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Rainfall Runoff Analysis using Artificial Neural Network

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Abstract

Background/Objective: The main objective of the present study is to conduct laboratory experiment for the generation of rainfall runoff data using rainfall simulator. For the validation this observed data, a model is establish for estimating observed runoff data using Artificial Neural Network (ANN) technique. **Methods:** A total 12 laboratory experiments were conducted using rainfall simulator to generate runoff hydrograph using various slope and rainfall intensity over the catchment. For the validation of observed runoff hydrograph data were simulate using ANN. The ANN model was developed using collected 1076 data point to compute runoff discharge. For developing ANN model, the available data were separated as 70% for training, 15% for testing and 15% for validation. **Results:** The predicted results using ANN model performed better estimation with observed values which is useful for water resources planning and management etc. For the testing of model performance Nash-Sutcliffe efficiency criteria were used which gives NSE greater than 95%. **Conclusion:** The comparison of observed and predicted runoff hydrograph reveals that the Artificial Neural Network (ANN) predicts the runoff data reasonably well in observed hydrograph. It is found that ANNs are promising tools not only in accurate modeling of complex processes but also in providing insight from the learned relationship, which would assist the modeler in understanding of the process under investigation as well as in evaluation of the model.

Keywords: ANNs, Laboratory Experiments, Rainfall-Runoff, Rainfall Simulator

1. Introduction

Rainfall-Runoff plays a vital role in the hydrological cycle. A number of models i.e. Artificial Neural Networks (ANNs), physically based, black box and conceptual models have been used to simulate the complex hydrological processes such as rainfall runoff process[1-3] which shown a useful tools in water resources. However, due to its complexity and spatio-temporal variation, a few models can accurately simulate this highly non-linear process. In recent years, Artificial Neural Networks (ANNs) have become one of the most important tools to model complex hydrological processes such as the rainfall-runoff process. In most of the studies, ANNs have demonstrated best results as compared to other methods. ANNs are able to map underlying relationship between input and output data without prior understanding of the process under investigation.

In hydrology, the main research challenges is to develop the models that are able to simulate the catchment response, so that such models are capable to forecast future river discharge, which required for safe and economical

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aspects of hydrologic and hydraulic engineering design and water management purposes.

The innovation of ANN method has added a new dimension to simulate such systems and has been applied as a successful technique to solve various problems associated with water resources engineering. The water resources applications using ANNs which include the simulation rainfall runoff event, climate change, evapotranspiration process, river flow forecasting, reservoir inflow modeling, ground water quality prediction[4-7]. The complex watershed rainfall–runoff process is non-linear and dynamic in nature indicated by[8,9]. The ANN was also applied in the unit hydrograph derivation. The application of ANN to flood forecasting in two flood-prone catchments in England using hourly hydrometric data was studied[10].

For modeling daily flows during monsoon flood events for a catchment in India using daily rainfall data as input vector of the network model using ANN[11]. Among many data-driven techniques like, statistics, computational intelligence, machine learning and data mining, the Artificial Neural Network (ANNs) is the most widely used[12]. The ANN has been applied for rainfall forecasting[13], the model provides better results compared to Multiple Linear Regression model (MLR) method[14]. Also, the comparison of Neuro-Fuzzy and regression models for prediction of outflow of on-farm reservoir studied[15-18]. The Neuro-Fuzzy and regression models was used to predict the outflow of the OFR of 3000 m^3 capacity, located at IARI, New Delhi. Both the models were compared with each other and it was found that Neuro-Fuzzy model has better performance than that of regression model.

To predict monthly stream flow for the Fraser River Watershed in Colorado State, ANN was applied[19]. The ANN model was developed to forecast daily runoff as a function of daily precipitation, temperature, and snowmelt for a watershed in Maryland[20]. One of the main research challenges in water resources is to develop the models that are able to simulate accurately a catchment's response to rainfall. Such models are capable of forecasting the river discharge under different return period, which are needed for hydrologic and hydraulic engineering design and water resources management. The objective of the present study is to conduct laboratory experiment for the generation of rainfall runoff data using rainfall simulator. For the validation this observed data, a model is establish for estimating observed runoff data using ANN technique.

2. Experimental Program

2.1 Advanced Hydrologic System

The laboratory based experimental study was performed for rainfall runoff process using Advanced Hydrologic System (AHS). Advanced Hydrologic System enables to demonstrate the physical processes found in hydrology, including rainfall-runoff process; well abstractions, formation of river features. Realistic results can be obtained from this small scale apparatus, which can be conveniently located in a laboratory and requires no special services. Thus the apparatus is useful to study the part of hydrological cycle bounded by the arrival of net rainfall on ground surface and catchment runoff either by surface streams or well abstraction. Figure 1 shows a photographic representation of the experimental setup.

Figure 1. Advanced hydrologic systems (rainfall simulator).

2.2 The Flume

The impermeable plane surface had a uniform rectangular cross-section having one meter wide and two meter long, the slope of the flume can be adjusted up to 0 to 5 %. The flume is filled with sand having particle size ranges between 0.5 to 1.0 mm. The runoff recording device was used i.e. depth sensor connected to a data logger which records the amount of runoff water passing through a collecting tank in time.

2.3 Rainfall Intensity Pattern

In the present investigation, the simulated rainfall intensity pattern is used having three different pattern of rainfall intensity i.e. 30 mm/hr to 90 mm/hr. For each value of rainfall intensity three different overland plane slopes of 1%, 2% and 3% were used. From the experimental data it is seen that for a given rainfall intensity the time to peak reduces with increase in the slope of overland plane. The range of the data used for present investigation is given in Table 1.

3. Artificial Neural Network (ANN) Modeling

ANN is a well recognized technique in research arena, used to acquire relationship between multiple input and specific output, this method found suitable for forecasting and runoff analysis[21,22]. An ANN generally consists of minimum three layers an input layer, hidden layer and an output layer as shown in Figure 2, hidden layer may be increased for complex problems.

ANN initially trained with a set of actual input and output data. As a result of this training process a coefficients-set (usually denoted as weights w_k and w_{kj}) are obtained. The process of this initial orientation carries out exploration for the optimum non linear correlation between inputs and output. As in linear regression, ANN involves inputs (x_j) linear functions operated upon by transfer function as depicted in Equation (1), such that each hidden unit receives contributions from every input. Mathematically we can describe network by writing the following pair of equations:

$$u_k = \phi\left(\sum_{j=1}^{m} w_{kj} x_j + b_{kj}\right) \tag{1}$$

$$y_i = \phi\left(\sum_{k=1}^{l} w_k u_k + b_k\right) \tag{2}$$

where x_1, x_2..x_m are input values; φ denotes hyperbolic tangent type transfer function; w_{k1}, w_{k2},…w_{km} and w_1, w_2,… w_k are the coefficients of network; u_1, u_2, … u_k denotes hidden nodes; b_{kj} *and* b_k are the constants, analogous to linear regression constant; and y_i is the network output signal. Hidden nodes linear function along with constant determines final output of the network as given in Equation (2). Initially normalization of complete data performed as per Equation (3) with the help of MATLAB-Neural network Toolbox within the limit of ±1.

$$p_n = 2\left(\frac{p_0 - p_{\min}}{p_{\max} - p_{\min}}\right) - 1 \tag{3}$$

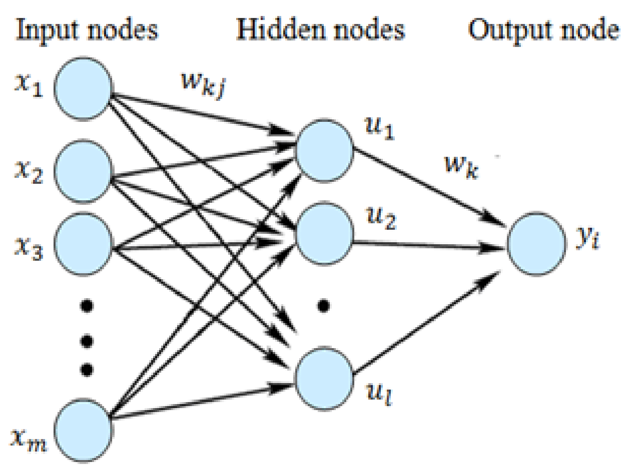

Figure 2. Schematic illustration of Artificial Neural Network with single hidden layer.

Table 1. Range of data used for conducting the experiments

	Parameters			
	Inputs			Output
	Slope (%)	Rainfall Intensity (mm/hr)	Rainfall Duration (sec)	Runoff Rate (ltr/min)
Minimum	1	30	0	0
Maximum	4	90	1090	3.2

In Equation (3), p_0 denotes observed data point, p_n is normalized data, p_{min} and p_{max} are minimum and maximum observed data points respectively. Ahead of training, complete database was randomly distributed into training, testing and validation datasets in 70%/15%/15% format. Firstly, network was trained with training dataset, afterwards testing dataset was utilized to test the behavior of trained models. Finally, validation dataset was used to validate the complete neural network model. While training the network, Gradient Descent (GD) algorithm was employed to reduce the network error by application of a function minimization routine. The routine feeds back error into the layers of network to improve the network output. Overall error (E_D) of a trained model is defined as the sum of squared error between desired (t_j) and calculated (y_j) output as shown in Equation 4.

$$E_D = \sum (t_j - y_j)^2 \tag{4}$$

To minimize the overall error during the training, gradient descent method iteratively find a minimum of error function *f(x)* by repeatedly computing minima of a function *g(t)* of a single variable *t*, as follows. Suppose that *f* has a minimum at X_0 and we start at a point *x*. Then we look for a minimum of *f* closest to *x* along the straight line in the direction of negative direction of divergence of *f(x)*, which is the direction of steepest descent (direction of maximum decrease) of *f* at *x*. That is, we determine the value of *t* and the corresponding point;

$$z(t) = x - t\nabla f(x) \tag{5}$$

for which the function; *g(t) = f(z(t))*, has a minimum. We take this *z(t)* as our next approximation to X_0.

4. Testing of Model Performance Using Nash-Sutcliffe Criteria

The Nash-Sutcliffe efficiency criteria is an important measures to estimates the model performance which can be experssed by the following equations;

Nash-Sutcliffe Efficiency in (%),

$$NES = \left(1 - \frac{\sum_{i-1}^{n} (Y_o - Y_c)^2}{\sum_{i-1}^{n} (Y_o - Y_m)^2}\right) \times 100 \tag{6}$$

Where, Y_o = Observed flow (Experimental rainfall flow) value at time *t*, Y_c = Predicted flow (kinemaic flow) value at time *t*, Y_m = Mean of observed values.

5. Error in Runoff Volum Computation

The error in runoff volume for the present study was estimated by,

$$\text{Volumetric error, in } \% = \left(1 - \frac{Y_c}{Y_o}\right) \times 100 \tag{7}$$

Where, Y_o = Runoff volume observed and Y_c = Runoff volume predicted.

6. Analysis of Data Results and Discussion

The ANN model for runoff discharge evaluation was developed using MATLAB environment, version 8. We collected 1076 data point for runoff discharge at laboratory model of water catchment for 12 events at various slope and various rainfall intensity. These recorded data were taken for model development using various input variables (slope, rainfall intensity and rainfall duration) and output runoff discharge, the data base used for ANN model generation is specified in Table 1. For development of ANN model, the observed data were used as 70 percent for training, 15 percent for testing and 15 percent for validation.

The behavior of model during training, testing and validating is represented in Figure 3 which shows its capability to predict the process input output relation. As much as the correlation coefficient value (R) is higher, better the model will predict.

The training process of ANN was terminated when the overall error on the testing dataset was minimal. The main function for training process is to reach an optimal solution based on some performance measurement such as overall error, coefficient of determination known as R value. The validation sets are usually used to select the best performing network model. In this paper, the ANN was the optimal at 1 million iterations with 5 hidden nodes. It was found that that training (R = 0.99) and validation (R = 0.98) phases gives good agreement with coefficient of determination value as shown in Figure 3. Note that the data pairs closer to diagonal line (also known as line of agreement) in model behavior plot (Figure 3.) give excellent prediction.

The comparison of observed and predicted runoff hydrograph using ANN model as shown in Figure 4 to Figure 6, reveals that the model used to predict the

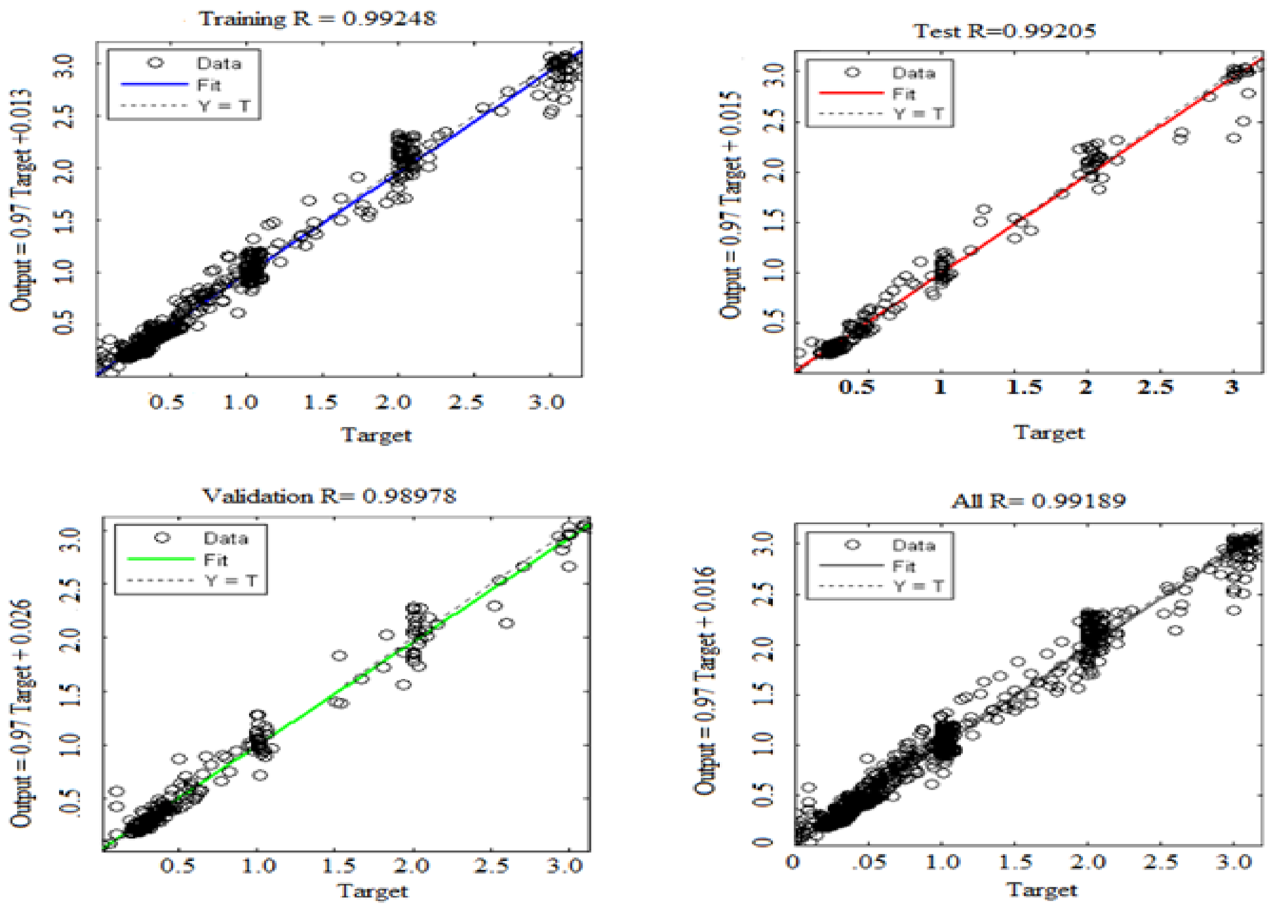

Figure 3. ANN model behaviors during training, testing and validation.

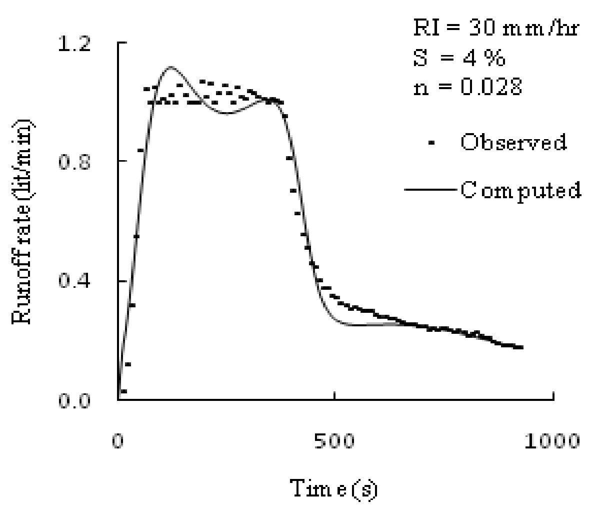

Figure 4. Comparison of predicted and observed hydrograph with ANN model (Here the notation, RI = Rainfall intensity (mm/hr,) S = Slope of the catchment (%), n = Manning's roughness (s/m$^{1/3}$).

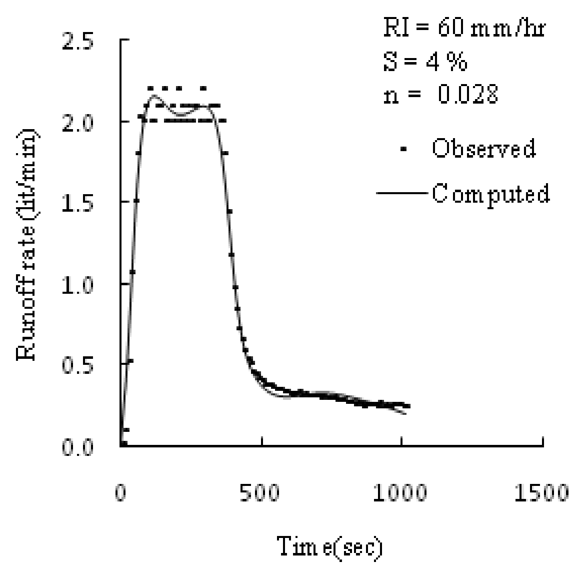

Figure 5. Comparison of predicted and observed hydrograph with ANN model.

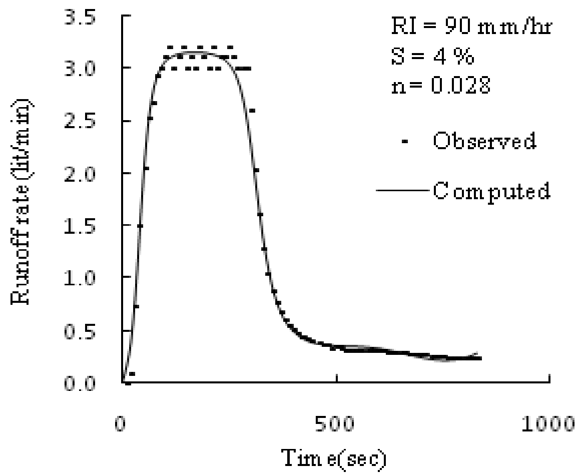

Figure 6. Comparison of predicted and observed hydrograph with ANN model.

laboratory runoff data is highly efficient for the rising, equilibrium discharge and recession limb of the hydrograph using manning's roughness coefficient is equals to 0.028, for all the events with Nash-Sutcliffe efficiency greater than 95%. Table 2, 3 and 4 shows the pertinent characteristics of observed and predicted hydrograph for 30, 60 and 90 mm/hr rainfall intensity.

The predicted results using ANN model shows that the model performed better estimation with observed runoff data which is also useful for decision making in the area of water resources management and planning, flood forecasting etc. Apart than that, modeling can assist rural and urban planner to undertake the necessary measures to face the river bed predictions. So it can help avoid losses due to ecological hazards that are likely to occur due to flooding, dam breakage, and drainage problems etc.

Table 2. Pertinent characteristics of observed and predicted hydrograph for 30 mm/hr intensity of rainfall (Here the notation NSE stands for Nash-Sutcliffe efficiency)

S.No	Slope	Volume			Time to Peak			NSE
		Observed	Predicted	Error	Observed	Predicted	Error	
	(%)	(ltr)	(ltr)	(%)	(sec)	(sec)	(%)	(%)
1	1	9.3	8.7	6.451613	120	113.5	5.416667	95
2	2	6.3	5.95	5.555556	90	86.8	3.555556	96.5
3	3	8.3	7.9	4.819277	83	77.7	6.385542	95.7
4	4	7.6	7.1	6.578947	75	71.5	4.666667	97.1

Table 3. Pertinent characteristics of observed and predicted hydrograph for 60 mm/hr intensity of rainfall

S.No	Slope	Volume			Time to Peak			NSE
		Observed	Predicted	Error	Observed	Predicted	Error	
	(%)	(ltr)	(ltr)	(%)	(sec)	(sec)	(%)	(%)
1	1	12.5	11.9	4.8	110	104.2	5.272727	96.5
2	2	10.4	9.7	6.730769	86	80	6.976744	97.1
3	3	16.2	15.3	5.555556	78	74.2	4.871795	95.5
4	4	12.5	11.6	7.2	71	66.8	5.915493	96.2

Table 4. Pertinent characteristics of observed and predicted hydrograph for 90 mm/hr intensity of rainfall

S.No	Slope	Volume			Time to Peak			NSE
		Observed	Predicted	Error	Observed	Predicted	Error	
	(%)	(ltr)	(ltr)	(%)	(sec)	(sec)	(%)	(%)
1	1	16.1	15.4	4.347826	110	102	7.272727	95.1
2	2	18.4	17.1	7.065217	82	77.2	5.853659	96.7
3	3	15.6	14.51	6.987179	66	62	6.060606	95.5
4	4	15.1	14.3	5.298013	63	59.9	4.920635	97.4

7. Conclusions

The laboratory experiments were conducted to investigate rainfall runoff process. The validation of collected dataset were analyzed and found that the ANN model estimate in better way to model rainfall runoff process. ANN technique is useful tools to handle the complex problems as compared to other technique. In the present study, the results obtained show clearly that the artificial neural network are capable to simulate rainfall runoff relationship, thus, confirming the general enhancement archived by ANN in other fields of hydrology. The results and comparative study indicate that the Artificial Neural Network (ANN) is more suitable to predict river runoff of a catchment than other classical regression model.

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