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REVIEW ARTICLE

An evaluation of existent methods for estimation of embankment dam breach parameters

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Abstract The study of dam-break analysis is considered important to predict the peak discharge during dam failure. This is essential to assess economic, social and environmental impacts downstream and to prepare the emergency response plan. Dam breach parameters such as breach width, breach height and breach formation time are the key variables to estimate the peak discharge during dam break. This study presents the evaluation of existing methods for estimation of dam breach parameters. Since all of these methods adopt regression analysis, uncertainty analysis of these methods becomes necessary to assess their performance. Uncertainty was performed using the data of more than 140 case studies of past recorded failures of dams, collected from different sources in the literature. The accuracy of the existing methods was tested, and the values of mean absolute relative error were found to be ranging from 0.39 to 1.05 for dam breach width estimation and from 0.6 to 0.8 for dam failure time estimation. In this study, artificial neural network (ANN) was recommended as an alternate method for estimation of dam breach parameters. The ANN method is proposed due to its accurate prediction when it was applied to similar other cases in water resources.

Keywords Embankment dam · Dam breach · Breach parameters · Uncertainty analysis

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1 Introduction

Dams are multipurpose structures that are constructed to improve human life. It is built for the production of hydroelectric power, economic improvement, providing water for irrigation and water supply and flood control (Hooshyaripor et al. 2014). Therefore, dams are essential element of infrastructure for any country (Wahl 2010; Razad et al. 2013). There are currently over 45,000 large dams being used throughout the world (DHI Water & Environment, 2009), and 800,000 dams have been constructed up to date (Zagonjolli 2007). Dams are usually classified under two different groups: earthen/rock and gravity. Figure 1 indicates the ratio of four dam types which are constructed in Europe and USA from 1900 to 1969. Most of the dams that are built during this period are earthfill and rockfill which is about 60% of the total number of dams. The second type is gravity dams that represent 25%, whereas the buttress and arch dams form the remaining 15%. Embankment (earthfill and rockfill) dams consist of compacted impermeable material (core) combined with coarse material (earth or rock) to return the water.

The huge water volume that is retained in the reservoir can cause a serious flood to the properties and population in the downstream area if a sudden release from the stored water occurs (Razad et al. 2013). Dam failures are very rare, but they do occur. When dams do fail, usually it contributes to the catastrophic consequences. This is often because local communities are not sufficiently prepared. The amount of life or property loss that can occur from a dam breach has increased to a larger number during the past few decades. This is because there has been a lot of development in these areas that would be affected if a dam breach occurs (DHI Water & Environment 2009). Janson (1980) summarized some well-known dam failures around the world. He found that about 2000 constructed dams were failed around the world since the twelfth century. There are approximately 200 dams that were failed during the last century which resulted in the death of more than 11,100 people. Johnstown dam in USA, Vajont dam in Italy and Machhu dam in India are the worst three dam failures which nearly caused 6800 of the deaths alone. Table 1 shows the examples of destructive dam failure throughout the world which collected from literature review.

Dam breach analysis is an important element in the dam failure assessment. There are many existing approaches for estimation of dam breach parameters. But most of these approaches included many uncertainties which affect the accuracy of their predictions. In

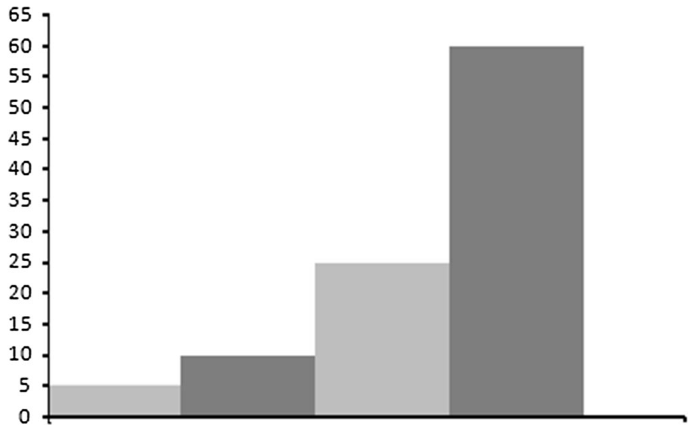

Fig. 1 Types of built dam present in Western Europe and USA

Table 1 Loss of life and property damage from notable dam failures

Dam name and location	Failure date	No. of live lost	Economic losses
Mohegan Park, Conn	1963	6	$3 million
Little Deer Greek, Utah	1963	1	Many summer cabins damaged
Baldwin Hills, Calif.	1963	5	1027 houses and 100 apartments destroyed and damaged
Swift, Mont.	1964	19	Unknown
Lower Two Medicine, Mont.	1964	9	Unknown
Lee Lake, Mass	1968	2	26 houses destroyed and damaged
One manufacturing plant destroyed or damaged			
Buffalo Creek, West Va.	1972	125	1084 houses destroyed or damaged
Lake "O" Hills, Ark.	1972	1	Unknown
Canyon Lake, South Dakota	1972	33*	Unable to separate the damage because the failure caused by natural flooding
Banqiao and Shimantan	1975	85,000	
Beer Wallow, North Carol.	1976	4	One house destroyed
Teton, Idaho	1976	11	1300 cattle died, and 80% of the city were destroyed (which resulted in over $2 billion in damages)
Laurel Run, Penn.	1977	39	25 houses destroyed and damaged
Sunday Run and 5 others, Penn.	1977	5	Unknown
Kelly Barnes, Georgia	1979	39	33 houses and trailers are damaged, and 7 college building destroyed and damaged
Swimming Pool, NY	1979	4	Unknown
About 20 dams in Conn.	1982	0	Unknown
Lawn Lake, Colo.	1982	3	18 bridges destroyed, 117 businesses damaged, 108 houses damaged, and campground, fisheries, power plant damaged
DMAD, Utah	1983	1	Unknown
Val di Stava, Italy	1985	268	Destroyed 63 buildings and demolished eight bridges
Kantale, Sri Lanka	1986	120–180	Destroyed over 1600 houses and 2000 acres of paddy, affecting over 8000 families
Meadow Pond, USA	1996	1	damaged some homes and many vehicles
Opuha, New Zealand	1997	0	Unknown
Shihgang, Taiwan	1999	–	Unknown
Zeyzoun, Syria	2002	22	Unknown
Hope Mills, USA	2003	0	$2.1 million
Big Bay, USA	2004	0	27 homes were destroyed, and 21 homes had major damage
Gusau, Nigeria	2006	40	500 homes were destroyed
Situ Gintung, Indonesia	2009	98	250 homes were damaged

Table 1 continued

Dam name and location	Failure date	No. of live lost	Economic losses
Kyzyl-Agash, Kazakhstan	2010	43	Unknown
Fujinuma, Japan	2011	8	Five homes were damaged, disabling a bridge and blocked roads
Köprü, Turkey	2012	10	Unknown
Tokwe Mukorsi, Zimbabwe	2014	0	Unknown
Bento Rodrigues, Brazil	2015	17	Unknown

* Lives that would not have been lost if the dam had not failed

this study, historical records of more than 140 failed dams around the world were used to assess the accuracy of these approaches and suggest a new approach in order to improve the accuracy of predicting dam breach parameters.

2 Causes of dam failure

Many researches have identified the reasons that have caused a dam failure. A survey of about 1620 failed dams was introduced by the Spanish publication in 1961 (Gruner 1963). About 308 dams which include 57% earth dams, 23% gravity dams, 3% arch dams and 17% of other types were failed during the period from 1799 to 1944. Biswas and Chatterjee (1971) investigated 300 failed dams around the world, and it was concluded that about 35% of these dams were failed by overtopping due to the insufficient capacity of the spillway, 25% by seepage and settlement and remaining 40% due to the results from different causes such as inaccurate design, poor maintenance and other reasons (Fig. 2).

Based on literature survey, causes of dam failure can be classified into three types: overtopping, seepage or piping and foundation problems. In the case of concrete dams, failure mainly occurred due to the foundation problems which formed about 53%, while the main sources of embankment dam failure are seepage or piping that represents 38%.

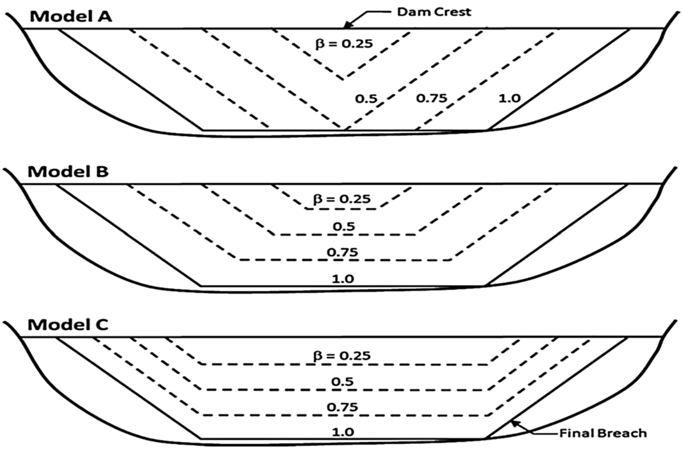

Fig. 2 Models of breach development (Froehlich 2008)

Table 2 Causes of dam failure during the period of 1975–2011

Causes of dam failure	Number of failure	Percentage (%)
Flood or overtopping	465	70.9
Piping or seepage	94	14.3
Structural	12	1.8
Human related	4	0.6
Animal activities	7	1.1
Spillway	11	1.7
Erosion/slide/instability	13	2.0
Unknown	32	4.9
Other	18	2.7
Total number of dam failures	656	100

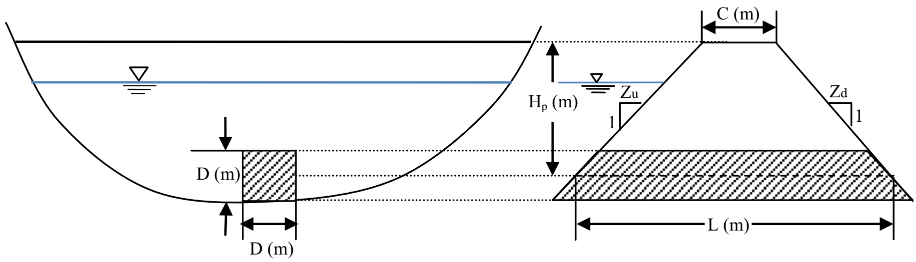

Fig. 3 Schematic of piping hole (State of Colorado Department of Natural Resources Division of Water Resources 2010)

Generally for all types of dam, about 34% of dam failures were caused by overtopping, 30% by foundation problems and about 28% by piping. The updated statistics of the causes of dams are given in Table 2.

The incidence of the causes of dam failures as a function of the dam's age during the time of failure is shown in Fig. 3. Foundation failure occurs early in the dam's history, whereas other causes take a relatively longer time to develop. A very large percentage of all dam failures occurs during the initial filling since this is the time when the design or construction flaws or latent site defects will appear.

3 Breach mechanisms for embankment dams

The breach is the opening which develops during the occurrence of dam failure. The actual mechanism of dam failure can be described partially for the embankment dams and lesser for the concrete dams. Before 1970, many researchers adopted the mechanism of complete and instantaneous dam failure to forecast the flooding in downstream, which results from dam failure (Ritter 1892; Schocklitch 1917; Re 1946; Dressler 1954; Stoker 1957; Su and Barnes 1970; Sakkas and Strelkoff 1973). There are several factors that affect the shape of breach in the embankment dam such as embankment dimensions, material used in construction, method of construction, slope protection cover, reservoir geometry and flow entering the reservoir during failure and failure mode. There are many sources of embankment dam breaches, but the most breach modeled is the overlapping or piping. Therefore, only these two mechanisms are described in this study.

3.1 Overtopping failure

Overtopping or flooding considers the commonest type of embankment dam failure. This type of failure may occur differently according to the composition of the embankment. There are three different models that are widely used to classify the failure of embankment dam as shown in Fig. 2. All of these models consider first stage of breach which happens at the top of embankment dam and expands in the form of triangle shape or is trapezoid with time.

The breach geometry can be represented by width, height and side slope of the final form of breach. In model A which is shown in Fig. 4, at the beginning the breach will start with a triangle form until the breach reaches its lowest elevation at the bottom. Then, the breach starts to grow laterally, and the shape of the breach becomes trapezoidal. In model B, the breach will continuously expand in both height and width until it reaches the final height and width. In model C, the breach bottom width is considered constant. Therefore, it is recommended from the previous survey and experimental research of dam failures that model A is considered as the most realistic model to describe the breach formation process. Ralston (1987); Powledge et al. (1989a, 1989b) have provided a useful description of the dam erosion mechanism that is caused by overlapping, whereas Miller and Ralston (1987) illustrated lots of past dam failures, but Hanson et al. (2005) explained the stages of breach formation and divided into four stages:

1. Development of a head cut on the slope of downstream side.
2. Head cut expansion through the crest of embankment dam.
3. Breach development as the head cut enters the reservoir.
4. And lateral expansion of the breach during reservoir drawdown.

3.2 Piping/internal erosion failure

Piping or seepage is the second commonest type of embankment failure. Piping can take place through the movement of water or concentrated seepage which will occur inside the dam. The embankment eroded by the seepage gradually, and large voids were taking place in the embankment. Generally, downstream toe is considered as a first place of piping initiation and continues toward the upstream side. The erosion of soil becomes fast when the voids are larger. The damage of the embankment crest may happen when the piping holes expand. Figure 3 shows the formation of piping hole.

In Fig. 3, D is piping hole width/height (assumed as a square), L is length of pipe, H_P is breach depth for piping, Z is the horizontal slope of the embankment, and C is dam top width. Piping failures can be divided into two stages. First stage occurs before dam crest damage, and the second stage occurs after the dam crest is damaged. Water flowing is modeled as orifice flow during the first stage and weir flow in the second stage. The reservoir may be completely released in the first stage for the small dams (State of Colorado Department of Natural Resources Division of Water Resources 2010).

4 Existing methods with its uncertainty

Embankment dams have considered the widely constructed type of dams around the world, and it fails with different mechanisms (Elmazoghi 2013). Their failures produce serious flood to the properties and population in the flooded or inundation regions and may put the infrastructures in these regions out of service. In order to study the failure of embankment dam failure, the breach parameters are considered as key variables and should be estimated accurately due to their effect on degree of failure risk and amount of peak outflow. The configuration of breach in embankment dams was assumed to grow from triangular to trapezoidal through the breach formation procedure (Wahl 1998).

There are two methods being adopted to estimate the dam breach parameters. The first method is a case study method which is based on the information from previous dam failures. The method is considered not accurate due to its small database. However, the method includes three submethods. The first submethod is parametric method which uses the hydraulic principles to estimate failure time, breach parameters and peak outflow. Also, this submethod can be used to route the flood hydrograph at downstream. The second submethod is empirical which based on the statistical analysis of past recorded dam failure. Table 3 shows empirical methods for breach parameter estimation. Comparative analysis method is the third submethod and considered as the simplest one. In this submethod, the parameters of the dam under study (height, width, side slope) and reservoir characteristics (area and volume) are compared with the dams that have similar characteristics and then the breach parameters and peak outflow for the most similar dam used for the dam under study. The second method is called physical, and it depends on the physical principles to construct the model. This model tries to determine the relationship between the inputs. This is a generally clear concept, but it may be more complex if the parameters change with time. In embankment breach analysis, the parameters change with time as the embankment erodes and the water in the reservoir is released. At this time, the models depend on geotechnical and sediment transport relationships. Despite many physical models presented for research purpose, the National Weather Service's BREACH program (NWS BREACH OR BREACH) is the most used model. This model (BREACH) provides broader information, but it is not considered to be accurate (Wahl 2010). Additionally, there are many physical

Table 3 List of existing methods for dam breach parameters estimation

Investigator	No. of case studies	Equation	Equation no.
Breach width equations			
Johnson and Illes (1976)	–	$0.5H_d < B_{avg} > 3H_d$	(1)
Singh and Snorrason (1982)	20	$2H_d < B_{avg} > 5H_d$	(2)
USBR (1988)	–	$B_{avg} = 3H_w$	(3)
Von Thun and Gillette (1990)	78	$B_{ave} = 2.5H\mathrm{w} + C_b$	(4)
Froehlich (1995a, b)	63	$B = 0.1803K_o.V_w^{0.32}.H_b^{0.19}$	(5)
Froehlich (2008)		$B_{avg} = 0.27K_o{**}\ (V_w)^{1/3}$	(6)
Xu and Zhang (2009)		$B_{ave}/H_b = 5.543\left(V_w^{\frac{1}{3}}/H_w\right)^{0.789}(e^{C_3})$	(7)
Failure time equation			
Von Thun and Gillette (1990)	36	$T_f = 0.15H_w$ (for high erodible) $T_f = 0.15H_w + 0.25$ (for erosion resistance)	(8)
Froehlich (1995a)	34	$T_f = 0.00254(V_w)^{0.53}(H_b)^{-0.9}$	(9)
Froehlich (2008)		$T_f = 0.0176[(V_w/(gH_b^2)]^{0.5}$	(10)
Xu and Zhang (2009)		$T_f = 0.304\ e^B\ T_r(H_d/H_r)^{0.654}(V_w^{1/3}/H_w)^{1.246}$	(11)

models for dam-break analysis, such as DAMBRK, HEC-RAS and MIKE 11 (Atallah 2002). Commonly, these models suffer from inadequate recognize of the breach progress and depend on sediment transport and water discharge equation. Practically, most common methods used regression analysis to estimate the dam breach parameters (U. S. Bureau of Reclamation 1988; Von Thun and Gillette 1990; Froehlich 1995b).

Where B_{avg} is average breach width (m), H_d is height of dam (m), H_b is height of breach (m), V_w is volume of water in reservoir at failure time (m^3), H_w is height of water in reservoir at failure time (m), K_o is factor which is 1.4 for overtopping and 1 for piping, C_3 is coefficient related to failure mode and dam erodibility, B is factor related to dam type, erodibility and failure mode, and C_b is factor depends on V_w as shown below:-

$V_w \div 10^6$	<1.23	1.23–6.17	6.17–12.3	>12.3
C_b	6.1	18.3	42.7	54.9

The regression analysis equations are beneficial, especially for the variables that have linear relationships (Costa 1985). In the regression analysis method, it is assumed that all points have equal value of variance and the distribution of them around the best fit line is almost followed Gaussian distribution. When this assumption is violated, the regression analysis will produce inaccurate results. Several existing regression methods proposed the linear relationship between the breach parameters and one or more parameters that are related to the dam and/or reservoir. This supposition may be true when applied to small dams that have similar dimensions and materials. Higher degree of uncertainty will result in the breaching process when the erodibility material changes. (Hanson et al. 2005).

Wahl (2004) assessed several of existing relationships that were presented to determine the dam breach parameters. He used 108 recorded dam failures and found the percentage error between predicted and actual values. He found that most of the estimated dam failure time was under-predicted compared with the recorded data. Also, Wahl (2004) explains the uncertainties in the predicted breach parameters and their effect on the risk evaluation when these methods were used. According to his analysis, the uncertainty of breach width was found to be around $\pm 1/3$ order of magnitude, while for failure time it is about ± 1 order of magnitude. For peak outflow, the uncertainty was about ± 0.5 to ± 1 order of magnitude, but when Froehlich peak flow equation was used, the uncertainty was about $\pm 1/3$ order of magnitude (Wahl 2004). Also, Pierce et al. (2010) described the uncertainty analysis of breach parameters.

Based on the above-mentioned facts, most of the methods used to estimate the dam breach parameters have some uncertainties. The sources of these uncertainties are the limited data that related to small dams and the nonlinear relationships between dam breach parameters. Therefore, it is very necessary to find out a more accurate method to estimate the dam breach parameters.

5 Performance evaluation of existing methods

Analysis of dam risk is considered very important and essential to prevent dam failure and to reduce their consequences. Hence, to evaluate the dam risk, quantitative analysis of dam breach development is considered necessary, and it can be represented by geometrical and hydrological parameters of breach (Xu and Zhang 2009). Also, routing the flood hydrology, estimation of inundated area and determining the available time for warning in the downstream region are more affected by breach parameters. Therefore, to simulate the flood wave and its effects on the downstream region the dam breach geometrically must be well described (Gee2009).

On the other hand, most of the analysis resulted from dam break has been carried out by using generated flood input data (Atallah 2002). In some cases, sensitivity analyses have also been adopted in which a range of input estimates are used to assess the robustness of decision justifications based on risk assessment outcomes. However, the approach of sensitivity analysis is considered limited because it does not provide the estimation of output distribution that would result from the joint distribution of input uncertainties. Therefore, sensitivity analysis provides little, if any, idea of the relative likelihood associated with the outputs that are obtained from a particular combination of inputs. In contrast, uncertainty analysis does provide any additional information (Atallah 2002).

In this study, analysis of uncertainties was performed using the database of more than 140 case studies of past recorded failures of dams, collected from different sources in the literature. The existing equations for breach parameters prediction were applied to the recorded database, and the plots of the predicted values against the observed values were performed. Table 4 and 5 show the results obtained from applying the existing approaches for predicting the average breach width and failure time. The nonlinear nature of the relationships between dam breach parameters makes the task of estimating these parameters or finding these relationships difficult. The most commonly used approach in the predicting dam breach parameters is the regression analysis. From the analysis of the results, it was noted that the prediction obtained from these methods is not accurate compared with the data of failed dams. The accuracy of the prediction was assessed using statistical indices such as mean absolute relative error (MARE) and root mean square error (RMSE). Table 4 shows the values of MARE and RMSE for approaches used for predicting the average breach width. Values of MARE are ranging from 0.39 to 0.72, while values of RMSE are ranging from 41.4 to 70.79 where the recorded values were ranging from 2.29 to 367 m. The lowest value of MARE was obtained by testing Eq. (7), while the highest value was obtained by testing Eq. (1). Table 5 shows the values of MARE and RMSE for approaches used for predicting failure time. Values of MARE are ranging from 0.69 to 0.72, while values of RMSE are ranging from 0.36 to 2.32 where the recorded values were ranging from 0.17 to 7.3 h. The lowest value of MARE was obtained by testing Eq. (9), while the highest value was

Table 4 Assessment of various approaches for predicting of dam breach width

Method	Equation	Equation no.	Statistical parameters	
			MARE	RMSE
Johnson and Illes (1976)	$0.5\mathrm{h_d} < B < 3\mathrm{h_d}$	(1)	1.05	70.79
Singh and Snorrason (1982)	$2\mathrm{h_d} < B < 5\mathrm{h_d}$	(2)	0.88	37.18
USBR (1988)	$B = 3h_\mathrm{w}$	(3)	0.51	49.63
Von Thun and Gillette (1990)	$B_\mathrm{avg} = 2.5h_\mathrm{w} + C_\mathrm{b}$*	(4)	0.47	44.57
Froehlich (1995a, b)	$B_\mathrm{avg} = 0.01803K_\mathrm{o}(V_\mathrm{w}^{0.32})(\mathrm{H_b^{0.19}})$	(5)	0.40	42.79
Froehlich (2008)	$B_\mathrm{avg} = 0.27K_\mathrm{o}$** $(V_\mathrm{w})^{1/3}$	(6)	0.41	41.37
Xu and Zhang (2009)	$\frac{B_\mathrm{ave}}{H_b} = 5.543\left(\frac{V_\mathrm{w}^{\frac{1}{3}}}{H_\mathrm{w}}\right)^{0.739}(\mathrm{e}^{C_3})$ $C_3 = b_4 + b_{5***}$	(7)	0.39	48.50

Table 5 Assessment of various approaches for predicting of dam failure time

Method	Equation	Equation no.	Statistical parameters	
			MAPE	RMSE
Von Thun and Gillette (1990)	$T_f = 0.015(h_w)$ for highly erodible dams $T_f = 0.015(h_w) + 0.25$ for erosion-resistant dams	(8)	0.80	2.32
Froehlich (1995a, b)	$T_f = 0.00254(V_w^{0.53})(h_b^{-0.9})$	(9)	0.6	1.5
Froehlich (2008)	$T_f = 0.0176[(V_w)/(gh_b^2)]^{0.5}$	(10)	0.6	1.5
Xu and Zhang (2009)	$T_f/T_r = 0.304(h_d/h_r)^{0.777}(V_w^{1/3}/h_w)^{1.228}\ e^{B5}$	(11)	0.7	1.84

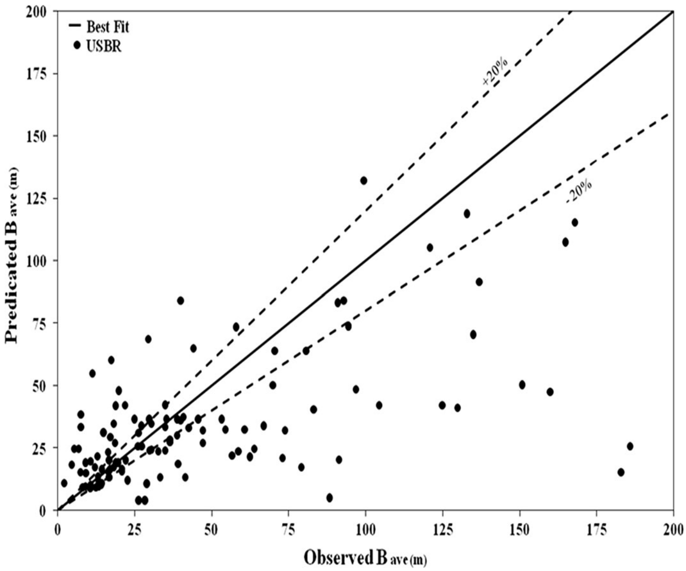

Fig. 4 Performance of Eq. (3) for dam breach width estimation

obtained by testing Eq. (8). The performances of Eqs. 3, 4, 5, 6 and 7 in predicting the average breach width are shown in Figs. 4,5,6,7 and 8. The highest accuracy in predicting the average breach width was obtained by applying Eq. (7) since most of the predictions obtained by applying this equation were located within ±20% from the line of perfect agreement. The performances of Eqs. 8, 9, 10 and 11 in predicting the failure time are shown in Figs. 9,10,11 and 12. Although the performance of Froehlich method in 2008 (Eq. 5) and (Eq. 10) is relatively better than the other tested methods for the dam breach width and dam failure time estimation, respectively, the prediction MARE from these two equations found more than 20% which is considered not acceptable for accurate prediction.

Nowadays, a new approach has been presented as an alternative to the conventional statistical approach in several fields. Artificial neural networks (ANNs) which are

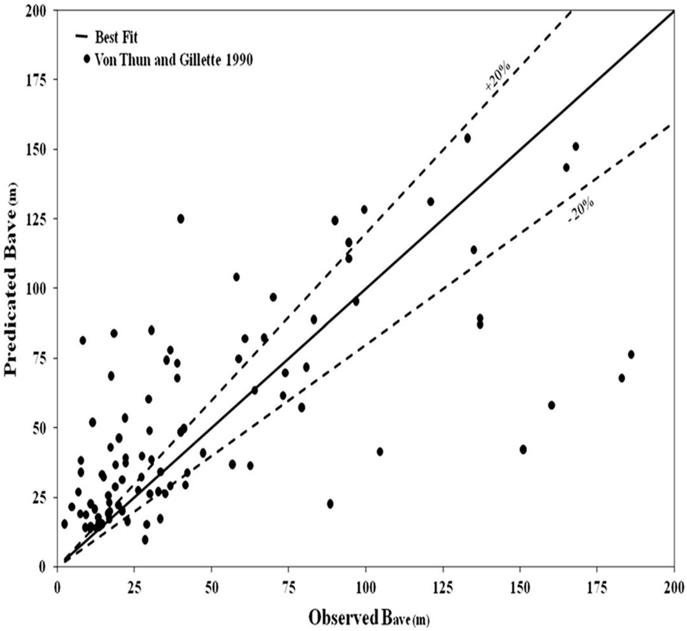

Fig. 5 Performance of Eq. (4) for dam breach width estimation

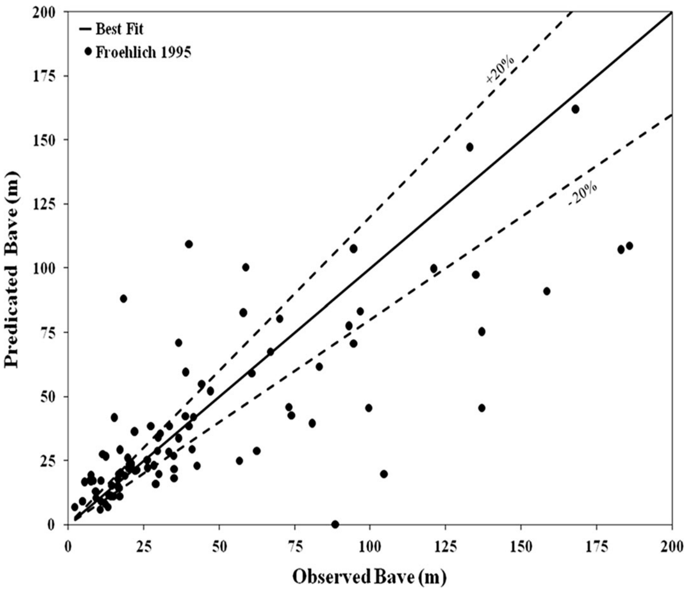

Fig. 6 Performance of Eq. (5) for dam breach width estimation

considered as the alternative technique having usefulness exceed traditional statistical models such as a free pattern of forecasting model, toleration to data inaccuracy and their data-driven nature (Azmatullah et al. 2005). ANN is considered as massively parallel

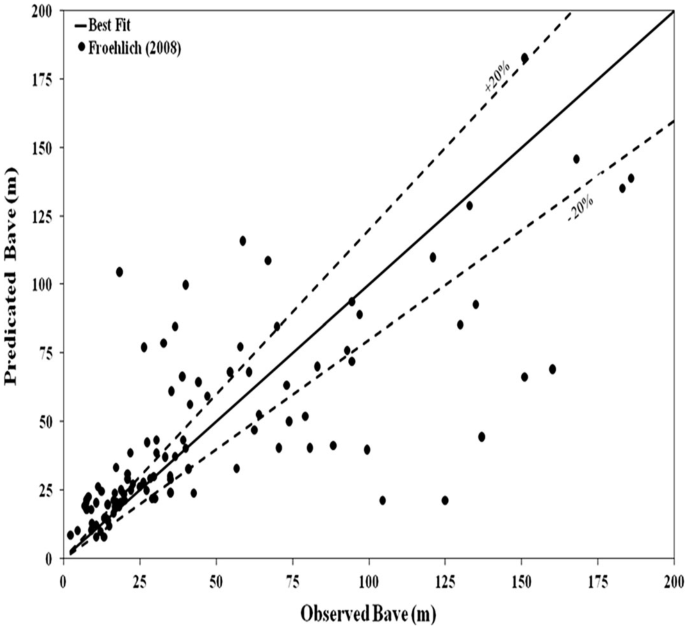

Fig. 7 Performance of Eq. (6) for dam breach width estimation

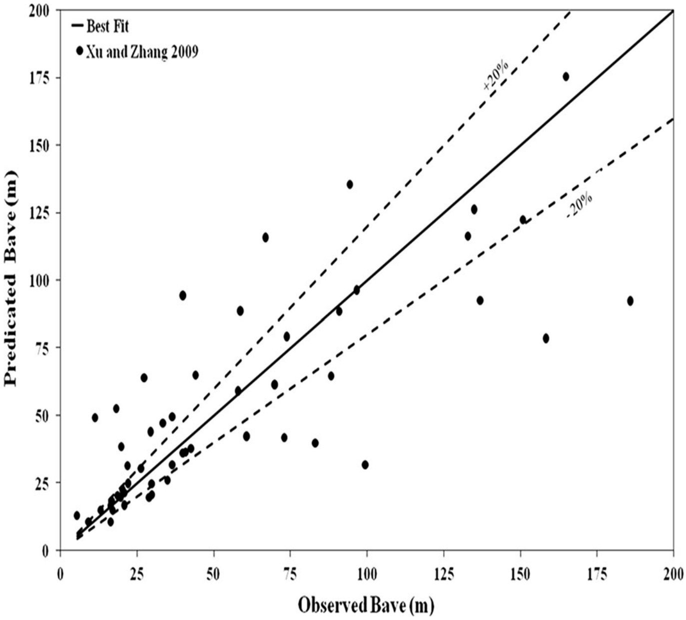

Fig. 8 Performance of Eq. (7) for dam breach width estimation

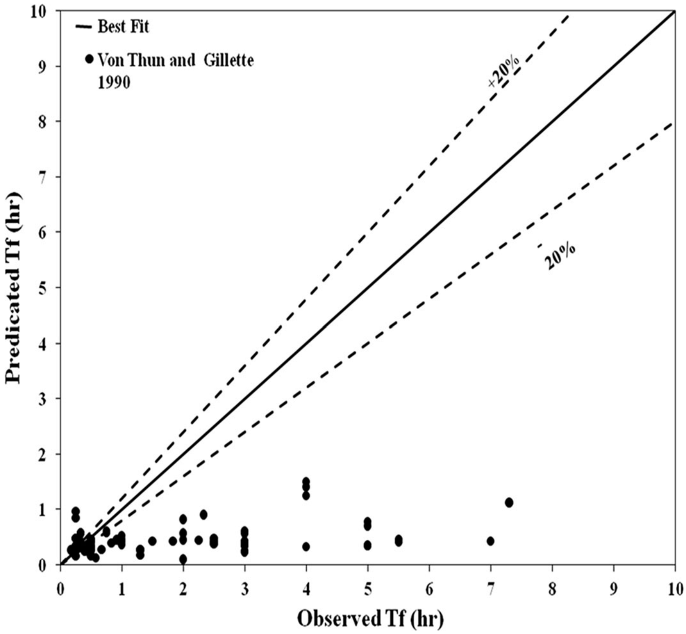

Fig. 9 Performance of Eq. (8) for dam failure time estimation

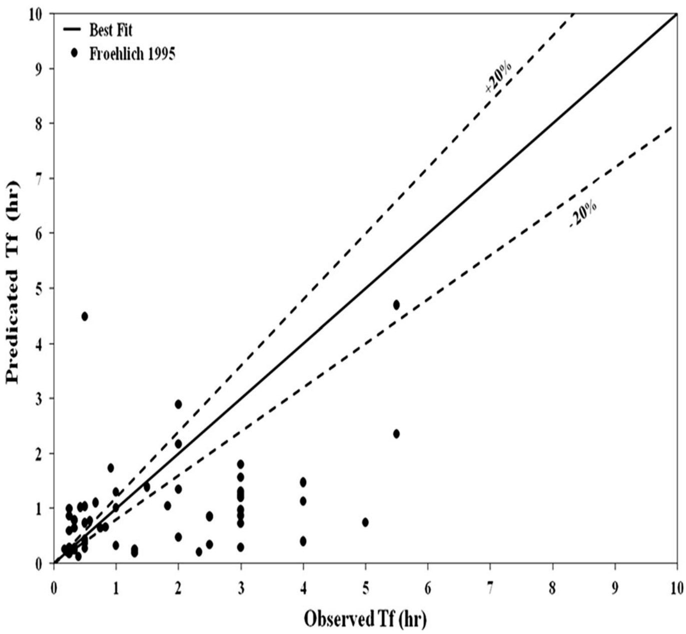

Fig. 10 Performance of Eq. (9) for dam failure time estimation

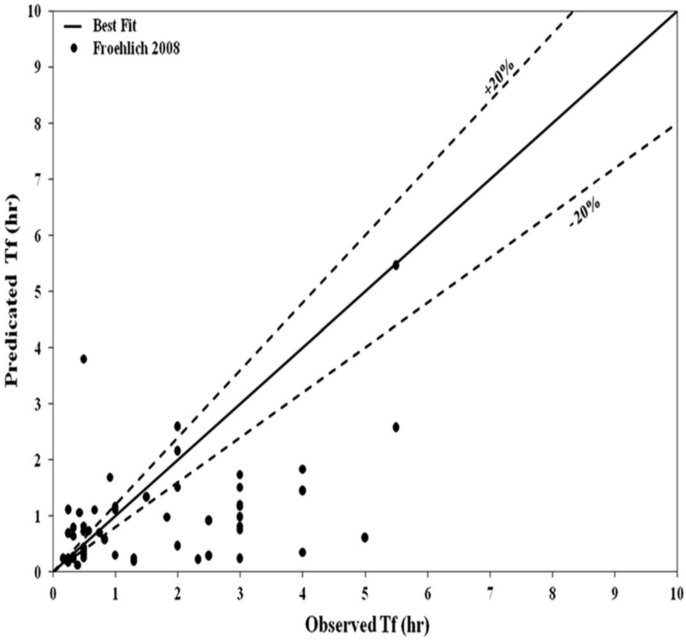

Fig. 11 Performance of Eq. (10) for dam failure time estimation

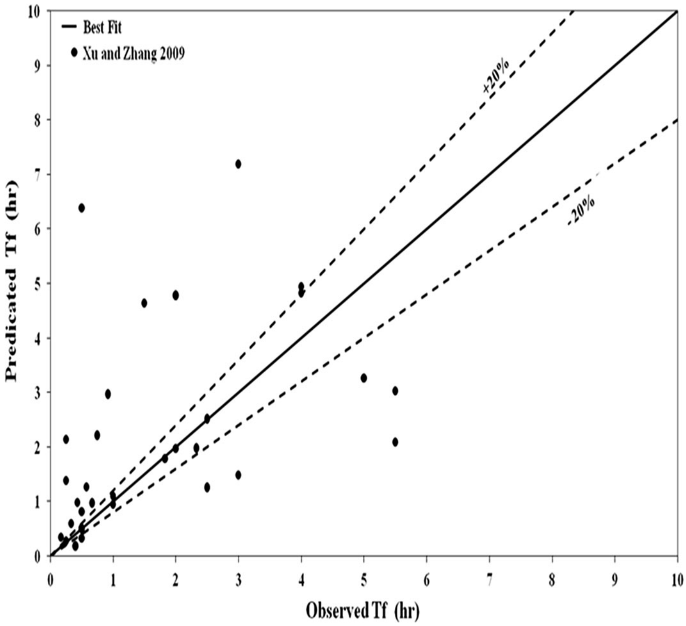

Fig. 12 Performance of Eq. (11) for dam failure time estimation

distributed data processing technique which has specific achievement aspects like biological neural networks of the human brain (Haykin1994).

6 Concept, approach and application of ANN

Design and management of water resource projects involve studying and analysis of hydrology, hydrogeology, hydraulic and environment concepts. There are many challenges related to modeling, forecasting and estimation of parameters such as precipitation, flood discharge, stream flow, water level and others that are facing water resource engineers. These challenges or difficulties are caused by the nonlinear nature of these parameters which make their accurate estimation difficult and uncertain. However, many attempts have been made to solve theses problems. One of the most effective solutions is using artificial neural network (ANN) in planning, design and management of water resource projects. ANN is one of the most effective artificial intelligence tools that have magnificent attributes that can recognize the pattern or relationship between variables without any more explanation. ANN has ability to extract the relationships between inputs and outputs, even if the data are little and have some noise. From all the above capabilities of ANN, it is recommended to apply this technique in water resource simulation and modeling.

McCulloch and Pitts (1943) were the first to introduce the concept of how the brain could produce complex patterns by using basic cells called neurons that are connected to each other. McCulloch and Pitts (1943) presented an artificial neuron model with binary input and output and an activation threshold. Neural networks are commonly thought as black boxes trained to a particular function on a substantial number of data tests. It is made out of countless interconnected handling components (neurons) working as one unit to solve different problems. Neural systems have impressive capability to get signed from confounding or lose information, and they can be utilized to concentrate designs and recognize patterns that are too complicated to be in any way observed by either people or other computer strategies. The general architecture of the neural network has three layers of neurons, including input, hidden and output layers, as shown in Fig. 13. The perceptron is a type of artificial neural network invented in 1957 by Rosenblatt (1958). The perceptron that shown in Fig. 14 takes a vector of real-valued inputs, calculates a linear combination of these inputs and then outputs results based on some activation function (Zagonjolli 2007). Numerous hypothetical and laboratory researches were explained that the ANN with one hidden layer or a single hidden layer is adequate to approximate the function which has a complex nonlinearity. It is likewise proposed that a furthest point for the numbers of neurons in the hidden layer be lesser than $2n + 1$, where n is the input neuron number (Hecht-Nielsen 1987).

Feed-forward back-propagation (FFBP) algorithm is considered a widely adopted algorithm in research accomplished using neural network and used more than back-propagation algorithm the second algorithm that has many problems such as the low speed in training convergence and entanglement and difficultly in a local minimum (Haykin1994). In later years, many attempts have carried out by researchers to solve or reduce these problems and enhance the artificial neural network efficiency. Ramirez et al. (2005) developed the back-propagation algorithm resilient for training the network to using ANN to forecast the rainfall in Brazil, and they find that the results can enhance when adopting of back propagation. In addition, Levenberg–Marquardt algorithm (LMA) has been suggested by other researchers. Noori et al. (2010) used artificial neural network to forecast

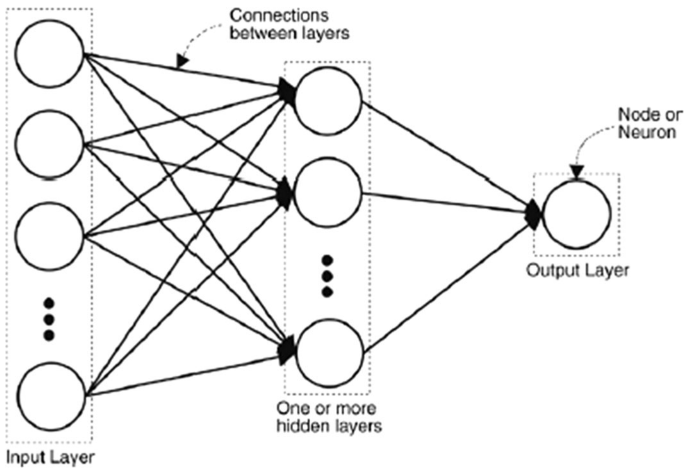

Fig. 13 Artificial neural network architecture (Gibbs et al. 2006)

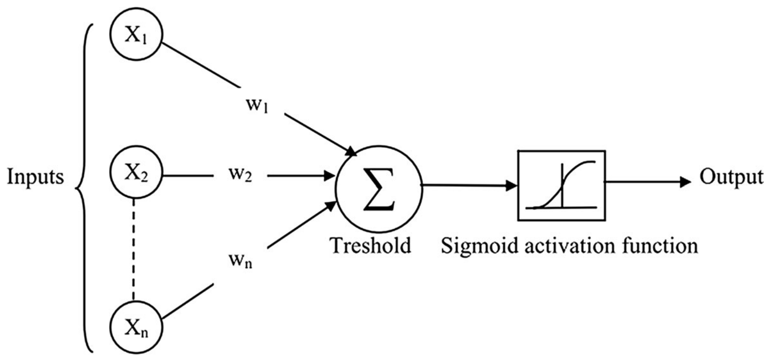

Fig. 14 A perceptron (Zagonjolli 2007)

weekly solid waste. Chau (2006) adopted particle swarm optimization to find the optimum weights and biases of the network to predict the Shing Mun river water level. He used the results and compared it with the standard back-propagation algorithm results, and he showed his model superiority. Rogers et al. (1995) proposed genetic algorithm (GA) instead of SBPA.

In addition to its simplicity and capability, the use of artificial neural network (ANN) in prediction, forecasting, modeling and estimation of the variables in water resources engineering is being increasing rapidly. Table 6 summarizes the application of ANN in water resources in recent years. From Table 6, it can be noted that ANN is widely used in various disciplines of water resources engineering and showed reasonable accuracy. Among those, it is recommended to use ANN for dam breach parameters prediction. Additionally, new parameters such as dam characteristics or reservoir characteristics will be used as input data to find new models which represent a new relationship for estimation of breach parameters.

Table 6 Application of ANN in water resources

Researcher	Year	Approach and achievement	Field of application
Rajurkar et al.	2002	They develop ANN coupled with multiple input—a single output (MISO) model to simulate the rainfall runoff relationship for a large catchment in India. They found that using ANN with MISO can give more accurate relationship for rainfall runoff than the MISO alone where Nash–Sutcliffe efficiency (E^2) was found 83.2% for MISO with ANN and 75.3% for MISO alone	Rainfall–runoff modeling
Riad and Mania	2004	They employed ANN technique to estimate the flow discharge in a semiarid region and compared the results from the ANN model with the results of the conventional regression analysis. The result of this comparison shows that the ANN model is superior to the traditional method where the value of R^2 was found 0.91 for ANN and 0.88 for the traditional method	Rainfall–runoff modeling
Lekkas et al.	2004	They use FFBP, adaptive linear NN and Elman recurrent NN to predict the flood discharge. From the result analysis, they recommend that all three types of ANN can be used for flood discharge estimation, but Elman recurrent NN is considered the best type where the value of R^2 was found 0.93	Flood discharge forecasting
Daliakopoulos et al.	2005	In this study, seven different types of network architectures and training algorithms are investigated for groundwater-level forecasting and compared in terms of model prediction efficiency and accuracy. Different experiment results show that accurate predictions can be achieved with a standard feed-forward neural network trained with the Levenberg–Marquardt algorithm where R^2 value was found about 0.95	Groundwater modeling
Cigizoglu and Alp	2006	In this study, sedimentation load was estimated by using two types of ANN (GRNN and FFBP), and the results of these two types have been compared. They found that the GRNN is faster. They use R^2 to assess the ANN model, where the value of R^2 was found about 0.95 for FFBP and 0.94 for GRNN	Sediment load prediction
Joorabchi et al.	2009	They adopted multilayer feed-forward neural network with back-propagation algorithm to simulate the groundwater fluctuations for different locations down the east coast of Australia. The results show that the ANN model is very successful in predicting groundwater fluctuations where the value of R^2 was found more than 0.9 for different cases that used	Ground water modeling
Palani et al.	2008	They adopt the ANN to modeling the quantitative characteristics of Singapore coastal waters. The results show that the NN has a good potential to simulate the water quality variables. The simulation accuracy, measured in the Nash–Sutcliffe coefficient of efficiency (R^2), ranged from 0.8 to 0.9 for the training and overfitting test data	Water quality modeling
Unal et al.	2010	They employed the LM algorithm for training ANN in order to predict the discharge for compound channels. Also, they use other conventional methods for discharge estimation and compared the results of the ANN model with these methods. They found that the predicted discharge values of ANN model are more accurate and concluded that ANN technique could be used as an alternative of the conventional methods because it can predict the discharge with MARE (5.7%) and R^2 (0.999)	Flood discharge forecasting

Table 6 continued

Researcher	Year	Approach and achievement	Field of application
Kalin et al.	2010	They used ANN to predict the water quality parameters with no prior water quality data. The approach is applied to 18 watersheds in West Georgia, USA. Model performances are evaluated on the basis of a performance rating system, whereby performances are categorized as unsatisfactory, satisfactory, good or very good. The results show that the model performed better in the pastoral and forested watersheds with an average rating of very good where the value of the Nash–Sutcliffe efficiency (*E*) was more than 70%, while the average model performance at the urban watershed was good where the value of E is ranging between 50 and 70%	Water quality modeling
El-shafie et al.	2011	In this study, ANN was used to represent the relationship between rainfall and runoff for catchment in Japan. They develop FFBP network with tangent function in the hidden layer and linear function in the output layer. They used the value of mean square error (MSE) correlation coefficient (R) and correlation of determination (R^2) for evaluation of ANN technique. They found MSE $= 6.70\text{E} - 04$, $R = 0.95$ and $R^2 = 0.91$ for ANN while MSE $= 0.17$, $R = 0.49$ and $R^2 = 0.24$ for multilayer regression	Rainfall–runoff modeling
Melesse et al.	2011	They employed three statistical methods to predict the sediment yield addition to ANN. These methods are: multiple linear regression (MLR), multiple nonlinear regression (MNLR) and autoregressive-integrated moving average (ARIMA). They suggest that the ANN is better than other methods for sediment estimation. They used the mean absolute percentage error (MAPE) and R^2 to compare the tested methods. The values of MAPE and R^2 were found (16.8%, 0.87); (23.1%, 0.76); (27.3%, 0.77); and (132%, 0.87) for ANN, MLR, MNLR and ARIMA, respectively	Sediment load prediction
Khalil et al.	2012	They examine the potential of the artificial neural network (ANN) on simulating interrelation between water quality parameters. Several ANN inputs, structures and training possibilities are assessed, and the best ANN model and modeling procedure are selected. The mean absolute relative error (MARE) was used to compare the two methods. From the results, it is concluded that the ANN models are more accurate than the linear regression models having the same inputs and output where the MARE was about 14.6% for ANN model, while it was about 65% for linear regression	Water quality modeling
Chitsazan et al.	2013	They develop ANN for groundwater-level simulation in Aghili plain, southwest Iran. Two hidden layers with four different algorithms: gradient descent with momentum (GDM), Levenberg–Marquardt (LM), resilient back propagation (RP) and scaled conjugate gradient (SCG) were used in this research. The results show that the ANN can predict the groundwater level with good accuracy and the best results can be obtained when the LM algorithm was used where the value of mean square error was smallest one and the value of R^2 was more than 0.94	Groundwater modeling
Elsafi	2014	This study aimed to forecast the River Nile flow at the Dongola Station in Sudan using an artificial neural network (ANN) as a modeling tool and validated the accuracy of the model against actual flow. The ANN model was formulated to simulate flows at a certain location in the river reach. The analysis indicated that the ANN provides a reliable means of detecting the flood hazard in the River Nile. She used RMSE and R^2 to assess the performance of ANN. The values of RMSE and R^2 for the best model were found 0.374 and 91.62%, respectively	Flood discharge forecasting

Table 6 continued

Researcher	Year	Approach and achievement	Field of application
Pektas and Erdik	2014	In this study, the peak outflow from the breached dam was estimated using ANN. They employed several activation functions with different number of layers and used different input parameters for ANN build. The values of coefficient of efficiency (COE), root mean-squared error (RMSE) were used to assess the models. The COE and RMSE were found (1.00) and (937.01) for ANN and (0.66) and (9927. 14) for regression analysis, respectively. Also, they found that the parameter which has more effect of peak outflow value is dam height	Flood discharge forecasting
Djurovic et al.	2015	They used the adaptive neuro-fuzzy inference system (ANFIS) and an artificial neural network (ANN) model for one-month water table forecasts at several wells located at different distances from the Danube River in Serbia. The results suggest that both these techniques represent useful tools for modeling hydrological processes in agriculture, with similar computing and memory capabilities. The value of RMSE was found ranging from 0.141 to 0.152 for ANN models and from 0.147 to 0.152 for ANFIS models	Groundwater modeling
Chakravarti et al.	2015	They conduct laboratory experiments for the generation of rainfall–runoff data using a rainfall simulator. And for the validation of this observed data a model is established for estimating observed runoff data using ANN technique. The predicted results using an ANN model performed better estimation with observed values which is useful for water resources planning and management. For the testing of model performance Nash–Sutcliffe efficiency criteria were used which gives MSE greater than 95%	Rainfall–runoff modeling
Heddam	2016	In this study, a new model based on feed-forward neural networks (FFNN) is developed and compared to the standard multiple linear regression (MLR) in modeling Secchi disk depth (SD) in the Saginaw Bay, Lake Huron, Michigan, USA. The FFNN and MLR were evaluated using well-known statistical indices. This work demonstrates that more accurate and more robust model of Secchi disk depth is the one obtained using an artificial neural network-based approach with input parameters, the total suspended solids and chlorophyll. The value of mean absolute error was found ranging from 0.874 to 0.924 for ANN models, while it ranging from 1.499 to 1.633 for MLR	Water quality modeling

7 Conclusion

This study presents a review of the previous studies that covered dam breach parameters estimation and discussed their accuracy. There are many existing approaches to estimate the dam breach parameters. It found that these approaches were based on regression analysis. These approaches were derived using limited data, and this affects the accuracy of the prediction obtained from these approaches. Moreover, the relationships used for determining the dam breach parameters are complex, and any simplification of these relationships will also affect their accuracy.

The prediction from the existing approaches (regression analysis) was validated using data of more than 140 failed dams around the world. The values of the computed MARE for the existing approaches confirm that linear approaches are less accurate than the nonlinear ones. Also, the results confirm the need for a more accurate approach.

The artificial neural network approach is widely applied for solving various types of problems of water resources. Although it is not specifically applied for dam-break analysis, it is possible to use it for such problems. ANN technique can be used instead of regression analysis to estimate the dam breach parameters due to the fact that this technique has ability to simulate the nonlinearity of variables and give accurate results.

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