A dynamic artificial neural network for assessment of land-use change impact on warning lead-time of flood

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Abstract: Floods always require innovative models for flood forecasting. This paper proposes a dynamic artificial neural network (DANN) model for evaluating land-use change impact (LUCI) scenarios on weighted average of warning lead-time of flood (WAWLTF) in an urbanised watershed. The simulated floods of a calibrated HEC-HMS hydrological model were used for training and testing of DANN model. The features of proposed DANN's structure were determined by minimisation of a new flood forecasting error (FFE) index. Results showed that the proposed procedure was able to optimise features of DANN structure by minimising FFE and produced an appropriate DANN model for assessment of LUCI on WAWLTF. The results also denoted that practicing suitable watershed management in future may improve WAWLTF encouragingly but never compensates negative impact of urbanisation completely. In conclusion, the model can be used as an efficient tool in similar urbanised watershed for assessment of LUCI on WAWLTF.

Keywords: dynamic artificial neural network; DANN; land-use change impact; forecast lead-time; watershed management; Tajrish; flood control; flood warning; Iran; Tehran.

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Azar Arabi holds an MSc in Irrigation and Drainage Engineering from Department of Irrigation and Drainage Engineering, University of Tehran, Iran. She studied flood forecasting and flood warning system for north of Tehran, Iran by using hydrological model and artificial neural network model. She has been an academic member of Rayan Pajooh Water Resources Management and Engineering Research Institute since 2012. Her research focus is flood and flow forecasting and ground water resources studies. She simulated several basins and studied more than ten aquifers in Iran.

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1 Introduction

Floods cause damages and deaths (casualties, property losses and environmental damages) in the world and always need innovative models such as artificial neural networks (ANNs) and support vector machines (SVM) to forecast (the time, place and magnitude of the event) and warn it. Numerous floods are reported in Malaysia (Alaghmand, 2012), USA (Johnson, 2000), Oman (Al-Rawas, 2009), Korea (Kim and Choi, 2012), Europe (Gaume, 2009; Sauvagnargues-Lesage and Ayral, 2007) and Iran (Golian, 2010), which require innovative measures to diminish their impacts. In addition, because of the climate change, floods are deliberated one of the most significant rising natural threats of the world (Choi, 2004; Hegedüs et al., 2013). The above mentioned papers and studies show that floods threat humankind lives and properties in worldwide, thus advanced methods are essential to assess and to improve the ability of flood forecasting and flood warning system (FFFWS).

FFFWS can be used to increase flood control plans efficiency and to reduce flood damages (Liu and Chan, 2003; Andjelkovic, 2001). Flood forecasting, as a non-structural measure, is an efficient flood control technique for reducing flood

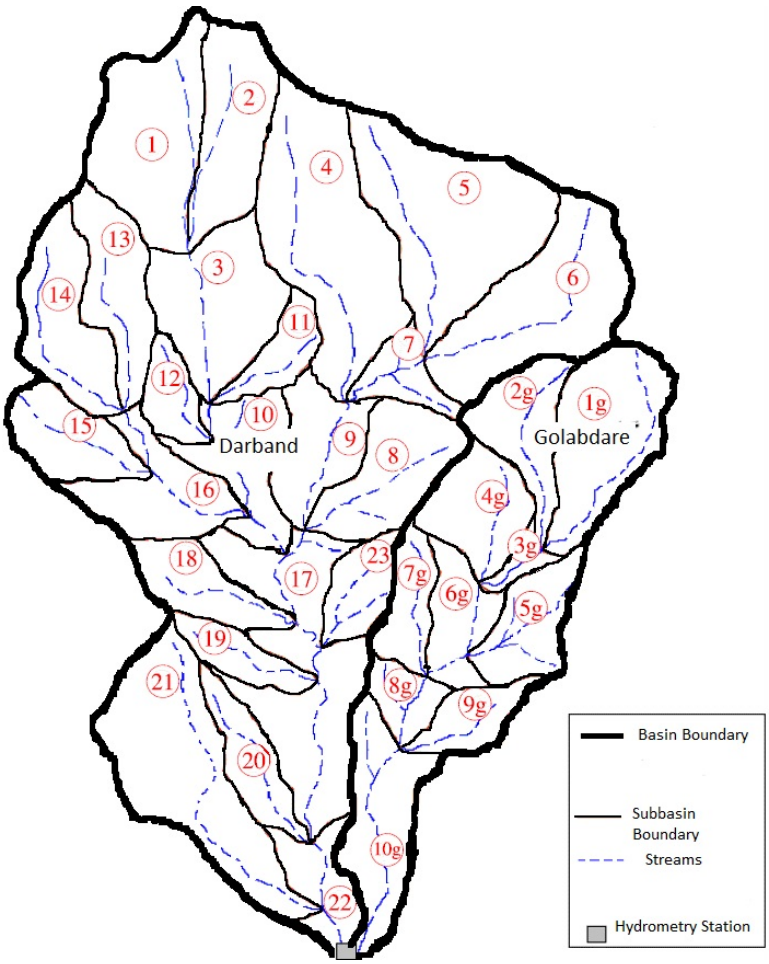
consequences. Land-use change and urbanisation of watersheds decreases watershed time-of-concentration but the implementing watershed management plan (IWMP) can increase it. Therefore, their impact should be examined to determine the efficiency of flood control plans. Yazdi (2013) stated recently that FFFWS are accepted as one of the most cost-effective and capable non-structural flood control method. Olang and Fürst (2011) addressed land cover change effects on flood peak in a case study in Kenya. However, since benefit to cost ratio of the FFWSs has been reported to be several times of other flood control measures for flood damage reduction worldwide (Yazdi, 2013), the effect of urbanisation and urban watershed management activities on warning lead-time flood of flood (WLTF) should be studied to measure their efficiency in action plans. WLTF is the time duration between the recognition of flood exceedance over specific threat threshold to the beginning of flood damage. During this time, disaster responders (authorities) should be able to implement action plan in order to reduce losses and damages. In principle, the extensive the WLTF is, the bigger the opportunity is to lessen losses and damages caused by floods. De Roo (1999) and De Roo et al. (2003) stated that urbanisation will grow flood risk in the next 30 years slightly. Where reports shows land-use change causes increase in peak flood flow (Niehoff, 2002; Saghafian, 2008), further researches are needed to determine its impact on WLTF. This risk is more significant for megacities like Tehran, Iran with the flooder steep watersheds in its northern side because of the short time for urgent action related to short watershed time-of-concentration. Therefore, annotative technique for determining WLTF such as ANN can add asset value for increasing WLTF.

There are several FFFWSs available and generally they include several interacting modules, which usually include: a rainfall-runoff forecasting model, a database for the management of historical and real-time data, a broadcasting module which issues warnings and a module which continually assesses and revises the forecasting outputs. Using FFFWS coupled with advanced models can increase the accuracy of WLTF determination and would increase flood control plans efficiency (Kneale et al., 2000). Some researchers studied flood of different watersheds via different rainfall-runoff forecasting models (Vieux and Moreda, 2013; Kafle et al., 2007). However, the effect of urbanisation and watershed management activities on WLTF needs to be tackled to assess flood control efficiency by utilising further advanced models. A rainfall-runoff model is a method for flood forecasting. Numerous researches have been done on developing rainfall-runoff models based on conceptual and deterministic models overtime (Hydrological Engineering Center, 1990; Vieux and Moreda, 2013; Kafle et al., 2007). However, the requirement for large number of field data to calibrate and simulate the models has restricted their use. Obviously, there is still a robust necessity to develop alternative models (Chiang et al., 2004).

ANN models can simulate nonlinearity of phenomenon and therefore are valuable approaches for solving water resources problems such as rainfall-runoff modelling (Hung et al., 2009; Nasseri et al., 2008; Jeevaragagam and Simonovic, 2012). Owing to this capability for simulating multifaceted nonlinear problems, ANNs is able to model hydrological processes (Chang et al., 2001, 2002; Chang and Chen, 2001; Cameron et al., 2002; Sivakumar et al., 2002; ASCE Task Committee on Application of Artificial Neural Networks in Hydrology, 2000a, 2000b; Maier and Dandy, 2000; Chiang et al., 2004). Signal delays concept has directed to the expansion of dynamic artificial neural network (DANN) in neural processing. DANN uses time delay units through feedback connections and are computationally more robust than feed forward networks and thus

have recently been considered preferably for forecasting and simulation (Assaad et al., 2005; Chang et al., 2012; Coulibaly and Baldwin, 2005; Coulibaly and Evora, 2007; Ma et al., 2008; Muluye, 2011; Serpen and Xu, 2003). The greatest success in flood forecasting is commonly achieved on large rivers. Nevertheless, flash urban floods associated with dense storms in cities are often very uncertain and are more problematic to forecast owing to complex dynamic phenomena involved (Chang et al., 2014). Moreover, the examination of above mentioned papers showed different type of ANNs were used for rainfall-runoff modelling, but the effect of land-use changing by watershed management on weighted average of WLTF (WAWLTF) was not studied. Consequently, the aim of this paper is to propose a DANN model for evaluating land-use change impact (LUCI) including prospect suitable and unsuitable watershed management (UWM) in the basin on WAWLTF. The novelty of this paper is to offer a new ANN model for evaluating LUCI counting suitable and UWM on the warning lead-time of floods. The research is limited to flash flood of urbanised watersheds.

Figure 1 Tajrish watershed and its sub-basins (see online version for colours)



2 Watershed description

Tajrish watershed located in the north of metropolitan city, Tehran, Iran was considered as study area in this research. The watershed with its sub-basins is shown in Figure 1 and has an area of 739 ha. A watershed management plan (WMP) was implemented in 2000–2001 to conserve water and soil of the watershed. The implemented WMP in the study area consists of several activities such as: structural measures (check dams, banquette and detention dams), biological measures (enhancing land cover) and other non-structural measures (prevention from overgrazing) and so affected its land-use. The watershed is one of major flooder of Tehran and is an appropriate case to test the proposed innovative model in assessing different management scenarios.

3 Scenarios

Four scenarios of land-use covers and watershed managements were examined to determine their impact on WTLF. Two of the tested scenarios were watershed conditions in 1988 (before implementing watershed management plan scenario: BIWMP scenario) and 2001 (after implementing WMP scenario: AIWMP scenario). These scenarios are inspected to determine the impact of implemented WMP and land-use change (Table 1). The other two scenarios were designed to examine possible land-use management in future by proposing suitable and UWM scenarios. They are designed based on land-use and condition of watershed in 2001. The UWM scenario applies two following assumptions on land-use and condition of watershed in 2001:

- in sub-basins close to the city, the poor land changed into urbanised areas
- in all sub-basins, pasture land cover changed to poor pasture.

Table 1 Land cover of basin for AIWMP and BIWMP scenarios on Tajrish Basin

Land cover type	*AIWMP*	*BIWMP*
Farmland (%)	1.3	1.7
Forest/garden (%)	6.0	3.9
Rich (%) pasture	5.3	5.0
Poor pasture (%)	19.0	16.6
Poor land (%)	65.3	71.4
Urbanised (%)	3.2	1.4

The suitable watershed management (SWM) scenario applies four following assumptions on land-use and condition of watershed in 2001:

- in sub-basins close to the city, changing 50% of poor pastures to garden and the other 50% to pasture
- in other sub-basins, changing 50% of poor pastures into pasture
- in sub-basins close to the city, 50% of poor lands changed to garden and the other 50% to poor pasture

- in other sub-basins, 50% of poor lands changed to pasture and the other 50% to poor pasture.

4 Dataset and general description of calibration and training

Recorded data of flood flow and rainfall data were used in calibration of HEC-HMS model. HEC-HMS is developed by the US army corps of engineers (Scharffenberg and Fleming, 2006). The simulated 10,000-year flood by HEC-HMS model was used for training of DANN (determining neuron's weights). The physical parameters of the watershed which were used in calibration of HEC-HMS model and simulation by it were length and width of the channels of the sub-basins and their cross-sections. Furthermore, watershed land-use conditions before and after IWMP were utilised to estimate initial curve number (CN) of soil conservation service (SCS) as given before in Table 1. The initial CNs were calibrated against observed flood hydrographs and rainfall data. The HEC-HMS model was first calibrated and validated by using observed flood hydrographs of 18 March and 29 March 2002, respectively. Then, 10,000-year flood was simulated by HEC-HMS using design rainfall temporal pattern of the watershed and one-hour rainfall intensity of Niyavaran Meteorological Station as shown in Tables 2 and 3. Our tests showed that DANN model has better verification results when we use the biggest flood hydrograph for training. Therefore, the 10,000-year flood was used for training and 25-, 50-, 100-, 200-, 1,000-year flood for testing (verification) of the DANN model and the trained DANN was applied to assess the management scenarios on WAWLTF.

Table 2 Distribution of rainfall pattern at Niyavaran Meteorological Station

Time (% of duration)	*Rainfall (% of depth)*
25	19.41
25	29.01
25	40.74
25	11.01

Table 3 One-hour rainfall intensity in Niyavaran Meteorological Station

Return periods (year)	10,000	1,000	200	100	50	25
Rainfall (mm/h)	41.65	33.04	27.5	24.4	21.6	19.1

5 Dynamic artificial neural network (DANN)

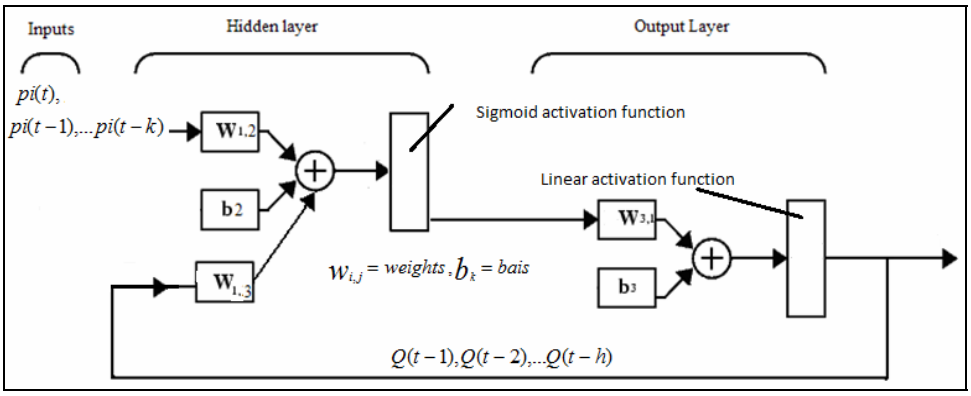
A DANN model is proposed in this paper to determine WAWLTF for four management scenarios. The proposed DANN was a three layer network as shown in Figure 2. The DANN model employs the dynamic feedback mechanism to handle the memory. The dynamic feedback mechanism means that the output of neurons in the output layer can also be utilised as the input of the DANN. In dynamic networks, the memory of the system is embedded implicitly within the network, so the amount of input data is less than that of the static networks. Features of the structure of proposed DANN were classified into two groups: general features and tested feature. General features of the

structure are number of layers and activation functions which were determined based on previous researches' suggestion. Tested features were optimum number of delayed input (K_{opt}), optimum number of recurred output to input (H_{opt}) and optimum number of neurons in hidden layer (NN_{opt}) which were deliberated based on minimisation of a proposed error index, Flood forecasting error (FFE), in Section 5.2. The DANN also requires the data of the current rainfall, the past rainfall and the past flow data as its input. It can be explained using the following equation:

$$Q(t) = F\left(pi(t),\ pi(t-1), \ldots pi(t-k),\ Q(t-1),\ Q(t-2), \ldots Q(t-h)\right) \quad i = 1, 2, \ldots, g \quad (1)$$

where F is the function of DANN and $pi(t)$ and $Q(t)$ are rainfall and flow data in t time step, respectively. k and h are number of delayed input and number of recurred output to input which are explained in tested features of the structure.

Figure 2 The structure of DANN (a three layer network)



5.1 General features of the structure of proposed DANN

General features of the structure (number of layers and activation functions) were selected based on former studies' recommendations (Chang et al., 2014). A three-layer ANN (input, hidden and output) is flexible enough to capture any nonlinear function and was used in this paper. The activation functions of hidden and output layers of proposed DANN were sigmoid and linear types, respectively. The proposed structure was completed by selecting tested feature of DANN structure.

5.2 Tested feature of DANN structure

The DANN with above described structure was examined to determine best inputs, using delayed output and number of hidden layer's neuron for forecasting flood. To have the best forecasting, a new criterion (FFE) is defended to minimise peak forecasting (EQ_{pa}) and hydrograph fitting error ($RMSE_a$) as follows:

$$FFE = EQ_{pa} \times RMSE_a \quad (2)$$

$$RMSE_a = \left(\frac{RMSE_{10,000} + RMSE_{1,000} + RMSE_{200} + RMSE_{100} + RMSE_{50} + RMSE_{25}}{6} \right) \quad (3)$$

$$EQ_{pa} = \frac{EQ_{p10000} + EQ_{p1000} + EQ_{p200} + EQ_{p100} + EQ_{p50} + EQ_{p25}}{6} \tag{4}$$

$$RMSE_T = \sqrt{\frac{\sum_{1}^{n}\left(Q_{ANN} - Q_H\right)^2}{n}} \tag{5}$$

$$EQ_{pT} = \frac{\left|Q_{PANN} - Q_{PH}\right|}{Q_{PH}} \tag{6}$$

where $RMSE_a$ is average of root mean square error, EQ_{pa} is average of peak of discharge error, $RMSE_T$ and EQ_{PT} are root mean square error and average of peak of discharge error of T return period, Q_{ANN} and Q_H are the flow discharges of computed flood hydrographs by DANN and HEC-HMS models and finally Q_{PANN} and Q_{PH} are the peak flows of flood flows computed by DANN and HEC-HMS models.

Number of delayed input (K_{opt}), number of recurred output to input (H_{opt}) and number of neurons in hidden layer (NN_{opt}) were tested and selected to minimise *FFE* by following six steps:

Step 1 k was tested as 1, 10, 20, 30, 40 and 50 to determine initial number of delayed input (K)

Step 2 h was tried as 0, 10, 20, 30 and 40 to determine initial number of recurred output to input (H)

Step 3 k was examined from $K - 10$ to $K + 10$ to determine optimum number of delayed input (K_{opt})

Step 4 h was tested from $H - 10$ to $H + 10$ to determine optimum number of recurred output to input (H_{opt})

Step 5 nn was tried as 1, 10, 20 and 30 to determine initial number of neurons in hidden layer (NN)

Step 6 nn was examined from $NN - 10$ to $NN + 10$ to determine optimum number of neurons in hidden layer (NN_{opt}). The proposed structure based on the general and optimal tested features is trained and then used to as part of the procedure for determining WAWLTF.

6 Procedure for determining WAWLTF

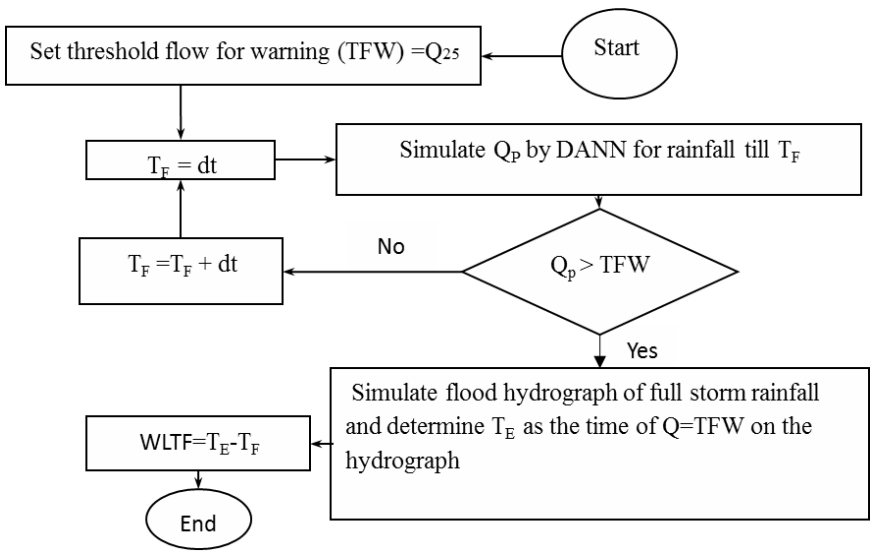
Figure 3 conceptually shows the procedure for determining WLTF for different return period of storms (T = 25, 50, 100, 200, 1,000, 10,000 years). As noted, a trained DANN model was utilised as a part of the procedure. First, the threshold flow for warning (TFW) was determined as the minimum discharge for the starting flood damage which is according to Iranian regulation for rivers equal to peak flow of 25-year flood (Q_{25}) (Standard and Technical Criteria Office, 1997). Second, to develop the storm, a time step (dt) must be selected. Typically, this value is selected based on the time increment of the rainfall-runoff model and here, we set dt equal to one minute. In next step, we set T_F

(duration of rainfall) equal to dt and the precipitation that occurs during that dt was used for the forecasting. Once the forecasting is complete, the forecasted peak flow is compared to TFW. Then, if the forecasted flow was less TFW, the precipitation that has fallen prior to T_F was not sufficient to threaten downstream of the river. Therefore, T_F was increased by adding dt, in next step ($T_F = T_F$ + dt) and the runoff is forecasted again. This recursive forecasting, illustrated in Figure 3, was repeated until the peak forecasted flow (Q_p) is equal to or greater than the TFW. If the flow threshold was exceeded, a warning should be issued (Pingel et al., 2005) and WLTF is determined as Figure 3 (WLTF = $T_F - T_E$). A weighted average of (WAWLTF) which uses (1/T) as weight of each WLTF was used for contracting the impact of scenarios on flood warning as follows:

$$\mathrm{WLTF}_i = \frac{\sum_{i=25}^{10,000} \frac{\mathrm{WLTF}_i}{T_i}}{\sum_{i=25}^{10,000} \frac{1}{T_i}} \tag{7}$$

where WLTF_i is warning lead-time flood of T_i-year return period.

Figure 3 Flowchart of the procedure for determining WLTF



7 Result and discussion

7.1 Results of calibration and verification of HEC-HMS

The results of calibration and verification of HEC-HMS validate using its outputs for training and testing DANN model. The relative errors of the peak flow results were 3.2% for both calibration and verification processes respectively of HEC-HMS model.

Accordingly, the calibrated-validated HEC-HMS can be used for training and testing DANN model.

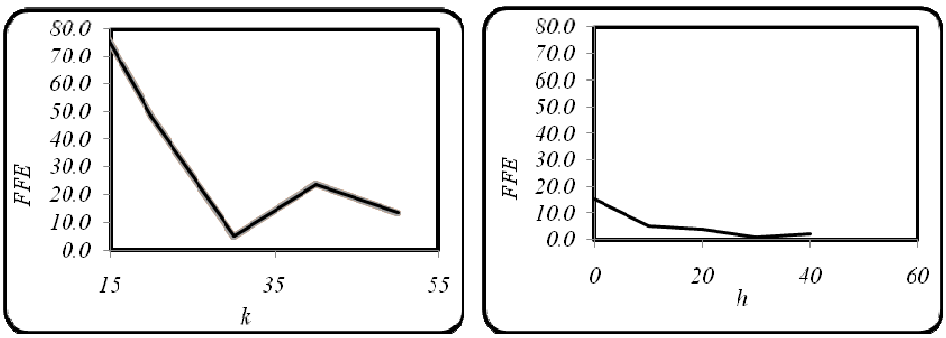
7.2 Result of determination of DANN structure

Optimum number of delayed input (K_{opt}), optimum number of recurred output to input (H_{opt}) and optimum number of neurons in hidden layer (NN_{opt}) were determined by minimisation of *FFE* as shown in Table 4 and Figure 4. These parameters are selected according to six steps illustrated in Section 5.2: first, number of delayed inputs examined was 1 to 50 in steps (1 and 3) and found that the best value for it is 37. Next, number of recurred outputs to inputs from 0 to 40 in steps (2 and 4) was tried and the best value selected for it is 30. Finally, number of neurons irritated in hidden layer 1 to 30 in steps (5 and 6) and the best value chosen for it is 28. These steps minimised *FFE* and determined optimum number of delayed input (K_{opt}), optimum number of recurred output to input (H_{opt}) and optimum number of neurons in hidden layer (NN_{opt}) as 37, 30 and 28, respectively. *FFE* is reduced step by step through steps 1 to 6 by determining tested feature of DANN structure. Consequently, the proposed steps were able to determine tested features of DANN structure by minimising *FFE*.

Table 4 Determination DANN structure's parameters

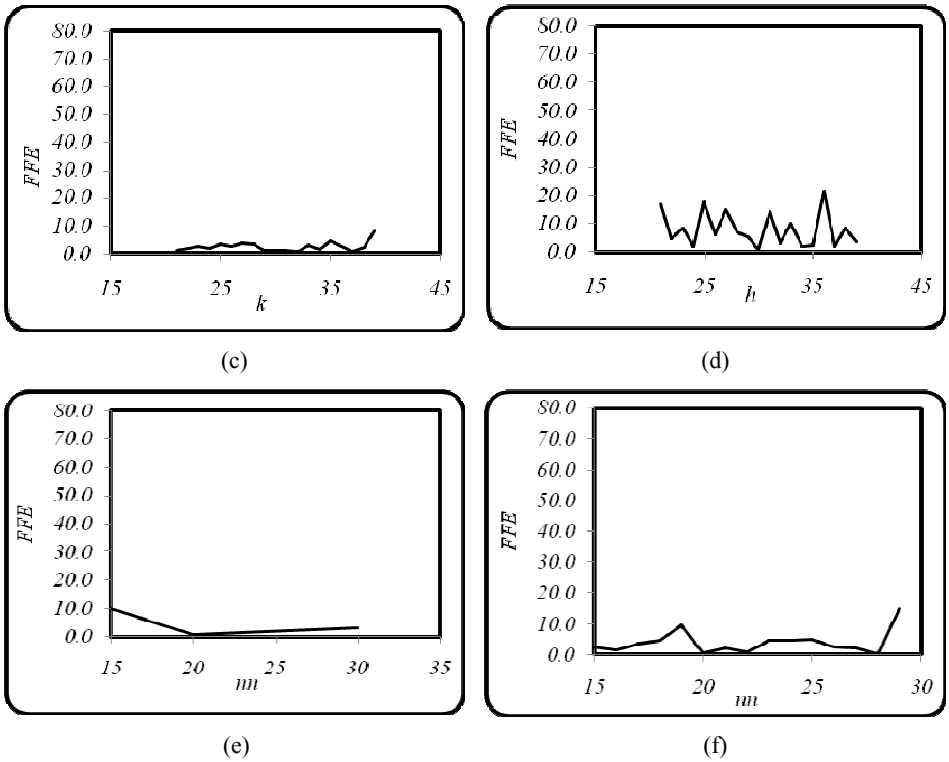
Step	*Parameter*	*Best value of parameter*	*FFE*
1	K	30	*1.022*
2	H	30	*1.022*
3	K_{opt}	37	*0.758*
4	H_{opt}	30	0.758
5	NN	20	0.758
6	NN_{opt}	28	0.338

Figure 4 Reduction of FFE through the steps of DANN structure, (a) step 1 (b) step 2 (c) step 3 (d) step 4 (e) step 5 (f) step 6



(a) (b)

Figure 4 Reduction of FFE through the steps of DANN structure, (a) step 1 (b) step 2 (c) step 3 (d) step 4 (e) step 5 (f) step 6 (continued)



(c) (d)

(e) (f)

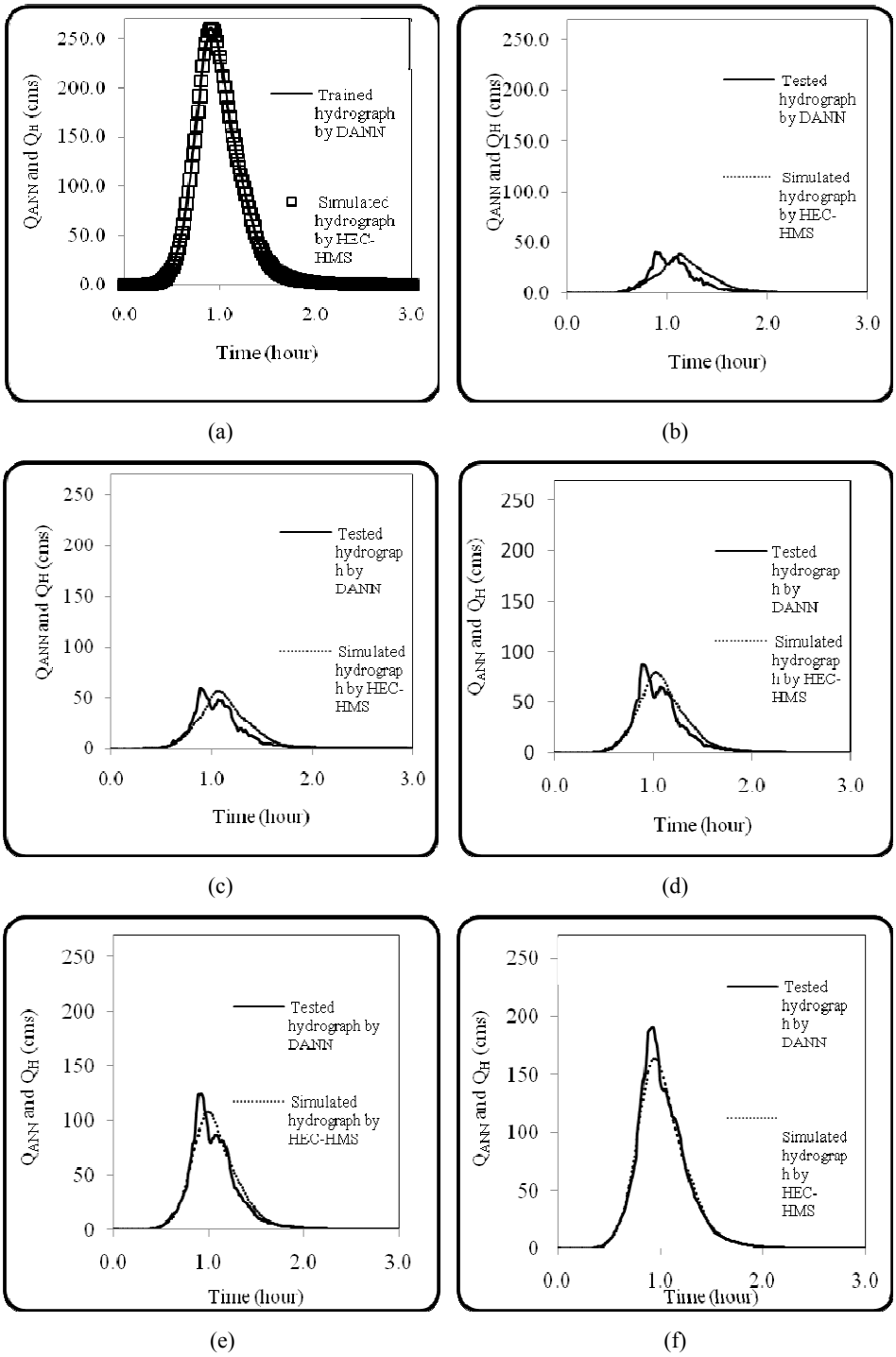
7.3 Result of training and testing DANN

The results of training and testing of DANN demonstrate the proposed DANN can be used for forecasting flood with reasonable confidence and certainty. Figure 5 compares the trained and tested hydrographs of DANN and simulated ones by HEC-HMS. This figure shows perfect training by 10,000-year flood hydrograph. It also demonstrates generally tested hydrographs of DANN follow better the simulated ones by HEC-HMS in rising and falling parts of hydrographs than other parts as return period of flood is increased. Table 5 denotes the result of training and testing DANN. *RMSE* represents the error of DANN to simulated floods via HEC-HMS. They show that the proposed DANN is well trained and fairly tested. Hence, the proposed DANN model is appropriate for utilising it as a part of procedure for determining WLTF.

Table 5 *RMSE* of the training and testing of DANN

Training	*Test*				
$RMSE_{10,000}$	$RMSE_{25}$	$RMSE_{50}$	$RMSE_{100}$	$RMSE_{200}$	$RMSE_{1,000}$
0.0048	4.323	4.945	5.393	5.335	4.740

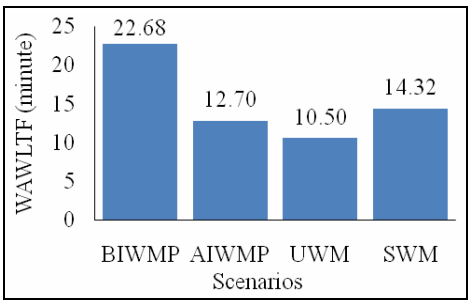
Figure 5 Comparison of the trained and tested and simulated hydrographs by HEC-HMS, (a) T = 10,000 years (b) T = 25 years (c) T = 50 years (d) T = 100 years (e) T = 200 yeas (f) T = 1,000 years



7.4 Result of WAWLTF for four land-use scenarios

Contracting the WAWLTF of the proposed scenarios showed negative effect of urbanisation overcome on IWMP impact. However, practicing suitable IWMP is necessary in the future to improve WAWLTF. Table 1 previously shows that not only forest and rich pasture increased but also urbanised land and poor pasture increased during 1988–2001 (IWMP). Thus, Figure 6 shows the negative impact of increasing urbanised land and poor pasture overcame positive impact of IWMP (improving forest and rich pasture and structural measures) and WAWLTF decreased after Implementing watershed management plan (AIWMP scenario). Contrasting WAWLTF of BIWMP and AIWMP scenarios with UWM and SWM scenarios reveals that practicing SWM in future may improve WAWLTF but never BIWMP condition will recover again. In addition, practicing UWM can decrease the WAWLTF to the lowest value of the studied scenarios. Therefore, a detailed examination impacts of scenarios on WAWLTF encourages keeping the practicing IWMP to compensate negative impact of urbanisation.

Figure 6 WAWLTF of scenarios (see online version for colours)



8 Conclusions

In this paper, an innovative technique (DANN model) is proposed to increase flood warning systems efficiency in one of major flooder watershed of Tehran, Iran. Minimising of a new index (*FFE*) was used to determine feature of DANN structure. Evaluating the impacts of land-use management on flood warning, including implemented watershed management and urbanisation, future possible suitable and UWM of the basin was successfully addressed. Weighted Average of WLTF (WAWLTF) was used for contracting the impact of different proposed scenarios on flood warning. Following main conclusion can be derived for this research:

- The results of this research display proper training of DANN. It also demonstrated tested hydrographs of DANN followed better the simulated ones by HEC-HMS in rising and falling parts of hydrographs than other parts as return period of flood was grown.
- The proposed steps were able to determine tested features of DANN structure by minimising FFE and it showed the proposed DANN model was appropriate for using as a part of procedure for determining WAWLTF.

- Practicing SWM in future may improve WAWLTF but it will compensate all negative impact of urbanisation.
- A detailed examination impact of scenarios on WAWLTF encourages keeping on practicing IWMP to reduce negative impact of urbanisation.

Finally, this paper proposes an innovative model to assess the impact of different watershed management scenarios on flood warning efficiency which can be used in similar flooder watershed of urbanised regions elsewhere. Therefore, this study extend previous studies of the impact of urbanisation (Niehoff, 2002; Saghafian, 2008) on peak flow to its impact on the warning lead-time of flood.

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