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WATERSHED MODELING USING ARTIFICIAL NEURAL NETWORKS

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ABSTRACT

Artificial Neural Networks analysis was used for modeling rainfall-runoff relationship. A new Instantaneous ANN watershed model was built and tried herein using Walnut Gulch watershed (catchment) area. For modeling the instantaneous response of a catchment to a rainfall event an ANN model was built shown herein. The built model can represent the actual response using descritized rainfall-runoff values, over a selected time interval (Δt). As this time interval decreases the actual response is more accurately modeled. This model was applied to one of the sub-catchment of Walnut Gulch watershed (sub-catchment No.9 (flume 11)). The model was found successful to represent the lag-time and time of runoff related to the hyetograph properties. The obtained correlation coefficient between observed and predicted runoff values were found to be (0.999), with mean square error equal to (1.02E-06) and the required hidden nodes were (13). The instantaneous ANN model was applied also for Goizha-Dabashan watershed area located north Sulaimaniyah city north-east Iraq. The results indicate the capability of the model to simulate the runoff-rainfall relationship with correlation coefficient (0.9987) and mean square error (9.74E-06) and the required hidden nodes were (8).

Keywords: Rainfall, Raunoff, Watershed, Time Interval, Lag Time, Hydograph.

INTRODUCTION

Artificial Neural Networks are powerful tools to simulate complex, nonlinear problems in many fields like science and engineering under the condition that input and output data sets are available. ANNs provide a new and appealing solution to the problem of relating input and output variables in complex systems. The runoff-rainfall relation is usually complex ,especially for large catchments ,since this increase the variability of the catchment related properties such as slope, plant cover, moisture content….etc., hence this led many researchers to use ANN for such modeling.

The following paragraph were completely taken from on [http://www.stowa-nn.ihe.nl/Applications_ANN_Fuzzy_Logic.htm], explaining some of the works that had been done in ANN modeling of Rainfall-Runoff.

This type of application is one of the areas where ANN is applied most often. The traditional techniques to model rainfall-runoff process are mainly computationally demanding. ANN approach is used for replicating those models. In case of more complicated catchments the ANN models are used to simulate the rainfall-runoff process on the basis of measurement data.

Minns and Hall [1996] investigated the use of multi-layer perceptron NN for rainfall- runoff modeling successfully. Minns and Fuhrman [2000] are also studied the rainfall-runoff modeling in snow covered catchment on the basis of measurement data. Most of such process modeling does not take into account the influence of snowmelt water. The study focused on choosing appropriate input variables for a rainfall-runoff model for a river, where the majority of runoff is due to snowmelt processes. Study shows that the raw measured data cannot guarantee the good model performance. The study also demonstrates how the simple hydrological measurement can be manipulated and can improve a performance of ANN model remarkably without requiring additional measurements.

The RBF network was used for rainfall runoff modeling in drainage system [Mason et al, 1996]. Comparatively good results were obtained by RBF network with radial centers fixed by a data clustering technique much rapidly than the error back propagation network. The advantage of RBF network is much faster than the error back propagation network and the traditional physically based modeling technique [average of 500 times]. Gautam [1998] applied regressive neural networks for modeling and forecasting the rainfall runoff relations in a Sieve river basin, Italy. Normal error back propagation networks trained with data insertion is studied for the same case study as well. From the correlation analysis it was obtained that six-hour time lag and moving average value till 48 hours have high correlation with the runoff.

The comparison of two different algorithms shows advantage of RNN above the training with data insertion for modeling rainfall stream flow relations. The river flow prediction at certain sampling station of Huron river catchment in Germany by making use of measured discharges at three other sampling stations in the same catchment was addressed by Karunanithi et al, 1994. The cascade correlation networks used for the study and simulation result are compared with the two-station power model where model coefficients are estimated by least square regression.

Two different neural network models were built: with current daily discharges at each three measuring stations [three inputs] and with 5 days non-overlapping average discharge for each station [total of 15 input nodes] as input variable. Different structures of neural networks are studied by trial and error in order to get the best result. The result of the power model and neural network approach indicated that the neural network performs better than the power model in case of extreme flow situations.

However, in low flow situations the two techniques perform with the same magnitude of accuracy. The neural network structure with input variables of 5-day discharge window without averaging performs better than the other structures. Another application of ANN for filling in gaps in measurement data and for rainfall-runoff modeling was investigated by Kusumastuti [1999]. MLP with error back propagation learning algorithm is used for filling in missing data of one rain gauge station from daily rainfall data [antecedent, present and next day] of surrounding stations.

The result obtained is not really satisfactory; however, on monthly basis the obtained result is more promising than daily data. Then Radial Basis Function [RBF] network is used for modeling stream flow on natural catchment in Indonesia and the result is compared with Chaos theory, nearest neighbor technique and Marginal Storage Loss model. The inputs for neural network model to determine monthly average runoff of the catchment were monthly rainfall from surrounding stations. The result confirms the ability of neural network to identify the rainfall runoff relations; however, the chaos theory gives better result for prediction. Regression Nearest Neighbor method also performs better than the RBF network.

Since the proposed model hereafter is a new formulation of an ANN watershed models, it needs, calibration and verification. In Kurdistan of Iraq, watersheds rainfall – runoff measurements are rarely available, and if so of little precise; hence the developed model will first calibrated and verified using sophisticated precise data of a Walnut Gulch Watershed. After the model calibration was done it was then applied on Goizha Dabashan Watershed near Sulaimaniyah city, in order to find the parameters of the ANN model for this watershed.

INSTANEOUS HYDROGRAPH ANN MODEL

In order to simulate the instantaneous response of a watershed to an excitation event such as a certain storm a real time data ANN model is proposed herein. In order to use ANN for modeling, a set of the input variables should be assigned to the nodes of the input layer. The same concept should be used for the output layer. First of all the rainfall-runoff data were studied and the maximum run time of the event was assigned according to the followings:

1- Let the starting and ending time of the storm is STST, ENST respectively.
2- Let the starting and ending time of the runoff is STRU, ENRU respectively.
3- Select the longest run time event (rainfall-runoff) interval (Tmax) from the data sample as:
   Tmax = max {(ENST – STST), (ENRU – STRU + Tlag)}
   = max {Tst, Tr + Tlag}

Where, Tlag = STRU – STST
Tst = ENST-STST, and T r = ENRU - STRU

4- Select a certain time interval of the instantaneous hydrograph (Δt)
5- Find No. of input nodes, No. of output nodes:
   No. of input nodes = Int [Tmax / Δt] = No. of out put nodes.

The input data for each input node will be selected from the hyetograph according to the selected (Δt) using interpolation. On the other hand the corresponding output data for each output node will be selected from the runoff hydrograph in the same way. This process should be done for all of the data samples.

It is important to mention that the accuracy of modeling the instantaneous response will be affected considerably by the selected (Δ t). The small values of time interval will give better simulation than the larger one. Moreover it is worth to note that this model will simulate the lag-time and the relation of the end of rainfall with the end of runoff. This is because the largest run in time scale of both rainfall and runoff was selected from the data set, hence for other storms, the rainfall input layer, and runoff output layer will include zeros, these zeros will simulate lag-time between hyetograph and hydrograph. Fig. (1) Shows the presentation of the Tmax estimation as explained above

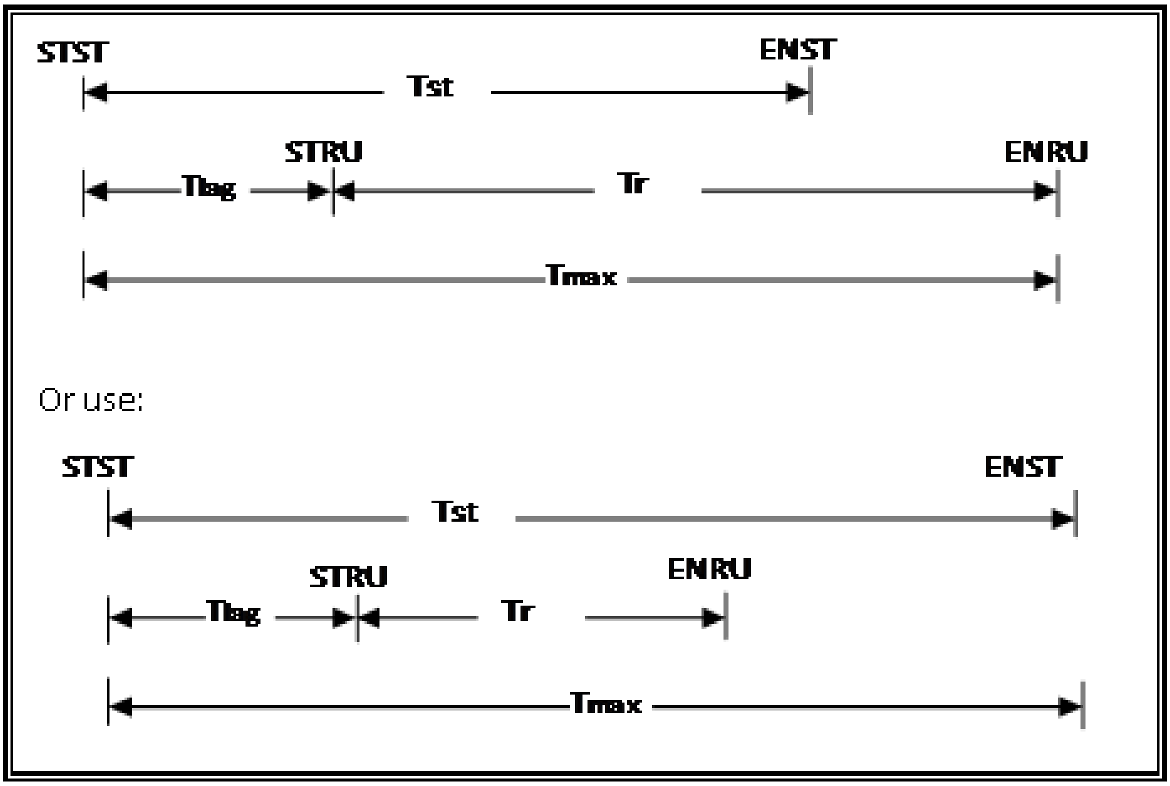

Figure (1) T_{max} estimation

ANN MODELS APPLICATIONS

The ANN model is a data dependable model just like stochastic models, hence the data used should be a representative sample with sufficient length and accuracy. Unfortunately local data of such properties are not always available; hence data was found from other references through the internet. After comprehensive internet search a web site was found, which contains detailed precise data collection and useful related information about the measured catchment, which is the Walnut Gulch watershed in USA.

The above mentioned data was used for validation of the built model, through the comparison of the predicted runoff with the observed one. After verification the models it was applied to a watershed area in Sulaimaniya governorate located north Iraq. This watershed named Goizha-Dabashan watershed. The rainfall-runoff data of this watershed area measured by Barzinji [2007].

The following paragraph about Walnut Gulch experimental Watershed was taken from: http://www.hydrology.princeton.edu/~luo/ceop/walnut_gulch.pdf

The Walnut Gulch Experimental Watershed (WGEW) encompasses the 150 square kilometers in southeastern Arizona, U.S.A. that surrounds the historical western town of Tombstone (31o 42'N, 110o 03'W). The watershed is contained within the upper San Pedro River Basin which encompasses 7600 square kilometers in Sonora, Mexico and Arizona. The watershed is representative of approximately 60 million hectares of brush and grass covered rangeland found throughout the semi-arid southwest and is a transition zone between the Chihuahuan and Sonoran Deserts. Elevation of the watershed ranges from 1250 m to 1585 m MSL. Cattle grazing is the primary land use with mining, limited urbanization, and recreation making up the remaining uses. Walnut Gulch, being dry about 99% of the time, is an ephemeral tributary of the San Pedro River.

The model explained above, for the instantaneous hydrograph was applied herein for Wallent-culch watershed. The sub-watershed No.9 (FL 11) was used. The data set used are the (16) rainfall runoff events shown in Table (1), in order to find Tmax as explained before. A value of Tmax =241min can be selected from this Table. The second step is to choose a value for time interval, which was chosen here as ten-minutes. Hence the No. of input-output layer nodes (each) is:
No. of input nodes = No. of output nodes = Int (241/10) = 24

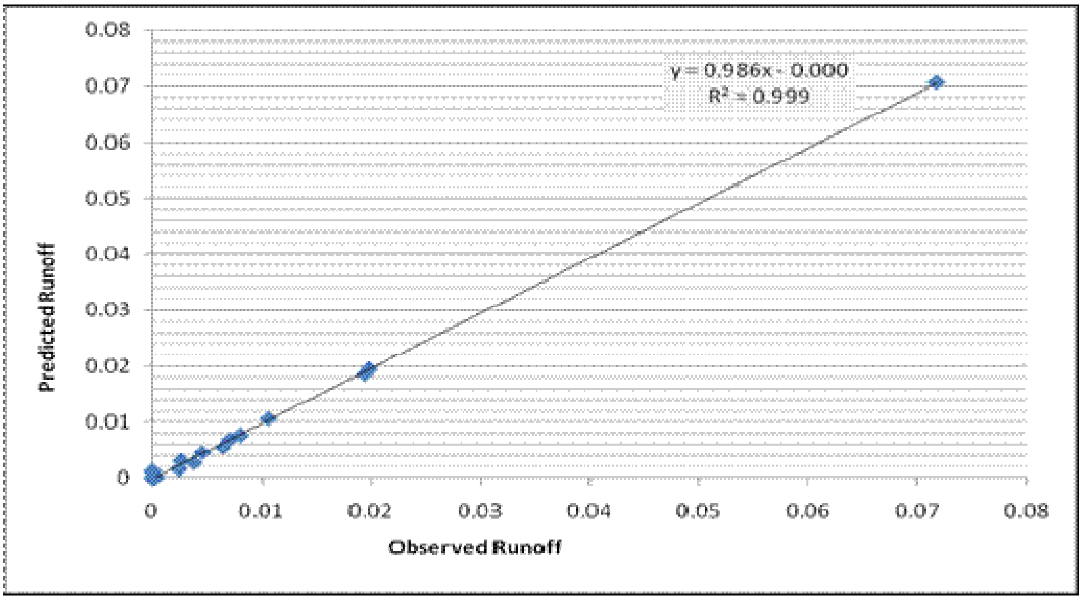

Fig. (2) Relation between the observed and predicted annual runoff for the validation data for instantaneous ANN model in Walnut Gulch watershed.

Fig. (2) shows the relation between observed and predicted runoff for the validation data. The correlation coefficient is (0.9994) and the mean square error is (1.02E-06). The No. of the hidden node in this model is (13) selected by trial and error.

The model explained above for the instantaneous hydrograph was applied herein for Goizha-Dabashan watershed. This watershed is located north Sulaimaniya city in Sulaimaniya Governorate north-east Iraq. (35o35.5' N, 45o28' E). The area is 2.014 km2, Barzinji[2007]. The number of storms of measured rainfall-runoff data is (19). These measured data can be considered as instantaneous hydrograph, hence, the instantaneous ANN model will be used for modeling this catchment.

The data set used are the (19) rainfall runoff events whose available for this watershed, in order to find Tmax. A value of Tmax =840 min can be selected from the data. The second step is to choose a value for the time interval, which was chosen here as fifteen-minutes. Hence the No. of input-output layer nodes (each) is:

No. of input nodes = No. of output nodes = Int (840/15) = 56

Fig. (3) shows the hydrographs of the observed and predicted runoff for the validation data for storm No.9 in Goizha-Dabashan watershed. The correlation coefficient is (0.9987) and the mean square error is (9.74E-06). The No. of the hidden node in this model is (8) selected by trial and error.

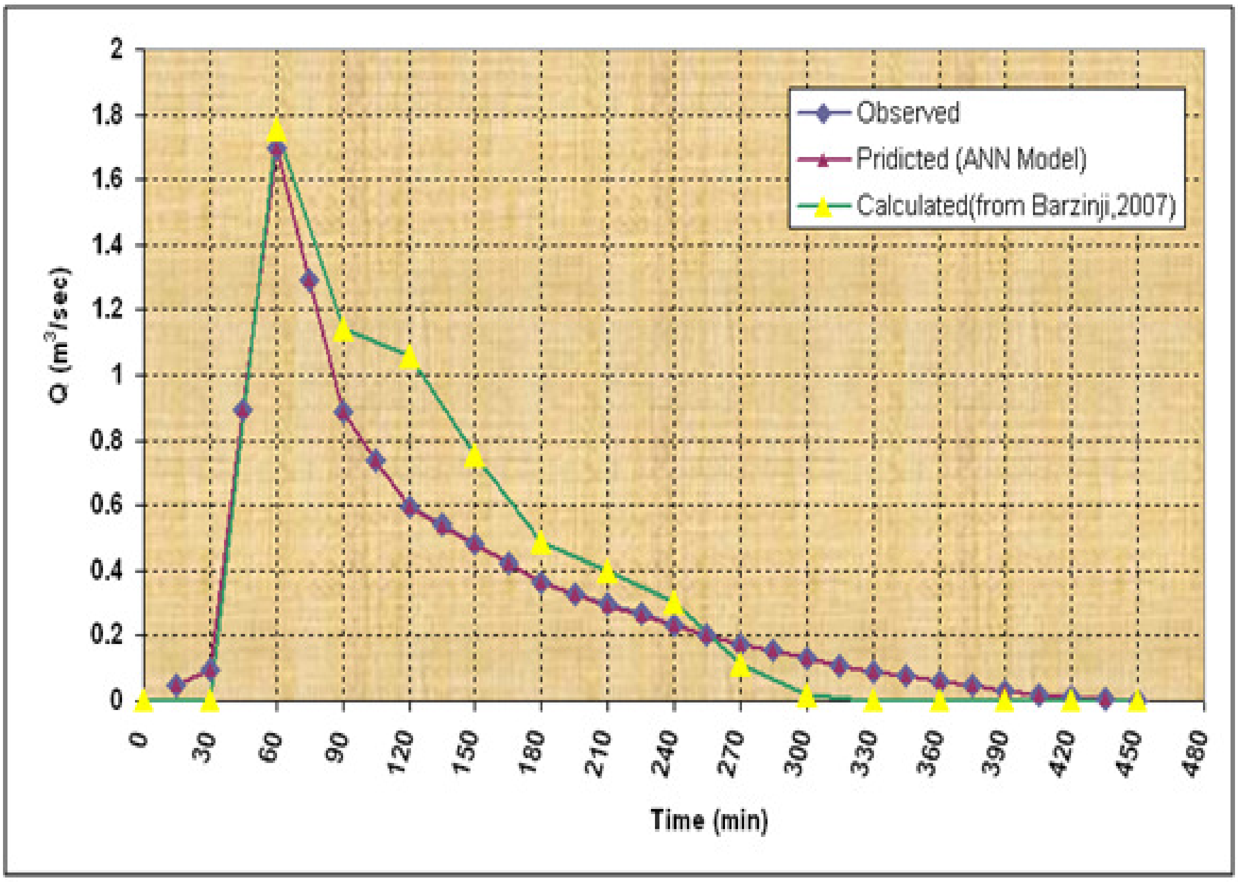

Fig. (3) Hydrographs of the observed and predicted runoff for the validation data for storm No.9 in Goizha-Dabashan watershed

Comparison for the other 18 storms of Goizha-Dabashan watershed. indicates that the Artificial Neural Networks model is always capable for simulating the observed (real) runoff for the observed rainfall as an input.

CONCLUSIONS

The following conclusion could be deduced:

1- The ANN model built herein can simulate the rainfall-runoff relationship for any watershed if a reliable representative observed rainfall – runoff storms are available.

2- The ANN model built herein can simulate the lag-time between the hyetograph and the hydrograph through the number of zeroes that occurs as input values for rainfall, and those occurs as output values for runoff.

3- The number of hidden nodes of the hidden layer that gives the better simulation of the rainfall-runoff relation through the ANN model for Goizha-dabashan watershed is 8 nodes.

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