Comparing the Performance of Neural Networks for Predicting Peak Outflow from Breached Embankments when Back Propagation Algorithms Meet Evolutionary Algorithms

Farhad Hooshyaripor, Ahmad Tahershamsi[*]

Faculty of Civil and Environment Engineering, Amirkabir University of Technology, Tehran, Iran

Abstract   This investigation provides a review of some methods for estimation of peak outflow from breached dams and presents an effective and efficient model for predicting peak outflow based on artificial neural network (ANN). For this reason the case study data on peak outflow discharge were compiled from various sources and reanalyzed using the ANN technique to see if better predictions are possible. By employing two important effective parameters namely, height (H_w) and volume (V_w) of water behind the dam at failure, four scenarios were addressed. To train the models two different algorithms were examined namely, back propagation (BP) and imperialist competitive algorithm (ICA). Among the BP algorithms, Levenberg–Marquardt (LM), resilient back propagation (RP), fletcher–reeves update (CGF), and scaled conjugate gradient (SCG) were utilized. Therefore, 20 different ANN models were developed and compared to each other. Results showed that both H_w and V_w parameters are similarly dominant in estimating the peak outflow discharge. Among the different training functions, LM was the best, because of higher coefficient of determination (R^2=0.87) and lower error (RMSE=9616). Comparing the results of ANN and empirical formulas indicated higher ANN performance, so such formulas are better to be replaced with superior ANN model.

Keywords   Dam Breach, Peak Outflow Discharge, Neural Network, Training Algorithm

1. Introduction

Dam failure is a catastrophic phenomenon that can lead to large damages to human life and property. Overviewing of historical dam failures shows that overtopping and piping were the major causes of dam failures. Overtopping is mostly dangerous for embankment dams because it washes away or erodes very quickly the dam's materials. In Piping, water seeps under the dam and gradually erodes the dam materials. The extension of this phenomenon may lead to dam collapse. The various modes of breach formation in embankment dams, and the large number of factors that influence the outflow characteristics, are difficult to describe with rigorously precise mathematical formulas. Because of complexity and uncertainty resulting from the wide range of values of the effective parameters, it is worthwhile to reduce the mathematical complexity of the problem and to present simple methods to predict the outflow characteristics from breached embankment. Prediction of peak outflow is very important because of the emergency action plan preparation

and risk assessment. In some former investigations, case study data were used to develop empirical formula by relating peak outflow to the height of water behind the dam and/or volume of water behind the dam. Some investigators developed single-variable equations[13],[21],[36-38],[42], and some others presented multi-variable equations[10], [16],[30],[31],[44]. Hagen[17] introduced "dam factor" as the product of height of water and reservoir storage volume at the time of failure, and proposed a formula relating the peak-breach outflow to the dam factor. Some investigators applied the dam factor in their proposed equations[11],[25].

Although applying empirical equations based on statistical regression is simple in practice, they are unable to estimate the values of peak outflow accurately. It is felt that this is partly due to the complexity of the phenomenon involved and low accuracy of data driven from historical dam failures[14], and partly because of the limitation of the analytical tool commonly used by most of the earlier investigators namely, traditional statistical regression. Nowadays, traditional statistical analysis has been replaced by newly alternative approaches in many cases. Artificial neural networks (ANN) as an alternative approach have advantages over statistical models like their data-driven nature, model–free form of predictions, and tolerance to data errors[4]. ANN beside its simplicity and generalizing ability

* Corresponding author:
tshamsi@aut.ac.ir(Ahmad Tahershamsi)

has been used widely in hydraulic[3],[5],[7],[24],[40],[41], [45]. Most of the studies have been done by feed forward back propagation (BP) neural network. The standard back propagation algorithm (SBPA) as the training algorithm in BP has some problems including the low training convergence speed and easy entrapment in a local minimum [19]. During last decades, researchers have tried to overcome these problems and improve the ANN performance. Ramirez et al.[32] proposed the resilient back propagation (RP) training function for network training to predict the rainfall in Sao Paulo, Brazil. According to their findings, using RP could improve the results. Some other researchers proposed Levenberg–Marquardt algorithm (LMA). Noori et al.[28] evaluated different training functions on ANN operation for predicting the monthly stream flow and found that fletcher – reeves update (CGF) and scaled conjugate gradient (SCG) models had the best performance in wet and arid periods, respectively. Chau[9] used particle swarm optimization to optimize the network weights and biases for predicting water level in Shing Mun River. He compared the results with the SBPA results and showed the superiority of his model. Rogers et al.[33] proposed genetic algorithm (GA) instead of SBPA.

Accordingly, the objective of this study is to compile previously presented case study data on peak outflow discharge from breached embankments, and reanalyze the resulting database using the technique of neural networks with a view towards seeing if better predictions are possible. Hereby, different training functions consisted of RP, CGF, SCG, and LMA are examined. Besides, a new evolutionary algorithm, imperialist competitive algorithm (ICA), proposed by Atashpaz-Gargari and Lucas[1] is used to optimize the network weights and biases. Finally, the results are compared to result of empirical formulas.

2. Material and Methods

2.1. Data Collection And Empirical Formulas

Valuable documented information is available from historical embankment failures. Babb and Mermel[6] summarized over 600 dam incidents throughout the world; however, high quality and detailed information was lacking in most cases. Here the data from 93 embankment dam failures (Table 1) are collected from variety of sources[15], [16],[30],[35],[39],[43],[44]. During the decades, several researchers compiled some data of well-documented case studies in efforts to develop predictive relations for breach peak outflows. Among them, Kirkpatrick[21] proposed a formula based on analysis of data from 13 failed embankment dams and 6 hypothetical failures:

$$Q_p = 1.268\left(H_w + 0.3\right)^{2.5} \tag{1}$$

where Q_p= peak outflow (m^3/s); and H_w = height of the water behind the dam at failure (m). USBR[42] developed an equation using case study data from 21 failed dams including several concrete arch and gravity dams:

$$Q_p = 19.1\left(H_w\right)^{1.85} \tag{2}$$

Table 1.   Data collected from historical dam failures

No.	Dam name	Location	V_w	H_w	Q_p	Reference
1	Apishapa	United States	22.2	28	6850	[44]
2	Armando de Salles Oliveira	Brazil	25.9	35	7195	[39]
3	Baldwin Hills, Calif.	United States	0.91	12.2	1130	[16]
4	Banqiao	China	607.5	31	78100	[44]
5	Bayi	China	23	28	5000	[44]
6	Big Bay	United States	17.5	13.59	4160	[30]
7	Boystown	United states	0.358	8.96	65.13	[30]
8	Bradfield	England	3.2	28.96	1150	[35]
9	Break Neck Run	United States	0.049	7	9.2	[39]
10	Buffalo Creek	United States	0.48	14.02	1420	[35]
11	Butler	United States	2.38	7.16	810	[43]
12	Caney Coon Creek	United States	1.32	4.57	16.99	[30]
13	Castlewood	United States	6.17	21.6	3570	[44]
14	Chenying	China	5	12	1200	[44]
15	Cherokee Sandy	United States	0.444	5.18	8.5	[30]
16	Colonial #4	United States	0.0382	9.91	14.16	[30]
17	Dam Site #8	United States	0.87	4.57	48.99	[30]
18	Danghe	China	10.7	24.5	2500	[44]
19	Davis Reservior	United States	58	11.58	510	[44]
20	Dells	United States	13	18.3	5440	[44]
21	DMAD	United States	19.7	8.8	793	[30]
22	Dongchuankou	China	27	31	21000	[44]
23	Eigiau	England	4.52	10.5	400	[35]
24	Elk City	United States	1.18	9.44	608.79	[39]
25	Frankfurt	Germany	0.352	8.23	79	[44]
26	Fred Burr	United States	0.75	10.2	654	[43]
27	French Landing	United States	3.87	8.53	929	[44]
28	Frenchman Dam	United States	16	10.8	1420	[44]

29	Frias	Argentina	0.25	15	400	[44]
30	Goose Creek	United States	10.6	1.37	492.7	[39]
31	Gouhou	China	3.18	44	2050	[44]
32	Grand Rapids	United States	0.255	7.5	7.5	[35]
33	Hatchtown	United States	14.8	16.8	3080	[16]
34	Hatfield	United States	12.3	6.8	3400	[44]
35	Haymaker	United States	0.37	4.88	26.9	[30]
36	Hell Hole	United States	30.6	35.1	7360	[44]
37	Hemet	United States	8.63	6.09	1600	[39]
38	Horse Creek	United States	12.8	7.01	3890	[44]
39	Horse Creek #2	United States	4.8	12.5	311.49	[30]
40	Huqitang	China	0.424	5.1	50	[44]
41	Ireland No. 5	United States	0.16	3.81	110	[16]
42	Johnstown	United States	18.9	22.25	7079.2	[43]
43	Kelly Barnes	United States	0.777	11.3	680	[44]
44	Knife Lake	United States	9.86	6.096	1098.66	[39]
45	Kodaganar	India	12.3	11.5	1280	[44]
46	lake Avalon	United States	31.5	13.7	2321.9	[39]
47	Lake Latonka	United States	4.09	6.25	290	[44]
48	Lake Tanglewood	United States	4.85	16.76	1351	[30]
49	Laurel Run	United States	0.555	14.1	1050	[16]
50	Lawn Lake	United States	0.798	6.71	510	[43]
51	Lijiaju	China	1.14	25	2950	[44]
52	Lily Lake	United States	0.0925	3.35	71	[16]
53	Little Deer Creek	United States	1.36	22.9	1330	[44]
54	Little Wewoka	United States	0.987	9.45	42.48	[30]
55	Liujiatai	China	40.54	35.9	28000	[44]
56	Lower Latham	United States	7.08	5.79	340	[16]
57	Lower Reservoir	United States	0.604	9.6	157.44	[30]
58	Lower Two Medicine	United States	19.6	11.3	1800	[44]
59	Mahe	China	23.4	19.5	4950	[44]
60	Mammoth	United States	13.6	21.3	2520	[44]
61	Martin Cooling Pond Dike	United States	136	8.53	3115	[44]
62	Middle Clear Boggy	United States	0.444	4.57	36.81	[30]
63	Mill River	United States	2.5	13.1	1645	[43]
64	Murnion	United States	0.321	4.27	17.5	[30]
65	Nanaksagar Dam	India	210	15.85	9709.5	[39]
66	North Branch	United States	0.022	5.49	29.5	[43]
67	Oros	Brazil	660	35.8	9630	[44]
68	Otto Run	United States	0.0074	5.79	60	[35]
69	Owl Creek	United States	0.12	4.88	31.15	[30]
70	Peter Green	United States	0.0197	3.96	4.42	[30]
71	Prospect	United States	3.54	1.68	116	[44]
72	Puddingstone Dam	United States	0.617	15.2	480	[16]
73	Qielinggou	China	0.7	18	2000	[44]
74	Quail Creek	United States	30.8	16.7	3110	[44]
75	Salles Oliveira	Brazil	71.5	38.4	7200	[35]
76	Sandy Run	United States	0.0568	8.53	435	[35]
77	Schaeffer Reservoir	United States	4.44	30.5	4500	[44]
78	Shimantan	China	117	27.4	30000	[44]
79	Site Y-30–95	United States	0.142	7.47	144.42	[30]
80	Site Y-36–25	United States	0.0357	9.75	2.12	[30]
81	Site Y-31 A–5	United States	0.386	9.45	36.98	[30]
82	Sinker Creek	United States	3.33	21.34	926	[39]
83	South Fork	United States	18.9	24.6	8500	[16]
84	South Fork Tributary	United States	0.0037	1.83	122	[30]
85	Stevens Dam	United States	0.0789	4.27	5.92	[30]
86	Swift	United States	37	47.85	24947	[44]
87	Taum Sauk Reservoir	United States	5.39	31.46	7743	[30]
88	Teton	United States	310	77.4	65120	[44]
89	Upper Clear Boggy	United States	0.863	6.1	70.79	[30]
90	Upper Red Rock	United States	0.247	4.57	8.5	[30]
91	Weatland Number	United States	11.6	12.2	566.34	[30]
92	Zhugou	China	18.43	23.5	11200	[44]
93	Zuocun	China	40	35	23600	[44]

Singh and Snorrason[37] used some simulated dam failures and presented Eq. (3):

$$Q_p = 1.776(S)^{0.47} \tag{3}$$

where S= reservoir storage at normal pool (m^3). To evaluate the applicability of peak outflow relationships as a function of reservoir volume, Evans[13] examined several man-made and natural dam failures and proposed a relationship described as below equation:

$$Q_p = 0.72(V_w)^{0.53} \tag{4}$$

in which V_w= volume of the water behind the dam at failure (m^3). MacDonald and Langridge-Monopolis[25] collected and analyzed data on a number of historical dam failures and developed graphical relationships for predicting breach characteristics for erosion type breaches. They also developed a relationship based on dam factor to estimate the peak outflows from dam failures:

$$Q_p = 1.154(H_w V_w)^{0.412} \tag{5}$$

where $H_w V_w$= dam factor (m^4). Using dam factor, Costa[11] analyzed 31 dam failures and presented a relationship based on regression analysis of the case studies:

$$Q_p = 0.763(H_w V_w)^{0.42} \tag{6}$$

Froehlich[16] assembled data from 22 embankment dam failures from various sources. The data were used to evaluate and compare several empirical equations as well as to obtain a new empirical expression for rapidly estimation of peak outflow from a breached embankment. The formula was derived based on multiple regression analysis:

$$Q_p = 0.607\left(H_w^{1.24} V_w^{0.295}\right) \tag{7}$$

Pierce et al.[30] compiled a database of 87 embankment failures including experimental data and performed a statistical analysis using multiple regression technique to predict peak outflow discharge as a function of the height and volume of water behind the dam:

$$Q_p = 0.038\left(H_w^{1.09} V_w^{0.475}\right) \tag{8}$$

2.2. Neural Network Models

An ANN is a 'black box' approach which has great capacity in predictive modeling[22]. It is a proper mathematical structure having an inter-connected assembly of simple processing elements or nodes. A typical network would consist of three layers of neurons namely, input, hidden, and output; in which each neuron acting as an independent computational element. Neural networks are universal approximators[20], and many theoretical and experimental works have shown that a single hidden layer is sufficient for ANNs to approximate any complex nonlinear function[12],[27],[29]. Accordingly, in this study single hidden layer ANNs were used. The tangent-sigmoid and linear functions were chosen as the activation function respectively in the hidden and output layers, and mean square error (MSE) was utilized as performance function. To check the over-fitting problem in the calibration and testing steps, stop training algorithm method was used.

There are different training functions to optimize the network weights and biases in the case of BP algorithm. They can be divided into two different categories; the first one uses heuristic techniques, while the second one uses standard numerical optimization techniques. On the other hand, some other algorithms are available which use evolutionary optimization techniques (e.g. ICA) for training the network. Some details of ICA are available in the literatures[1,2]. The quick review of the above algorithms is as follow:

Heuristic techniques

Heuristic techniques were developed from an analysis of the performance of the standard steepest descent algorithm. Gradient descent, gradient descent with momentum, gradient descent which has variable learning rate, gradient descent with momentum which has variable learning rate and RP are the most famous training functions which use heuristic techniques to update the network parameters. Because of using sigmoid transfer function in the hidden layer of multi-layer ANN with BP algorithm, the performance of the above training functions except RP can be affected[28]. So, in this research just RP is evaluated among the heuristic techniques.

Standard numerical optimization techniques

The SBPA adjusts the weights in the steepest descent direction (negative of the gradient) which the performance function is decreasing most rapidly. Although it decreases most rapidly along the negative of the gradient, this does not necessarily produce the fastest convergence. Conjugate gradient algorithms (CGA) are one of the fastest optimization techniques. In the CGAs for faster convergence than steepest descent directions a search is performed along conjugate directions. All the CGAs start out by searching in the steepest descent direction on the first iteration[28]. Discussion of CGAs and their application in neural networks are available in Hagan and Demuth[18]. The CGAs require that a line search be performed. Charalambous method, which was worked out in the present research, is a hybrid search which was designed to be used in combination with a CGA for neural network training. It uses a cubic interpolation together with a type of sectioning[8]. Various algorithms for CGA are available, e.g. CGF, SCG, Polak – Ribiere updates (CGP), and Powell–Beale restarts (CGB). Comparison of these algorithms on ANN operation for predicting the monthly stream flow has been done by Noori et al.[28]. Results indicated that the CGF and SCG were the best algorithms with superior performance, so they are employed in the present study.

LMA developed by Levenberg[23] and Marquardt[26] is another type of standard numerical optimization techniques. LMA provides a numerical solution to the problem of minimizing a nonlinear function over a space of parameters of the function. These minimization problems arise especially in least squares curve fitting and nonlinear programming. LMA interpolates between the Gauss – Newton algorithm (GNA) and the method of gradient descent. LMA is more robust than GNA, which means that in

many cases it finds a solution even if it starts very far off the final minimum. LMA is a very popular curve-fitting algorithm used in many software applications for solving generic curve-fitting problems; however, it finds only a local minimum, not a global minimum.

Imperialist competitive algorithm

ICA is a new evolutionary algorithm in the evolutionary computation field based on the human's socio-political evolution. The algorithm starts with an initial random population called countries. Some of the best countries in the population be selected as the imperialists and the rest form the colonies of these imperialists. In an N dimensional optimization problem, a country is a $1 \times N$ array. This array is defined as below:

$$country = [p_1, ..., p_N] \qquad (9)$$

The cost of each country is found by evaluating the cost function f at the variables $(p_1, p_2, ..., p_n)$. Then

$$c_i = f(country_i) = f(p_{i1}, ..., p_{iN}) \qquad (10)$$

The algorithm starts with N initial countries and the N_{imp} best of them (countries with minimum cost) chosen as the imperialists. The remained countries are colonies that each of them belongs to an empire. The initial colonies belong to imperialists in convenience with their powers. To distribute the colonies among imperialists proportionally, the normalized cost of an imperialist is defined as follow:

$$C_n = \max_i c_i - c_n \qquad (11)$$

where, c_n is the cost of nth imperialist and C_n is its normalized cost. Each imperialist that has more cost value, will have less normalized cost value. The power of each imperialist is calculated as below and based on that the colonies distributed among the imperialist countries:

$$p_n = \left| \frac{c_n}{\sum_{i=1}^{N_{imp}} c_i} \right| \qquad (12)$$

On the other hand, the normalized power of an imperialist is assessed by its colonies. Then, the initial number of colonies of an empire will be:

$$NC_n = rand\{p_n.(N_{col})\} \qquad (13)$$

where, NC_n is initial number of colonies of nth empire and N_{col} is the number of all colonies. To distribute the colonies among imperialist, NC_n of the colonies are selected randomly and assigned to their imperialist. The imperialist countries absorb the colonies towards themselves using the absorption policy. The absorption policy shown in Fig. 1, makes the main core of this algorithm and causes the countries move towards to their minimum optima.

The imperialists absorb these colonies towards themselves with respect to their power that described in Eq. (14). The total power of each imperialist is determined by the power of its both parts, the empire power plus percents of its average colonies power.
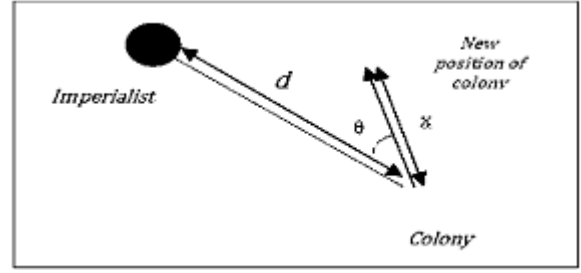

Figure 1. Moving colonies toward their imperialist

$$TC_n = cost(imperialist_n) + \\ \xi mean\left\{cost\left(colonies \ \ of \ \ empire_n\right)\right\} \qquad (14)$$

where TC_n is the total cost of the nth empire and ξ is a positive number which is considered to be less than one. In the absorption policy, the colony moves towards the imperialist by x unit. The direction of movement is the vector from colony to imperialist, as shown in Fig. 1. In this figure, the distance between the imperialist and colony shown by d and x is a random variable with uniform distribution.

$$x \sim U(0, \beta \times d) \qquad (15)$$

where β is greater than 1 and is near to 2. So, in this investigation the proper choice is $\beta = 2$.

In ICA, to search different points around the imperialist, a random amount of deviation is added to the direction of colony movement towards the imperialist. In Fig. 1, this deflection angle is shown as θ, which is chosen randomly and with a uniform distribution. While moving toward the imperialist countries, a colony may reach to a better position, so the colony position changes according to position of the imperialist.

$$\theta \sim U(-\gamma, \gamma) \qquad (16)$$

In our implementation γ is π/4 (Rad).

In this algorithm, the imperialistic competition has an important role. During the imperialistic competition, the weak empires will lose their power and their colonies. To model this competition, firstly we calculate the probability of possessing all the colonies by each empire considering the total cost of empire.

$$NTC_n = \max_i\{TC_i\} - TC_n \qquad (17)$$

where NTC_n is the normalized total cost of nth empire. The possession probability of each empire is calculated as below:

$$p_{p_n} = \left| \frac{NTC_n}{\sum_{i=1}^{N_{imp}} NTC_i} \right| \qquad (18)$$

After a while, all the empires except the most powerful one will collapse and all the colonies will be under the control of this unique empire. ICA had a great performance in both convergence rate and better global optima achievement[2,34]. In the present research, this algorithm is also employed in ANN modeling as a training algorithm to determine the network's parameters.

3. Results and Discussion

To evaluate different models, a database containing of 93 field and experimental dataset was used (Table 1). Out of the total input–output pairs, 85% were used for calibration (training and validation) and the remaining 15% were saved for testing. Since it was needed that the testing data be used for evaluating the empirical formulas, these data were chosen randomly from the category which had not been used in derivation of those formulas. Among the Eqs. 1 to 8, some take H_w as the independent variable (Eqs. 1 and 2), some take V_w as the independent variable (Eqs. 3 and 4), some take the dam factor as the independent variable (Eqs. 5 and 6), and the others take both of H_w and V_w as the independent variables (Eqs. 7 and 8). Accordingly, four scenarios were defined here and four sets of ANNs were developed in which the input variables were different. Furthermore, in order to evaluate the various training algorithms in each scenario, RP, CGF, SCG, LMA, and ICA were examined. So, totally 20 models were developed and compared to each other. To evaluate and compare the results, three statistical measures were utilized namely, coefficient of determination (R2); mean absolute error (MAE); and root mean square error (RMSE). For confidently evaluating the results, each modeling procedure, including calibration and testing steps, was iterated 50 times and the average values of the statistical measures were calculated. Therefore the expected values of the statistical measures were presented in this research.

3.1. First scenario's Results (Considering H_w as the Input Variable)

In the first scenario it was assumed that peak outflow discharge (Q_p) just relates to H_w. Table 2 shows the quantitative results of the ANN models as well as the empirical formulas. According to the results, all ANN models have moderate R^2 value and high error. The RMSE for LMA is 14405 in testing step, which shows a high error. The error measures values in Table 2 show a different performance in training and testing steps e.g. the MAE values in testing steps are almost 3 times more than training step's values. This ratio for RMSE values is almost equal to 2. Such results may be due to the below reasons:

1. The H_w parameter can't be sufficient for a model to predict the peak outflow discharge, lonely. In other words, some other parameters are important in peak discharge prediction and consequently the models developed based on just H_w has low efficiency.

2. The datasets are insufficient, so lower training may be happened; however, lack of datasets is a general problem in ANN application. It is clear that the more data available, the more accuracy in ANN modeling.

3. The method of data derivation in the field or laboratory has been inaccurate, and consequently some inaccurate data in the database may have been led to such error. Scale effects in experimental researches as well as estimation of peak outflow discharge from water-mark and stage-discharge

curves in the field may be the main sources of error in recording the data.

Fig. 2 presents the schematic performance of ANN model with ICA training function as the best model compared with observed values for both calibration and testing steps. As most of the values of peak outflow in training and testing step aren't estimated correctly, the model performance isn't satisfactory. Besides, as can be seen in Table 2, the Kirkpatrick and USBR formulas have a weak performance. The coefficient of determination for Kirkpatrick formula is very low (near 0.76) and its RMSE is 11732 which shows very high error. The situation is a little better for USBR formula but it is not satisfactory too because of low R^2 (=0.74) and high error (RMSE =10656).

Table 2.   Results of ANN model for the first scenario

Training function /Formula			Statistical indices		
			R^2	MAE	RMSE
FFBP	RP	train	0.84	2973	8839
		test	0.74	7211	15942
	CGF	train	0.68	3849	8387
		test	0.63	8243	15026
	SCG	train	0.69	3351	8141
		test	0.66	8134	14099
	LMA	train	0.60	2991	8175
		test	0.65	7803	14405
ICA		train	0.72	3618	8388
		test	0.80	5704	9346
Kirkpatrick		test	0.76	6590	11732
USBR		test	0.74	6547	10656

Table 3.   Results of ANN model for the second scenario

Training function/ Formula			Statistical indices		
			R^2	MAE	RMSE
FFBP	RP	train	0.76	2729	5004
		test	0.84	6236	14740
	CGF	train	0.91	2189	4284
		test	0.82	5420	11251
	SCG	train	0.92	2224	4456
		test	0.80	3718	6737
	LMA	train	0.89	2181	4273
		test	0.82	5737	12313
ICA		train	0.75	3857	7290
		test	0.90	5001	10676
Singh and Snorrason		test	0.78	6705	13595
Evans		test	0.79	6381	11977

Schematic comparison between ANN model and empirical formulas is available in Fig. 3. This figure indicates that most of the points are scattered and the predicted values are underestimated or overestimated. This figure confirmed that H_w can't be sufficient for effective prediction of Q_p from breached embankments.

3.2. Second Scenario's Results (Considering V_w as the Input Variable)

In the second scenario the same database was used for training and testing steps, but the simulation was done with V_w instead of H_w as the input variable. The quantitative results are presented in Table 3. The coefficient of determination of each ANN model is good in both steps but the error measures are relatively high. Among the models RP has the highest RMSE value in the testing step and SCG has the lowest one. In this scenario although ICA has a good R^2 value in testing step, it can't be effective because of different R^2 values in training and testing steps as well as high RMSE value.

According to Table 3, it can be inferred that SCG has the best performance. The R^2 values of Singh and Snorrason and Evans formulas respectively are 0.78 and 0.79, which means moderate performance compared to SCG. Fig. 4 shows the performance of ANN model compared to observed values. Although the results are some better than the first scenario, there are some points that aren't predicted satisfactorily. Fig. 5 shows the ANN performance compared to empirical formulas. It is obvious that all the models underestimate the observed values especially extreme values. However the situation for SCG is much better, but not satisfactory.
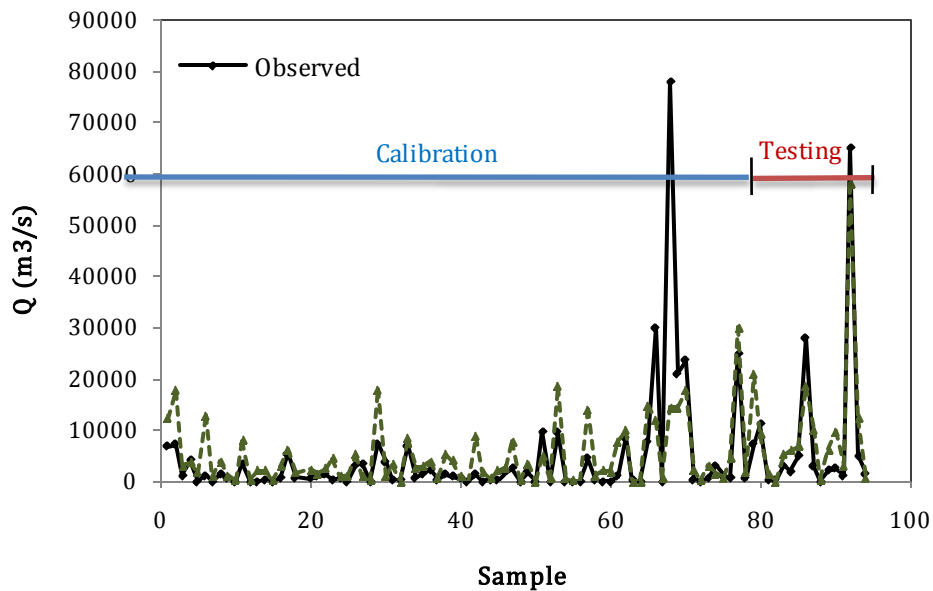

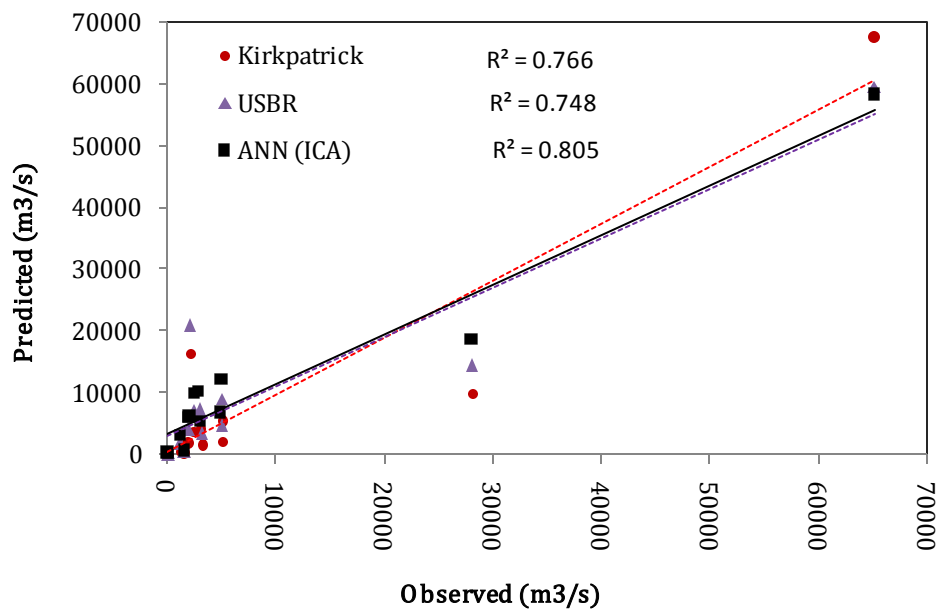**Figure 2.**   Results of the best ANN model (ICA) in the first scenario

Figure 3.   Comparing the ANN results (ICA model) with empirical formulas results in the first scenario
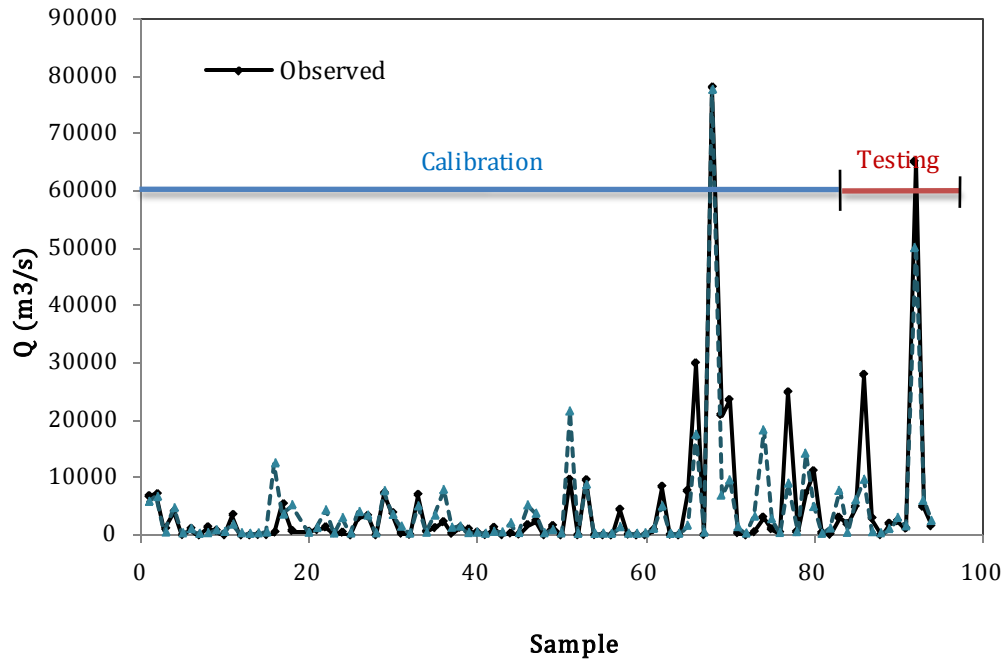
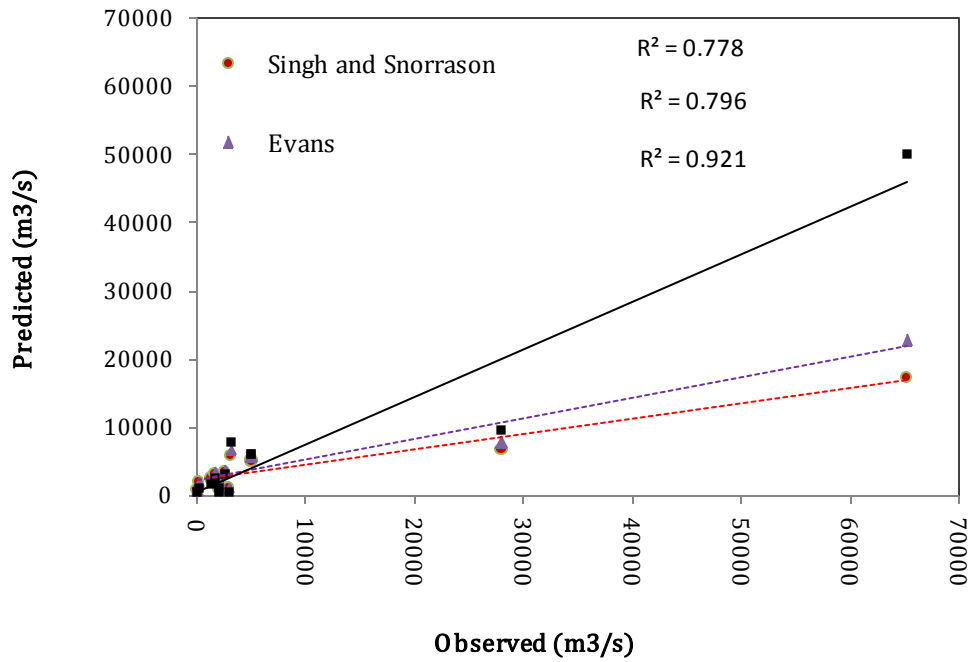**Figure 4.**   Results of the best ANN model (SCG) in the second scenario

Figure 5.   Comparing the ANN results (SCG model) with empirical formulas results in the second scenario

By comparing Tables 2 and 3, it is found that R^2 and error values for different models in the second scenario are more satisfactory. Therefore the models based on V_w parameter may lead to more reliable results due to extensive range of V_w parameter in dam breach database (3700 - 600 $\times 10^6$ m³).

3.3. Third Scenario'S Results (Considering Dam Factor as the Input Variable)

In the third scenario, dam factor was employed in ANN modeling. Results of the best ANN model is presented in Fig. 6. It is observed that the predicted values are not so good. In some points the prediction values are about two times over than the observed values. The quantitive results are prepared in Table 4. In this scenario ICA has high R^2 value and low RMSE in testing, so the ICA can be a good model but not exactly an effective model due to difference between the model performance in training and testing steps. Fig. 6 shows the results of ICA in calibration and testing steps.
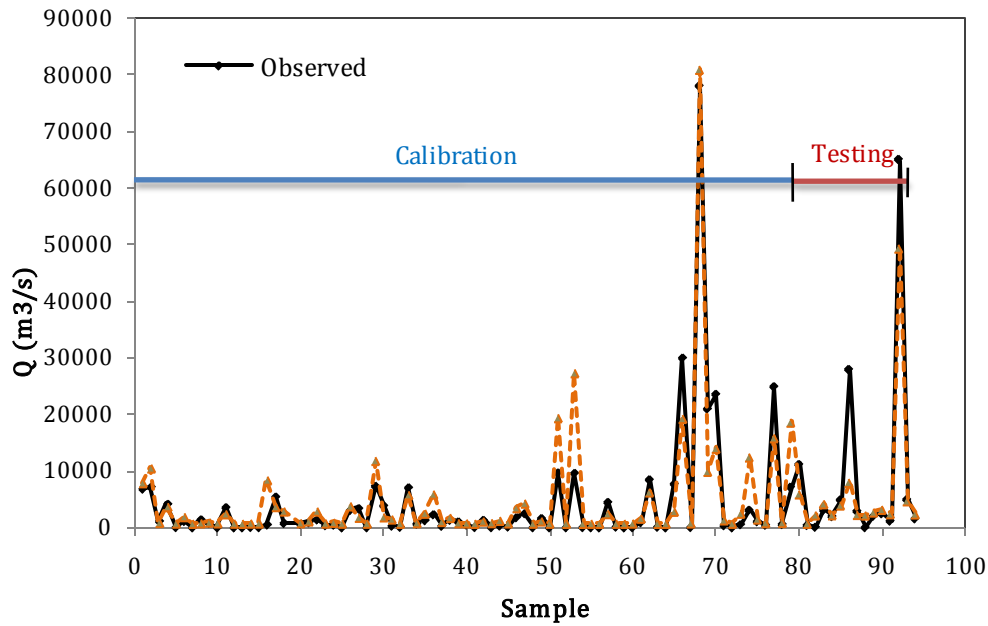
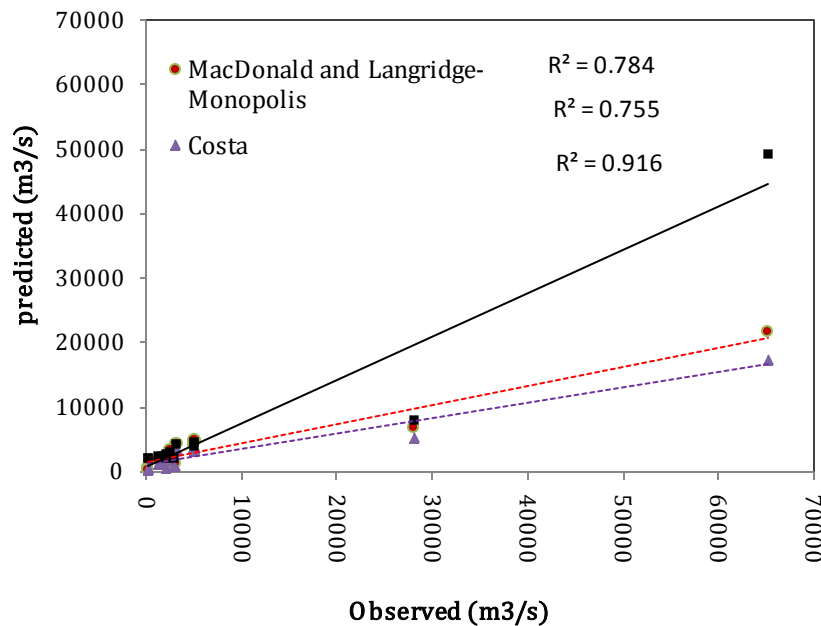**Figure 6.** Results of ANN model (ICA) in the third scenario

Figure 7. Comparing the ANN results (ICA model) with empirical formulas results in the third scenario

Table 4 is also consisted of quantitative results of two empirical formulas which use dam factor for peak outflow estimation. The coefficient of determination for these formulas is almost good, but their prediction error is very high (RMSE ≈ 14000). Therefore, practical using of such empirical formulas may lead to high error and undesirable effects. The effects may be irrecoverable because of their underestimation especially for large dams (Fig. 7). Comparing Table 2, 3, and 4 indicates that the models in the third scenario have better performance than the models in the first and second scenario.

3.4. Fourth Scenario's Results (Considering H_w and V_w as the Input Variables)

In the last scenario both variables (H_w and V_w) are independently used in the ANN modelling. The quantitive results are presented in Table 5. As the results show, all the ANN models could predict peak outflow values very well because of high coefficient of determinations ($R^2 > 0.80$). Comparing the results indicates that MAE and RMSE values of ICA model are lower and its R^2 value is higher than the other models' in both training and testing steps.

Fig. 8 shows ANN model performance in calibration and testing steps separately. It is clear that the model have a good so that most of the predictions are approximately coincided with their corresponding observed values. As it is illustrated in Fig. 8, there are approximately 5 points in the testing step and one point in the testing step which aren't predicted satisfactorily. Like to the previous scenarios, most of the badly predicted points are corresponding to extreme values (large dams). Accordingly, one can strongly conclude that insufficient data or lack of historical data of large breached embankments is the main reason of lower training of the network.

Table 4.   Results of ANN model for the third scenario

Training function/ Formula			Statistical indices		
			R^2	MAE	RMSE
FFBP	RP	train	0.84	2135	4086
		test	0.95	5214	12670
	CGF	train	0.88	1946	3826
		test	0.92	5348	12931
	SCG	train	0.87	1964	3707
		test	0.81	5896	14906
	LMA	train	0.86	2563	5422
		test	0.90	5287	11880
ICA		train	0.85	3538	6797
		test	0.91	3581	7122
MacDonald and Langridge-Monopolis		test	0.78	6484	14245
Costa		test	0.75	6781	15271

The information on number of nodes, number of epochs required to achieve the error goal, and the CPU time taken in the case of each training scheme has been presented in Table 6. It is remarkable that the information is the average result of 50 iterations for each model. A PC having a Pentium IV processor (CPU: Core i5, 2.53 GHz), was utilized in this study. As a matter of general information, it can be seen that ICA trains the network with fewer epochs compared to the other BP algorithms, but in a higher amount of time. LMA trains the network in a more number of epochs but in a fraction of the time compared with ICA. The other BP algorithms also had similar performance as LMA, which indicates their acceptable training efficiency. the results of Froehlich and Pierce formulas are presented in Table 5.

These formulas have relatively weak performance due to low R^2 value and high errors.

Table 5.   Results of ANN model for the fourth scenario

Training function		Statistical indices		
		R^2	MAE	RMSE
FFBP	RP train	0.89	2248	4861
	RP test	0.80	3650	6900
	CGF train	0.89	2212	4979
	CGF test	0.81	3632	6568
	SCG train	0.88	1733	3456
	SCG test	0.88	6352	1320
	LMA train	0.89	1756	3276
	LMA test	0.89	4449	7331
ICA	train	0.88	1838	3497
	test	0.96	2032	3839
Froehlich	test	0.63	4473	9974
Pierce et al.	test	0.72	3938	8236

Table 6.   Network architecture in the fourth scenario

		Algorithms				
		RP	CGF	SCG	LMA	ICA
node	Input	2	2	2	2	2
	Hidden layer	4	3	3	4	3
	output	1	1	1	1	1
Epoch No.		254	175	209	215	70
CPU time (sec)		3	1	1	2	53

Schematic comparison of ANN model with empirical formulas is available in Fig. 9. It is seen that empirical formulas underestimate the observed values, but ANN model doesn't have such problem. Comparing Table 5 with Tables 2-4 shows that fourth scenario is more realistic and reliable than other scenarios due to its better results. Thus, it can be concluded that ANN with ICA as the training function and both H_w and V_w as the inputs is the most effective and efficient model. Furthermore, according to the obtained results from all scenarios, it may be concluded that the effect of various parameters (i.e. height and volume of water behind the dam) on the amount of peak outflow discharge is approximately the same.
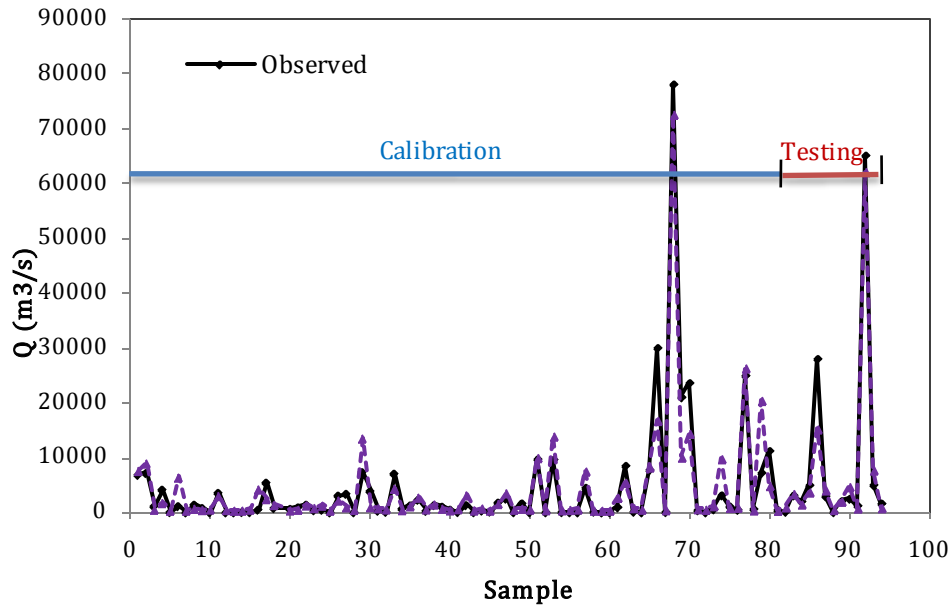
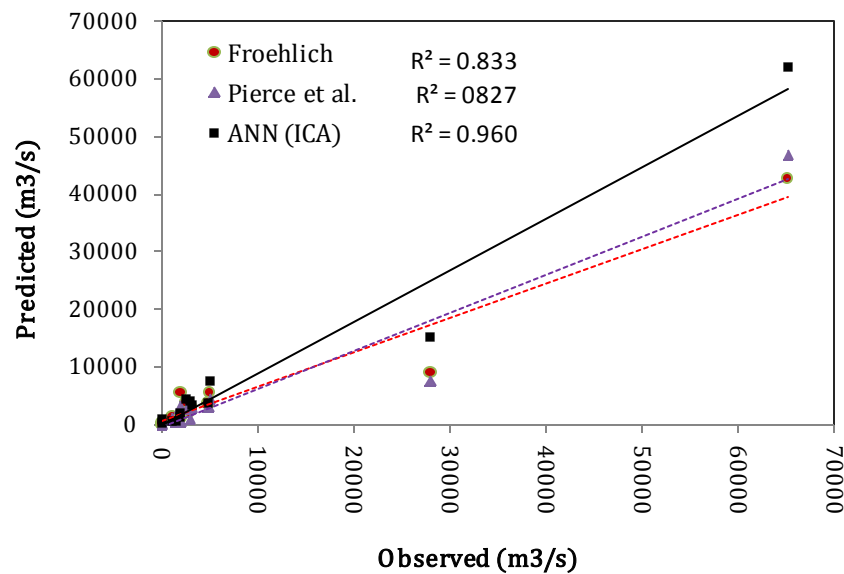**Figure 8.**   Results of the best ANN model (ICA) in the fourth scenario

Figure 9.   Comparing the ANN results (ICA model) with empirical formulas results in the fourth scenario

4. Conclusions

This investigation focused on evaluating the ANN performance for predicting peak outflow from breached embankment dams. In order to find an effective model, four scenarios were defined. In scenarios I and II, it was assumed that Q_p related respectively to H_w and V_w. In scenario III it was assumed that Q_p related to the dam factor, and in scenario IV it was assumed that Q_p related to the both H_w and V_w. Also to train the network, two training algorithms were employed: ICA and BP. ICA is a new evolutionary algorithm, in the evolutionary computation field, and BP algorithm is a common method of teaching ANNs called multi-stage dynamic system optimization method. By considering the statistic indices as well as CPU time taken, ICA was

recognized as the best training algorithm in most of the scenarios. However, ICA takes a little more CPU time taken in comparison with the other algorithms. Also among the different scenarios, scenario IV was the best. In the scenarios I to III all ANN models underestimate the real extreme values, because the values related to large dam cases (i.e. $H_w>15$ m and/or $V_w>50$ mcm) are limited, so ANNs have not effectively been calibrated around the extreme values. Accordingly, enlarging the database by adding the values of new breached large dam cases or generating the synthetic extreme data may be effective. Moreover, results showed that the effect of H_w and V_w on the amount of peak outflow discharge was the same. This investigation indicated that although empirical formulas were simply applicable in practice, they lead to unsatisfactory results due to low R^2 value and high error in their estimation especially for large

breached dams. This is because of limited databases which were used in the formulas derivation as well as the low flexibility of the traditional method of regression analysis to data variation.

REFERENCES

[1]   E. Atashpaz-Gargari, and C. Lucas, "Imperialist competitive algorithm: An algorithm for optimization inspired by imperialistic competition", IEEE Congress on Evolutionary Computation, pp. 4661–4667, 2007.

[2]   E. Atashpaz-Gargari, F. Hashemzadeh, R. Rajabioun, and C. Lucas, "Colonial competitive algorithm, a novel approach for PID controller design in MIMO distillation column process", International Journal of Intelligent Computing and Cybernetics, vol.1, no.3, pp. 337–355, 2008.

[3]   F. Avarideh, M.A. Banyhabib, and A. Taher-shamsi, "Application of artificial neural networks in river Sediment estimation", 3th Iran Hydraulic Conference, Kerman, Iran, pp. 269-275, 2001.

[4]   H.Md. Azmatullah, M.C. Deo, and P.B. Deolalikar, "Neural networks for estimation of scour downstream of a ski-jump bucket", J. Hydraul. Eng., vol.131, no.10, pp. 898–908, 2005.

[5]   H.Md. Azamathulla, and A. Ghani, "ANFIS-based approach for Predicting the scour depth at culvert outlets", Journal of Pipeline Systems Engineering and Practice, vol.2, no.1, pp. 35-40, 2011.

[6]   A.O. Babb, and T.W. Mermel, "Catalog of Dam Disaster, Failures and Accidents", Bureau of Reclamation, Washington, Denver, Colo., 1968.

[7]   S.M. Bateni, and D.S. Jeng, "Estimation of pile group scour using adaptive neuro-fuzzy approach", Ocean Engineering, vol.34, no.8-9, pp. 1344–1354, 2006.

[8]   C. Charalambous, "Conjugate gradient algorithm for efficient training of artificial neural networks", IEEE Proceedings, vol.139, no.3, pp. 301–310, 1992.

[9]   K.W. Chau, "Particle swarm optimization training algorithm for ANNs in stage prediction of Shing Mun River", J. Hydrol., vol.329, no.3-4, pp. 363-367, 2006.

[10] S. Coleman, D. Andrews, and M.G. Webby, "Overtopping breaching of noncohesive homogeneous embankments", J. Hydraul. Eng., vol.128, no.9, pp. 829–838, 2002.

[11] J.E. Costa, "Floods from dam failures", U.S. Geological Survey, Denver, 54, Open-File Rep. No. 85-560, 1985.

[12] G. Cybenko, "Approximation by superposition of a sigmoidal function", Math. Cont. Sig. Syst., vol.2, no.4, pp. 303-314, 1989.

[13] S.G. Evans, "The maximum discharge of outburst floods caused by the breaching of man-made and natural dams", Can. Geotech. J., vol.23, no.4, pp. 385–387, 1986.

[14] D.L. Fread, "Some limitations of dam-break flood routing models", Preprint, American Society of Civil Engineers, Fall Convention, St. Louis, Mo., October, 1981.

[15] D.C. Froehlich, "Embankment dam breach parameters revisited", Water Resources Engineering, Proc. 1995 ASCE Conf. on Water Resources Engineering, New York, pp.887 – 891, 1995a.

[16] D.C. Froehlich, "Peak outflow from breached embankment dam", J. Water Resour. Plann. Manage., vol.121, no.1, pp. 90–97, 1995b.

[17] V.K. Hagen, "Re-evaluation of design floods and dam safety", Proc., 14th Congress of Int. Commission on Large Dams, Rio De Janeiro, Brazil, vol.1, pp.475-491, 1982.

[18] M.T. Hagan, and H. Demuth, "Neural Networks Design", Boston, MA: PWS Publishing, 11.1-12.52, 1996.

[19] S. Haykin, "Neural Networks: A Comprehensive Foundation ", 2nd Ed., Prentice-Hall, Upper Saddle River, N.J, 1994.

[20] K. Hornik, M. Stinchcombe, and H. White, "Multilayer feedforward networks are universal approximators", Neural networks, vol.2, no.5, pp. 359-366,1989.

[21] G.W. Kirkpatrick, "Evaluation guidelines for spillway adequacy", The evaluation of dam safety, Engineering Foundation Conf., ASCE, New York, pp.395–414, 1977.

[22] S. Lek, and J.F. Guegan, „Artificial neural networks as a tool in ecological modelling, an introduction", Ecol. Model., vol.120, no.2-3, pp.65-73,1999.

[23] K. Levenberg, "A method for the solution of certain non - linear problems in least squares", Quart. Appl. Math, vol.2, no.2, pp.164–168,1944.

[24] S.L. Liriano, and R.A. Day, "Prediction of scour depth at culvert outlets using neural networks", J. Hydroinformatics, vol.3, no.4, pp.231–238, 2001.

[25] T.C. MacDonald, and J. Langridge-Monopolis, "Breaching characteristics of dam failures", J. Hydraul. Eng., vol.110, no.5, pp.567–586, 1984.

[26] D.W. Marquardt, "An algorithm for least-squares estimation of nonlinear parameters", J. Soc. Ind. Appl. Math., vol.11, no.2, pp.431–441, 1963.

[27] R. Noori, M.A. Abdoli, A. Farokhnia, and M. Abbasi, "Results uncertainty of solid waste generation forecasting by hybrid of wavelet transform-ANFIS and wavelet transform - neural network", Expert Systems with Applications, Vol.36, pp.9991–9999, 2009.

[28] R. Noori, M.S. Sabahi, and A.R. Karbassi, "Evaluation of PCA and Gamma test techniques on ANN operation for weekly solid waste predicting", J. Environ. Manage., vol.91, no.3, pp.767-771,2010.

[29] R. Noori, A.R. Karbassi, H. Mehdizadeh, and M.S. Sabahi, "A framework development for predicting the longitudinal dispersion coefficient in natural streams using artificial neural network", Environ. Prog. Sustain. Energ., vol.30, no.3, pp.439-449,2011.

[30] M.W. Pierce, C.I. Thornton, and S.R. Abt, "Predicting peak outflow from breached embankment dams", J. Hydrol. Eng., vol.15, no.5, pp.338–349, 2010.

[31] M. Pilotti, M. Tomirotti, G. Valerio, and B. Bacchi, "Simplified method for the characterization of the hydrograph following a sudden partial dam break", J. Hydraul. Eng., vol.136, no.10, pp.693–704, 2010.

[32] M.C.V. Ramirez, N.J. Ferreira, and H.F. Velho, "Artificial neural network technique for rainfall forecasting applied to the Sa͂o Paulo region", J. Hydrol., vol.301, no.1-4, pp.146 – 162, 2005.

[33] L.L. Rogers, F.U. Dowla, and V.M. Johnson, "Optimal field-scale groundwater remediation using neural networks and the genetic algorithm", Environ. Sci. Techno., vol.29, no.5, pp.1145–1155,1995.

[34] H. Sepehri Rad, and C. Lucas, "Application of imperialistic competition algorithm in recommender systems", 13th Int. CSI Computer Conference (CSICC'08), Kish Island, Iran, 2008.

[35] V.P. Singh, and P.D. Scarlatos, "Analysis of gradual earth dam failure", J. Hydraul. Eng., vol.114, no.1, pp.21–42,1988.

[36] K.P. Singh, and A. Snorrason, "Sensitivity of outflow peaks and flood stages to the selection of dam breach parameters and simulation models", State Water Survey (SWS) Contract, Illinois Dept. of Energy and Natural Resources, SWS Div., Surface Water at the Univ. of Illinois, Rep. no.288,1982.

[37] K.P. Singh, and A. Snorrason, "Sensitivity of outflow peaks and flood stages to the selection of dam breach parameters and simulation models", J. Hydrol., vol.68, pp.295–310, 1984.

[38] Soil Conservation Service, "Simplified Dam-Breach Routing Procedure", Technical Release, No.66 (Rev.1), 39p, December 1981.

[39] A. Taher-shamsi, A. V. Shetty, and V. M. Ponce, "Embankment Dam Breaching: Geometry and Peak Outflow Characteristics", Dam Engineering, vol.14, no.2, pp.73-87, 2004.

[40] A. Taher-shamsi, M.B. Menhaj, and R. Ahmadian, "Sediment loads prediction using multilayer feedforward neural networks", Amirkabir Journal of Science and Technology, vol.16, no.63, pp.103-110, 2006.

[41] R. Trent, N. Gagarin, and J. Rhodes, "Estimating pier scour with artificial neural networks", Proc., Stream Stability and Scour at Highway Bridges, E. V. Richardson, ed., ASCE, Reston, Va., pp.171–171,1999.

[42] U.S. Bureau of Reclamation, "Guidelines for defining inundated areas downstream from bureau of reclamation dams", Reclamation Planning Instruction, no. 82-11,1982.

[43] T.L. Wahl, "Prediction of embankment dam breach parameters", A literature review and needs assessment, Bureau of Reclamation, U.S. Department of the Interior, Denver, 60, Rep. no. DSO-98-004, 1998.

[44] Y. Xu, and L.M. Zhang, "Breaching parameters for earth and rockfill dams", J. Geotech. Geoenviron. Eng., vol.135, no.12, pp.1957-1970,2009.

[45] M. Zounemat-Kermani, A. Beheshti, B. Ataie-Ashtiani, and S. Sabbagh-Yazdi, "Estimation of current-induced scour depth around pile groups using neural network and adaptive neuro-fuzzy inference system", Appl. Soft Comput., vol.9, no.2, pp.746–755,2009.