$H(t) = f[Q_u(t), Q_u(t-1), Q_u(t-2), Q_u(t-3), \ldots, Q_u(t-10), Q_l(t), Q_l(t-1), Q_l(t-2), Q_l(t-3), \ldots, Q_l(t-10)]$

Flood routing using alternative approach of neural network for a flood warning system

Ahmad Tahershamsi[1], Farhad Hooshyaripor[1,2], Hosein Ghalkhani[2], Abdollah Ardeshir[1]

[1]Amirkabir University of Technology (Tehran Polytechnic), [2]Water Research Institute

Abstract

This investigation focuses on the mechanism of flood routing for using in a Flood Warning System (FWS). Numerical solution of the governing 1D Saint Venant equations is a common method; however it is time consuming and sometimes results in computational instability (Peters et al. 2006). As the acceleration and stability of the routing model is very significant for FWSs, this study introduces alternatives approach of Artificial Neural Network (ANN) which seems to be helpful (Shamseldin et al. 2007; Schmitz & Cullmann 2008).

Location

The system has been developed for Tangrah Basin, upstream Golestan dam, Golestan state, Iran. The basin is located between 37°00′ and 37°00′N longitude, and 55°40′ and 56°30′E latitude with the area of 1796 Km^2.

Methodology

In this study, HEC-1 precipitation-runoff model was used to acquire the input flood hydrographs to the main branch of the river considering different rainfall patterns. The soil conservation service curve number method (SCSCN) for infiltration estimation and Clark unit hydrograph for rainfall-run-off transformation were applied (USACE 1998). Then the achieved hydrographs were used as the inputs of an unsteady HEC-RAS model to route the flood downstream (USACE, 2006). Hence, the values of real arrival time, water level and flood rate were estimated using the hydraulic model. This procedure was repeated several times considering some probable precipitations and the results were stored. Then the obtained results were used to train an ANN model. Fig. 1 shows the methodology applied for developing the process.

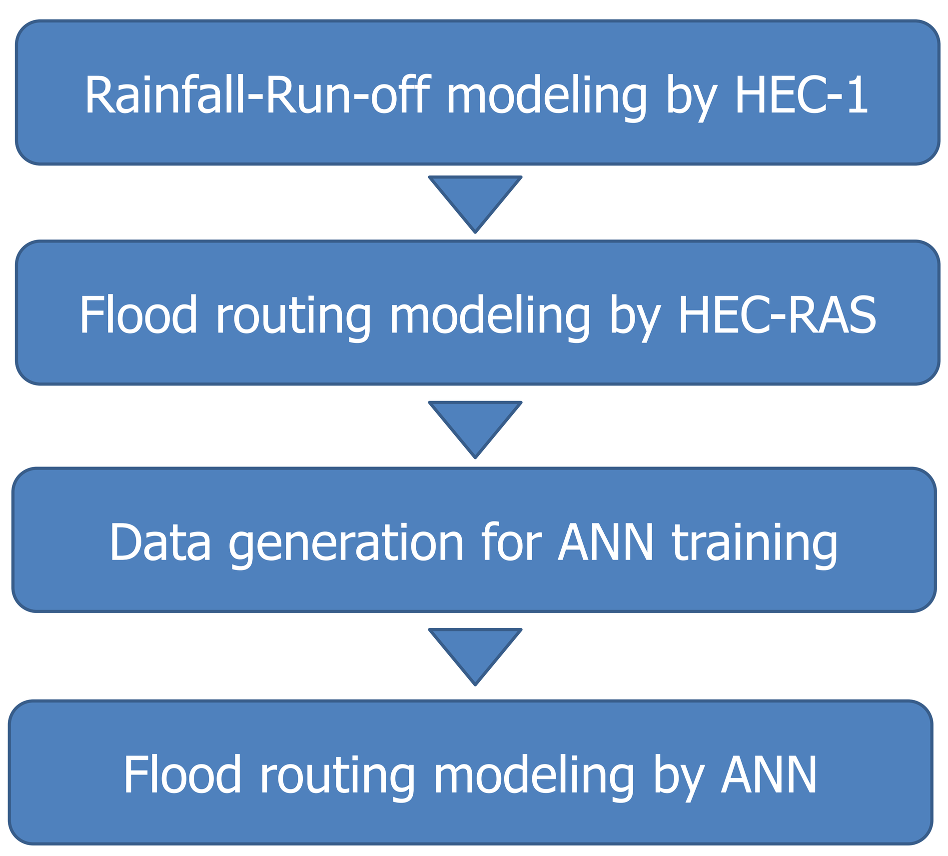

Figure 1. Methodology of the research

ANN model

In this study, a multi-layer perceptron (MLP) neural network model with one hidden layer and sigmoid and linear activation function respectively in the mid-layer and output layer was applied to approximate the flood characteristics at downstream. Accordingly, two ANN models were set up; the first (model I) for water level prediction (*H(t)*), and the second (model II) for flood rate prediction at downstream (*Q(t)*). To train the models, input flood rate to the main river at upstream ($Q_u(t)$) and input flood rate from the lateral reaches ($Q_l(t)$) were used as follow:

$$H(t) = f[Q_u(t), Q_u(t-1), Q_u(t-2), Q_u(t-3), \ldots,$$
$$Q_u(t-10), Q_l(t), Q_l(t-1), Q_l(t-2), Q_l(t-3), \ldots, Q_l(t-10)]$$

$$Q(t) = f[Q_u(t), Q_u(t-1), Q_u(t-2), Q_u(t-3), \ldots,$$
$$Q_u(t-10), Q_l(t), Q_l(t-1), Q_l(t-2), Q_l(t-3), \ldots, Q_l(t-10)]$$

where t is the time step. The networks architecture is shown in Fig. 2.

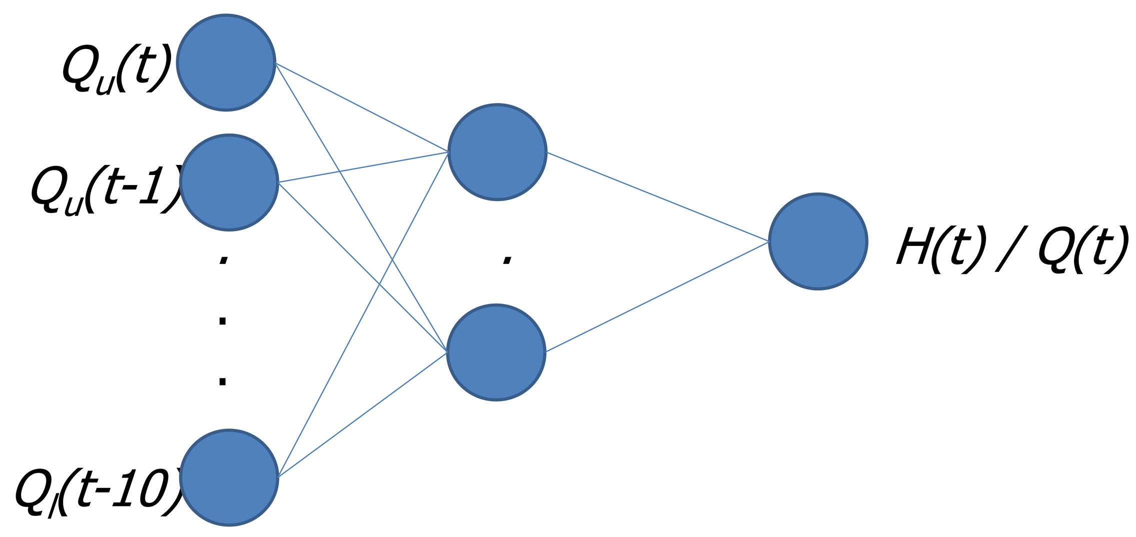

Figure 2. The networks Architecture

Result and Discussion

Figs. 3 and 4 show the values of maximum water level and flood rate estimated by HEC-RAS model versus ANN predictions, respectively.

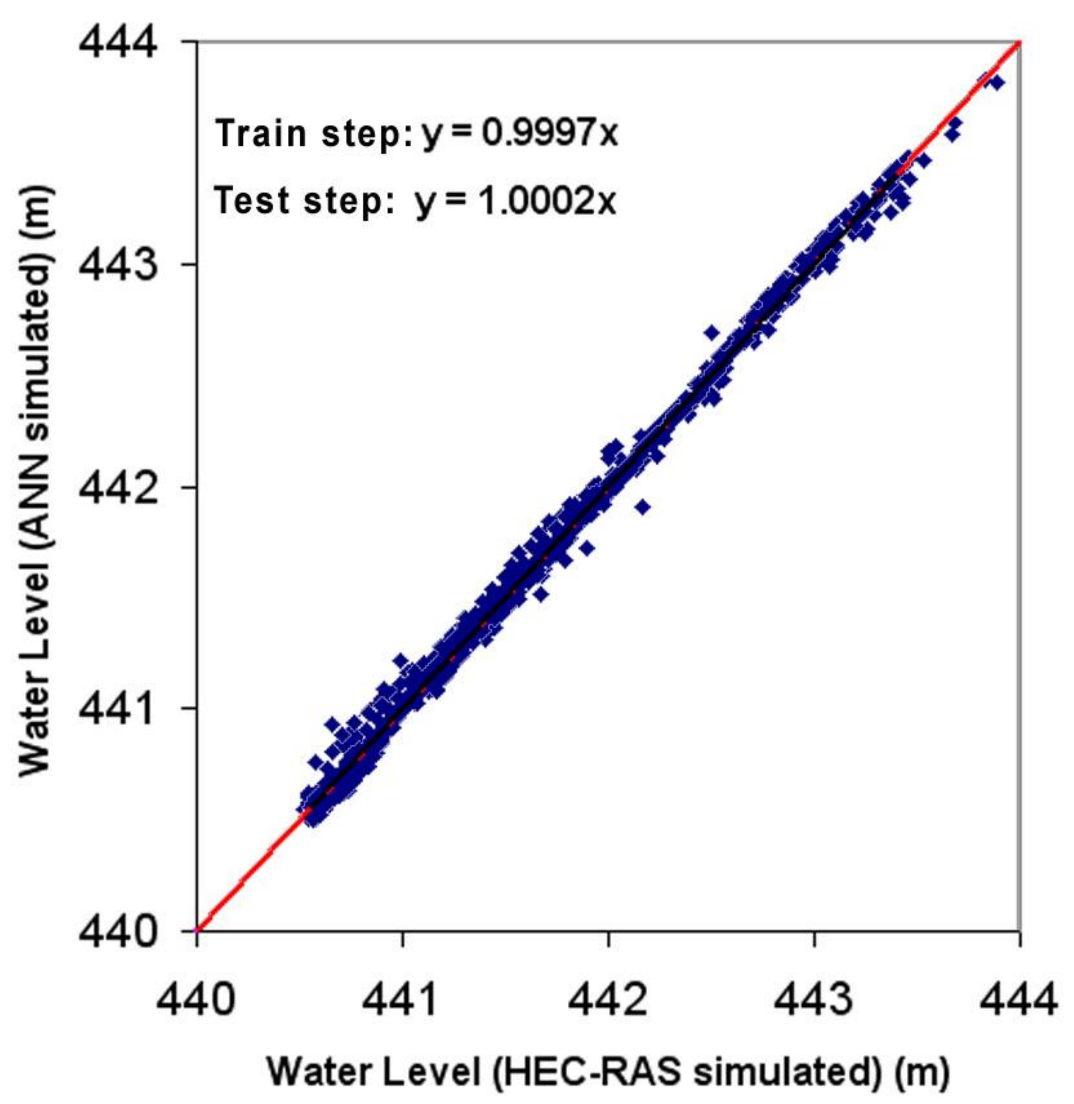

Figure 3. Scatter plot of maximum water level estimated by HEC-RAS model versus ANN predictions

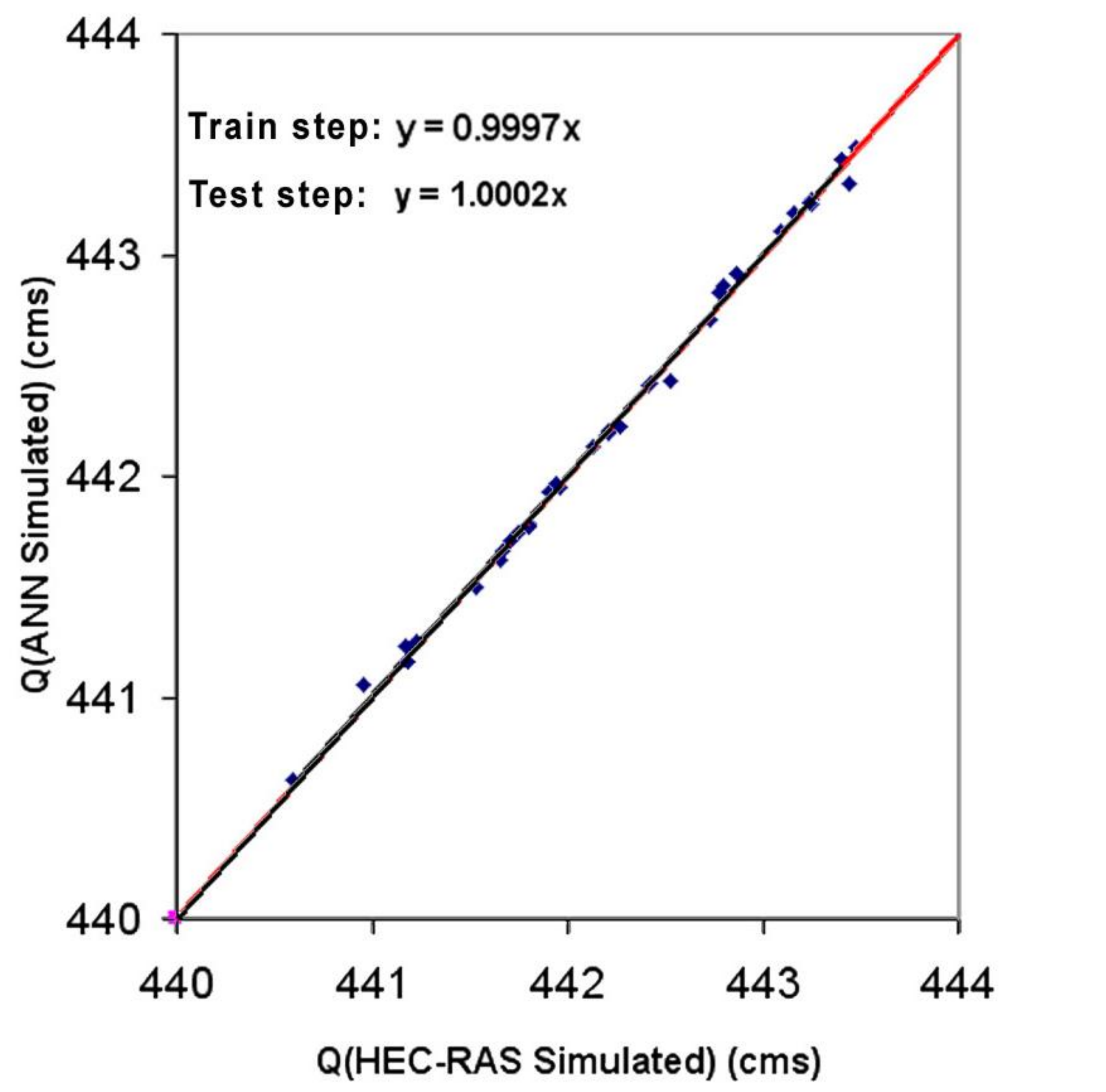

Figure 4. Scatter plot of maximum flood rate estimated by HEC-RAS model versus ANN predictions

To evaluate the models' performance, three statistical measures were applied, namely Nash–Sutcliff parameter (E), mean relative error (MRE), and mean square error (RMSE). The values of E index closer to one indicate higher performances, while lower MRE and RMSE are more desirable.

Table 1. The results of ANN models in different steps

ANN model	Training step			Testing Step		
	E	MRE	RMSE	E	MRE	RMSE
I	0.999	33E-6	0.023	0.999	37E-6	0.026
II	1.00	0.114	4.687	1.00	0.114	4.719

According to Table 1 the error values are negligible and the correlation is very high, so ANN's performance is acceptable and FWS would be confidently effective when ANN uses instead of the more complicated hydrodynamic model of HEC-RAS.

CONCLUSION

Accuracy and acceleration are two essential features of a successful FWS. FWS needs to forecast the flood reliably, then send an alarm to residential areas at downstream. This is done by routing the flood to downstream by a hydrodynamic model, e.g. HEC-RAS. As hydraulic models are usually time-consuming, we used alternative approach of neural network to forecast the maximum level and discharge of the flood at downstream areas. The study was conducted for Madarsou river, Tangrah Basin, Iran. The results indicated that ANN model performs well. Besides, it is much faster than the hydraulic model which deals with instability and diverges in some runs.

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