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ANN Modeling for Estimation of Surface and Subsurface Flows Based on Watershed Geomorphology

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ABSTRACT

In recent years, artificial neural networks (ANNs) have been widely used for flood estimation. In this study, an ANN model based on the geomorphologic characteristics of a watershed such as the number of possible paths and their probabilities is developed (GANN model). Nodes in the input layer are allocated to the surface flows, subsurface flows, excess-rainfall and infiltrated rain. The number of nodes related to excess rainfall is predetermined according to the time of concentration of the watershed. The dependability of the infiltrated rain and surface and subsurface flows on previous time steps are calculated by assigning a different number of nodes to each component. The results of the study showed that the simulated hydrographs by the proposed ANN model have good agreement with the hydrographs observed.

Keywords: Artificial neural networks, characteristics, Geomorphologic, Subsurface flow, Surface flow.

INTRODUCTION

The rain in a watershed may be directed into two paths: 1) the surface flow (overland flow) which moves over the land surface when the rainfall rate is greater than the infiltration capacity or when surface saturation exists, and 2) the subsurface flow which includes interflow and groundwater. The rainfall that infiltrates the soil surface moves through the upper soil layers into the streams as interflow and/or some of it percolates deeply and joins the groundwater (Lee and Chang, 2005). The proportions of these three parts of the flow depend on the geomorphologic and hydrologic characteristics of the watershed as shown schematically in Figure 1.

Estimation of the runoff from a watershed follows two major modeling approaches: 1) the conceptual modeling approach which uses some physical laws in its mathematical formulation; and 2) the black-box modeling approach, which relies heavily on an input-output description of the conceptual model. Conceptual models require a large amount of data and, thus, make the black-box models more attractive to hydrologists (Wu *et al*., 2005).

Artificial Neural Networks (ANNs) have provided many promising results in the field of hydrology simulation. This interest has been motivated by the complex nature of hydrological systems and the ability of ANNs to model the non-linear phenomena in this field. The role of ANNs in hydrology and its comparison with other modeling philosophies is reviewed by the ASCE Task Committee on Application of ANNs in Hydrology. Elshorbagy *et al*. (2000) compared

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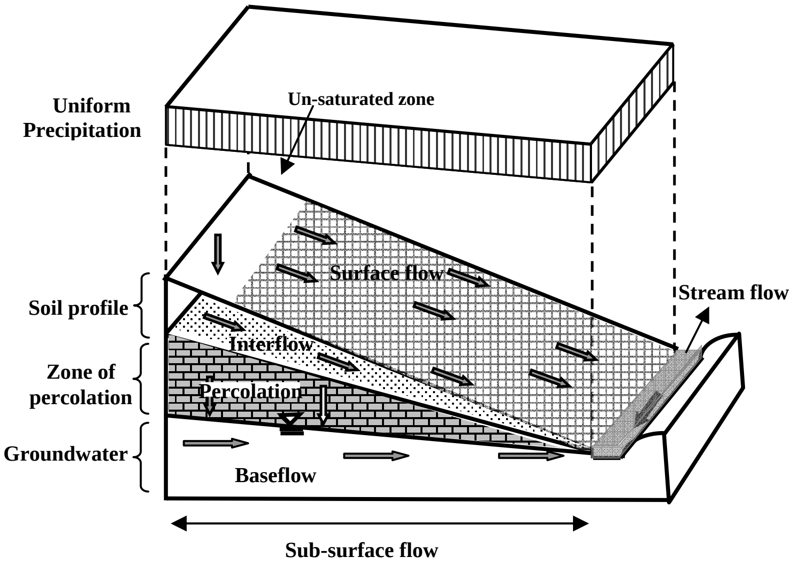


Figure 1. Interaction between surface, sub-surface and interflow.

the ANN technique with linear and non-linear regression techniques for runoff prediction in the Red River, remarking on the superiority of the ANN model. Kisi (2004) has suggested that the ANN approach may provide a superior alternative to the autoregressive (AR) model in situations that do not require modeling of the internal structure of the watershed for prediction of mean monthly streamflows. Anctil *et al*. (2005) applied an ANN model at a daily time step for 47 watersheds. In their developed ANN model, a predetermined range of precipitation duration that is roughly equal to the time of concentration of the watersheds and the potential evapotranspiration have been considered as the nodes in the input layer. Sudheer (2005) has discussed the use of perturbation analysis for determining the order of influences of the elements in the input vector on the output vector in the ANN model. Analyses of the results indicated that each variable in the input vector influences the shape of the hydrograph in different ways. The selection of an appropriate ANN depends on a lot of tests and trials which are often time-consuming. Application of the ANN model for the estimation of direct runoff in ungaged watersheds has recently become interesting to many hydrologists. Zhang and Govindaraju (2003) developed an ANN model that explicitly accounts within its architecture for the geomorphologic characteristics of the watershed for direct runoff prediction. They called their developed model the 'GANN model'. They compared results of the GANN model with results obtained by using in order the Geomorphologic Instantaneous Unit Hydrograph theory (GIUH). Their study reveals the GANN model in order to be a promising tool for estimating direct runoff. Lee and Chang (2005) revised the GIUH model to consider both the surface and sub-surface flow components where kinematic-wave approximation was used for the travel-time function of the surface flow and Darcy's law for definition of the travel-time function of the sub-surface flow.

In this study, an ANN model based on the Zhang and Govindaraju's GANN algorithm was developed for both surface and subsurface flow mechanisms. This model incorporates the GIUH model characteristics in an ANN model structure. Hence, in the architecture of this model, the geomorphologic

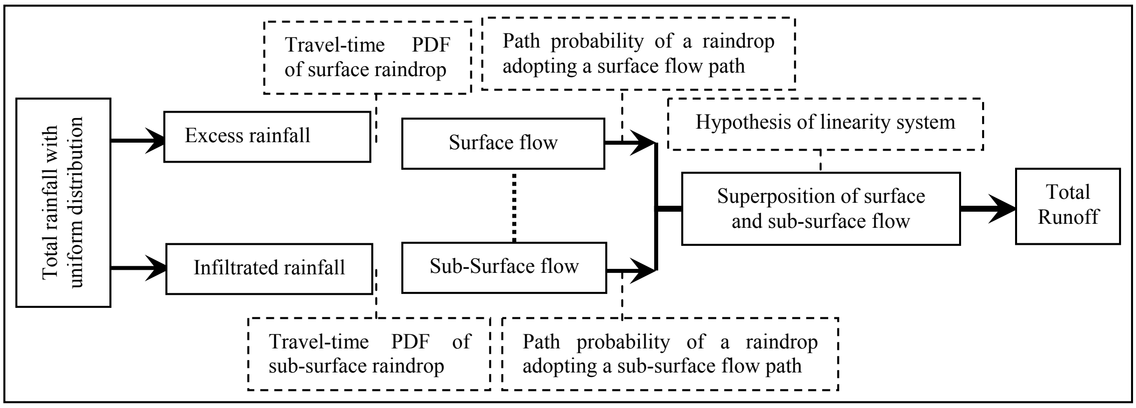


Figure 2. Flow diagram of surface and subsurface flows in GIUH theory.

characteristics of the watershed such as the number of possible paths and their probabilities were used. The model efficiency is enhanced in terms of the run time of the ANN model in estimating watershed runoff while using predetermined components of the ANNs structure (weights and nodes) based on the geomorphological characteristics of a watershed.

MATERIALS AND METHODS

The GIUH theory assumes that the watershed is a linear and time-invariant system with uniformly distributed rainfall (Zhang and Govindaraju, 2003). Figure 2 illustrates schematically a flow diagram of surface and subsurface flows comprising streamflow and their interrelations based on GIUH theory. Here, the theory described by Rodriguez-Iturbe and Valdes (1979), and Lee and Chang (2005) for the derivation of Instantaneous Unit Hydrograph (IUH) is adopted for the surface flow and subsurface flow of the watershed as follows:

Let x_{o_i} denote the ith overland flow region, x_{sub_i} the ith subsurface flow order, x_i the ith surface flow order, and i= 1, 2, 3, …, Ω (where Ω is the watershed order). The total IUH of a watershed $u(t)$ as a linear system of surface and subsurface flows is expressed as follows:

$$u(t) = u_s(t) + u_{sub}(t)$$
$$= \sum_{w_s \in W_s} \left[f_{x_{o_i}}(t) * f_{x_i}(t) * f_{x_j}(t) * ... * f_{x_\Omega}(t) \right]_{w_s} . P(w_s),$$
$$W_s = \langle x_{o_i}, x_i, x_j, ..., x_\Omega \rangle$$
$$= \sum_{w_{sub} \in W_{sub}} \left[f_{x_{sub_i}}(t) * f_{x_i}(t) * f_{x_j}(t) * ... * f_{x_\Omega}(t) \right]_{w_{sub}} . P(w_{sub})$$
$$, W_{sub} = \langle x_{sub_i}, x_i, x_j, ..., x_\Omega \rangle \quad (1$$

where $u_s(t)$= the surface flow IUH of the watershed, $u_{sub}(t)$= the subsurface flow IUH of the watershed, $f_{x_j}(t)$= the travel-time probability density function in state x_j, W_s= the surface flow path space which includes {x_{oi}, x_i, x_j, …, x_Ω}, W_{sub}= the subsurface flow path space which includes { x_{sub_i}, x_i, x_j, …, x_Ω}, $P(w_s)$= the probability of the surface flow adopting path w_s (the path probability of the path w_s) and $P(w_{sub})$= the probability of the subsurface flow adopting path w_{sub} (the path probability of the path w_{sub}).

$P(w_s)$ and $P(w_{sub})$ are defined by Lee and Chang (2005) as follows:

$$P(w_s) = P_{OA_i} . P_{x_i x_j} ... P_{x_k x_\Omega} \quad (2$$

$$P(w_{sub}) = P_{OA_i} . P_{x_{sub_i} x_i} . P_{x_i x_j} ... P_{x_k x_\Omega} \quad (3$$

P_{OA_i} is the ratio of the surface/subsurface flow region of the ith order hillslope to the total watershed area which is expressed as follows:

$$P_{OA_i} = \frac{N_i}{A_\Omega}\left[\overline{A}_i - \sum_{j=1}^{i-1} \overline{A}_j \frac{N_j P_{x_i x_j}}{N_i}\right] \text{ and } i=2,\ldots,\Omega \quad (4$$

where A_Ω= total area of watershed, N_i= number of ith order, and $\overline{A}_i$= average area of ith order subwatersheds.

In equations (2) and (3), P_{x_i,x_j} denotes the transition probability of the runoff moving from the ith order surface/subsurface flow region to the ith order channel as follows:

$$P_{x_i x_j} = \frac{(N_i - 2N_{i+1})E[j,\Omega]}{\sum_{k=j}^{\Omega} E[k,\Omega] N_i} + \frac{2N_{i+1}}{N_i}\delta_{i+1,j}, \quad (5$$

$i = 2,\ldots,\Omega$

and $\delta_{i+1,j} = \begin{cases} 1 & if\ j = i+1 \\ 0 & otherwise \end{cases}$

$E[i,\Omega]$ is average number of upstream channel orders joining ith order stream, which can be defined as:

$$E[i,\Omega] = N\prod_{j=2}^{i}\frac{(N_{j-1}-1)}{2N_j - 1} \text{ and } i=2,\ldots,\Omega \quad (6$$

The required parameters to compute the flow path probabilities using equations (2) to (6) are directly measurable from the geomorphological characteristics of a watershed, where the travel-time probability density function $f_{x_j}(t)$ must be estimated for computing the transition probabilities of different orders. In this research, an attempt was made to estimate the transition probabilities of different orders using the capabilities of ANNs model.

Artificial Neural Network Technique

A three-layer ANN model was adopted in this study. In the developed ANN model the output of node j, y_j, is obtained by computing the value of function f with respect to the inner product of vectors X and W_j minus b_j, where b_j and the function f are called the bias and the transfer function of this node, respectively. The following equations define this process (Wu *et al*., 2005).

$$y_i = f(X.W_j + b_j) \quad (7$$

$$f(X) = \frac{1}{1+e^{-X}} \quad (8$$

According to the sketch given in Figure 3 for sigmoid functions, it has a range between (0, 1), therefore all input data were initially normalized to lie within the values in this range. In this study, the normalized values are obtained by dividing the data by the maximum value of each corresponding data set.

The configuration of the developed ANN model is shown in Figure 4, in which E_t refers to excess rainfall at time step t, I_t is infiltrated rainfall at time step t, $Q_s(t)$ is surface-runoff at time step t, and $Q_{sub}(t)$ is subsurface flow at time step t.

A back-propagation algorithm was adopted

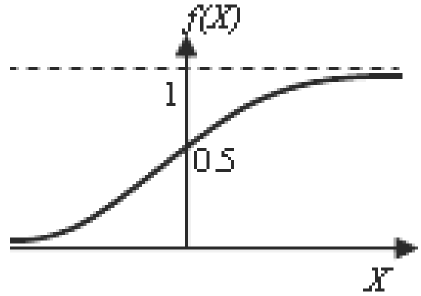
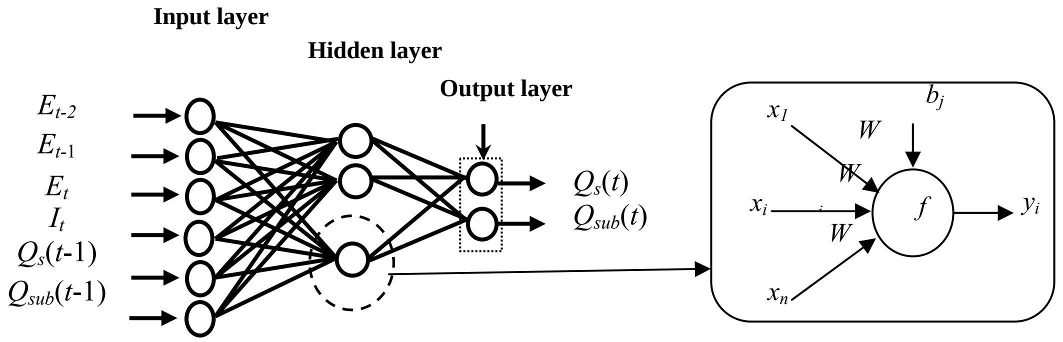


Figure 3. Sigmoid transfer function.

for the training process. In this process, connection weights of the layers and values of biases are derived through a continuous process of simulation by the environment in which the network is embedded by minimizing a predetermined error function (usually the mean squared error, *MSE*) as follows:

$$MSE = \frac{1}{n}\left\{\sum_{t=1}^{n}\left[Q_s(t) - \hat{Q}_s(t)\right]^2 + \sum_{t=1}^{n}\left[Q_{sub}(t) - \hat{Q}_{sub}(t)\right]^2\right\} \quad (9$$

where n= the number of data sets used in training process, $Q_s(t)$= observed value of surface flow in time step t, $\hat{Q}_s(t)$= estimated value of surface flow in time step t, $Q_{sub}(t)$= observed value of subsurface flow in time



Input layer= Includes three nodes for excess rain based on time of concentration of watershed, and infiltrated rain, surface and subsurface flows with un-known number of nodes from previous time steps, which are optimized by trial and error.

Weights connecting the input and hidden layer= Optimum values are obtained during the training process.

Hidden layer= Include seven nodes according to number of possible flow paths of watershed.

Weights connecting the hidden and output layers= Are initialized with the probabilities of flow paths.

Output layer comprises surface and subsurface flows from next time step.

Figure 4. Configuration of the three-layer adopted ANN model.

step t, and $\hat{Q}_{sub}(t)$= estimated value of subsurface flow in time step t.

The GIUH theory and ANN model structures developed by Zhang and Govindaraju (2003) were merged to develop the GANN model. For this purpose, the following assumptions were made:

1. The travel-time of a raindrop in surface/subsurface flow is considered as the connection weight between input and hidden layers, which is estimated during the training process.

2. The path probability values are considered as the initial connection weights between the hidden and output layers, which would be updated during the training process.

3. The number of nodes in the hidden layer is equal to the number of possible flow paths in a watershed.

In runoff estimation based on GIUH theory, the main step is the introduction of the probability density function (PDF) of travel-time for the computation of transition probabilities of different orders. Different forms of PDF of travel-time are proposed by different researchers (Rodriguez-Iturbe and

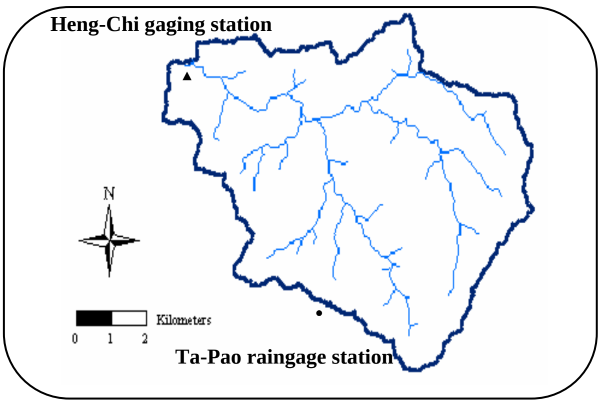


Figure 5. The channel network and location of gaging stations.

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Table 1. Geomorphologic data of the watershed.

i	N_i	P_{oAi}	$\bar{A}_i\,(km^2)$
1	30	0.635	1.043
2	6	0.215	6.919
3	2	0.092	19.898
4	1	0.058	53.227

Valdes, 1979; Gupta *et al*., 1980; Lee and Chang, 2005) none of them being unique. In the GANN model the transition probabilities of different orders of watershed, incorporated as the connection weights between input and hidden layers, are obtained during the training process using trial and error procedure.

Data and Study Watershed

The Heng-Chi watershed located in northern Taiwan was selected for investigating the applicability of the proposed GANN model where the results could be compared with the results obtained by Lee and Chang (2005). This watershed is of the fourth order and covers an area of 53 km^2. Figure 5 shows the location of a discharge ganging station, raingage station and the channel network. The watershed geomorphologic factors are listed in Table 1. Based on equations (2) to (6) the path probabilities and transition probabilities for this watershed are computed and their values are given in Tables 2 and 3.

The available rainfall-runoff data comprise 10 events recorded during 1984 to 2000. For each rainfall-runoff event, initial abstractions were subtracted from rainfall and, subsequently, the subsurface flow was subtracted from hydrographs to arrive at the values of direct runoff using the variable slope method (Zhang and Govindaraju, 2003). The excess rain and infiltrated rain were computed based on the equivalent heights of direct runoff and groundwater runoff. For separation of base-flow from subsurface flow, the constant slope method was used (Figure 6). Tables 4 and 5 show the characteristics of the ten storm events used in this study.

RESULTS AND DISCUSSION

The Heng-Chi watershed is of the fourth order with eight possible paths. Hence, eight

Table 2. The transition probabilities ($P_{xi,xj}$) for the watershed.

$P_{xi,xj}$	Value
$P_{x1,x2}$	0.727
$P_{x1,x3}$	0.400
$P_{x1,x4}$	0.600
$P_{x2,x3}$	0.888
$P_{x2,x4}$	0.333
$P_{x3,x4}$	1

Table 3. Path probabilities $P(w)$ for the watershed.

Path number	Path	Path Probabilities $P(w)$
1	$O_1 \rightarrow C_1 \rightarrow C_2 \rightarrow C_3 \rightarrow C_4$	0.4099
2	$O_1 \rightarrow C_1 \rightarrow C_2 \rightarrow C_4$	0.1537
3	$O_1 \rightarrow C_1 \rightarrow C_3 \rightarrow C_4$	0.2538
4	$O_1 \rightarrow C_1 \rightarrow C_4$	0.3810
5	$O_2 \rightarrow C_2 \rightarrow C_3 \rightarrow C_4$	0.1909
6	$O_2 \rightarrow C_2 \rightarrow C_4$	0.0716
7	$O_3 \rightarrow C_3 \rightarrow C_4$	0.092
8	$O_4 \rightarrow C_4$	0.058

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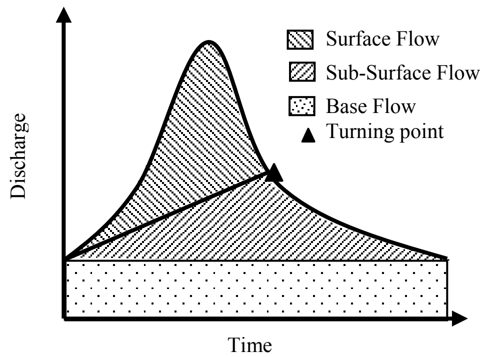

Figure 6. Separation of surface, sub-surface and base flow from total hydrograph.

nodes in the hidden layer were considered. Based on GIUH theory, the connection weights between the hidden and output layers were initially considered as the path probabilities which were updated during the training process.

From the 10 available rainfall-runoff events, seven events were chosen randomly for the training process and the three remaining events were used for model validation.

In the training process, for optimizing the number of nodes related to infiltrated rainfall, six nodes were initially considered in the input layer including E_{t-2}, E_{t-1}, E_t, I_t, Q_{t-1}

Table 4. Rainfall characteristics of the storm events of the watershed.

Sl No.	Date	Excess rain		Infiltrated rain	
		Depth (mm)	Duration (hr)	Depth (mm)	Duration (hr)
1	08/16/1984	242.50	78	129.50	83
2	09/16/1985	300.50	19	46.50	23
3	09/17/1986	246.00	49	139.22	71
4	07/27/1987	54.35	9	41.65	11
5	09/08/1987	148.19	40	61.90	43
6	08/18/1990	235.20	39	87.40	42
7	06/05/1993	72.20	13	43.80	15
8	07/10/1994	27.95	10	23.17	12
9	07/30/1996	133.00	36	114.70	38
10	10/31/2000	329.53	27	81.74	29

Table 5. Runoff characteristics of the storm events of the watershed.

Sl. No.	Date	Surface flow			Subsurface flow	
		Peak (m^3/s)	Peak time (hr)	Duration (hr)	Peak (m^3/s)	Duration (hr)
1	08/16/1984	135.80	67	105	22.00	111
2	09/16/1985	552.35	8	26	35.35	43
3	09/17/1986	428.00	41	37	27.90	100
4	07/27/1987	140.00	7	33	21.50	46
5	09/08/1987	305.95	36	47	11.50	50
6	08/18/1990	468.00	32	61	18.40	65
7	06/05/1993	156.94	11	20	12.96	52
8	07/10/1994	49.90	12	46	7.10	78
9	07/30/1996	199.00	30	40	43.10	97
10	10/31/2000	290.40	18	45	19.43	59

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and q_{t-1} (E_t refers to excess rainfall at time step t, I_t is infiltrated rainfall at time step t, Q_{t-1} is surface-runoff at time step t-1 and q_{t-1} is subsurface flow at time step t-1) were considered. The numbers of nodes related to excess rainfall in the input layer are predetermined. It is equal to three nodes and compatible with the time of concentration of Heng-Chi watershed (the time of concentration based on Lee and Chang (2005) is approximately 3 hours). By altering the number of time steps for subsurface flow in the input layer, and calculating the *MSE* of predicted and observed data during the training process, the optimum number of time steps for subsurface flow were obtained (Table 6).

The results given in Table 6 indicate that the infiltrated rainfall at time step t significantly depends on the infiltrated rainfall at previous time steps, as the minimum value *MSE*= 236.873 is related to this pattern. As the next step, the optimum numbers of time steps for surface and subsurface flows corresponding to the best results were selected. The patterns considered for this purpose are shown in Table 7.

The results given in Table 7 indicate that the minimum *MSE* is related to the pattern which uses the surface and the subsurface runoffs in the two previous time steps. With this pattern, the simulation process has been conducted. The final result in training process was achieved with 600 epochs and *MSE*= 36.907.

In the ANN optimum pattern, by assigning all the inputs values equal to 1, the IUHs for surface and subsurface flows were obtained. These IUHs were compared with the surface and subsurface flow IUHs derived from observed data as reported by Lee and Chang (2005). These are presented in Figure 7.

The ordinates of surface and subsurface flows for the events considered for model validation were computed. As a sample result, the storm event dated September 16, 1985 is presented in Figure 8.

Based on the linear system assumption, using GIUH theory, the hydrologic response function of a watershed can be recognized as the superposition of the ordinates resulting from the surface and subsurface flow. So, with a summation of the ordinates of surface and subsurface flows obtained from ANN model, the ordinates of the outflow hydrographs were computed. Detailed results for the storm events of 7/30/1996 and 10/31/2000 are presented in Figure 9. The results of applying the model to these storm events indicate that the overall shape, rising and receding limbs of surface flow, subsurface flow and total streamflow hydrograph are well simulated by the developed ANN

Table 6. The MSE values for different number of infiltrated rainfall nodes in training mode.

Number	Nodes in input layer	MSE value
1	E_{t-2}, E_{t-1}, E_t, I_t, Q_{t-1},q_{t-1}	432.910
2	E_{t-2}, E_{t-1}, E_t, I_{t-1}, I_t, Q_{t-1},q_{t-1}	236.873
3	E_{t-2}, E_{t-1}, E_t, I_{t-2}, I_{t-1}, I_t, Q_{t-1},q_{t-1}	1127.559
4	E_{t-2}, E_{t-1}, E_t, I_{t-3}, I_{t-2}, I_{t-1}, I_t, Q_{t-1},q_{t-1}	1128.23

Table 7. The MSE values for different number of surface and sub-surface runoff nodes in training mode.

Number	Nodes in input layer	MSE value
1	E_{t-2}, E_{t-1}, E_t, I_{t-1}, I_t, Q_{t-2}, Q_{t-1}, q_{t-2},q_{t-1}	36.907
2	E_{t-2}, E_{t-1}, E_t, I_{t-1}, I_t, Q_{t-3}, Q_{t-2}, Q_{t-1}, q_{t-3}, q_{t-2},q_{t-1}	500.109
3	E_{t-2}, E_{t-1}, E_t, I_{t-1}, I_t, Q_{t-4}, Q_{t-3}, Q_{t-2}, Q_{t-1}, q_{t-4}, q_{t-3}, q_{t-2},q_{t-1}	1233.404
4	E_{t-2}, E_{t-1}, E_t, I_{t-1}, I_t, Q_{t-5}, Q_{t-4}, Q_{t-3}, Q_{t-2}, Q_{t-1}, q_{t-5}, q_{t-4}, q_{t-3}, q_{t-2},q_{t-1}	1156.270

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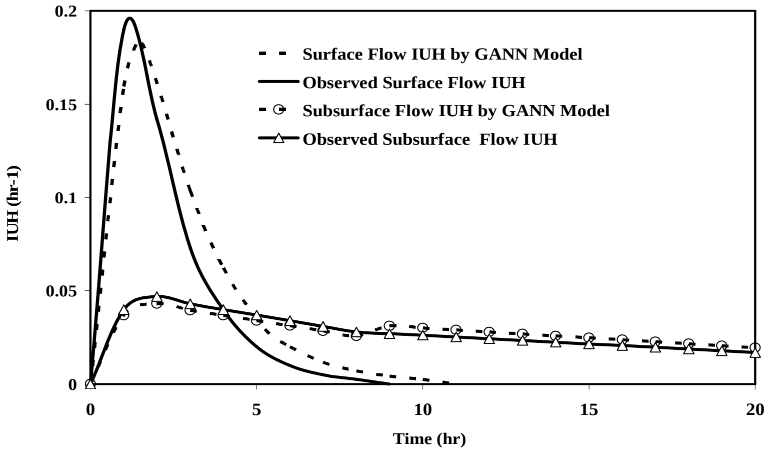

Figure 7. Observed and simulated surface and subsurface flow IUH.

model. To evaluate the suitability of the developed ANN model, three criteria (Lee and Chang, 2005) were chosen to analyse the degree of goodness of fit.

1) The coefficient of efficiency (*CE*):

$$CE = 1 - \frac{\sum_{t=1}^{n}\left[Q_{obs}(t) - Q_{cal}(t)\right]^2}{\sum_{t=1}^{n}\left[Q_{obs}(t) - \bar{Q}_{obs}\right]^2} \qquad (10$$

where $Q_{obs}(t)$ is the recorded discharge at time t, $Q_{cal}(t)$ is the simulated discharge at time t, $\bar{Q}_{obs}$ is the average recorded discharge value during the storm event, and n is the number of hydrograph ordinates.

2) The error in peak discharge:

$$EQ_p(\%) = \frac{(Q_p)_{cal} - (Q_p)_{obs}}{(Q_p)_{obs}} \times 100 \qquad (11$$

where $(Q_p)_{cal}$ is the peak discharge of the simulated hydrograph and $(Q_p)_{obs}$ is the observed peak discharge.

3) The errors in time to peak of the simulated hydrograph:

$$ET_p = (T_p)_{cal} - (T_p)_{obs} \qquad (12$$

where $(T_p)_{cal}$ is the simulated time to peak

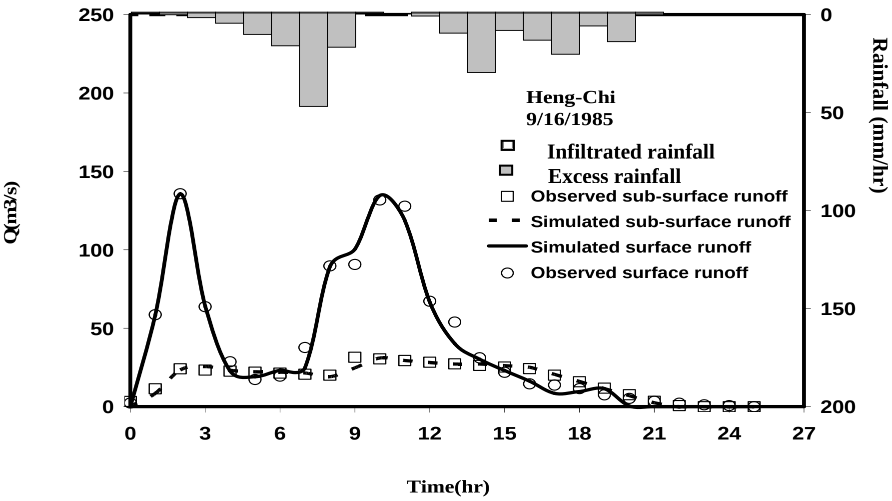

Figure 8. Comparison of observed surface and subsurface hydrographs with results from ANN model.

discharge and $(T_p)_{obs}$ is the recorded time to peak discharge.

Equations (10) to (12) were applied to all the events used for the training process and the corresponding computed values are presented in Table 8. It is evident that the GANN model performs efficiently in terms of the magnitude of the predicted peak discharge and time to peak while the subsurface flow concept was further included in modeling.

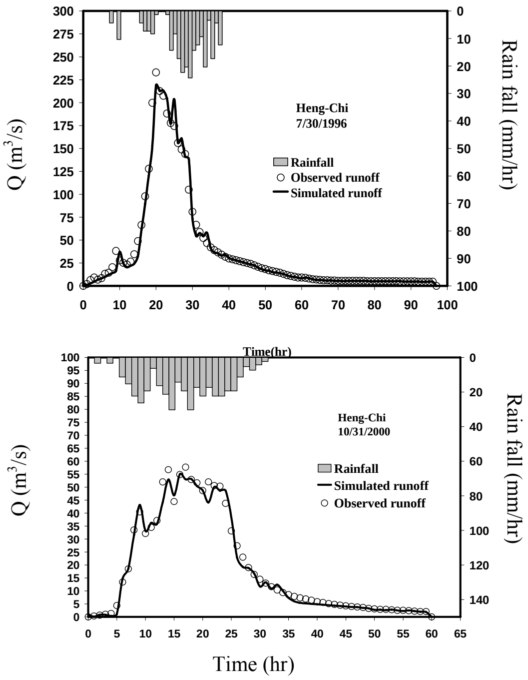

Figure 9. Comparison of the observed and simulated direct runoff hydrographs by the ANN model.

The results obtained from model validation were compared with the results reported by Lee and Chang (2005). Both the results are summarized in Table 9. The values in Table 9 indicate the higher efficiency of the GANN model in terms of *CE*, ET_p, and EQ_p.

CONCLUSION

The ANN models are criticized for their perceived weakness of being black-box models for rainfall-runoff computations. Nevertheless, if these models are equipped with the geomorphological characteristics of a watershed and a suitable training algorithm, they become efficient physiographic-based instead of being black-box.

Finding the best architecture of the ANNs model as the optimum number of nodes in hidden layers and searching the best weights connected between layers is time consuming, while the GANN model uses watershed geomorphologic characteristics to reach the best performance in a lower run time compared to common methods.

The optimum number of nodes in the input layer in an ANN model for the estimation of the surface and subsurface flow was obtained when the surface flow and subsurface flow at a time step is related to the two previous time steps. By setting the infiltrated rain and excess rainfall in the present and the preceding time steps, better results were obtained. As the Heng-Chi is a steep slope

Table 8. Results of criteria for determining the goodness of fit of the ANN model in training mode.

Date	Recorded		Simulated		Evaluation criteria		
	Q_p (m^3/s)	T_p (hr)	Q_p (m^3/s)	T_p (hr)	CE (-)	EQ_p (%)	ET_p (hr)
08/16/1984	157.8	67	157.5	67	0.99	0.00	0
09/17/1986	455.9	41	449.5	41	0.96	-1.39	0
07/27/1987	161.5	7	161.2	7	0.99	-0.14	0
09/08/1987	318.0	36	315.4	37	0.95	-0.51	1
08/18/1990	486.4	32	471.0	31	0.91	-3.02	-1
06/05/1993	173.4	11	172.5	11	0.93	-0.02	0
07/10/1994	57.0	12	58.2	12	0.88	-.006	0

Table 9. Criteria for evaluating the goodness of fit of the ANN model in validation mode and Lee and Chang (2005) model.

Date	Recorded		Simulated				Evaluation criteria					
			GANN model		Lee and Chang (2005) model		GANN model			Lee and Chang (2005) model		
	Q_p (m^3/s)	T_p (hr)	Q_p (m^3/s)	T_p (hr)	Q_p (m^3/s)	T_p (hr)	CE (-)	EQ_p (%)	ET_p (hr)	CE (-)	EQ_p (%)	ET_p (hr)
07/30/1996	242.1	30	254.1	29	237.2	29	0.96	-2.02	-1	0.98	-2.22	-1
10/31/2000	309.8	18	224.0	18	307.6	17	0.98	-1.37	-1	0.97	-3.36	0
09/16/1985	587.7	8	567.5	8	589.3	7	0.80	0.28	-1	0.98	-0.07	0

watershed, the subsurface flow and the infiltrated rain at a time step cannot be related to infiltrated rainfall or subsurface flows of much earlier time steps.

By comparing the results of this study with the results reported by Lee and Chang (2005) it can be concluded that the formulated model is competent.

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مدل ANN مبتنی بر ژئومورفولوژی حوضه برای برآورد جریان‌های سطحی و زیرزمینی

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چکیده

در سالهای اخیر از شبکه عصبی مصنوعی برای برآورد سیلاب بطور گسترده استفاده می‌شود. در این مطالعه یک مدل شبکه عصبی مصنوعی مبتنی بر خصوصیات ژئومورفولوژی حوضه توسعه داده شده است. گره‌های لایه ورودی شامل باران اضافی, جریان‌های سطحی و زیرزمینی و باران نفوذ یافته می‌باشد. تعداد گره‌های مربوط به باران اضافی از قبل تعیین و برابر با زمان تمرکز حوضه در نظر گرفته شد. وابستگی باران نفوذ یافته، جریان سطحی و زیرزمینی به گام‌های زمان قبل با اختصاص دادن تعداد گره‌های مختلف هر مؤلفه در لایه ورودی، محاسبه شد. نتایج این مطالعه نشان می‌دهد که هیدروگراف‌های برآورد شده توسط مدل شبکه عصبی مصنوعی دارای هماهنگی خوبی با هیدروگراف‌های مشاهده شده می‌باشد.

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