entire Ramganga is low runoff producing watershed.

METHODOLOGY

The RBFANN model has gained popularity and momentum in hydrological science in recent years (Fernando and Jayawardena, 1998; Dawson et al., 2002; Moradkhani et al., 2004). This model was introduced into the ANN literature by Broomhead and Lowe (1988). Since then, several studies indicate the superiority of RBFANN over the BPANN and it is well outlined in the review of the literature. Following are the steps involved in the development of the RBFANN model.

Network Topology

An RBFANN having input, function, and output layers of nodes with j, i, and k are shown in Fig. 2. The structure of RBFANN shows jj-dimensional input pattern (x) being mapped to kk-dimensional output (O). The values j and k are problem-dependent, the value i is to be determined by the network designer. In RBFANN operation, the input of nth pattern with each pattern made up of jj variables represents a point in the jj -dimensional input space. It enters the network at the input layer such that one variable is fed into one node. The input layer does not transform the pattern, but it transfers a copy of variables to each node in the function layer. The nodes in each function layer are specified by a transfer function f(d), which radically transforms the incoming information. For n input patterns x having jj dimensionality (x^n_{jj}), the response of O_i of function layer, through radial transformation, can be expressed in mathematical terms as:

$$Q_i = f(d) \quad (1)$$

where Q_i is the output of the function layer and f(d) is a nonlinear function. In the present study, the RBFANN model was optimized with Gaussian activation function, unsupervised learning (k-means clustering algorithm) in the function layer, and supervised learning (backpropagation) in the output layer to fine-tune the weights of the network as an optional strategy. The algorithm k-means (MacQueen, 1967) is one of the simplest unsupervised learning algorithms that solve the well-known clustering problem.

Concept of Model Development

For a discrete lumped hydrological system, the rainfall-runoff relationship can be generally expressed as (Hsu et al., 1995).

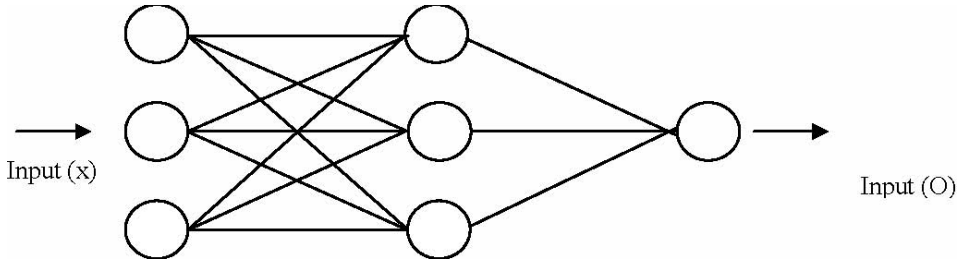


Fig. 2: Structure of RBFANN

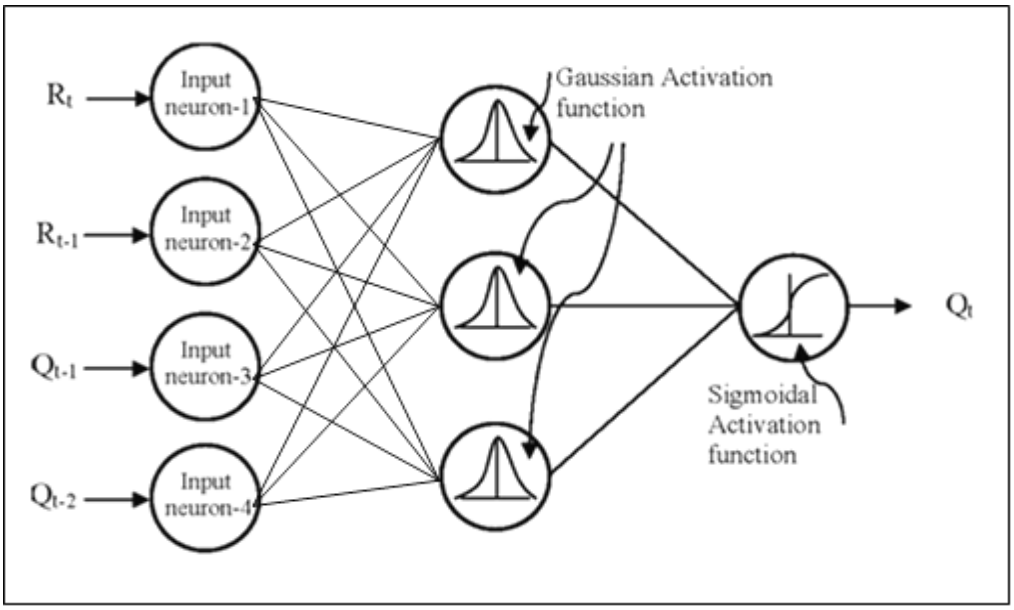


Fig. 3: Configuration of an RBFANN with model input.

$$Q_t = f\left[R(t), R(t-\Delta t)\ldots\ldots\ldots\ldots R(t-n_x\Delta t), Q(t-\Delta t)\ldots\ldots\ldots\ldots Q(t-n_y\Delta t)\right] \quad (2)$$

where R represents rainfall, Q represents runoff at the outlet of the watershed, f is any kind of model structure (linear or nonlinear), Δt is the data sampling interval, n_x and n_y are positive integer numbers reflecting the memory length of the watershed. RBFANN architecture clearly shows the network topology with the input determination and the activation function used (Fig. 3).

Outline of Algorithm (Dynamic Model)

The algorithm of dynamic model can be outlined as follows:

1. Initialize the weights to small random values and take the average of weights for the calculation of center.
2. Select an input pattern (x) from the training set and feed it to the network.
3. Calculate the spread value based on the input, weight vector, and cluster center.
4. Find the best matching or "winning" node whose weight vector w_{ij} is closest to the current input vector x using the vector distance (i.e. euclidean distance).
5. Find the network response for the winning node by Gaussian activation function.
6. Update the weight values using Mexican hat function.
7. Repeat steps 1-6 with a number increase in iterations until weights are stabilized.

Normalization of Input Data

Data were normalized (between 0-1) before the start of model training using the following equation:

$$x_n = \frac{x_0}{x_{max}} \quad (3)$$

where x_n and x_o represent the normalized and original data, respectively; and x_{max} is the maximum value of the selected variable. After training the network, the de-normalization is performed at the output nodes.

MODEL EVALUATION

The output from the model was evaluated statistically as well as hydrologically, as follows:

Statistical Evaluation Criteria

The network was trained on the training dataset and its performance was evaluated both in validation and in cross-validation periods following the different standard statistical error criteria. The statistical performance evaluation criteria include root mean square error (RMSE), correlation coefficient (CC), Nash-Sutcliffe efficiency (NSE) were used.

i) Root Mean Square Error (RMSE): It is described as:

$$RMSE = \left[\frac{\sum_{t=1}^{N}\{Q_{oi} - Q_{pi}\}^2}{N}\right]^{0.5} \quad (4)$$

where Q_{oi} and Q_{pi} are the observed and model predicted runoff, respectively in m^3/s for the ith observation and N is the total number of samples.

ii) Correlation Coefficient (CC)

$$r = \frac{n\sum Q_{oi}Q_{pi} - \sum Q_{oi}\sum Q_{pi}}{\sqrt{\left\{n\sum Q_{pi}^{2} - \left(\sum Q_{pi}\right)^{2}\right\}\left\{n\sum Q_{oi}^{2} - \left(\sum Q_{oi}\right)^{2}\right\}}}$$

(iii) Nash-Sutcliffe Efficiency (NSE): It was given by Nash and Sutcliffe (1970) and is given as:

$$\text{NSE } (\%) = 1 - \left[\sum_{i=1}^{N}(Q_{oi} - Q_{pi})^2 \Big/ \sum_{i=1}^{N}(Q_{oi} - Q_{av})^2\right] X\,100 \quad (5)$$

where Q_{av} is the mean runoff in m^3/s for the observed runoff data.

Hydrological Evaluation Criteria

(i) Volumetric error (EV)

This is also called an absolute prediction error (Kachroo and Natale, 1992) and is estimated as:

$$EV = \left\{\frac{\sum(Q_{pi} - Q_{oi})}{\sum Q_{oi}}\right\} x100 \quad (6)$$

This is mainly used to represent the error in peak observation, error in low observation, and error in time to peak.

RESULTS AND DISCUSSION

The proposed model was applied to the data of three watersheds of the Ramganga River basin. The fourteen years daily rainfall-runoff data of the monsoon period (June to September) for the years 1974-1988 (except 1984), 1974-1987, and 1979-1992 were used for rainfall-runoff modelling of Naula, Chaukhutia, and Ramganga, watersheds, respectively. The data from 1974 to 1979 were used for calibration whereas the data from 1980 to 1983, and 1985 to 1988 were used for cross-validation and verification, respectively, for Naula watershed. However, the data from 1974 to 1979 for calibration and the data from 1980 to 1983, and 1984 to 1987 were used for the cross-validation and verification, respectively, for Chaukhutia watershed. In case of Ramganga watershed, data from 1979 to 1984 were used for model calibration whereas the data from 1985 to 1988, and 1989 to 1992 were used for cross-validation and verification, respectively.

Proposed Model

The RBFANN model was trained by both the k-means clustering algorithm and gradient descent algorithm employing the best-trained input to the network which consists of daily rainfall and discharge values. Considering different inputs, the following model was finalized using the correlation matrix method, maintaining the parsimony of the model for all three study watersheds:

$$Q_t = f\left[R_t, R_{t-1}, Q_{t-1}, Q_{t-2}\right] \quad (15)$$

where Q_t represents the runoff at time (t) and R_t represents rainfall at time (t). In this study, the dynamic RBFANN model was developed based on the criteria to estimate spread. The spread value is described as the average distance between the cluster center and training instances (number of input variables) in that cluster.

The learning rate for models was selected in such a way that it should increase the convergence ability of the network. The learning rate cannot be negative because this would cause the change of weight vector to move away from the ideal weight vector position. If the learning rate is zero, no learning takes place and hence the learning must be positive. In this study, the learning rate in the function layer (ALR) and learning rate in the output layer (ALRG) has been selected according to network behavior. The program code was developed in the FORTRAN environment for the dynamic RBFANN model. The program code was developed with the objective that a user can alter the program for different conditions and can see the network behavior. This is the major advantage of this model.

Application

In the proposed dynamic RBFANN model, the spread value changes in successive iteration, and therefore, not required to be fixed; and two different values of learning rate have been used as ALR in unsupervised part and ALRG in supervised part. To optimize the learning rate and the number of iterations, the first ALRG and number of iterations were kept fixed and varied the ALR value. Based on experience and from literature, initially, the value of ALRG and number of iterations were taken as 0.5 and 1000, respectively (Agarwal, 2002). After getting the best ALR value, ALRG was optimized for fixed ALR and the number of iterations. After optimizing the ALR and ALRG, the number of iterations was evaluated to get the best performance of the model. To ensure the proper selection of ALR, ALRG, and the number of iterations from lower network to higher network, based on literature three network structures (4-4-1, 4-16-1, and 4-32-1) were selected. In this study, particular values of ALR, ALRG, and the number of iterations have been optimized through the network behavior for three selected study watersheds.

(a) Naula watershed

The model performance for different ALR values and three different networks for fixed ALRG (= 0.5) and iterations (= 1000) was evaluated. The results are presented in Table 1. The model performance improves rapidly when ALR increases from 0.5 to 20 in calibration, cross-validation, and verification for the network (4-4-1). The volumetric error increases as ALR deviates from 20 on either the higher side or lower side. Thus, ALR = 20 is suitable for the network (4-4-1). From Table 1, it can be seen that the values of CC and NSE decrease and RMSE increases as ALR increases beyond 20 in calibration and cross-validation for the network (4-16-1). The volumetric errors are quite low when ALR = 20. For network (4-32-1), NSE tends to decrease as ALR other than 20 in calibration, cross-validation, and verification. A low value of volumetric error in calibration and cross-validation suggests that the most suitable value of ALR was 20.

Table 1: Performance of (4-4-1), (4-16-1), and (4-32-1) dynamic RBFANN models. ALRG = 0.5, number of iterations = 1000, ALR = 0.5 to 25 for Naula watershed.

Period	RMSE			CC			NSE			EV		
	4-4-1	4-16-1	4-32-1	4-4-1	4-16-1	4-32-1	4-4-1	4-16-1	4-32-1	4-4-1	4-16-1	4-32-1
						ALR = 0.5						
Calibration	156.57	154.12	153.06	56.27	57.08	57.44	-558.8	-538.4	-529.6	182.3	175.4	172.7
Cross-validation	162.57	159.88	158.82	61.08	61.97	62.28	-1168	-1126.3	-1110.1	236.7	227.8	224.1
Verification	154.18	151.46	150.37	56.21	56.95	57.21	-793.6	-762.3	-750	215.4	206.5	202.7
						ALR = 5						
Calibration	51.28	50.87	50.95	78.56	78.55	78.73	29.32	30.44	30.22	-8.52	-10.85	-10.27
Cross-validation	44.86	44.45	44.58	79.83	79.57	79.78	3.44	5.23	4.66	-13.19	-15.76	-15.31
Verification	44.06	43.89	43.87	81.3	81.17	81.42	27.04	27.58	27.65	-20.7	-22.79	-22.43
						ALR = 10						
Calibration	38.39	30.86	27.29	83.36	86.35	89.07	60.39	74.4	79.24	-1.23	3.92	2.81
Cross-validation	31.08	21.18	20.25	85.19	89.67	90.62	53.66	78.47	80.34	-1.65	8.76	7.47
Verification	31.96	22.34	21.08	86.21	90.38	91.39	61.61	81.24	83.29	-6.74	5.66	4.09
						ALR = 15						
Calibration	30.99	27.74	23.61	87.24	89.11	92.25	74.19	79.31	85.02	-0.94	2.95	2.47
Cross-validation	23.52	19.96	18.58	89.04	90.91	91.99	73.47	80.89	83.44	0.08	7.02	6.27
Verification	24.44	20.95	19.76	90.13	91.6	92.76	77.55	83.49	85.32	-3.43	4.18	5.97
						ALR = 20						
Calibration	29.5	25.77	22.59	87.99	90.77	92.92	76.61	82.16	86.28	-0.31	-0.68	1.61
Cross-validation	21.83	19.37	17.74	89.52	91.79	92.44	77.14	81.99	84.91	1.33	2.61	5.18
Verification	22.92	20.92	18.73	90.67	91.82	93.5	80.25	83.55	86.81	-1.06	-1.29	6.35
						ALR = 25						
Calibration	29.07	26.29	23.01	88.03	90.35	92.66	77.29	81.43	85.77	3.83	3.98	2.52
Cross-validation	20.92	20.05	18.92	89.98	91.3	91.94	78.99	80.72	82.83	7.83	8.11	5.54
Verification	21.83	19.89	19.29	91.04	93.03	93.63	82.09	85.2	86.08	5.65	5.3	5.31

After fixing ALR at 20, the learning rate in the output layer (ALRG) was assigned. To this end, different values of ALRG varying from 0.5 to 10 were tried and the results are given in Table 2 for all three networks. As seen from the table, the model performance does not improve significantly when ALRG ranges from 0.5 to 10. The error in volume however slightly fluctuates with ALRG. A lower value of ALRG may be selected (i.e. 0.5) for lower network (i.e. 4-4-1). The selection of a higher value does not justify if similar model performance can be achieved using a lower value. Therefore, ALRG = 0.5 is suitable for network 4-4-1. Similarly, RMSE, CC, and NSE do not change significantly with ALRG varying from 0.5 to 10 for the network (4-16-1) (Table 2). The resulting EV, however, fluctuates with ALRG variation and it considerably increases especially in cross-validation when ALRG is varied from 2 to 10. Therefore, ALRG should lie in the range of 0.5 to 2. It is seen from Table 2 that RMSE, CC, and NSE values are almost the same for different ALRG values ranging from 0.5 to 10 for network 4-32-1. But at the same time, error in volume gradually increases with an increase in ALRG from 0.5 to 10. It follows that ALRG equal to 0.5 is most suitable for network 4-32-1. The value of ALRG = 0.5 is also supported by the literature (Agarwal, 2002) to run the model in the range of all networks selected for the study.

Table 2: Performance of (4-4-1), (4-16-1), and (4-32-1) dynamic RBFANN models. ALR = 20, number of iterations = 1000, and ALRG = 0.5 to 10 for Naula watershed.

Period	RMSE			CC			NSE			EV		
	4-4-1	4-16-1	4-32-1	4-4-1	4-16-1	4-32-1	4-4-1	4-16-1	4-32-1	4-4-1	4-16-1	4-32-1
ALRG = 0.5												
Calibration	29.5	25.77	22.59	87.99	90.77	92.93	76.61	82.16	86.28	-0.31	-0.68	1.61
Cross-validation	21.83	19.37	17.74	89.52	91.79	92.44	77.14	81.99	84.91	1.33	2.61	5.18
Validation	22.92	20.92	18.73	90.67	91.82	93.5	80.25	83.55	86.81	-1.06	-1.29	6.35
ALRG = 1												
Calibration	29.21	25.37	22.51	88.22	91.11	92.98	77.06	82.69	86.38	-0.56	-1.04	2.02
Cross-validation	21.59	19.35	17.73	89.71	91.95	92.51	77.65	82.04	84.92	0.83	2.11	5.61
Validation	22.52	20.67	18.72	90.47	92.15	93.54	80.94	83.94	86.83	-1.44	-1.63	6.65
ALRG = 2												
Calibration	29.16	25.17	22.37	88.31	91.3	93.08	77.24	82.97	86.55	-0.63	-1.01	2.4
Cross-validation	21.5	19.48	17.68	89.78	91.95	92.63	77.82	81.79	85	0.68	2.04	6.09
Validation	22.34	20.62	18.65	91.11	92.29	93.63	81.24	84.01	86.93	-1.54	-1.53	6.9
ALRG = 5												
Calibration	28.95	24.82	22.15	88.43	91.56	93.25	77.47	83.44	86.81	-0.16	0.25	2.72
Cross-validation	21.38	19.58	17.17	89.91	91.95	92.91	78.07	81.6	85.86	1.32	3.27	6.82
Validation	22.16	20.62	18.04	91.24	92.36	93.88	81.54	84.02	87.77	-0.92	0	6.2
ALRG = 10												
Calibration	28.86	24.25	22.51	88.52	91.98	93.26	77.61	84.19	86.38	0.6	2.2	-1.95
Cross-validation	21.33	19.63	16.62	90.04	91.97	93.2	78.17	81.52	86.74	2.27	5.29	6.89
Validation	22.04	20.61	17.33	91.34	92.4	94.23	81.74	84.03	88.71	0	2.46	6

Fixing ALR = 20 and ALRG = 0.5, the initial selection of the number of iterations is rechecked. To fix the optimum value, the number of iterations in different runs for three networks (4-4-1, 4-16-1, and 4-32-1) were varied from minimum (100) to maximum (10000), and the results are given in Table 3. It is evident from Table 3 that CC and NSE values are considerably increases while RMSE decreases up to 1000 iterations for the network (4-4-1) during calibration, cross-validation, and verification. However, the results are inconclusive as EV fluctuates with the increase in number of iterations beyond 500. Therefore, RMSE, CC, and NSE suggest 1000 iterations to be suitable for the network (4-4-1). However, EV slightly increases in calibration and validation, and decreases in cross-validation after 500 iterations. The model efficiency due to network (4-16-1) significantly increases up to the first 500 iterations, gradually increases up to 1000 iterations, and finally becomes almost stable after 1000 iterations (Table 3). The minimum volumetric error occurred around 500 iterations in calibration and cross-validation. In other words, the model performed best around 500 iterations. Furthermore, the performance of the network (4-32-1) improves up to 500 iterations, and no further improvement was seen with increasing iterations. EV reduces up to 500 iterations and thereafter it slightly vibrates.

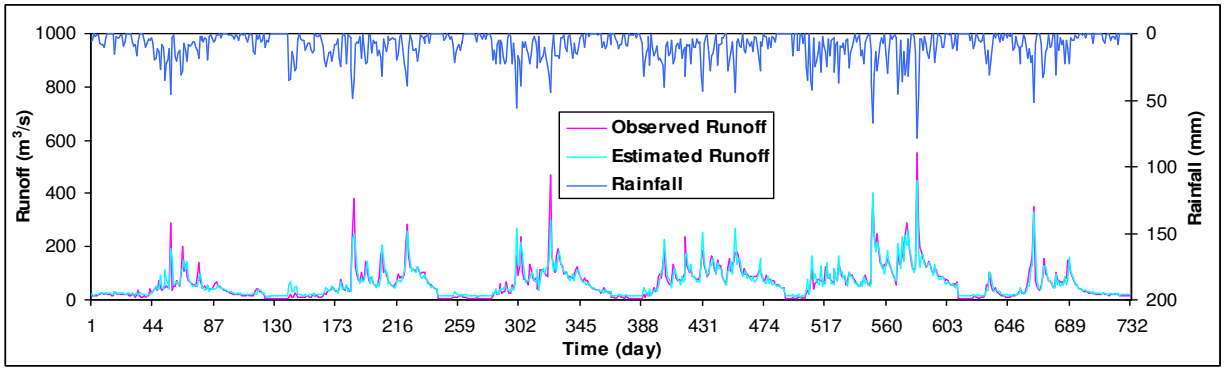
Thus, the number of iterations required for optimal results for network 4-4-1 is about 1000, and the number for networks 4-16-1 and 4-32-1 is about 500. It can be inferred that, in general, the number of iterations decreases as the network changes to 4-16-1 or 4-32-1 from 4-4-1. Moreover, there is no need to go beyond 1000 iteration for all networks.

Overall, ALR = 20 was found suitable for all RBFANN structures. The lower network structure is independent of the ALRG variation from 0.5 to 10. Notably, the higher values of ALRG with a higher network resulted in the higher volumetric error, and therefore, not suitable for good results. Thus, the value of ALRG is fixed to 0.5 to suit all network structures. The maximum number of iterations required for lower networks (4-4-1) is 1000, and it reduces to 500 with an increase in network structure. Moreover, the efficiency of the RBFANN model was around 85% in the prediction of daily 14 years' monsoon runoff patterns of the Naula watershed. The observed and estimated values of runoff in calibration, cross-validation, and verification for best model i.e. networks (4-32-1) with ALR

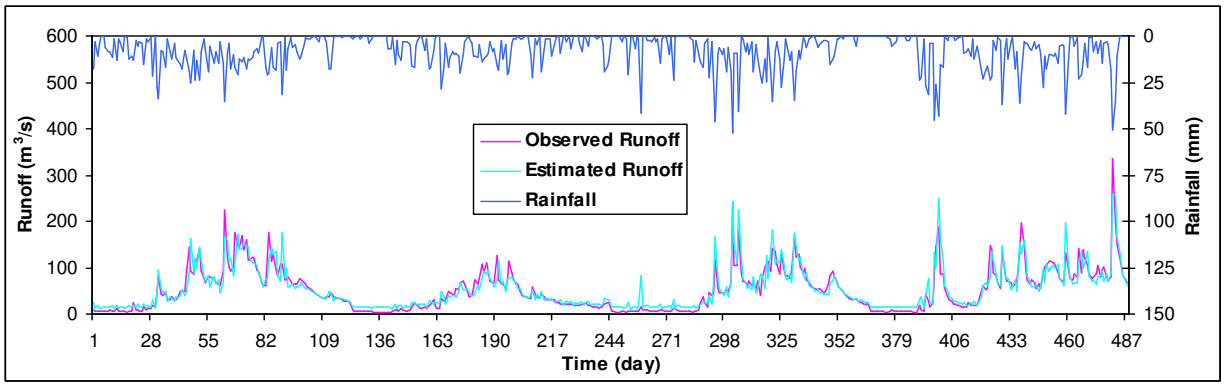
= 20 and ALRG = 0.5 are shown in Fig. 4(a-c). It is evident from Fig. 4(a-c) that the daily runoff pattern predicted by the proposed RBFANNs model is well-matched with observed in calibration, cross-validation, and verification with high values of NSE i.e. 79.1%, 82.24%, and 86.62%, respectively.

Table 3: Performance of (4-4-1), (4-16-1), and (4-32-1) dynamic RBFANN models. ALR = 20, ALRG = 0.5, and number of iterations = 100 to 10000 for Naula watershed.

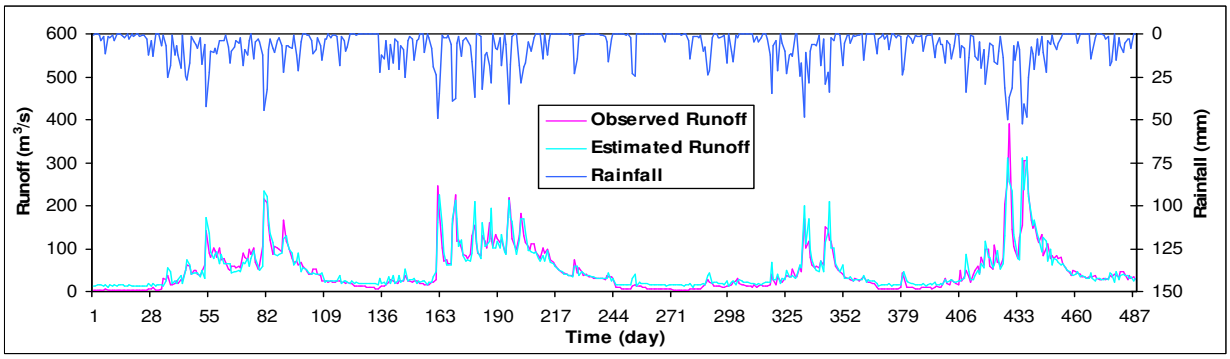
Period	RMSE			CC			NSE			EV		
	4-4-1	4-16-1	4-32-1	4-4-1	4-16-1	4-32-1	4-4-1	4-16-1	4-32-1	4-4-1	4-16-1	4-32-1
ITERATION = 100												
Calibration	31.83	29.06	23.89	85.79	88.11	92.14	72.77	77.3	84.66	5.06	1.49	3.38
Cross-validation	23.65	20.97	18.43	88.18	90.14	91.98	73.17	78.91	83.7	9.86	5.06	7.75
Validation	24.64	22.62	19.67	88.99	90.31	92.81	77.19	80.76	85.45	6.36	1.42	8.07
ITERATION = 500												
Calibration	30.03	26.44	22.7	87.6	90.24	92.87	75.77	81.21	86.15	-0.21	0.08	1.8
Cross-validation	22.32	19.67	17.85	89.12	91.44	92.34	76.09	81.43	84.72	1.63	3.48	5.41
Validation	23.58	21.37	18.86	90.19	91.38	93.4	79.1	82.84	86.62	-0.87	-0.44	6.62
ITERATION = 1000												
Calibration	29.5	25.77	22.59	87.99	90.77	92.93	76.61	82.16	86.28	-0.31	-0.68	1.61
Cross-validation	21.83	19.37	17.74	89.52	91.79	92.44	77.14	81.99	84.91	1.33	2.61	5.18
Validation	22.92	20.92	18.73	90.67	91.82	93.5	80.25	83.55	86.81	-1.06	-1.29	6.35
ITERATION = 2000												
Calibration	29.22	25.38	22.48	88.2	91.1	93	77.05	82.68	86.42	-0.65	-1.2	1.55
Cross-validation	21.57	19.34	17.64	89.71	91.94	92.53	77.67	82.06	85.07	0.75	1.94	5.1
Validation	22.51	20.68	18.65	90.97	92.13	93.53	80.96	83.92	86.92	-1.53	-1.82	6.15
ITERATION = 5000												
Calibration	29.07	25.13	22.26	88.31	91.32	93.14	77.29	83.03	86.68	-0.88	-1.41	1.49
Cross-validation	21.45	19.47	17.49	89.79	91.91	92.67	77.93	81.81	85.32	0.46	1.58	5.01
Validation	22.28	20.64	18.55.	91.12	92.26	93.59	81.34	83.98	87.07	-1.78	-1.97	5.81
ITERATION = 7500												
Calibration	29	24.98	22.14	88.35	91.42	93.22	77.39	83.23	86.83	-0.87	-1.25	1.44
Cross-validation	21.38	19.46	17.42	89.83	91.9	92.74	78.06	81.83	85.45	0.54	1.7	4.96
Validation	22.2	20.63	18.48	91.17	92.26	93.63	81.48	84	87.17	-1.71	-1.73	5.63
ITERATION = 10000												
Calibration	28.95	24.82	22.04	88.39	91.52	93.28	77.47	83.44	86.95	-0.85	-1.04	1.41
Cross-validation	21.33	19.43	17.36	89.87	91.89	92.79	78.17	81.89	85.54	0.62	1.89	4.91
Validation	28.45	20.61	18.41	88.39	92.26	93.67	77.47	84	87.25	-0.85	-1.44	5.5



(a) Calibration



(b) Cross-validation



(c) Verification

Fig. 4a-c: Observed and estimated runoff by dynamic RBFANN model having (4-32-1) network with ALR as 20 and ALRG as 0.5 for Naula watershed in (a) Calibration; (b) Cross-validation; and (c) Verification period.

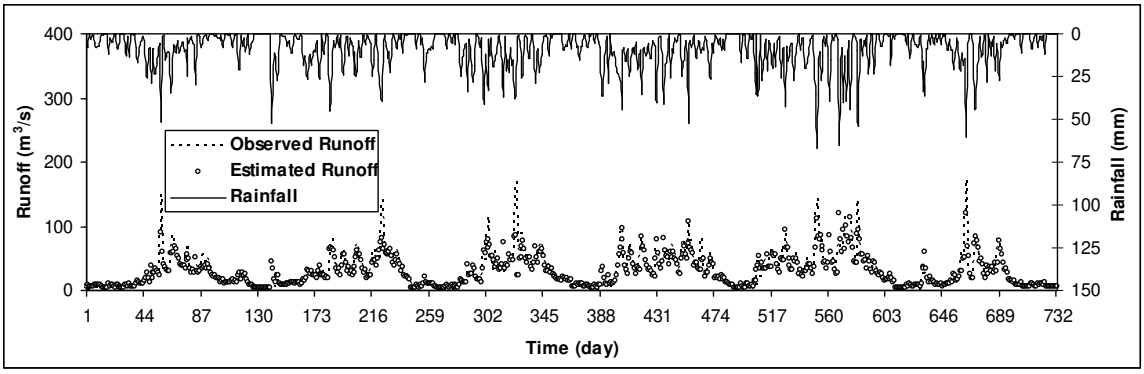
(b) Chaukhutia watershed

Following the similar procedure adopted for the Naula watershed, different parameters of RBFANNs networks such as ALR, ALRG, and the number of iterations were optimized for Chaukhutia watershed. Taking initial values of ALRG as 0.5 and the number of iterations as 1000, the model was run for different values of ALR and based on the statistical criteria, the most suitable value of ALR was found to be 15. After fixing ALR, the model was performed for the different values of ALRG ranging from 0.5 to 10, and it was observed that the lower network structure (4-4-1) is independent of ALRG values ranging from 0.5 to 10. However, with an increase in network (4-16-1 or 4-32-1) structure, ALRG sticks to 0.5 or a maximum of 1.0. Notably, the higher values of ALRG in a higher network resulted in higher volumetric error. Overall, the value of ALRG as 0.5 suited for all networks and durations. Consequently, taking ALR = 15 and ALRG = 0.5, the model was performed for all three networks (4-4-1, 4-16-1, and 4-32-1) for iterations ranging from 100 to 10000. Based on the statistical error used in the study, the model gives the best results around 5000 iterations for the network (4-4-1), around 1000 iterations for (4-16-1), and around 500 iterations for the network (4-32-1). This indicated that the lower network required a higher number of iterations, while the higher network required less iteration for the best

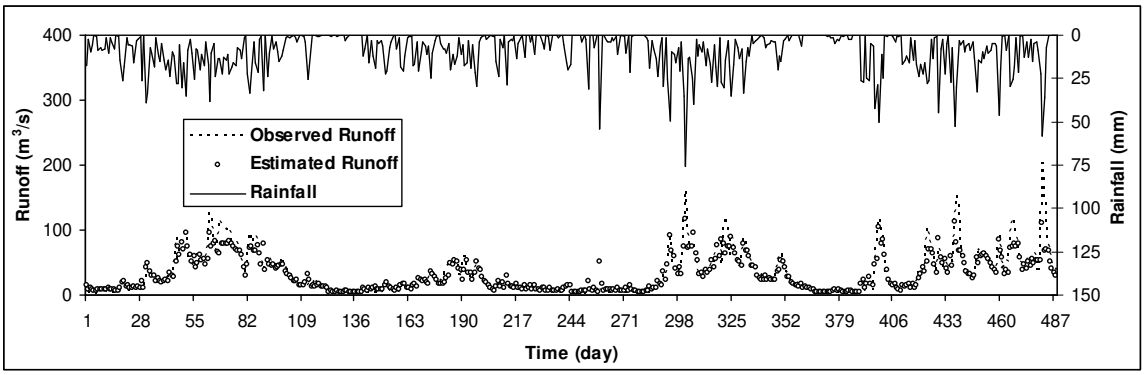
performance of the model. The observed and estimated daily values of runoff for the calibration, cross-validation, and verification of best model networks i.e. 4-32-1 with ALR = 15 and ALRG = 0.5 and 500 iterations are plotted in Fig. 5(a-c). Moreover, the coefficients of efficiencies of the best RBFANNs model were found to be 77.48%, 84.76%, and 84.59% during calibration, cross-validation, and verification, respectively, for the Chaukhutia watershed.

(c) *Ramganga watershed*

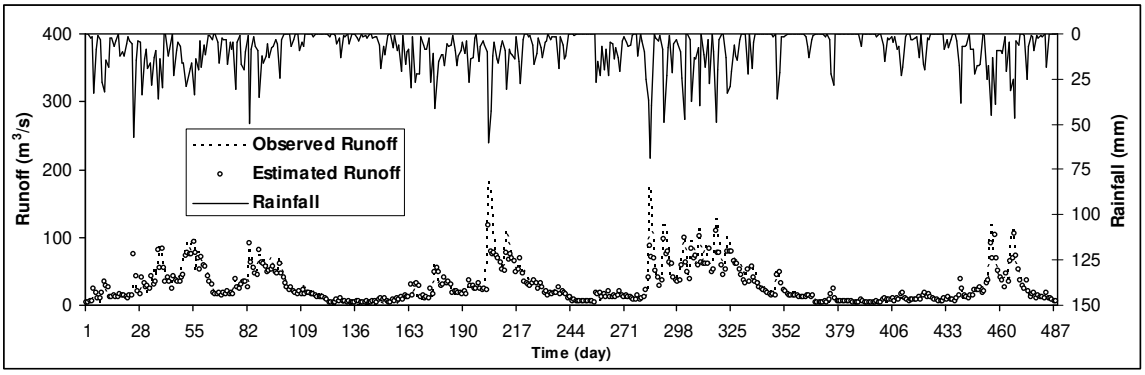
Similar to the Naula watershed, the suitable ALR and ALRG values for Ramganga watershed were found to be 20 and 0.5, respectively for all periods and networks by following the statistical criteria as above. However, the model performed best around 1000 iterations for the 4-4-1 network and around 500 iterations for networks (4-16-1) and (4-32-1). The observed and estimated daily values of runoff for the calibration, cross-validation, and validation of network 4-32-1 with ALR = 15 and ALRG = 0.5 are plotted in Fig. 6(a-c). It is evident from Fig. 6(a-c) that simulated runoff values are to be in good agreement with daily observed runoff values. The maximum coefficient of efficiency (NSE) was obtained as 76%, 77.68%, and 68.25% in calibration, cross-validation, and verification, respectively, for the network 4-32-1.



(a) Calibration

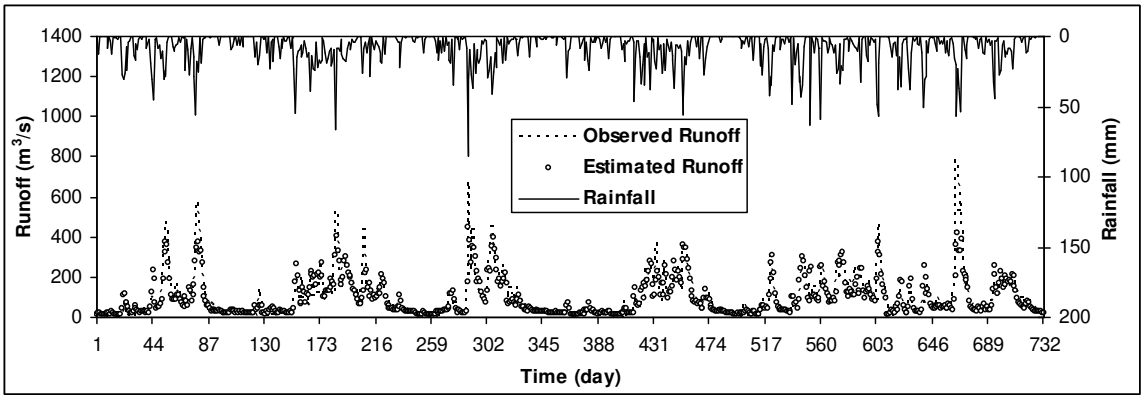


(b) Cross-validation

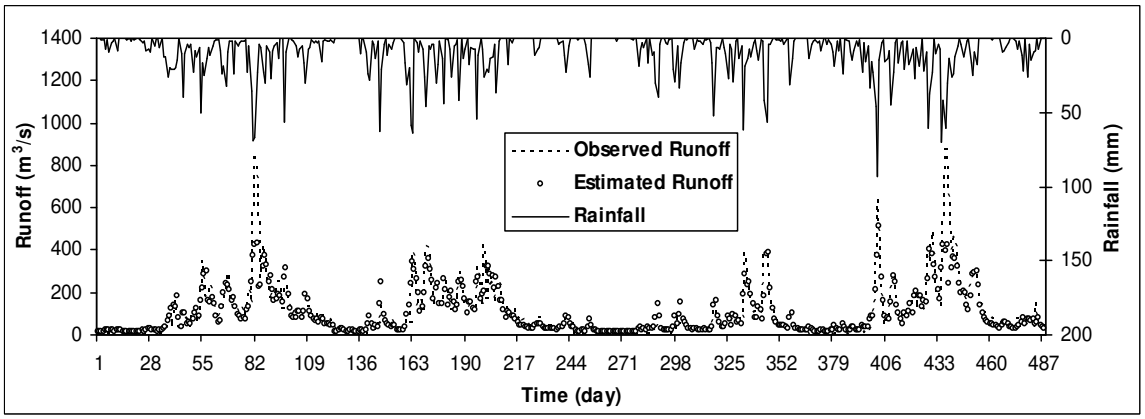


(c) Verification

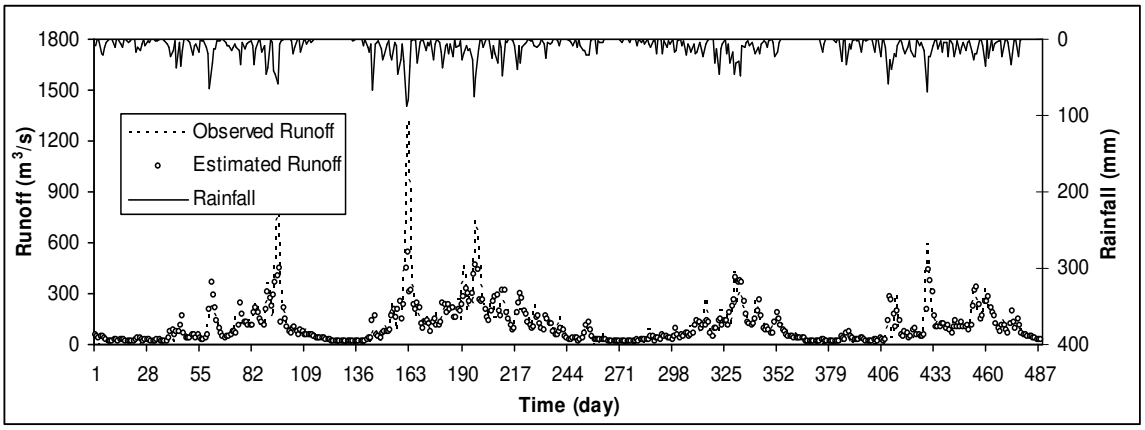
Fig. 5a-c: Observed and estimated runoff by dynamic RBFANN model having (4-32-1) network with ALR as 20 and ALRG as 0.5 for Chaukhutia watershed during (a) Calibration; (b) Cross-validation; and (c) Verification periods.



(a) Calibration



(b) Cross-validation



(c) Verification

Fig 6a-c: Observed and estimated runoff by dynamic RBFANN model having (4-32-1) network with ALR as 20 and ALRG as 0.5 for Ramganga watershed during (a) Calibration; (b) Cross-validation; and (c) Verification periods.

CONCLUSIONS

A Radial Basis Function Artificial Neural Network (RBFANN) model was proposed based on a k-means clustering algorithm to model the daily rainfall-runoff process for three Himalayan watersheds of India. For improved model performance, different parameters of the model like learning rate in function layer (ALR), learning rate in the output layer (ALRG), and the number of iterations were optimized for three different network structures. The available fourteen years rainfall-runoff dataset of three watersheds was divided into three periods, calibration, cross-validation, and verification. Following the standard statistical criteria such as Root Mean Square Error (RMSE), Correlation Coefficient (CC), Nash-Sutcliffe Efficiency (NSE), and Volumetric Error (EV) were used to evaluate the model performance. The performance of RBFANNs was excellent and consistent in all three periods

in case of Naula watershed and it was 86.28%, 84.91%, and 86.81%, in calibration, cross-validation, and verification, respectively. However, the efficiency of the model was found excellent and consistent in cross-validation and verification (84.76% and 84.59%) and good in calibration (77.48%) for the Chaukhutia watershed. In case of Ramganga watershed, the model performed well in both calibration and cross-validation (76% and 77.68%) and reasonable (68.25%) in verification. Furthermore, the efficiency of the RBFANN model to converge the error was excellent with 1000 iterations. However, the higher networks (4-32-1) mostly achieved their best performance within 500 iterations. The RBFANN model was very sensitive to the learning rate in the function layer (ALR). However, there is no significant difference seen with variation in learning rate in the output layer (ALRG). Overall, Radial Basis Function can be a better solution for rainfall-runoff modelling as physically-based models with partial differential equations of mass and energy are difficult to employ due to lack of data in mountainous areas. The selection of learning rate, especially in the function layer (ALR) as well as the number of iterations required is very important in optimization. The proposed program has the flexibility to change the input and output variables and fix the radial basis nodes.

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