SEISMIC VULNERABILITY ANALYSIS OF ARCH DAMS BASED ON ARTIFICIAL NEURAL NETWORK

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Abstract

In the lifetime of an arch dam, it could withstand significant earthquakes, and the vulnerability of the structure has attracted much attention in dam engineering. Generally, the seismic vulnerability analysis of concrete dams is based on numerical methods, such as the method of finite element analysis. The vulnerability analysis of arch dams requires a large number of calculation cases. Recently, data-driven methods, including machine learning and neural networks, have been applied to long-term behavior of concrete dams based on in situ measurements. These data-driven methods show great ability in interpretation of long-term behavior and prediction of displacements of concrete dams. The data-driven methods could also be a promising procedure for seismic vulnerability assessment of dams, but there is few, if any, study investigating the seismic response of arch dams using neural networks. Given the current shortage of related research, and the limited previous attempts to address this vulnerability of the structure question, there is a need for a tentative interdisciplinary work. In this study, a combination of artificial neural networks and genetic algorithms is presented to predict the seismic vulnerability of arch dams. The presented method can significantly reduce the calculation time compared with the seismic analysis of arch dams using finite element method. More than five hundred cases of dynamic response of arch dams are analyzed with the finite element method and the responses of the structure are used as output of the artificial neural networks. The earthquake intensity and material properties of dam concrete are considered as input. The results show that the proposed method can predict accurate seismic response of the arch dam in seconds and gives a reasonable seismic vulnerability analysis of the arch dam.

Keywords: arch dams; seismic vulnerability analysis; artificial neural networks; genetic algorithms

1. Introduction

Dams throughout the country currently play an important role in the development of the national economy. But the potential threat of the dam is huge, once the accident would be a direct threat to lives and property downstream. Among many disasters that threaten the safety of dams, earthquakes are one of the most threatening. Therefore, it is extremely important to evaluate the seismic safety of dams [1]. Damage analysis of dams under earthquake conditions has also received extensive attention and research in recent years. For arch dams, the degree of damage is affected by many factors, such as ground motion and concrete material, etc. Through finite element method (FEM), the structural response (such as displacement) under a variety of preset earthquake conditions can be obtained [2]. However, the amount of simulation work performed by FEM is undoubtedly huge. If the results of the FEM can be compared with the predicted values obtained by the statistical mathematical model, it can help to establish a statistical mathematical model to determine if the structure's behavior is still reasonable, and if not, appropriate measures should be taken to prevent disaster[3].

Unlike deterministic models (such as FEM), statistical mathematical models do not rely on physical governing laws to calculate dam responses [4,5]. For the clear question: the response of an arch dam under seismic conditions, the coupling effect of ground motion and concrete material changes can be more clearly discussed by the finite element method. FEM provides more flexibility in analyzing special or unconventional conditions [6].Therefore, in the early stage of the analysis process, FEM can provide sufficient data to help establish effective statistical models for prediction, and the assumptions and predictions of arch dam behavior based on sufficient analysis data require the participation of statistical mathematical models. The artificial intelligence technique is one of the statistical techniques most widely used for estimating the dam response [7]. When it comes to dam body vulnerability analysis, if only rely on FEM, the workload will be extremely large, and statistical techniques can greatly improve computing efficiency.

Artificial intelligence techniques such as artificial neural networks and genetic algorithms have been used as efficient tools to simulate the response of complex structural engineering systems under external forces. Furthermore, they have been successfully applied to model of the dam behavior [7,8]. The development of artificial neural networks dates back to the 1940s. S. McCulloch and W. Pitts et al. proposed a formal mathematical description of neurons and a method of network structure [9]. At that time, its role was to help humans understand the intricacies of the nervous system [3]. By 1982, J. J. Hopfield proposed the Hopfield neural grid model, introduced the concept of "computing energy", and gave a judgment of network stability [10]. Later, he proposed a continuous-time Hopfield neural network model, which pioneered a new way for neural networks to use in associative memory and optimized computing. This pioneering research work has strongly promoted the research of neural networks [11]. In 1985, Rumelhart and Hinton et al. Proposed a Back Propagation (BP) algorithm, which makes the training of neural networks simple and feasible [12].Because of the artificial intelligence neural network's powerful capability such as self-studying, and its ability to handle non-linear systems, it is widely used in monitoring and analysis of dam safety [13,7,8]. Many scientists have applied artificial neural networks to identifying structural damage sites and input-output problems of multi-degree-of-freedom systems [14,16]. For example, Pandey and Barai [15] explored how artificial neural networks can help identify damage in bridge structures. It turns out that structures using artificial neural networks can obtain accurate damage analysis and the structures are correctly simulated under the premise of analysis.

Genetic algorithm is an evolutionary computing technology based on biological evolution models. As human genetic processes, this method is useful in search spaces that not clearly presented, and it can avoid local convergence problems by searching in parallel [13]. In 1965, J.H. Holland first proposed the importance of artificial intelligence operations. Later, his student J.D. Bagley developed replication, crossover, mutation, and dominant and inversion genetic operators based on adaptive genetic algorithms. In the early 1970s, Holland put forward the basic theorem of genetic algorithms, and thus laid the theoretical foundation for genetic algorithms [17]. The model theorem reveals that the number of samples of good individuals in the population will increase exponentially, thus theoretically ensuring that the genetic algorithm is an optimization process.

Generally, genetic algorithms obtain global optimality through selection, crossover, and mutation calculations [18].

In this paper, a model combining BP artificial intelligence neural network and genetic algorithm is proposed for dam vulnerability prediction. The arch dam response under earthquake conditions obtained by FEM calculation simulation provides input materials for neural network learning. The results obtained through artificial intelligence are compared with the results by FEM. The performance of the combination of BP artificial intelligence neural network and genetic algorithm in predicting vulnerability analysis has been verified by predicting more than 500 cases. Results show that the combined model is practical to consider the effects of earthquakes and dam concrete materials on dam response.

2. Method

2.1 BP neural networks

Artificial neural network is an artificial intelligence method widely used in recent years by simulating the function of the human brain nervous system. It has strong learning and adaptive capability, and widely used in many subjects to investigate influencing factors. Basically, all artificial neural networks have a similar structure: input layer, hidden layer, output layer. In the input layer, some neurons interact with the real world to receive input. Output may present a visual display. All the remaining neurons are not visible [19]. The BP (back propagation) neural network is a kind of typical multilayer feedforward artificial neural network with continuous transfer function.

Assume that input layer neurons are $A=[a_1,a_2,\ldots,a_m]$, hidden layer neurons are $B=[b_1,b_2,\ldots,b_u]$, and output layer neurons are $C=[c_1,c_2,\ldots,c_n]$. ω_{mu} represents the connection weight between the m-th neuron in the input layer and the u-th neuron in the hidden layer, and v_{un} represents the u-th neuron in the hidden layer and the n-th neuron in the output layer. The topology of the multilayer neural network model is shown in Figure 1. [20].

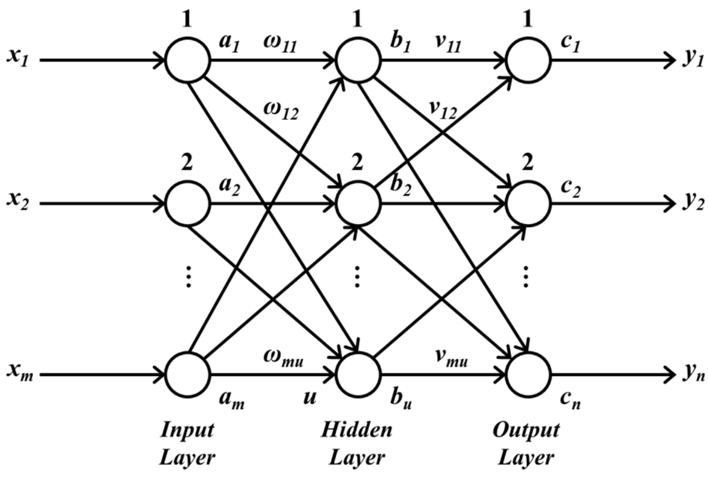


Fig. 1 – Neural network structure diagram

The excitation function of the hidden layer is f^1, and the excitation function of the output layer is f^2. While assuming that k_m represents the threshold value of each neuron in the hidden layer, and p_u is the threshold value of each neuron in the output layer.

The processes of signal forward transmission and back propagation are expressed as follows:

In the process of positive signal transmission, the first neuron b_1 in the hidden layer generates by adding the threshold value k after weighted summation of neurons in the input layer, and then substituting into the function f^1 as follows:

$$b_1 = f^1((a_1 \times \omega_{11} + a_2 \times \omega_{12} + \ldots + a_m \times \omega_{1m}) + k_1) \tag{1}$$

Similarly, the first neuron c_1 in the output layer receives the output value of each neuron in the hidden layer, and then weights and sums them to obtain:

$$c_1 = f^2((b_1 \times v_{11} + b_2 \times v_{12} + \ldots + b_u \times v_{1u}) + p_1) \tag{2}$$

In the process of back propagation, the input sample x enters the input layer, and passes through the hidden layer according to the above process. The first batch of output values y_1 to y_n are obtained, and then they are compared with the expected output Z. If the mean square error between Y and Z does not meet the predetermined requirement ε, then the back-propagation process occurs as follows: the mean square error is returned in a gradient form and distributed to the neurons in each layer. Repeat this process until the mean square error converges to ε [20].

2.2 Genetic algorithms

Genetic algorithms appeared in the 1960s. Genetic algorithms have been applied in many fields, due to its convenience and efficiency. As an algorithm that simulates the principle of survival of the fittest in nature, genetic algorithm combines the principle of survival of the fittest with the exchange of random information to try to achieve the dual effect of eliminating unsuitable factors in the solution and inheriting the existing knowledge [22].

The flow of genetic algorithm is shown in the figure 2.

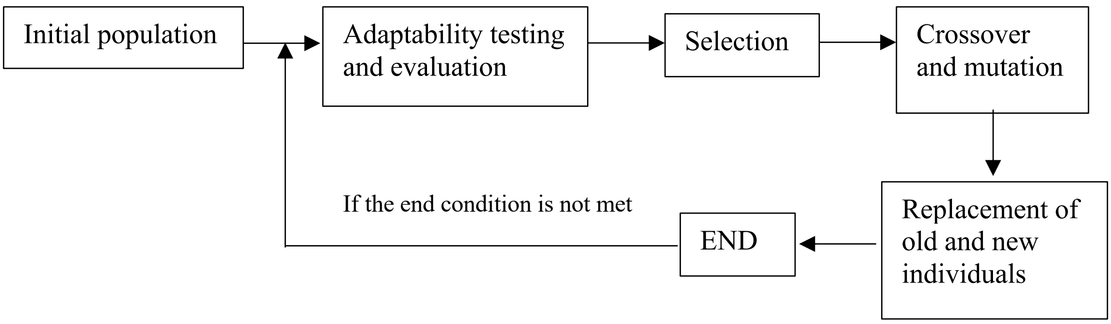


Fig. 2 – Genetic Algorithm Flowchart

At first, a set of first-generation populations as the starting point of evolution are randomly selected in the feasible domain, and the individual adaptability value of each individual is calculated. The adaptability reflects the optimization information of the objective function. Next, several individuals are randomly selected from the population as the sample set before the breeding process. The selection mechanism ensures that individuals with higher adaptability can be selected preferentially, while individuals with lower adaptability have fewer chance to be selected. In the breeding process, crossover and mutation operators are used to mate the selected samples with a certain crossover rate and mutation rate to give a new generation of individuals. Finally, the next generation of groups is generated through the replacement between old and new individuals. The algorithm repeats until the end conditions are met [23].

Then how does crossover and selection work?

Just as the reproduction of many organisms is accomplished by the crossover of chromosomes, crossover is also an important operator in genetic algorithms. Two individuals x_1 and x_2 are selected as parents to cross the gene chain code, thereby generating two new individuals x'_1 x'_2. One method is widely used in crossover operations: randomly select a truncation point in parents' gene, cut the gene at the truncation point, and exchange the latter half of the gene.

	Parents		Generation
x_1	**1000 | 10011110**	x'_1	**1000 11000110**
x_2	**0110 | 11000110**	x'_2	**0110 10011110**

Fig. 3 – Genetic crossover

Like crossover, mutation occurs when changes occur at one or some locations on the gene chain that make the newly created individuals different from other individuals. The implementation method of the operator is as follows: for an individual in the population, if the selected certain gene in its gene chain is 0, change it to 1, and vice versa.

1100111001 $\longrightarrow$ **1100110001**

Fig. 4 – Genetic mutation

2.3 Optimize the neural networks' weights based on GA

Because the BP neural network is based on the gradient descent method, it has two obvious shortcomings at instability in system training process and local convergence problems. One of the most effective methods to improve the performance of the BP neural network, is self-modifying parameters in training process, that means adjusting weight and threshold values by additive momentum factors [13]. As a type of random search algorithm, genetic algorithm draws on natural selection and natural genetic mechanisms in the biological world, and it has a good ability of limiting the risk of local optimal solution, which is suitable for searching without relying on gradient information. So genetic algorithms can be used to optimize neural networks [24].

The number of hidden layers in the BP neural network structure is usually determined through testing, that is, the weights and thresholds corresponding to the hidden layers will also be adjusted accordingly. The addition of GA can generate an optimal individual in different network structures.

At first, to perform crossover and mutation operations easily, normalizing the samples of the BP network by using floating point encoding when encoding the initial population. A real number array formed by the weight and threshold of the BP network is a chromosome of GA. The second step is to select a fitness function such as the mean square error function, and then judge the viability of the chromosome by the function. New individuals are generated according to a certain cross probability and mutation probability, and the judgment of whether the chromosome reaches the optimal is continued. Repeat the process by changing the number of neurons in the hidden layer. If the optimal individual obtained after the loop can satisfy the global network error, it means that the optimal weight and threshold have been obtained. Finally, a BP neural network is constructed.

3. Case Study

In this section, the performance of the combination of artificial neural networks and genetic algorithms was demonstrated to predict the seismic responses of an arch dam. The method is adopted by three layers as mentioned above: input layer, hidden layer and output layer. In the input layer, a monotonic scalable ground motion intensity measure (or simply intensity measure, IM) of a scaled accelerogram and the parameters of concrete materials are variables that affect results. Common examples of scalable IMs are the peak ground acceleration (PGA), peak ground velocity (PGV), the ξ=5% damped spectral acceleration at the structure's first-mode period (Sa(T_1; 5%)), and acceleration spectral intensity (ASI)[25].In the output layer, there are three outputs that represents the predicted maximum displacements along the dam crest, contraction joint opening and damage volume ratio of concrete.

3.1 Description of the concrete arch dam and data set

The Dagangshan arch dam with a height of 210 meters and a dam crest arc length of 609.8 meters is located on the Dadu River of Southwest China. The thicknesses of the crown cantilever are 52 meters at the bottom and 10 meters at the crest. The arc length-height ratio and thickness-height ratio are 2.90 and 0.248 respectively. The total number of contraction joints in the dam is twenty-eight. The normal depth of reservoir water is 205 meters and the lowest reservoir depth in operation is 195 meters, and the depth of silt sedimentation during operation is 125 meters [26]. To evaluate the safety of the dam under strong design earthquake, three groups of FE models under different ground motions and materials of concrete are established.

The 3 groups contain a total of 510 cases:

Group A (195 cases): Random material for concrete (normal random elastic modulus and uniformly random damping) and random ground motions (scaled to Sa = 7 to 17, 19, 21, and 15 ground motions for each).

Group B (195 cases): Uniform material for concrete and random ground motions (scaled to Sa = 7 to 17, 19 and 21, and 15 ground motions for each).

Group C (120 cases): Uniform material for concrete and uniform ground motions (scaled to Sa = 7 to 21 at 2 intervals, and 15 ground motions for each).

A total of 80 real ground motions from Pacific Earthquake Engineering Research Center provide data for simulation of ground motion. The data set was established between 1978 and 2010. Table 1 lists 20 of the earthquake records selected to create an ensemble for the seismic simulations. All have epicentral distances of 6.13 to 57.65 km with magnitudes ranging from 5.42 to 7.62. And the equivalent shear wave velocity Vs (30) near the surface is provided in the table. Figure 5 shows 5 of the normalized spectral accelerations of these selected records.

Table 1 – Part of the earthquake records selected

	Earthquake	Year	Mag.	Epicentral distance (km)	Vs30 (m/s)	Station Name
1	"Chi-Chi_ Taiwan"	1999	7.62	51.8	617.52	"HWA046"
2	"Chi-Chi_ Taiwan"	1999	7.62	57.65	734.26	"TTN032"
3	"Basso Tirreno_ Italy"	1978	6	19.59	620.56	"Naso"
4	"Niigata_ Japan"	2004	6.63	39.37	653.28	"NIGH10"
5	"Iwate_ Japan"	2008	6.9	25.56	655.45	"Yuzawa"
6	"Tottori_ Japan"	2000	6.61	9.12	616.55	"SMN015"

7	"Iwate_ Japan"	2008	6.9	21.25	655.45	"Minase Yuzawa"
8	"Chi-Chi_ Taiwan-06"	1999	6.3	25.85	614.98	"TCU076"
9	"Chi-Chi_ Taiwan"	1999	7.62	54.29	614.05	"HWA029"
10	"Chi-Chi_ Taiwan-03"	1999	6.2	16.46	624.85	"TCU071"
11	"Duzce_ Turkey"	1999	7.14	8.03	638.39	"Lamont 531"
12	"Chi-Chi_ Taiwan-05"	1999	6.2	67.47	665.2	"CHY086"
13	"Chi-Chi_ Taiwan"	1999	7.62	28.17	665.2	"CHY042"
14	"Loma Prieta"	1989	6.93	18.41	713.59	"UCSC Lick Observatory"
15	"Whittier Narrows-01"	1987	5.99	18.12	969.07	"Pasadena - CIT Kresge Lab"
16	"Loma Prieta"	1989	6.93	18.33	663.31	"Gilroy Array #6"
17	"Loma Prieta"	1989	6.93	71.33	582.9	"SF - Diamond Heights"
18	"Iwate_ Japan"	2008	6.9	41.72	552.38	"Misato_ Akita City - Tsuchizaki"
19	"Tottori_ Japan"	2000	6.61	15.59	967.27	"SMNH10"
20	"Chi-Chi_ Taiwan"	1999	7.62	56.14	1525.85	"HWA003"

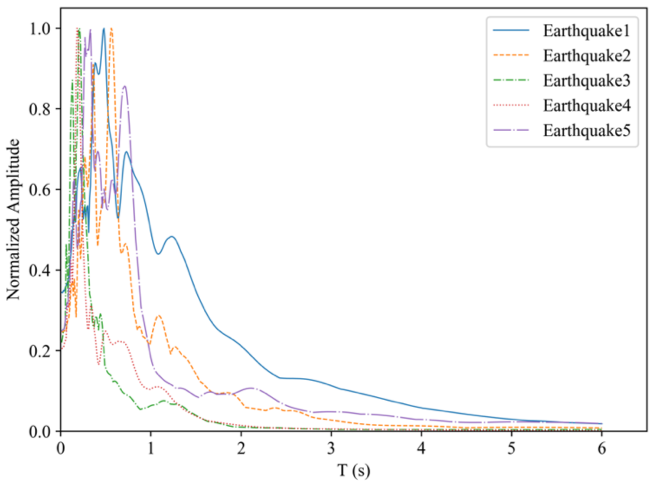


Fig. 5 – Normalized spectral accelerations

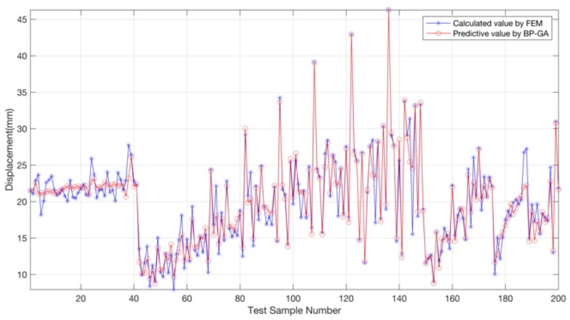
3.2 Prediction of vulnerability of Dagangshan based on AI model

In this section, the response analysis of the arch dam takes into account maximum displacements along the dam crest, contraction joint opening and damage volume ratio of concrete, respectively. A three-layer neural network structure with one hidden layer is capable of such response prediction problems. In the input layer, the factors are supposed to have a significant impact on the dam's vulnerability and easy to obtain. According to engineering experience, the structural parameters of the concrete are selected from the modulus of elasticity, tensile strength, damping, PGV, PGA, SA, and ASI as the basic factors. The output layer outputs corresponding displacement and damage volume ratio of Dagangshan Dam from the results of FEM, that means there are three neurons in the output layer. Besides, the hidden layer selects 30 neurons after testing.

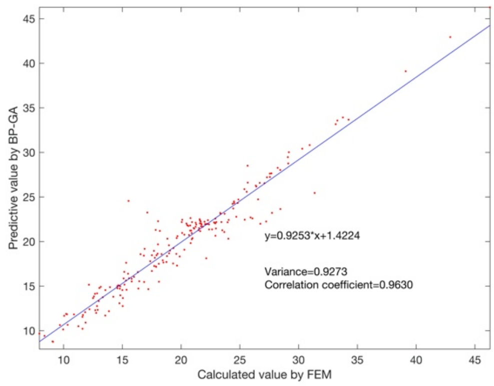
A total of 80 earthquakes that obtained from the Pacific Earthquake Center are used as input layer data after normalizing operations based the magnitude. A total of 310 sets of data of 500 are used as training samples, and the remaining 200 sets of data are testing data.

The magnitude of each input variable is quite different. In order to obtain better training results, the training sample set is normalized during pre-processing.

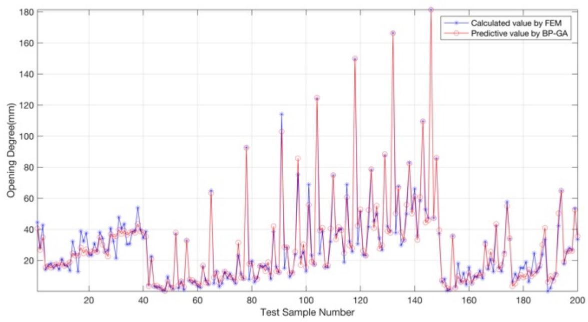
Figure 6 shows the comparison of the prediction results of maximum displacements along the dam crest, contraction joint opening and damage volume ratio, respectively.



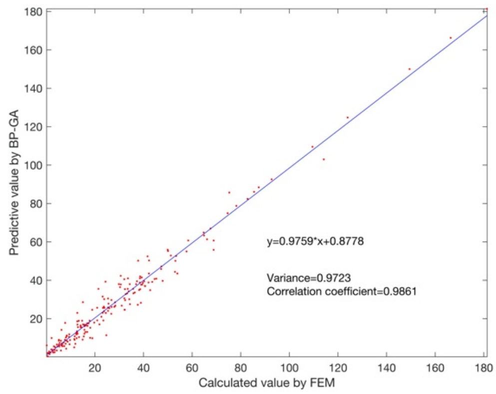
(a)



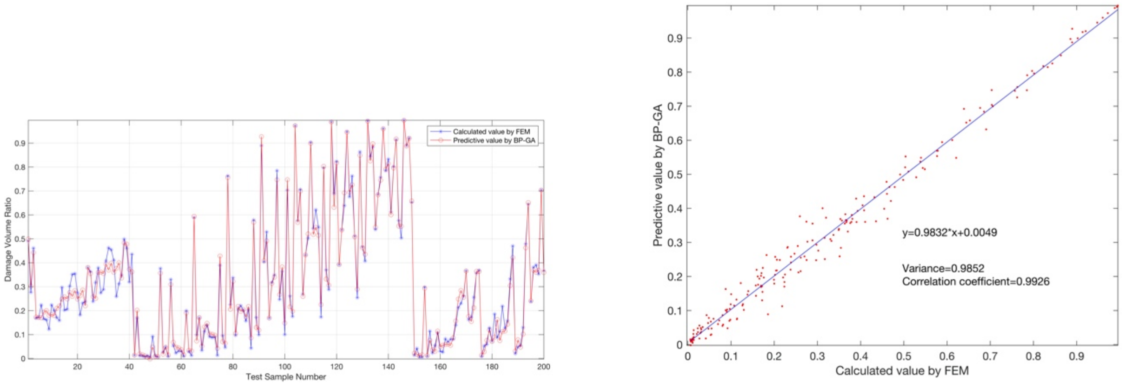
(b)



(c)



(d)



(e) (f)

Fig. 6 –Performance of the BP-GA model: (a) comparison of test results of displacement of maximum displacements along the dam crest; (b) fitting of test results to expected simulation results of displacement of maximum displacements along the dam crest; (c) comparison of test results of displacement of contraction joint opening; (d) fitting of test results to expected simulation results of displacement of contraction joint opening; (e) comparison of test results of damage volume ratio; (f) fitting of test results to expected simulation results of damage volume ratio

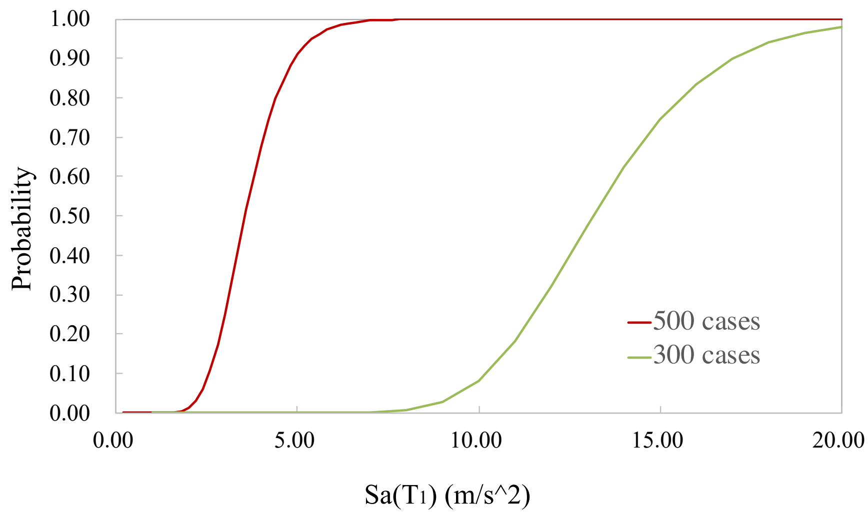
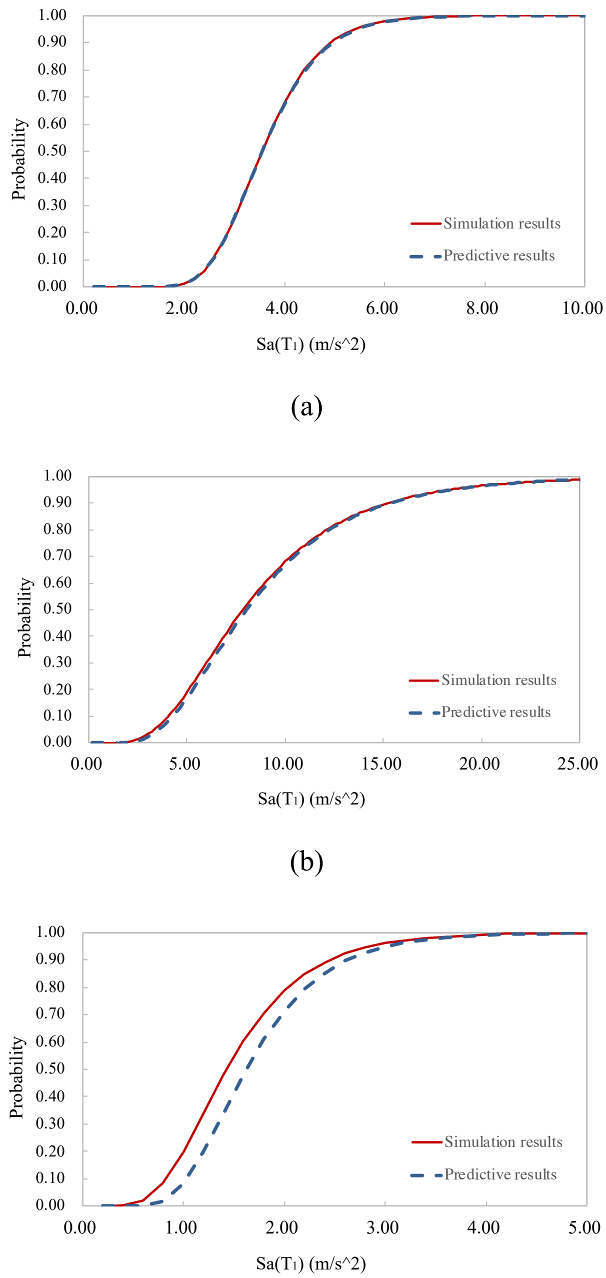


Fig. 7 –Fragility curves of the maximum displacements along the dam crest of 500 FEM cases results and 310 FEM results



(a)

(b)

(c)

Fig. 8 –Fragility curves of predictive and simulated results: (a) displacement of maximum displacements along the dam crest; (b) displacement of contraction joint opening; (c) damage volume ratio

From Figure 6, the results of the predictions of 200 testing data are satisfactory, no matter the displacement, opening degree, or volume of damage. Although the results of individual predictions are with some difference from those obtained by FEM, the overall fit is ideal. Give an example, for the displacement of contraction joint opening, the mean and standard deviation of the calculated value by FEM are 29.0 mm and 28.0 mm, respectively. And these two parameters appear in the prediction results are 28.6 mm and 27.1 mm. This shows that the test results of the displacement of contraction joint opening have similar distribution rules with the FEM. For the maximum displacements along the dam crest, both the comparison result and the fitted curve show similar effects to the contraction joint opening, which also illustrates the credibility of the prediction results of the BP-GA model. As for the damage volume ratio, fig. 6(f) shows the fitted results between the predicted results and actual values of damage volume. It can be seen that the degree of fit of the damage volume to the actual FEM results is in line with expectations due to the sample data that contains enough sample information.

According to the probability distribution obeyed by the characteristics of ground motion, concrete strength, elastic modulus, and damping, a fragility curve between possibility of displacement, opening or damage happening and spectral acceleration $Sa(T_1)$ is established. $Sa(T_1)$ is from $0.2m/s^2$ to $25\ m/s^2$ with an interval of $0.2m/s^2$. Select 500 finite element calculation results and 300 finite element calculation results to draw their vulnerability curves. As shown in Figure 7, it can be found that the curves drawn by the 300 finite element results cannot represent 500 at all. In order to describe the agreement between the prediction result of BP-GA model and the calculation result of finite element, where the blue dotted line in the Figure 8 represents a fragility curve composed of the learned 310 finite element calculation results and 200 predicted results from the BP-GA model, and the red line represents 510 finite element calculation results. The three figures presented reflect the probability of the displacement of maximum displacements along the dam crest is greater than 7mm, the displacement of contraction joint opening is greater than 7mm, and the damage volume ratio is greater than 0.5, respectively. It can be seen from the three figures that the two fragility curves are very similar, almost completely coincide, that is, the prediction result by the neural network trained from 310 finite element results can respond well to the remaining 200 finite element results, while in a much shorter period of time than FEM, which verifies the validity of the BP-GA model.

4. Conclusions

An artificial neural network based on genetic algorithms is proposed for prediction of nonlinear seismic response of arch dams. The performance of the proposed model was verified on the calculated data of a real concrete arch dam. Considering statistical regularity of data, the accuracy is greatly guaranteed. Therefore, the proposed model based on BP-GA can reflect the effect of earthquake on structural behavior. A concrete arch dam with a height of 210 meters and a dam crest arc length of 609.8 meters was taken as the example.

The predicted results of the damage volume, displacement of maximum displacements along the dam crest and contraction joint opening have similar distribution to the results from finite element analysis. Moreover, for vulnerability analysis of the arch dam, using this proposed model significantly saves time costs compared with finite element analysis. The proposed method can provide new ideas for vulnerability analysis of dams.

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