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Performance of ANN for rainfall-runoff prediction

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■ **ABSTRACT :** The use of artificial neural network is becoming increasingly common in the analysis of hydrology and water resource problems. In present study, the observed rainfall and runoff data of four years (2010, 2011, 2013 and 2014) were used as input data. In ANN, input data was divided in three segment 70 per cent, 15 per cent and 15 per cent for training, validation and testing purpose, respectively. Rainfall-runoff relationship is an important component in water resource evaluation and therefore, the predicted runoff of 70 numbers of different types of model was tested statistically with observed runoff using statistical parameter, *i.e.* root mean square error (RMSE), mean absolute error (MAE), co-efficient of determination (R^2) and correlation (r). This study showed that out of 70 ANN architectures, ANN architectures 1-48-1 could be adopted to estimate runoff from ungauged watershed with rainfall as input.

■ **KEY WORDS :** ANN, Rainfall-runoff modeling, Co-efficient of determination, Correlation

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Determining the relationship between rainfall and runoff for a watershed is one of the most important problems faced by hydrologists and engineers. Information about rainfall and runoff is needed for hydrologic engineering design and management purpose. This relationship is known to be highly non-linear and complex. In addition to rainfall, runoff is dependent on numerous factors such as initial soil moisture, infiltration, distribution, duration of rainfall and so on. ANN mimic the functioning of a brain by acquiring knowledge through a learning process that involves finding an optimal set of weights for the connections and threshold values for the nodes. Mathematically, an ANN may be treated as universal approximator. The ability to learn and generalize knowledge from sufficient data pairs makes it possible for ANNs to solve large-scale complex problem such as pattern recognition, non-linear modelling, classification, association, control and other all of which find application in hydrology today. ANN able to provide a mapping from one multivariate space to another, given set of data representing that mapping. Even if the data is noisy and contaminated with errors, ANNs have been known to identify the underlying rule. These properties suggest that ANNs may be well-suited to the problems of estimation and prediction in hydrology (Anonymous, 2000).

METHODOLOGY

Artificial neural network (ANN) model:

Artificial neuralnetwork (ANN) is a massively parallel distributed information processing system that has certain performance characteristics resembling biological neural network of the human brain (Junsawang *et al.*, 2005). 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 rangeto some finite value.

The mathematical expression of the logistic function is given by $f(n)=\frac{1}{1+e^{-n}}$

The output from sigmoid function is always bounded between 0 to 1 and input to the function can vary between - ∞ to +∞. 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 to compute and then the error (difference between actual and expected results) was calculated. The idea of the back propagation algorithm was to reduce the error, until ANN learns the training data.

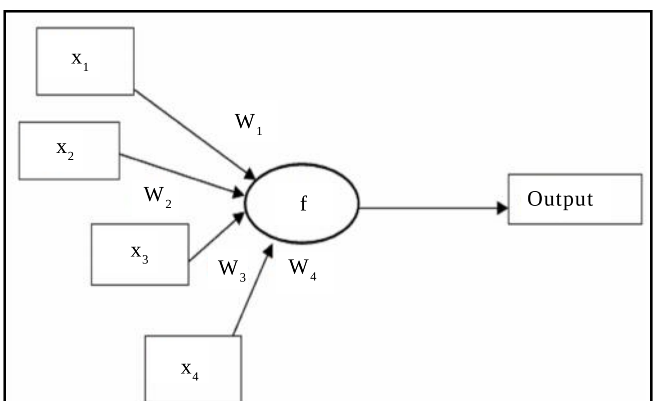

Fig. A : Architecture of an artificial neuron

where,

X_1, X_2, X_3, X_4 = Rainfall inputs to ANN,

W_1, W_2, W_3, W_4 = Weights to the rainfall.

O = Output of ANN, f = Logistic sigmoidal function

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

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

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).

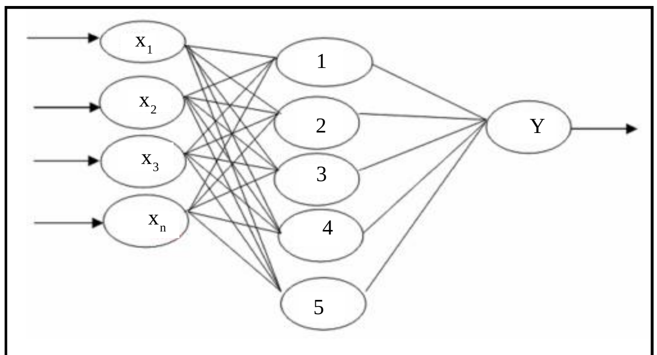

Fig. B : Architecture of feed forward multilayer perception (MLP)

where,

X_1, X_2, X_3, X_4.......X_n = Rainfall inputs to ANN in input layer.

1, 2, 3, 4, 5 = Number of neurons in hidden layers.

Y = Runoff as output of neuron.

Procedure for ANN model simulation:

To operate ANN initially data was arranged in one notepad sheet and observed runoff in another notepad sheet format. Transfer notepad format data as input and that was taken into the ANN model as an input for computing estimated output. In the ANN model epochs were set upto 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 and output as observed runoff was added in neural network toolbox of MATLAB 7.9 training of the network automatically stops whenever recommended output reached with least errors. The output from ANN was statically tested with the observed runoff by using various statistical parameters *viz.*, RMSE, MARE, co-efficient of determination (R^2) and correlation (r) (Mehendale, 2013). By comparing these statistical parameters best ANN architecture was computed.

Performance criteria:

Root mean square error (*RMSE*):

The root mean square error (RMSE) is used as a measure to assess the prediction accuracy of the developed model. It always produces positive values by squaring the errors. The RMSE is zero for perfect fit and increased values indicate higher deviations between predicted and observed values (Salunke, 2013). The root mean square error between observed and predicted values is determined by the following relationship.

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}\left(Q_i - \hat{Q}_i\right)^2}{n}}$$

Mean absolute error (MAE):

Mean absolute error (MAE) statistic measures was used to quantify the errors between observed and predicted runoff value. MAE is equal to zero.

$$\text{MAE} = \frac{\sum_{i=1}^{n}\left|\frac{Q_i - \hat{Q}_i}{Q_i}\right|}{n} \times 100$$

Co-efficient of determination (R^2):

The co-efficient of determination (R^2) statistic measures the linear correlation between the actual and predicted runoff values. The optimal value for R^2 is equal to 1.

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(Q_i - \hat{Q}_i)^2}{\sum_{i=1}^{n}(Q_i - \overline{Q}_i)^2}$$

Correlation (r):

The correlation co-efficient (r) is an indicator of degree of closeness between observed and predicted runoff values. The correlation co-efficient is determined by the following relationship.

$$\text{COR} = \frac{\sum_{i=1}^{n}(Q_i - \overline{Q}_i)(\hat{Q}_i - \overline{\hat{Q}}_i)}{\sqrt{\sum_{i=1}^{n}(Q_i - \overline{Q}_i)^2 \sum_{i=1}^{n}(\hat{Q}_i - \overline{\hat{Q}}_i)^2}}.$$

where,

n -The number of data.

Q_i -The observed value.

$\hat{Q}_i$ -The predicted value.

$\overline{Q}_i$ -The average of observed value.

$\overline{\hat{Q}}_i$ -The average of predicted value.

Model development:

Priyadarshini watershed of CAET was used for development of ANN model for rainfall-runoff. Daily rainfall data of last four year and corresponding runoff data (2010, 2011, 2013 and 2014) were used for this study.Thus, the total number of samples for four year's period was 198. Each 198 samples of observed rainfall and observed runoff were taken as input data and output data, respectively for analysis and model development purpose. These 198 samples were distributed as 138 samples (70%) for training, 30 samples (15%) for validation and 30 samples (15%) for testing purpose.

■ RESULTS AND DISCUSSION

Rainfall runoff relationship was studied by artificial neural network (ANN) using Matlab 7.9 software. Total 70 numbers of ANN architectures were used for the computation of runoff. The 5 best suitable architectures were selected from the 70 model architecture based on statistical parameter which having low RMSE and MSE value and higher (*i.e.* upto 1) co-efficient of determination and correlation value. The 5 best suitable architectures are 1-18-1, 1-34-1, 1-35-1,1-40-1 and 1-48-1. Out of these 5 best suitable architectures, the ANN of architecture 1-48-1 found most suitable for estimation of runoff based on statistical parameter as it has low RMSE and MSE value and higher (*i.e.* upto 1) co-efficient of determination and correlation value than any other ANN architectures (Table 1). The 1-48-1 ANN architecture gives 13.46, 472.06, 0.84 and 0.92 values for RMSE, MAE, R^2 and r, respectively. The results obtained from Table 1 and ANN of architecture 1-48-1 found suitable for estimation of runoff. Other architectures show over estimated or under estimated results.

The best model architecture found to be 1-48-1

Table 1: Most suitable ANN architectures based on statistical performance

Sr. No.	ANN architecture	RMSE	MAE	R^2	r
1.	1-18-1	14.0803	967.39	0.8223	0.9074
2.	1-34-1	14.1348	862.28	0.8209	0.9066
3.	1-35-1	13.6192	1032.70	0.8338	0.9136
4.	1-40-1	14.0307	590.22	0.8236	0.9078
5.	1-48-1	13.4597	472.06	0.8376	0.9188

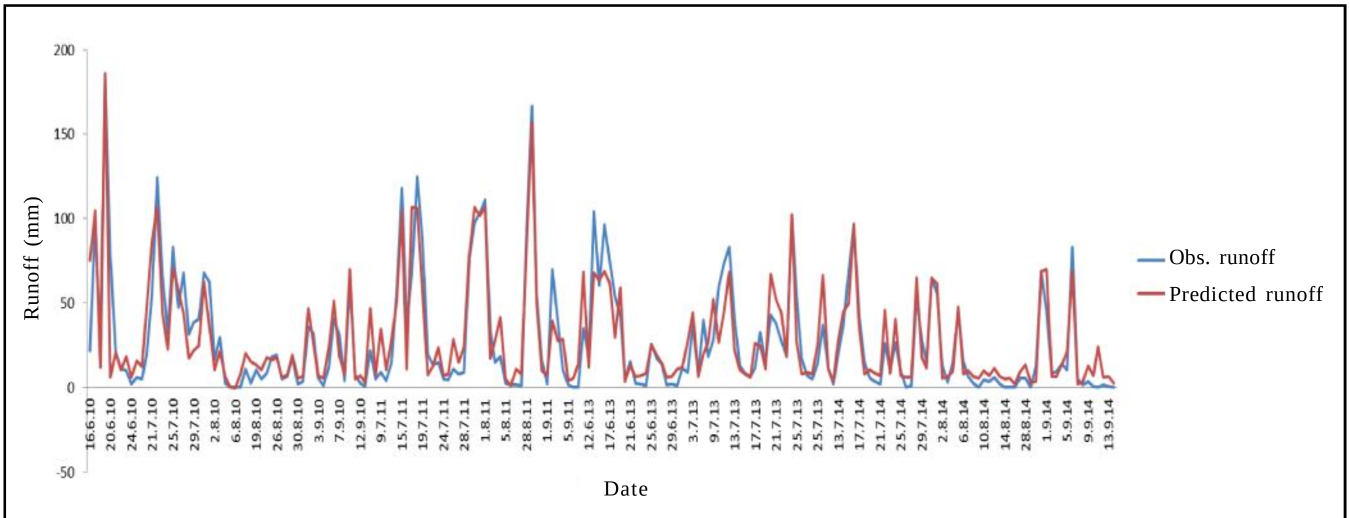

Fig. 1 : Observed vs predicted runoff for architecture 1-18-1

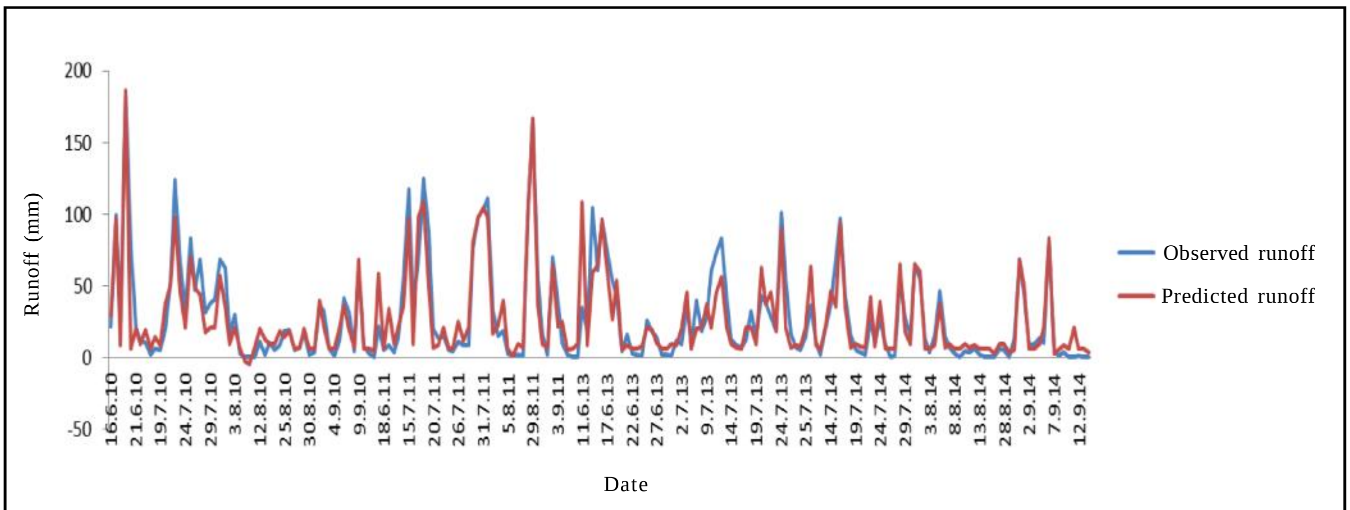

Fig. 2 : Observed vs predicted runoff for architecture 1-34-1

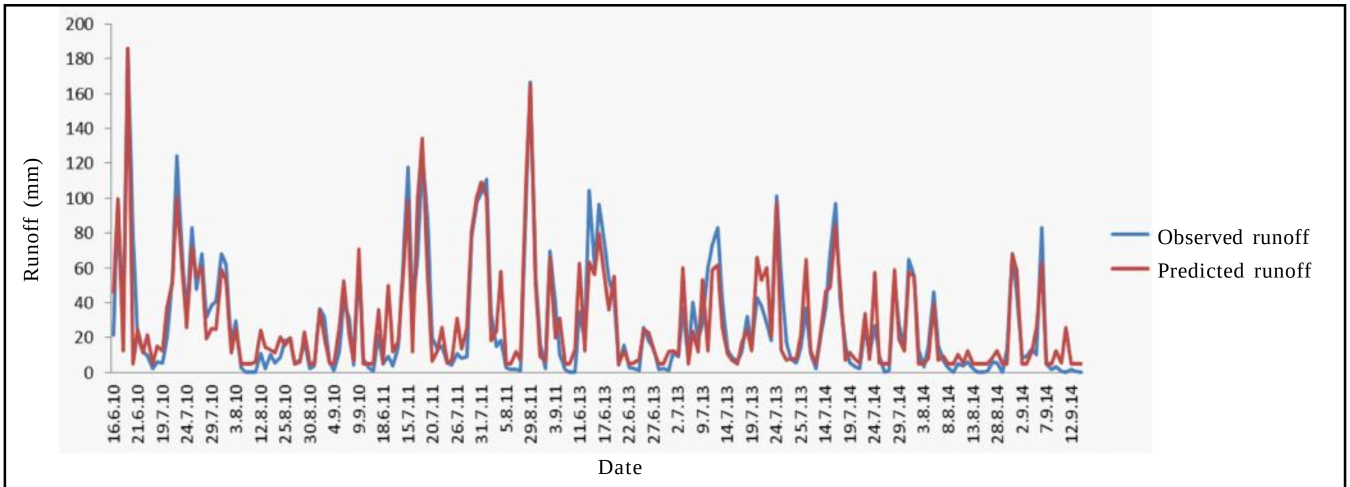

Fig. 3 : Observed versus predicted runoff for architecture 1-35-1

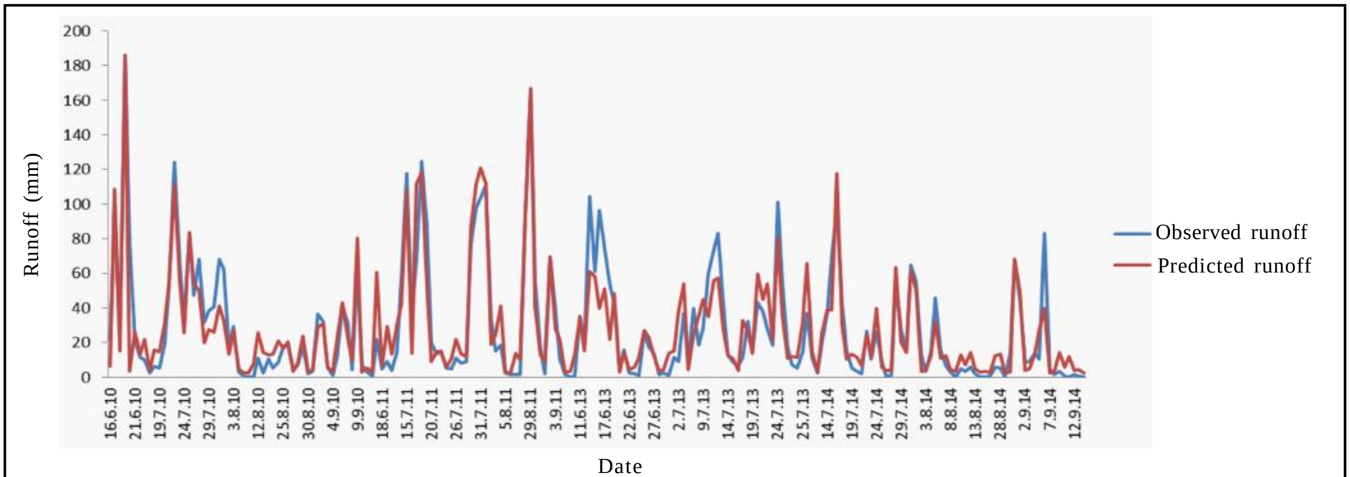

Fig. 4 : Observed vs predicted runoff for architecture 1-40-1

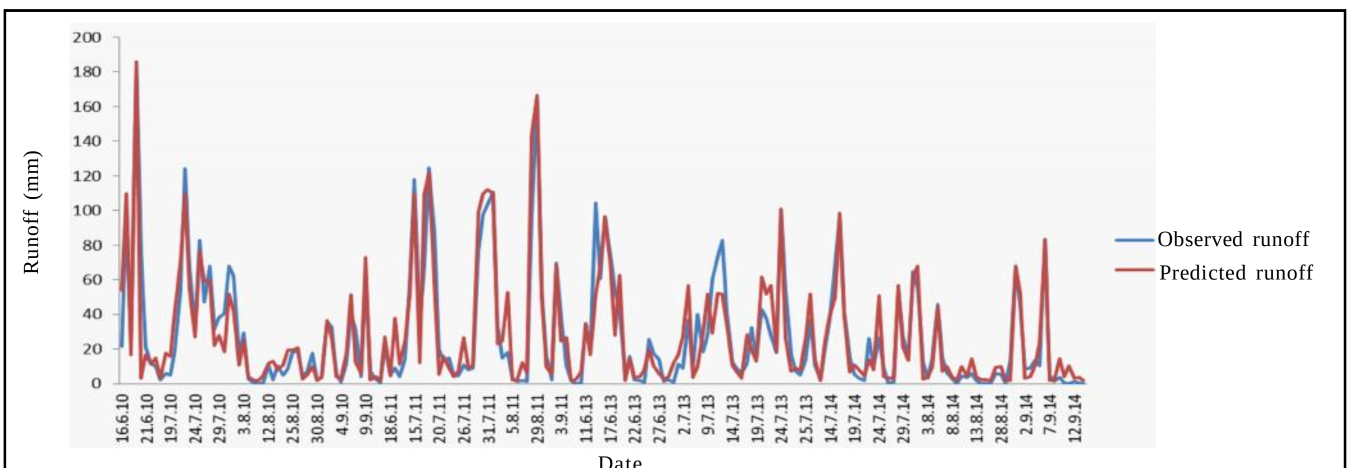

Fig. 5 : Observed versus predicted runoff for architecture 1-48-1

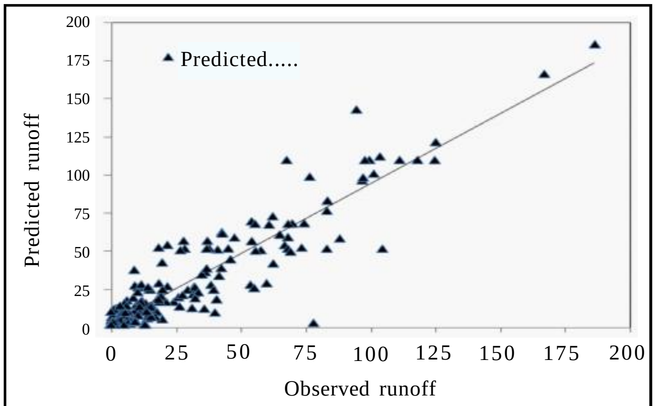

Fig. 6 : Scatter plot of observed vs predicted runoff for architecture 1-48-1

based on statistical performance. The curve has been plotted for the observed runoff and predicted runoff of architecture 1-48-1 and it is shown in Fig. 5. As shown in Fig 6 the number of scatter points above the average line are more in number hence the result shows that runoff has been over estimated.

Conclusion:

The artificial neural network ANN models show an appropriate capability to model hydrological process. Out of 70 ANN model, the 1-48-1 as best model configuration and indicated that 48 neuron in hidden layer fitted best on test data and shows high degree of accuracy with training data set than other ANN architectures. The performance of ANN 1-48-1 architecture in estimation of runoff from rainfall data was checked statistically. Hence, ANN 1-48-1 architectures can be adopted to estimate runoff from ungauged watershed with rainfall as input. ANN model with 1-48-1 architecture is found to be better which gave 13.4597, 472.0640, 0.8376 and 0.9188 values for root mean square error, mean absolute error, co-efficient of determination (R^2) and correlation (r), respectively.The proposed approach can be a very efficient tool and useful alternative for the computation of rainfall-runoff relationship for similar watershed.

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