Probabilistic-Based Analysis of Concrete Gravity Dams under Synthetic Ground Motion Excitation

Yasaman Afkhami[1], Mohammad Alembagheri[2]

1- Department of Civil Engineering, Sharif University of Technology, Tehran, Iran
2- Department of Civil and Environmental Engineering, Tarbiat Modares University, Tehran, Iran

Email: Yasaman_a44@yahoo.com

Abstract

This research investigates seismic analysis of concrete gravity dams subjected to synthetic ground motions in the uncertainty framework. Many studies focused on only epistemic randomness due to material properties of concrete gravity dams and the impact of aleatory randomness due to seismic excitation is neglected. The latter source of randomness can significantly affect the results of analyses. Hence, in the current study, uncertainty due to earthquake excitation is tackled using synthetic ground motions. In addition, probabilistic characteristics of materials are taken into account along with artificial ground motion to form the seismic probabilistic-based analysis. The dam-reservoir-foundation model is employed for the uncertainty analysis. Generation of synthetic accelerogram utilized in this study is an iterative process based on Fourier transformation and target spectrum as well as baseline and PGA correction. Latin Hypercube sampling is utilized for the purpose of reliability analysis because of its lower computational cost relative to crude Monte Carlo Simulation for the same accuracy. The utmost goal of this research is to determine the exceedance probabilities of defined limit-state functions as well as the probability distribution function of the dam's response.

Keywords: Concrete Gravity Dam, Seismic Analysis, Reliability, Synthetic Ground Motion, Exceedance Probability.

1. INTRODUCTION

As the dams are considered one of the critical infrastructures, the safety level and accurate simulation of these infrastructures are of paramount importance. Simulation of seismic loading in analysis of concrete dams has received considerable attention in recent studies, as it is one of the main factors causing extensive damages [1-4]. On the other hand, there is a great deal of uncertainty in concrete dam modeling which have to be taken into account. Hence, the aforementioned problem can be tackled by employing reliability approaches [5, 6]. Utilizing reliability approaches provide information about the safety level of the structures under the defined loading conditions. The first step toward uncertainty analysis is to have the comprehensive understanding of the source of randomness. The randomness is categorized into aleatory and epistemic. The aleatory randomness is irreducible and is related to the nature of the phenomenon. The epistemic randomness is due to lack of information which can be reduced by gathering more information on the subject [7]. In a seismic analysis, a primary source of modeling uncertainty lies in the ground motion characteristics. As a deduction, synthetic ground motions are used in seismic analysis to consider more realistic simulation of earthquake along with inherent randomness existing in earthquake nature. Moreover, the uncertainty in the model parameters (epistemic randomness) is taken into account by assigning probabilistic characteristics to them. The probabilistic characteristics of input parameters are defined through experiments, probabilistic modeling or engineering judgment.

Recently, the probabilistic analysis of concrete dams has received considerable attention from many researchers [8, 9]. Application of seismic reliability analysis to concrete dams with the consideration of epistemic randomness is reviewed in the literature [4, 10]. In these studies, the uncertainty due to seismic excitation was considered by applying a single record or a set of natural ground motion to the model. Moreover, the reliability method used in these researches was limited to crude Monte Carlo Simulation and the main drawback of this method is its high computational cost. By reviewing papers in the field of reliability methods, other approaches such as importance sampling, directional sampling, Latin Hypercube sampling (LHS), point-estimate method, first-order and second-order reliability method were widely used [11, 12]. Although these approaches were employed for the purpose of reliability analysis of miscellaneous structures, there are few studies considering these methods in the field of dam engineering. Utilizing the new approaches will lead to more accurate results along with less computational cost.

In this research, the aforementioned issues are handled using effective reliability method which is LHS and generating synthetic ground motions. Furthermore, the effect of foundation is considered in this study. The epistemic uncertainty is tackled by defining dam and foundation properties as random variables. Concrete density and Young's elasticity modulus of concrete and foundation are assumed as the source of epistemic randomness. Generation of synthetic accelerogram utilized in this study is an iterative process based on Fourier transformation and target spectrum as well as baseline and PGA correction. As the main potential failure mode of concrete gravity dams due under seismic excitation is due to tensile cracking, the performance function is defined by tensile overstressing of the dam body. The utmost goal of this research is to determine the exceedance probabilities of defined limit-state functions as well as the probability distribution function of the dam's response.

2. Uncertainty Approach

The risk in dam safety analysis is affected by the combined impact of failure scenario, probability of occurrence and the associated consequences [1]. Therefore, the risk analysis of dams firstly requires identification of potential failure scenarios, and then quantification of the conditional probability of these scenarios for different loading conditions. The failure scenario can be presented as limit-state inequality given by:

$$g(\mathbf{x}) \le 0 \tag{1}$$

where g(**x**) is the limit-state (performance) function with the failure condition defined by the above inequality, and **x** is the vector of random variables in the problem. g(**x**) = 0 defines the failure or limit-state surface. The probability of occurrence of the failure scenario, Pf [g(**x**) ≤ 0], which is equal to the exceedance probability of the corresponding limit-state function, can be computed through the probabilistic framework [10]

$$P_f[\mathrm{g}(\mathbf{x}) \le 0] = \int_{\mathrm{g}(\mathbf{x})\le 0} h(\mathbf{x})d(\mathbf{x}) \tag{2}$$

where $h(\mathbf{x})$ is the joint probability density function of the random variables. There are various statistical techniques to quantify the risk. These techniques, which are known as structural reliability methods, use different mathematical formulations. Assuming that the random variables are normally distributed, the reliability index, β, is defined as

$$\beta = -\varphi^{-1}(P_f) \tag{3}$$

where Φ is the standard normal cumulative distribution function.

The benchmark and most reliable method is sampling, such as Monte-Carlo method, which is used for its ease of application in problems formulated in terms of a performance function [12]. In Monte-Carlo method realizations of each random variable are generated, which form a simulation model, and then the model is analyzed to determine the thermal response. By repeating the process for thousands of sets of realizations, distribution of response results associated with the input random variables is determined [13]. The exceedance probability of failure scenario, P_f, is estimated by dividing the number of simulations where failure scenario occurred to the total number of simulations. While conceptually straightforward, the Monte-Carlo procedure can become computationally very intensive because the number of simulations performed should be large enough to capture the searched probability. The remedy can be using more efficient sampling methods, among them Latin hypercube sampling (LHS) is selected for this research because of its efficiency and simplicity. The LHS is a variance reduction sampling method that stratifies variable marginal distributions in order to fully cover the range of each variable in a more efficient way than pure Monte-Carlo sampling [14]. Unfortunately, the appropriate sample size N, cannot be formerly determined to achieve a certain confidence level. However, using a relatively high N that is substantially larger than the number of random variables will result in reasonably accurate estimates for practical purposes.

3. Generating Synthetic Ground Motion

The calculation method used in this research is given by the algorithm which is described in the following [15]. The artificial accelerogram is defined starting from a synthetic one, compatible with the target spectrum, and adapting its frequency content using the Fourier Transformation Method.

The correction of the random process is carried on at every iteration using the relationship below [16]:

$$F(f)_{i+1} = F(f)_i[SRT(f)/SR(f)_i] \tag{4}$$

where $SRT(f)$ is the value of the target spectrum and $SR(f)_i$ is the value of response spectrum corresponding to the accelerogram of the current iteration for frequency f. $F(f)_{i+1}$ and $F(f)_i$ are the values of the accelerogram in the frequency domain for the current and previous iteration respectively. At each iteration a

Fourier Transformation is applied to move from time domain to frequency domain, where the correction to the accelerogram is carried on. Then an Inverse Fourier Transformation is applied in order to return to the time domain, where the corresponding spectrum is calculated, convergence is checked and it is evaluated whether or not further correction is needed. A schematic summary is given below.

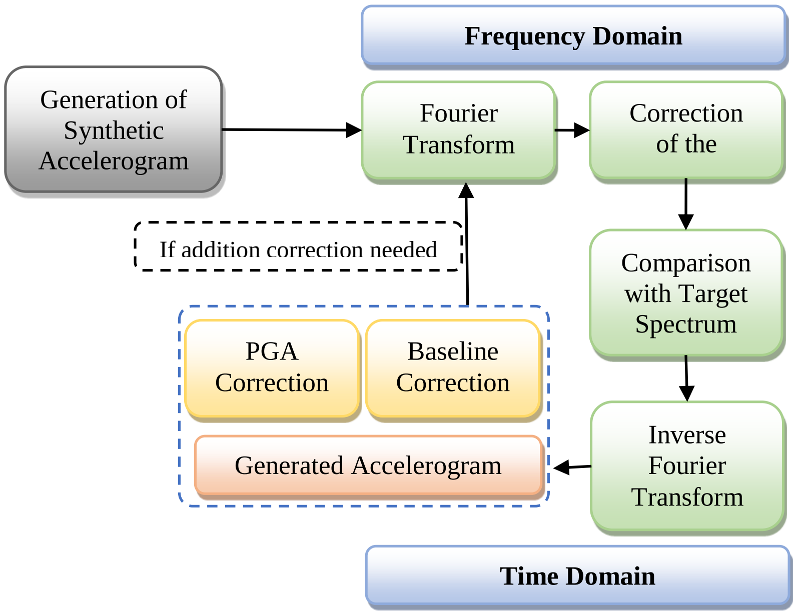

Figure 1. Algorithm of generating synthetic ground motion

In this calculation method framework, the Envelope Shape module is not explicitly shown to the user, since the procedure does not start from a random process, but rather from a synthetic accelerogram. The generation of the synthetic accelerogram starts from a Gaussian white noise which is multiplied by envelope shape and then adapted to a certain source spectrum [17]. The duration of the ground motion is calculated from the input parameters.

4. Case Study: Deterministic and Probabilistic Modeling

In this study, Pine Flat concrete gravity dam is selected as the case study. The tallest monolith of the dam is used for the analyses. The geometry of the dam body and the finite element model of the dam-foundation-reservoir system are illustrated in Figure 2. The foundation rock is assumed as a homogeneous, isotropic, viscoelastic half-plane media. The foundation is extended twice the structural height of the dam in vertical direction, and five times in horizontal direction. The length of reservoir was assumed five times the dam height and non-reflective planar boundary condition was assigned as far-end boundary condition.

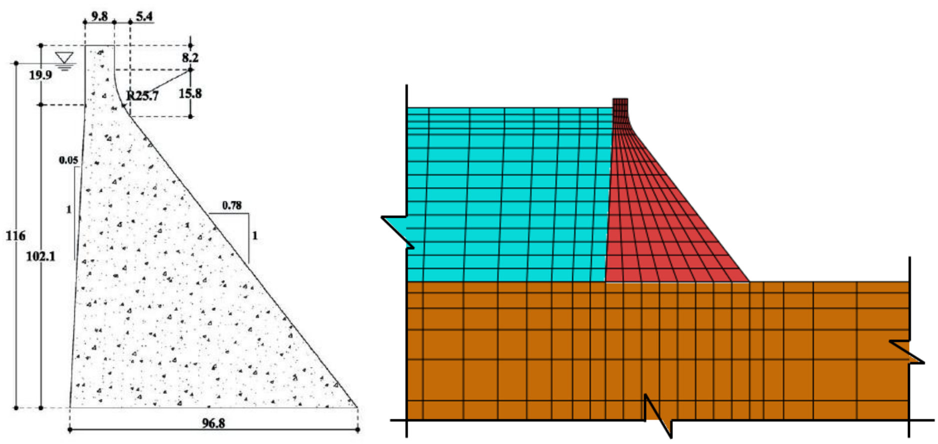

Figure 2. Geometry and the finite element model of the structure

The material and structural properties of the dam-foundation-reservoir system is given in Table 1. In the current research, concrete density and the Young's elasticity modulus of the dam and foundation are assumed as random variables. The probabilistic characteristics of these random variables are shown in Table 1.

Table 1- Material and structural properties

		Mean Value	Distribution Type	Coefficient of Variation
Concrete	Young's modulus (GPa)	30	Lognormal	10 %
	Poisson's ratio	0.2	NA	
	Density (kg/m³)	2400	Lognormal	15 %
	Rayleigh damping coefficients	$\alpha = 1.64$ $\beta = 0.0012$	NA	
	First and third mode damping (%)	5	NA	
Foundation Rock	Ratio of rock's Young's modulus to concrete Young's modulus	0.625 Range: [0.25-1]	Uniform	34.64 %
	Poisson's ratio	0.33	NA	
Water	Density (kg/m³)	1000	NA	
	Bulk modulus (GPa)	2.07	NA	

For the purpose of generating synthetic ground motion with the method described in previous section, Taft ground motion, Kern County, 7/21/1952, Taft Lincoln School, 111, is utilized. The spectrum of this record is employed so synthetic accelerogram can be generated as considering this target spectrum. Seven synthetic ground motions are generated and their statistics along with the characteristics of the target ground motion, Taft record, can be found in Table 2. As it can be noticed from Table 2, the mean error are below 10 percent and the arias intensity values are varied from 0.334 to 0.552.

Table 2- Statistical characteristics of generated ground motion

Synthetic Record No.	Mean Error (%)	CoV (%)	PGA (g)	PGV (cm/sec)	PGD (cm)	Arias Intensity (cm/sec)	Significant Duration (cm)
1	7.68	10.22	0.151	63.607	102.445	0.522	14.67
2	9.28	9.48	0.145	29.028	61.114	0.375	11.58
3	9.34	11.39	0.187	13.582	5.681	0.387	8.91
4	9.13	10.23	0.157	25.971	19.265	0.415	9.62
5	9.30	10.09	0.156	24.026	35.197	0.393	8.40
6	9.40	10.14	0.179	13.739	13.572	0.334	9.02
7	9.57	9.91	0.179	19.642	15.445	0.390	8.81
Taft Record	-	-	0.180	18.626	9.352	0.599	28.78

The only considered failure scenario for this model is the tensile overstressing which is quantified using the following limit-state function:

$$g(\mathbf{x}) = TS - \sigma_t \qquad (5)$$

where TS is the concrete tensile strength, and σ_t is the peak value of the maximum principal (tensile) stress of the dam body. The performance index of this limit-state function can be in the form of:

$$g(\mathbf{x}) \leq 0 \qquad (6)$$

which represents the exceedance of the maximum tensile stress in one or more elements within the dam body from the threshold value TS. Additional analyses have shown that the compressive overstressing is not a critical limit-state for the concrete gravity dam models under the seismic loading.

5. RESULTS

The exceedance probabilities for the defined limit-state are calculated using LHS with 1,000 realizations and the results are presented in Figure 3. The analyses are repeated for seven synthetic records and the probabilities are determined for different thresholds of the limit-state function. In the aforementioned figure, the exceedance probability curves illustrated for all synthetic records along with the mean, 84th and 16th

percentile values. The 84th and 16th percentile indicate the confidence interval and they are the mean value plus standard deviation and mean value minus standard deviation, respectively. It is concluded from exceedance probability curves that there are slight differences between the results for threshold values below 3 MPa. As the threshold values are increased, the differences are more obvious. The reason for this observation is since the larger thresholds values result in lower probabilities, the accuracy of the results are lower in the tail of the distributions which low probabilities are located there.

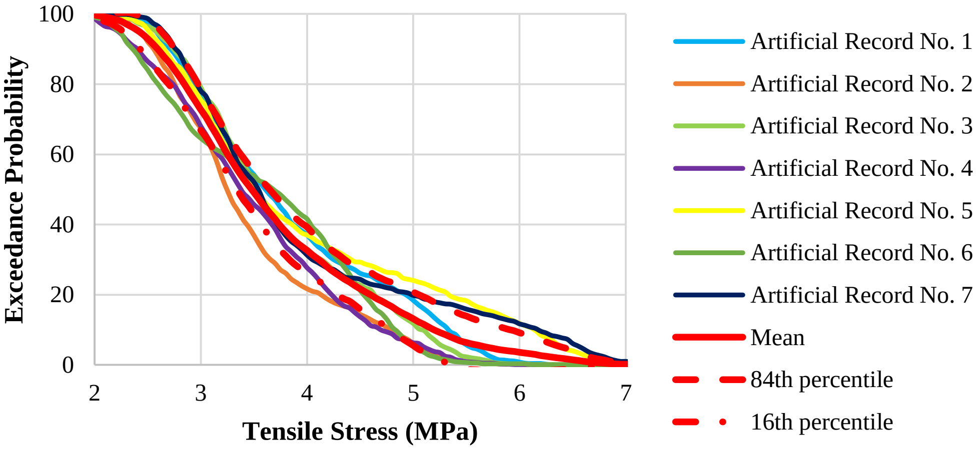

Figure 3. Exceedance probability curves for artificial records applied to the finite element model

Moreover, the results indicate that the confidence interval illustrated in Figure 3. encompass the results of all synthetic records. This means the further interpretation of the results will be more accurate considering the aforementioned confidence interval. In addition to these results, the histogram of the dam responses is depicted in Figure 4. These histograms indicate 1,000 results of the time history analysis of the Pine Flat dam under seven generated synthetic records. As mentioned earlier, the results are based on maximum tensile stress in the dam body under seismic excitation. The histograms imply that the maximum tensile stress in the dam body varies between 2 to 7 MPa.

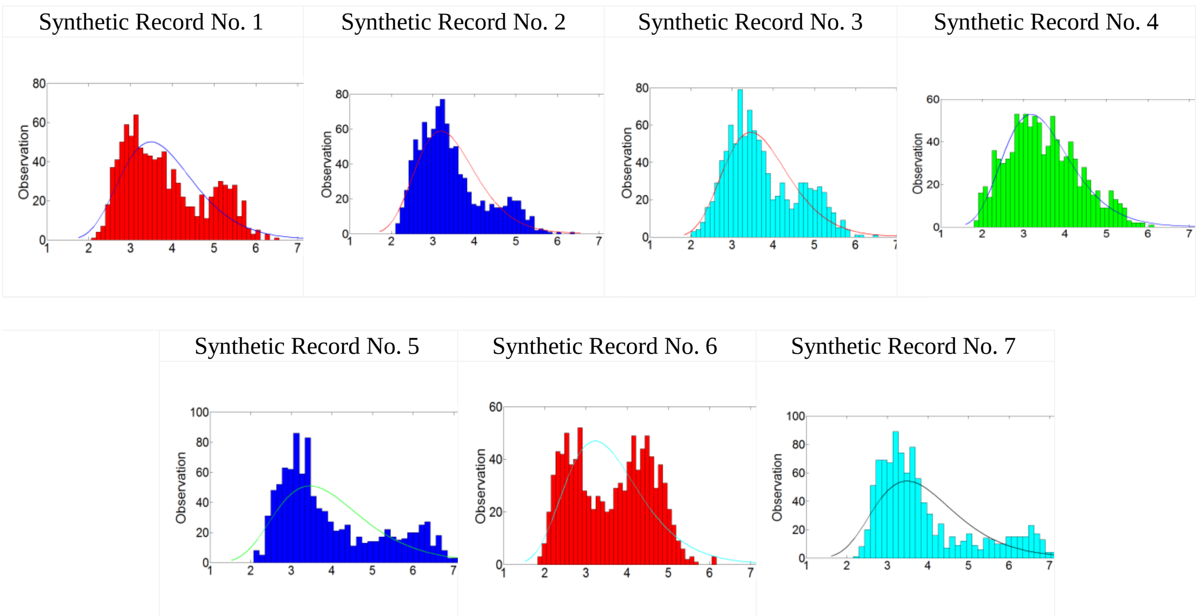

Figure 4. The histograms of the maximum tensile strees obtained by LHS under synthetic ground motion excitation. The horizontal and vertical axes are the tensile stress (MPa) and number of observation, respectively.

Although the histograms reveal different pattern but the fitted distributions express identical results. The probabilistic characteristics of the results along with their fitted probability distribution are shown in Table 3. For the purpose of the goodness of fit tests, Anderson-Darling test is utilized. This procedure is a general test to compare the fit of an observed cumulative distribution function to an expected cumulative distribution function. Anderson-Darling test is the most standard way to control goodness-of-fitting for distributional models. According to the fitting results, the first three distributions which fit the observation the best is presented in Table 3. As it is obvious, Beta distribution is the best fitted distribution for all the results of the model under seven synthetic ground motions.

Table 3- Probabilistic characteristics and fitted distribution of the outputs

Synthetic Record No.	Mean (MPa)	Standard Deviation	Fitted Distribution		
			1st rank	2nd rank	3rd rank
1	3.827	0.972	Beta	Gumbel Max	Lognormal
2	3.444	0.808	Beta	Gumbel Max	Lognormal
3	3.733	0.865	Beta	Gumbel Max	Lognormal
4	3.490	0.862	Beta	Gamma	Lognormal
5	3.977	1.274	Beta	Gumbel Max	Lognormal
6	3.607	0.948	Beta	Weibull	Normal
7	3.937	1.226	Beta	Gumbel Max	Lognormal

6. CONCLUSIONS

In this research, seismic reliability analysis of concrete gravity dam subjected to artificially generated earthquake is investigated. The aleatory randomness due to earthquake nature along with epistemic randomness is taken into account. The synthetic records are generated using a target spectrum with the algorithm based on Fourier transformation and target spectrum as well as baseline and PGA correction. The epistemic uncertainty is tackled by defining concrete density, Young's modulus of concrete and the ratio of Young's modulus of concrete to foundation rock as random variables. The dam-foundation-reservoir system is considered in this study. As the potential failure mode of concrete gravity dam due to ground motion is tensile cracking, the limit-state function is defined based on maximum tensile stress. The reliability methods employed in this investigation is Latin Hypercube sampling. With one thousands realizations, the exceedance probabilities of the defined thresholds are calculated and depicted as exceedance probability curves. Moreover, the histograms of the outputs are determined. The Anderson-Darling goodness of fit test indicates that for all outputs, the best fitted distribution is Beta. The results indicate that the confidence interval determined using exceedance probability curves, encompass the results of all synthetic records. This means the further interpretation of the results will be more accurate considering the aforementioned confidence interval.

7. REFERENCES

1. Altarejos-García, L., Escuder-Bueno, I., Serrano-Lombillo, A., & de Membrillera-Ortuño, M. G. (2012), "Methodology for estimating the probability of failure by sliding in concrete gravity dams in the context of risk analysis," Structural safety, 36, 1-13.
2. Gaspar, A., Lopez-Caballero, F., Modaressi-Farahmand-Razavi, A., & Gomes-Correia, A. (2014), "Methodology for a probabilistic analysis of an RCC gravity dam construction. Modelling of temperature, hydration degree and ageing degree fields," Engineering Structures, 65, 99-110.
3. Kartal, M. E., Bayraktar, A., & Başağa, H. B. (2012), "*Nonlinear finite element reliability analysis of Concrete-Faced Rockfill (CFR) dams under static effects*," Applied Mathematical Modelling, 36(11), 5229-5248.
4. Lupoi, A., & Callari, C. (2012), "*A probabilistic method for the seismic assessment of existing concrete gravity dams,*" Structure and Infrastructure Engineering, 8(10), 985-998.
5. Vanmarcke, E. H. (1973), "*Matrix formulation of reliability analysis and reliability-based design,*" Computers & Structures, 3(4), 757-770.
6. Ditlevsen, O., & Madsen, H. O. (1996), "*Structural reliability methods (Vol. 178),*" New York: Wiley.
7. Haukaas, T., & Der Kiureghian, A. (2004), "*Finite element reliability and sensitivity methods for performance-based earthquake engineering (No. 14),*" Pacific Earthquake Engineering Research Center, College of Engineering, University of California, Berkeley.
8. Mohammadi, P. M., Noorzad, A., Rahimian, M., & Omidvar, B. (2009), "*The effect of interaction between reservoir and multi-layer foundation on the dynamic response of a typical arch dam to P and S waves*," Arabian Journal for Science and Engineering, 34(1B), 92.
9. Hariri-Ardebili, M. A., & Saouma, V. E. (2016), "*Probabilistic seismic demand model and optimal intensity measure for concrete dams,*" Structural Safety, 59, 67-85.
10. Alembagheri, M., & Seyedkazemi, M. (2015), "*Seismic performance sensitivity and uncertainty analysis of gravity dams,*" Earthquake Engineering & Structural Dynamics, 44(1), 41-58.
11. Karamchandani, A., & Cornell, C. A. (1992), "*Sensitivity estimation within first and second order reliability methods*," Structural Safety, 11(2), 95-107.
12. Val, D., Bljuger, F., & Yankelevsky, D. (1997), "*Reliability evaluation in nonlinear analysis of reinforced concrete structures,*" Structural Safety, 19(2), 203-217.
13. Liel, A. B., Haselton, C. B., Deierlein, G. G., & Baker, J. W. (2009), "*Incorporating modeling uncertainties in the assessment of seismic collapse risk of buildings*," Structural Safety, 31(2), 197-211.
14. McKay, M. D., Beckman, R. J., & Conover, W. J. (1979), "*Comparison of three methods for selecting values of input variables in the analysis of output from a computer code*," Technometrics, 21(2), 239-245.
15. Halldorsson, B., & Papageorgiou, A. S. (2005), "*Calibration of the specific barrier model to earthquakes of different tectonic regions,*" Bulletin of the Seismological society of America, 95(4), 1276-1300.
16. Gomes, R. C., Santos, J., & Oliveira, C. S. (2006), "*Design spectrum-compatible time histories for numerical analysis: Generation, correction and selection,*" Journal of earthquake engineering, 10(06), 843-865.
17. Rodolfo Saragoni, G., & Hart, G. C. (1973), "*Simulation of artificial earthquakes,*" Earthquake Engineering & Structural Dynamics, 2(3), 249-267.