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Rainfall-Runoff Prediction based on Artificial Neural Network: A Case Study Priyadarshini Watershed

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A B S T R A C T

Hydrological modelling is a powerful technique of hydrologic system investigation for both the research hydrologists and the practicing water resources engineers involved in the planning and development of integrated approach for management of water resources. In present study, the observed rainfall and runoff data of 2010, 2011, 2013 and 2014years were used as input data. In ANN, input data was divided in 70 per cent, 15 per cent and 15 per cent for training, testing and validation purpose, respectively. Rainfall-runoff models play an important role in water resource management planning and therefore, 70 numbers of different types of models with various degrees of complexity have been developed for this purpose. The output from ANN was tested with statistical parameters, viz. root mean square error (RMSE), mean absolute error (MAE), coefficient of determination (R^2) and correlation coefficient (r). The rainfall-runoff relationship is one of the most complex hydrologic phenomena and it is based on tremendous spatial and temporal variability of watershed characteristics, precipitation patterns, etc. Therefore other models were not performing well. The ANN model 1-48-1 architecture was selected as the best. The comparisons between the measured and predicted values of runoff showed that the ANN model could be successfully applied and provide high accuracy and reliability for estimation of runoff from un-gauged watershed with rainfall as input parameter.

Introduction

It is likely that most watersheds or basins of the world are ungauged or poorly gauged. There is a whole spectrum of cases which can be collectively embraced under the term “ungauged basins”. Some basins are genuinely ungauged, whereas others are poorly gauged or were previously gauged, where measurements discontinued due to instrument failure and/or termination of a measurement programme. Also, the term “ungauged basin” refers to a basin where meteorological data or river flow, or both, are not measured. In ungauged watersheds, where there are no data, the hydrologist has to develop and use models and techniques which do not require the availability of long time series of meteorological and hydrological measurements. One option is to develop models for gauged watersheds and link the model parameters to physiographic characteristics and apply them to ungauged watersheds, whose physiographic characteristics can be determined. Another option is to establish regionally valid relationships in hydrologically similar gauged watersheds and apply them to ungauged watersheds in the region. The stream flow of a watershed is often measured for a limited period and these stream flow data are inefficient for hydrological model calibration and statistical analysis. In this paper, a technique that couples a hydrological model with artificial neural networks (ANNs) is proposed to improve the stream flow simulation and estimation of peak flows for watersheds with limited stream flow data. In recent years, ANNs have become extremely popular for prediction and forecasting of climatic, hydrologic, and water resource variables (Govindaraju and Rao, 2000; Abrahart *et al.*, 2004). Artificial Neural Networks (ANNs) have been used for modelling complex hydrological process, such as rainfall-runoff and have been shown to be one of the most promising tools in Hydrology (Arslancheleng, 2011). Combination of computational efficiency measures and ability of input parameters which describe the physical behavior of hydro-climatologic variables, improvement of the model predictability is possible in artificial neural network environment (Arslancheleng, 2011). Artificial Neural Network (ANN) models have been used successfully to model complex non-linear input-output relationships in an extremely inter disciplinary field. The natural behaviour of hydrological processes is appropriate for the application of ANN method. In recent years, ANNs have been used intensively for prediction and forecasting in a number of water-related areas, including water resource study (El-Shafie *et al.*, 2007), prediction of evaporation (Sudheer *et al.*, 2002), hydrograph simulator, rainfall forecasting. Rainfall runoff relationship is an essential component in the process of water resources evaluation. The relationship of rainfall-runoff is known to be highly nonlinear and complex. Controlling the runoff would require a complete assessment of soil erosion and associated non-point source pollution impacts in the watershed from a long-term perspective. Hence it is needed to study the ANN structure to simulate runoff from rainfall data for particular soil conservation measure and different cropping pattern in un-gauged watershed. Keeping this in view study was carried out with the objective that to develop of Rainfall- Runoff model using Artificial Neural Network.

Materials and Methods

Artificial neural network (ANN) model

Artificial neural network (ANN) is a massively parallel distributed information processing system that has certain performance characteristics resembling biological neural network of the human brain. An ANN normally consists of three layers, an input layer, a hidden layer and an output layer. Input layer usually receives the input signal values. Neurons in output layer produce the output signal. ANN is essentially useful for modeling and prediction of uncertain and complex phenomena. A neural network can be trained from the previous data to forecast future events, without accurately understanding the physical parameters which influences the presents and future events.

Activation function

The activation function of a neuron in a neural network is only processing function. It is utilized for the limiting the amplitude of the output of a neuron. Also known as transfer function is referred to as squashing function as quashes (limits) the permissible amplitude range to some finite value. It gives output in a range of 0 to 1.

The mathematical expression of the logistic function is given by

$$f(n) = \frac{1}{1 + e^{-n}}$$

An attempt to improve the accuracy is to use data on discharge excess and sum of rainfall during the last 24 hours from the prediction time is additional input to the network model.

The back propagation algorithm

The back propagation algorithm uses supervised learning, which means that provide the algorithm with examples of the inputs and outputs we want the network to compute, and then the error (difference between actual and expected results) was calculated. The idea of the back propagation algorithm was to reduce this error, until the ANN learns the training data.

The expression can be written in the mathematical form as follows:

$Q(t) = f(SR, DQ, R(t_1\text{-}3), R(t_1\text{-}2), R(t_1\text{-}2), R(t\text{-}3ts), Q(t\text{-}ts), Dq)$

Where,
T = time of prediction, h; t_1 = time period, (3hrs)
t_1 = time to incorporate rainfall (in this case, t_1=t-4)
R = rainfall intensity, (mh^1); Q = discharge, (cumec)
SR = summation of rainfall value from t-8t to t-3ts, (mm/hr)
DQ = discharge excess between Q (t-8ts) and Q (t-3ts), (cumec).
Dq = discharge excess between Q (t-3ts) and Q (t-ts), (cumec).

Procedure for ANN model simulation

In the ANN model epochs were set up to 1000 iterations. Model training was carried out by using Levenberge-Marquadt algorithm and performance was checked by using mean square error (MSE). Data was divided on random basis. When input as rainfall was given and output as observed runoff in neural network toolbox in MATLAB 7.9 training of the network automatically stops whenever recommended output reached with least errors. After the training of ANN, it gives output in the form of performance plot, training state plot, fit plot and regression plot. The output from ANN was statically tested with the observed runoff by using various statistical parameters viz. RMSE, MARE, coefficient of determination (R^2) and correlation (r). By comparing these statistical parameters best ANN architecture was selected.

Rainfall-Runoff simulation

Priyadarshini watershed of CAET was used for development of ANN model for rainfall-runoff. Daily rainfall data of 2010, 2011, 2013 and 2014 year and corresponding runoff data were used for this study.

Results and Discussion

Runoff estimation by using ANN model

In the present study, artificial neural network was tested by using logistic sigmoid function and trained with a Levenberg-Marquardt back-propagation algorithm to estimate runoff by artificial neural network. For this purpose the neural network toolbox in MATLAB 7.9 was used. Four years i.e. 2010, 2011, 2013 and 2014 observed rainfall data and observed runoff data sets were used as input data for operation and it consist of total 198 events (Fig. 1).

Table.1 The Statistical performance of various ANN architectures

Sr. No.	ANN architecture	RMSE	MAE	R^2	r	Sr. No.	ANN architecture	RMSE	MAE	R^2	r	Sr. No.	ANN architecture	RMSE	MAE	R^2	r
1.	1-1-1	26.94	1604.74	0.3495	0.6926	26.	1-26-1	17.91	999.97	0.7124	0.8448	51.	1-51-1	17.60	948.78	0.7224	0.8565
2.	1-2-1	16.54	923.17	0.7546	0.8693	27.	1-27-1	15.19	455.49	0.7930	0.8973	52.	1-52-1	37.90	313.87	0.2873	0.6387
3.	1-3-1	18.67	529.79	0.7071	0.8440	28.	1-28-1	53.85	3224.27	-1.5989	0.4937	53.	1-53-1	20.57	1096.96	0.6205	0.8401
4.	1-4-1	16.47	919.44	0.7567	0.8700	29.	1-29-1	29.33	1148.58	0.2290	0.7657	54.	1-54-1	23.40	1116.13	0.5091	0.7285
5.	1-5-1	46.87	2567.35	-0.9089	0.7038	30.	1-30-1	22.59	718.50	0.5424	0.8369	55.	1-55-1	26.73	778.92	0.3597	0.7874
6.	1-6-1	17.37	1052.46	0.7295	0.8552	31.	1-31-1	17.99	1032.16	0.7099	0.8545	56.	1-56-1	16.16	786.27	0.7658	0.8767
7.	1-7-1	16.52	993.512	0.7554	0.8692	32.	1-32-1	14.55	1026.65	0.8100	0.9002	57.	1-57-1	19.83	708.07	0.6474	0.8277
8.	1-8-1	20.00	812.24	0.6415	0.8146	33.	1-33-1	23.87	1182.66	0.4892	0.7442	58.	1-58-1	20.28	543.23	0.6314	0.8060
9.	1-9-1	34.28	833.16	-0.053	0.6424	34.	1-34-1	14.13	862.28	0.8209	0.9066	59.	1-59-1	21.57	736.40	0.5829	0.7733
10.	1-10-1	34.84	904.57	-0.0876	0.6307	35.	1-35-1	13.61	1032.70	0.8338	0.9136	60.	1-60-1	16.93	931.16	0.7428	0.8623
11.	1-11-1	16.75	842.25	0.7484	0.8654	36.	1-36-1	29.96	1095.43	0.1952	0.7453	61.	1-61-1	31.03	1059.23	0.1370	0.6994
12.	1-12-1	62.23	6762.68	-2.4707	0.7985	37.	1-37-1	43.88	771.81	0.7256	0.5625	62.	1-62-1	28.99	854.96	0.2468	0.7308
13.	1-13-1	29.83	743.80	0.2025	0.7576	38.	1-38-1	17.94	1358.47	0.7115	0.8637	63.	1-63-1	72.24	836.94	-3.6763	0.3991
14.	1-14-1	17.76	810.76	0.7173	0.8523	39.	1-39-1	17.55	1193.56	0.7239	0.8631	64.	1-64-1	25.51	498.95	0.4168	0.7364
15.	1-15-1	49.47	100.75	-1.1927	0.5740	40.	1-40-1	14.03	590.22	0.8236	0.9078	65.	1-65-1	14.28	1103.38	0.8172	0.9057
16	1-16-1	15.55	863.65	0.7832	0.8864	41.	1-41-1	14.65	799.40	0.8076	0.9002	66.	1-66-1	19.55	839.17	0.6572	0.8253
17.	1-17-1	15.96	794.54	0.7717	0.8806	42.	1-42-1	20.02	624.04	0.6408	0.8169	67.	1-67-1	19.34	892.22	0.6645	0.8491
18.	1-18-1	14.08	967.39	0.8223	0.9074	43.	1-43-1	20.12	1007.51	0.6338	0.7978	68.	1-68-1	21.24	868.55	0.5954	0.8158
19.	1-19-1	302.5	963.35	-81.014	0.2704	44.	1-44-1	16.40	903.66	0.7590	0.8729	69.	1-69-1	36.04	1025.63	0.1638	0.6425
20.	1-20-1	16.16	931.97	0.7659	0.8763	45.	1-45-1	14.41	761.47	0.8138	0.9021	70.	1-70-1	31.80	1025.33	0.093	0.6870
21.	1-21-1	18.25	946.21	0.7015	0.8528	46.	1-46-1	117.1	700.30	-11.300	0.3124						
22.	1-22-1	14.48	924.73	0.8120	0.9023	47.	1-47-1	91.81	998.66	-6.6533	-0.0865						
23.	1-23-1	15.60	1033.53	0.7818	0.8843	**48.**	**1-48-1**	**13.45**	**472.06**	**0.8376**	**0.9188**						
24.	1-24-1	27.72	1039.06	0.3111	0.7348	49.	1-49-1	18.60	883.96	0.6898	0.8481						
25.	1-25-1	16.30	1048.31	0.7617	0.8732	50.	1-50-1	34.08	530.92	-0.0406	0.6960						

Fig.1 Comparison of predicted and observed runoff for ANN model 1-48-1

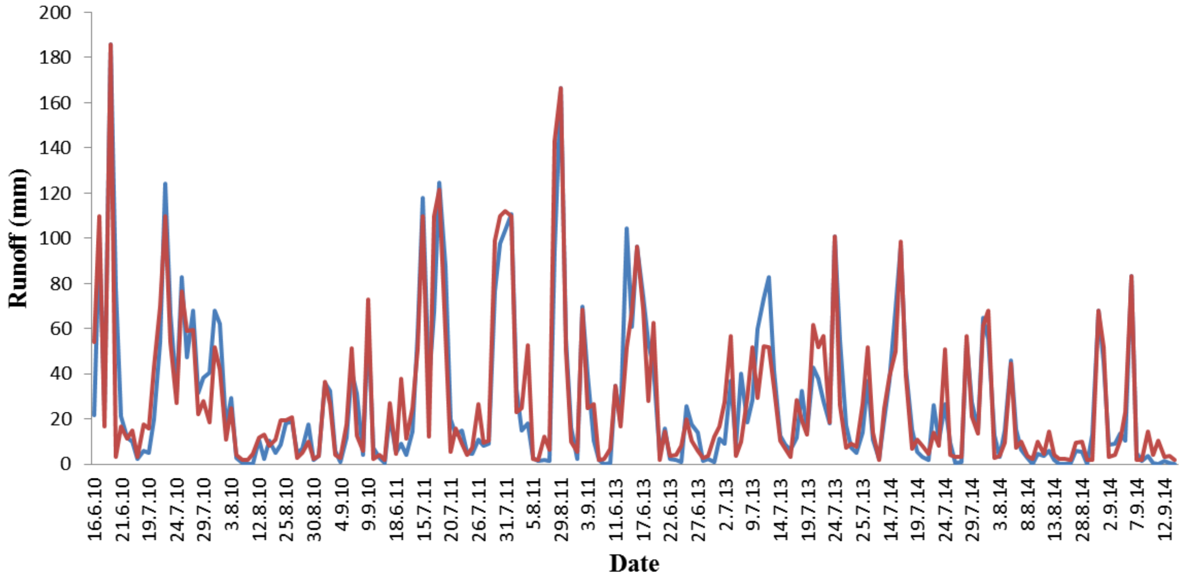
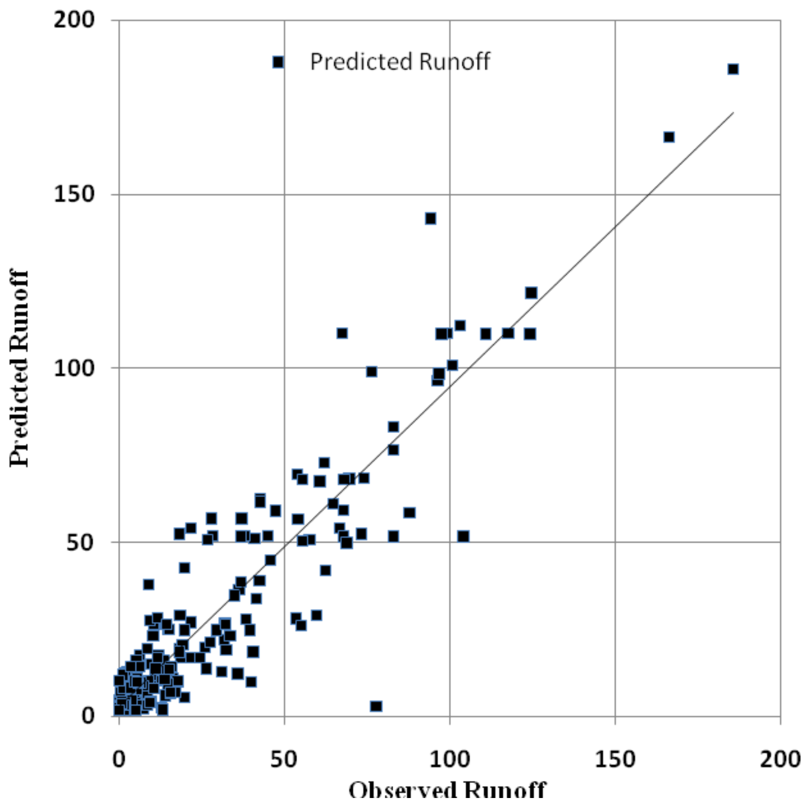


Fig.2 Scatter plot of predicted Vs observed runoff for ANN model 1-48-1



These 198 samples were distributed as 138 samples (70%) for training, 30 samples (15%) for validation and 30 samples (15%) for testing purpose in ANN model.

Statistical analysis by ANN method

In this case neural network up to 70 hidden neurons in hidden layer were studied, as after 70 hidden neurons it gives very high mean square error. This resulted 1-48-1 as best model configuration and indicated that 1 neuron in hidden layer fitted best on test data and shows a high degree of accuracy with training data set. ANN with above configuration was trained several iterations and best result were obtained with 13 iterations on the basis of minimum percent mean square error (PMSE) (Fig. 2).

ANN with one input

Initially neural network was trained by using single input (rainfall) and single output (runoff) and data was divided into 70 percent for training, 15 per cent for validation and 15 percent for testing respectively. From the table 1 the 1-48-1 ANN architecture gives 13.4597, 472.06, 0.8376 and 0.9188 values for RMSE, MAE, Coefficient of Determination (R^2) and Correlation (r), respectively. The results obtained from Table 1 and ANN of architecture 1-48-1 found suitable for estimation of runoff. As shown in graph the number of scatter points above the average line were more in number hence the result shows that runoff has been slightly over estimated.

In conclusion, the artificial neural network ANN models shows an appropriate capability to model hydrological process. It was useful and powerful tools to handle complex problems compared with other traditional models. In this study, the influences of back propagation efficiencies and enabling of input dimensions on rainfall–runoff modelling capability of the artificial neural network was applied by trying different input dimension. The 1-48-1 ANN architecture gave 13.4597, 472.06, 0.8376 and 0.9188 values for RMSE, MAE and Coefficient of Determination (R^2) and Correlation (r), respectively. The performance of ANN 1-48-1 architecture in estimation of runoff from rainfall data was checked statistically. Hence, this ANN 1-48-1 architectures can be adopted to estimate runoff from ungauged watershed with rainfall as input. The comparisons between the measured and predicted values showed that the ANN model could be successfully applied and provide high accuracy and reliability for estimation of runoff from un-gauged watershed with rainfall as input parameter.

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