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Uncertainty reduction of seismic fragility of intake tower using Bayesian Inference and Markov Chain Monte Carlo simulation

Jahangir Alam[1a], Dookie Kim[*1] and Byounghan Choi[2b]

[1]*Civil and Environmental Engineering, Kunsan National University 558 Daehak-ro, Gunsan-si 54150, Republic of Korea*
[2]*Rural research Institute, 870, Haean-ro Sangnok-gu, Ansan-si Gyeonggi-do, 15634, Republic of Korea*

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Abstract. The fundamental goal of this study is to minimize the uncertainty of the median fragility curve and to assess the structural vulnerability under earthquake excitation. Bayesian Inference with Markov Chain Monte Carlo (MCMC) simulation has been presented for efficient collapse response assessment of the independent intake water tower. The intake tower is significantly used as a diversion type of the hydropower station for maintaining power plant, reservoir and spillway tunnel. Therefore, the seismic fragility assessment of the intake tower is a pivotal component for estimating total system risk of the reservoir. In this investigation, an asymmetrical independent slender reinforced concrete structure is considered. The Bayesian Inference method provides the flexibility to integrate the prior information of collapse response data with the numerical analysis results. The preliminary information of risk data can be obtained from various sources like experiments, existing studies, and simplified linear dynamic analysis or nonlinear static analysis. The conventional lognormal model is used for plotting the fragility curve using the data from time history simulation and nonlinear static pushover analysis respectively. The Bayesian Inference approach is applied for integrating the data from both analyses with the help of MCMC simulation. The method achieves meaningful improvement of uncertainty associated with the fragility curve, and provides significant statistical and computational efficiency.

Keywords: bayesian inference; markov chain monte carlo simulation; seismic fragility; uncertainty; intake tower

1. Introduction

This paper proposes the procedure for updating fragility parameters using Bayesian Inference with the help of Markov Chain Monte Carlo (MCMC) simulation of the intake tower as well as to get the tight confidence interval of median fragility curve. The intake tower is often used to reconnoiter the release of water through concrete and earthen dam as well as for maintaining hydropower plant. In the event of an earthquake, prevention of failure of the dam and sudden release of water of the reservoir is the main concern for the reservoir engineers. For most of the earthen and concrete dam, the intake tower is used for controlling the release of water of the reservoir. Consequently, the intake tower is an important component for the estimation of the system risk of reservoir. A cantilever freestanding tower of height 62.70m has been modeled. Due to its higher height and complexity, seismic fragility analysis is one of the main factor taken into consideration.

Probabilistic seismic risk models play a pivotal role for assessing and managing the risk due to the earthquake. In the probabilistic seismic risk model, a fragility curve illustrates the probability of failure corresponding the intensity measure like Peak Ground Acceleration (PGA). Lognormal model is the commonly used method for estimating fragility parameters where PGA value is considered as a lognormal distribution. However, this method provides a wide band of the confidence interval. Many researchers use numerical analysis, professional judgment and experimental result data for developing the structural fragility model since huge data is required for minimizing the wide confidence interval. Kennedy *et al*. (1980) were the first who presents a detailed procedure for the estimation of median ground acceleration capacity. Shinouzuka *et al*. (2000) first proposed maximum likelihood estimation method to determine the fragility parameter. Ellingwood *et al*. (2002) used Incremental Dynamic Analysis (IDA) for probabilistic seismic demand. Seismic fragility and risk of seismically isolated extradosed bridges with lead rubber bearings were illustrated (Kim *et al*. 2008). Lagaros *et al*. (2009) used artificial neural networks (ANN) into the fragility analysis framework to enhance the computational efficiency of seismic fragility. The seismic fragility curves were developed for existing reinforced concrete buildings based on the post-earthquake field survey and the seismic performance using capacity design (Mehani *et al*. 2013). Estimation of fragility parameters using these direct statistical approach requires available numerical analysis data. A large number of dynamic analyses of structure require significant computational time.

The Bayesian Inference technique with MCMC

∗Corresponding author, Professor
E-mail: kim2kie@kunsan.ac.kr
[a]Master student
[b]Ph.D

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simulation is used in this investigation to reduce the total number of time history analysis by adding prior information of fragility curve with simulation data from time history analyses. The main purpose of this study is to reduce the confidence interval of the median fragility curve. The Bayesian Inference method is a powerful tool for updating prior information with a newly available data. A number of researchers used Bayesian Network for estimating fragility parameters. Singhal *et al*. (1998) used Bayesian framework for updating fragility parameters of Reinforced Concrete (RC) frames. Koursourelakis (2010) suggested a Bayesian framework considering four different ground motion intensity measure to calculate fragility parameters and applied it in geotechnical field. Pei and Lindt (2009) applied the Bayesian approach to update and develop the probabilistic capacity and demand model using experimental data of wood frame structure. Gokkaya *et al*. (2015) illustrated a Bayesian approach for seismic collapse risk assessment on a four-story reinforced concrete moment frame building.

In the case of the intake tower, the seismic response was evaluated of an independent intake tower in the spillway tunnel (Zhang *et al*. 2008), and a nonlinear seismic response capacity spectrum method was developed intake towers of dams (Cocco *et al*. 2010). The U.S. Army Corps of Engineers (USACE) had multi year's research efforts and progress on the survival of intake tower.

Most of these studies have a common theme, like incorporated analysis and test results of structure for estimating the seismic fragility. In this study, Bayesian Inference method is used with different MCMC simulation for decreasing the uncertainty of the median fragility curve of the intake tower. Total 30 time history analyses and a nonlinear static pushover analysis of the intake tower are conducted. Then conventional lognormal approach is applied for constructing fragility curve from the both numerical analysis data. Finally, the fragility curve is updated using those small number of numerical analysis data with the help of Bayesian Inference and MCMC simulation. The aim of combining the different numerical analysis data is to improve computational and statistical efficiency as well as improving the confidence interval of median fragility curve.

2. Structural fragility

Structural fragility is a generalized part of structural reliability, which estimates the vulnerability of a structure conditioned upon some other given parameter. Alike, the seismic structural fragility is defined as the probability, that the seismic demand placed on the structure (D) is greater than the capacity of structure (C). Mathematically, it is often expressed as

$$\mathrm{G}(C,D) = C - D \tag{1}$$

where damage gate $\mathrm{G}(C,D)$ is a function of at least two variable representing various experimental, material, modeling and loading uncertainties for the structure. The probability statement controlled by a chosen intensity measure (IM) which represents the level of seismic loading. Mathematical representation of this conditional probability is given as

$$\text{Seismic fragility } = P[C - D \leq 0|IM] \tag{2}$$

The capacity C also called strength of a structure can be defined as the maximum seismic load that the structure can resist without occurring any damage. It relies on materials properties and other strength parameters like compression strength, yield stress, design code etc. The demand D typically is evaluated from modelling and analysis variables like finite element models, ground motion histories, damping, soil-structure interaction etc. Capacity is considered to be deterministic. The fragility of the structure is assumed to follow some probability distribution function, to be identified specifically to each damage state (i) and ground motion intensity (j)

$$P[C - D \leq 0|IM] = F_{ij}(C_i) \tag{3}$$

where $F_{ij}(C_i)$ denotes the fragility function for ground motion IM, defined as the probability that the structure exceeds damage state of IM. PGA is used in this study as a IM. Singhal and Kiremidjian (1996) verified such assumption at a 5% confidence level by the Kolmogorov-Smirnov test and assumed a lognormal distribution function to express the fragility curve as well, identified by ordinary fitting. It is very common for seismic risk assessment to use the two parameters (x_m and β) of the lognormal distribution. A lognormal cumulative distribution function is often used to define a fragility function

$$P(C|IM) = F_{ij}(C_i) = \phi\left(\frac{\ln IM - \ln x_m}{\beta}\right) \tag{4}$$

where $\phi(.)$ denotes the standard normal cumulative distribution function(CDF), x_m is the median value of the distribution function, and β denotes the logarithmic standard deviation or dispersion of $\ln IM$.

There are different ways to estimate fragility parameters. The Incremental Dynamic Analysis (IDA) is a method of determining fragility parameters that are utilized to estimate the seismic performance of structural systems. The IDA involves scaling each ground motion in a suite until it causes a collapse of the structure (Vamvatsikos and Cornell 2002). In an IDA, the intensity measure of the ground motion is incremented and put into the structural model up to the point at which instability occur for lateral displacement. Fragility function parameters can be estimated from analysis data by taking logarithms of each ground motion's IM value associated with the onset of collapse, and computing their mean and standard deviation (Ibarra and Krawinkler 2005).

Let, M be the number of specimens tested to failure, i is the index of specimen $(i = 1,2, \dots . M)$ and IM are the value associated with the beginning of collapse for the ith ground motion. From the basic definition of x_m and β (Ang and Tang 2006)

$$x_m = \exp\left(\frac{1}{M}\sum_{i=1}^{M} \ln IM_i\right) \tag{5}$$

$$\beta = \sqrt{\frac{1}{M-1}\sum_{i=1}^{M}\left(\ln\frac{IM_i}{x_m}\right)^2} \tag{6}$$

The fragility function is fitted using this approach with Bayesian Inference and Markov Chain Monte Carlo (MCMC) simulation.

3. Bayesian inference

The structural fragility model $P(C|IM)$ depends on a vector of random variables θi where $(i = 1,2, \ldots . k)$ with prior relative likelihood $p_i = P(\Theta = \theta_i)$. Also we can express our current knowledge as a joint density function $f'_\Theta(\theta_1, \theta_2 \ldots .)$, which is often referred to as prior information and generally available from experimental information, professional knowledge of the expert, past studies etc. (Ng *et al*. 2015). Suppose, some additional information like a vector of M observation $\mathrm{Y} = (\mathrm{y}_1, \mathrm{y}_2 \ldots \mathrm{y}_\mathrm{m})$ of structural fragility have been collected. The prior information $f'_\Theta(\theta_1, \theta_2 \ldots .)$, may be modified formally through the Bayes theorem using observed data to posterior information $f''_\Theta(\theta_1, \theta_2 \ldots . |Y)$ as (Tadinada 2012)

$$f''_\Theta(\theta_1, \theta_2 \ldots . |\mathrm{Y}) = \frac{P(\theta_1, \theta_2 \ldots . |\mathrm{Y}) f'_\Theta(\theta_1, \theta_2 \ldots .)}{P(\mathrm{Y})} \tag{7}$$

$$P(Y) = E(\theta_i|\mathrm{Y}) = \int P(\theta_1, \theta_2 \ldots . |\mathrm{Y}) f'_\Theta(\theta_1, \theta_2 \ldots .) d\theta_i \tag{8}$$

where $P(\theta_i\,|\mathrm{Y})$ is referred to as the likelihood function of the random parameter. After updating the prior information, MCMC simulation is used to sampling the data, and the fragility parameters are calculated using the Eqs. (5) and (6).

4. Markov Chain Monte Carlo (MCMC)

The posterior statistics $f''_\Theta(\theta_i\,|\mathrm{Y})$ are computed by numerically generating a large number of posterior samples employing a special class of computational algorithms called Markov Chain Monte Carlo (MCMC) simulation (Congdon 2006). Let us assume that the density function $f(\theta_1, \theta_2 \ldots .)$ of a random variable enables us to easily generate random values (Ioannis Ntzoufras 2009). Mathematically

$$\mathrm{I} = \int \frac{g(\theta)}{f(\theta)} f(\theta) d\theta = \int g^*(\theta)\, f(\theta) d\theta \tag{9}$$

Therefore the integral I can be precisely calculated by generating $\theta_1, \theta_2 \ldots ., \theta_T$ from the target distribution with probability density function and we can calculate the sample mean from the following equation

$$\hat{\mathrm{I}} = \frac{1}{\mathrm{T}}\sum_{t=1}^{T}\left[\frac{g(\theta^{(t)})}{f(\theta^{(t)})}\right] \tag{10}$$

The main advantage of this approach is its simplicity. For a suitable large generated sample (e.g., T = 10,000), this approach is very accurate (Gamerman and Lopes 2006). The Monte Carlo simulation cannot be applied in all cases because of we want the sample from posterior distribution $P(\theta|\mathrm{Y})$ but in case of independent sampling from $P(\theta|\mathrm{Y})$ may be difficult. Simulation techniques based on Markov Chain overcome such problems because of their generality and flexibility.

There are several standard methods available for designing Markov Chains with required stationary distribution $P(\theta|\,\mathrm{Y})$. The Gibbs Sampling (Casella and George 1992) is a special case of the Metropolis-Hastings algorithm which generates a Markov chain by sampling from full conditional distribution.

Let us assume a vector θ consist of k sub-components, $\theta = (\theta_1, \theta_2, \ldots ., \theta_k)$.

1) Choose starting values $\theta_1^{(0)}, \theta_2^{(0)}, \ldots \ldots \ldots \theta_k^{(0)}$
2) Sample $\theta_1^{(1)}$ from $P(\theta_1|\theta_2^{(0)}, \theta_3^{(0)} \ldots \ldots \ldots \theta_k^{(0)}, \mathrm{Y})$

Sample $\theta_2^{(1)}$ from $P(\theta_2|\theta_1^{(1)}, \theta_3^{(0)} \ldots \ldots \ldots \theta_k^{(0)}, \mathrm{Y})$

Sample $\theta_k^{(1)}$ from $P(\theta_k|\theta_1^{(1)}, \theta_2^{(1)} \ldots \ldots \ldots \theta_{k-1}^{(1)}, \mathrm{Y})$

Eventually, we obtain a sample from $P(\theta|\,\mathrm{Y})$ by repeating the step 2 many times. The Markov Chain Monte Carlo simulation method enables quantitative researchers to use highly complicated model and estimate the corresponding posterior distribution with accuracy.

5. Structural analysis of intake tower

In this research, the seismic risk assessment of the high rise intake tower is analyzed. The tower is in underwater and independent.

5.1 Tower geometry

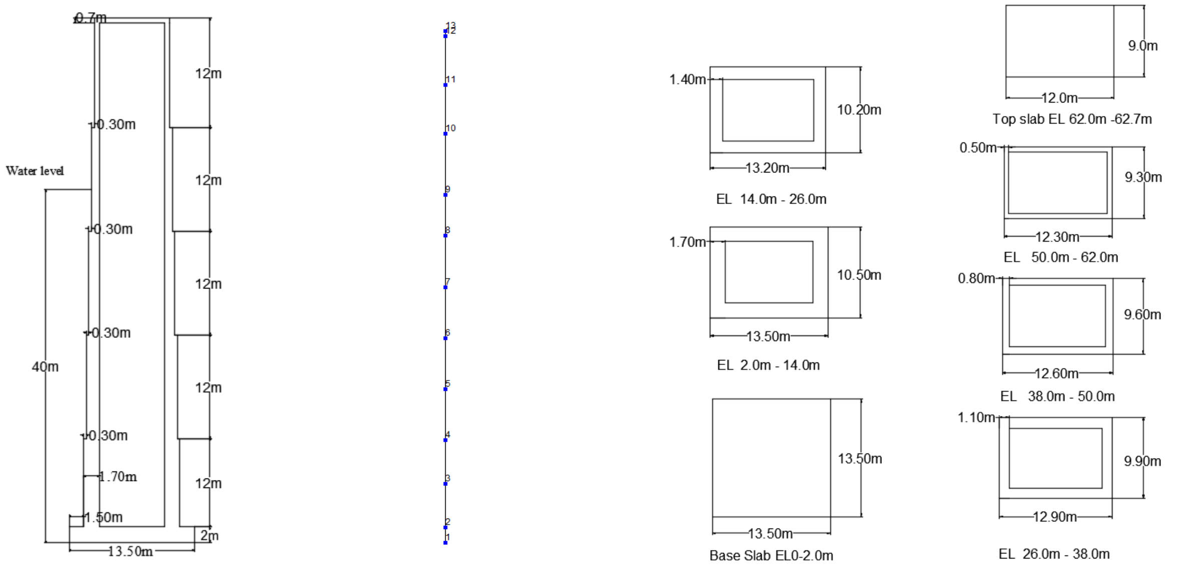
A cantilever freestanding tower of height 62.70 m shown in Fig. 1(a). The cross sections of the tower which are rectangular vary from (13.50 m×13.50 m) at the base to (12.0 m×11.0 m) at the top as shown in Fig. 1(c). In addition, the thickness of the sections differs from 1.70 m at the base to 0.50 m at the top of the tower. The tower has a 2.0 m deep concrete slab at the bottom and 0.70 m deep concrete slab at the top of the tower.

5.2 Material properties

An OpenSees lumped mass model is chosen for the numerical analysis of the intake water tower where 13 lumped masses are considered for specified the load as shown in Fig. 1(b). The masses are lumped at the node of half of the opposite two elements. The Young's Modulus of elasticity is considered as 3.0×1010 GPa and the unit weight of concrete is equivalent to 2402.7 kg/m^3.

5.3 Hydrodynamic masses

Inside and outside hydrodynamic masses are calculated using the refined method which is carried out by converting



(a) Elevation (b) lumped-mass model (c) Typical section and dimension of intake tower

Fig. 1 Details of intake tower model

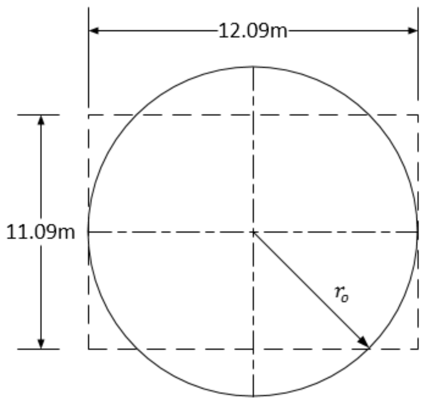


Fig. 2 Added hydrodynamic mass calculation: circular area equivalent to average tower dimensions

each uniform rectangular section to an equivalent circular section. The normalized hydrodynamic added mass $m_\infty^0/\rho_w A_0$ due to outside water is calculated from the width to depth ratio of the average cross-section. Finally, we can calculate the absolute added mass m_∞^0 by multiplying $\rho_w A_0$ with the normalized added mass, where ρ_w is the water mass density and A_0 $(\pi r_o{}^2)$ is the outside area of the average section (see Fig. 2).

5.4 Displacement-based analysis

According to USACE guidance documents (U.S. Army Corps of Engineers, 2003), a displacement based analysis may be used to identify the failure of the intake tower. If the displacement demand δ_D surpass the ultimate displacement capacity δ_U for Maximum Design Earthquake (MDE) is considered as the failure mode. The maximum top deflection of the tower named as the displacement demand estimated using time history analysis with linear spring properties, beam- column elements properties and added hydrodynamic mass due to circumambient or contained water. The ultimate displacement capacity at the top of the tower is allied to the height of the tower, the width of the plastic hinge and the fracture strain capacity which is calculated by the following equation

$$\delta_u = \frac{\phi_E l^2}{3} + \theta_p l^2 \tag{11}$$

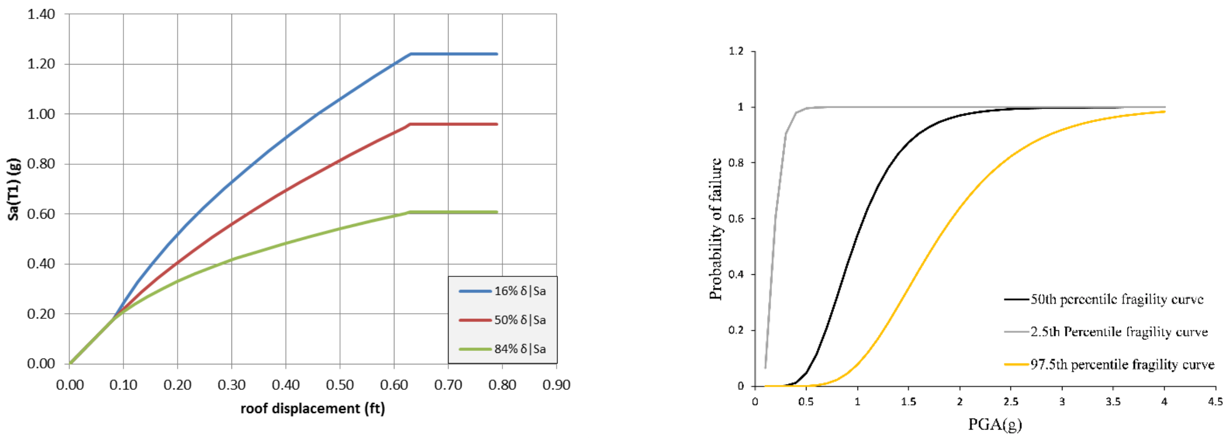
$$\phi_E = \frac{M}{EI_g} \tag{12}$$

where δ_u is the ultimate displacement capacity, ϕ_E is the elastic curvature at cracking (at the base of the tower), θ_p is the plastic rotation at failure, M is the moment at the base of the tower and l is the height of the tower above the crack. The ultimate deflection capacities at the top of the tower are calculated as 10.1 cm and 12.8 cm about the strong axis and weak axis and weak axis, respectively.

6. Results and discussion

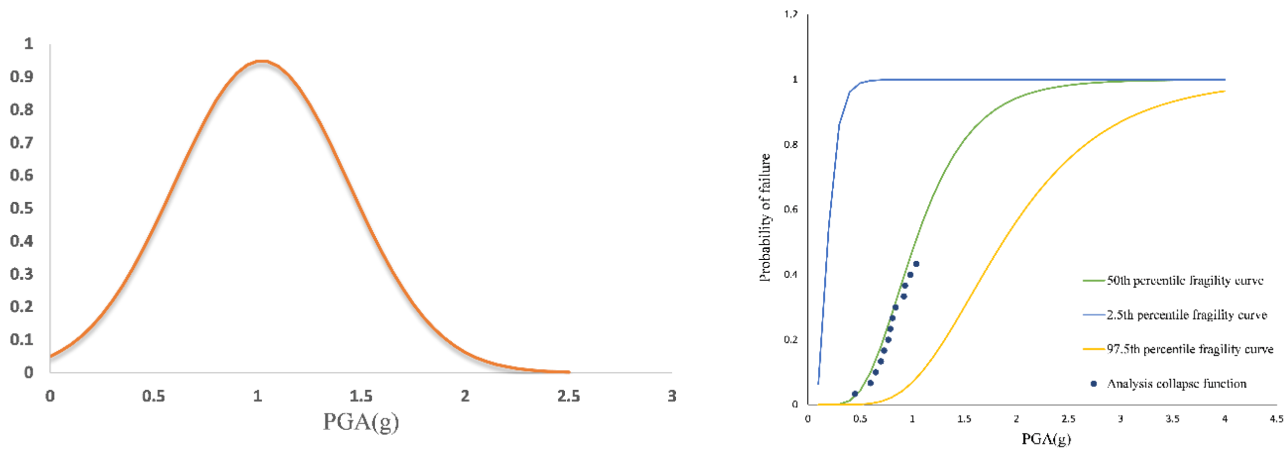
Prior information usually estimates from existing studies of similar structure, professional experience or any simplified analysis method. Median (x_m) and dispersion or standard deviation (β) of lognormal distribution were considered as the main fragility parameters.

The nonlinear static analysis is generally conducted to check the nonlinear structural analysis model. Vamvatsikos and Cornell (2005 and 2006) provided a fast and accurate method named SPO2IDA to estimate the seismic demand and capacity. The method makes the connection between the Static Pushover (SPO) and the Incremental Dynamic Analysis (IDA) and infers nonlinear dynamic response using pushover analysis result. In this paper, the method



(a) 16, 50 and 84% fractal IDA curves (b) 95% confidence bound of fragility curves

Fig. 3 lognormal fragility curves with 95% confidence interval from pushover analysis using SPO2IDA software by Vamvatsikos and Cornell (2005)



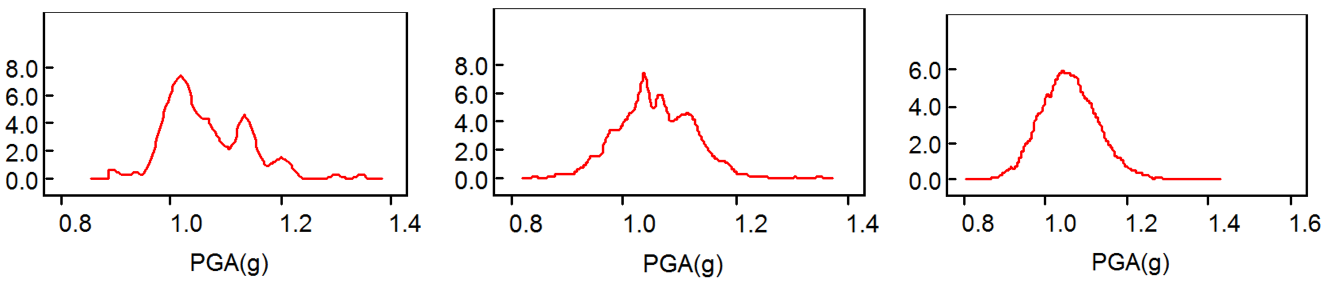
(a) Density Curve (b) 95% confidence interval of fragility curve

Fig. 4 Density curve and lognormal fragility curve from 30 time history analyses

Table 1 Updated Fragility parameters for 100, 1000 and 10000 MCMC simulation using Bayesian Inference

Fragility Parameters	Percentile of confidence band	Updated Parameters		
		MCMC simulation		
		100	1000	10000
x_m	2.5	0.81	0.88	0.93
	50	1.05	1.06	1.07
	97.5	1.29	1.24	1.21
β	2.5	0.19	0.22	0.25
	50	0.39	0.36	0.35
	97.5	0.59	0.50	0.45

mention above is followed for estimating initial collapse response of structure since the method is not computationally demanding and is generally performed before the dynamic analysis. The 16, 50 and 84% fractal IDA curves are obtained based on the base shear data from static pushover analysis by using the software SPO2IDA as shown in Fig. 3(a). The IDA curves imply the 68% confidence bound with mean and ± one standard deviation curves. These IDA curves lead to lognormal fragility function having median collapse capacity 0.96 g and dispersion of 0.39. Fig. 3(b) illustrates the 95% confidence bound of median fragility curve using the fragility parameters mention above. The 50th percentile fragility curve, 2.5th percentile fragility curve, and 97.5th percentile fragility curve illustrate the median fragility curve, lower bound of fragility curve at 2nd standard deviation and upper

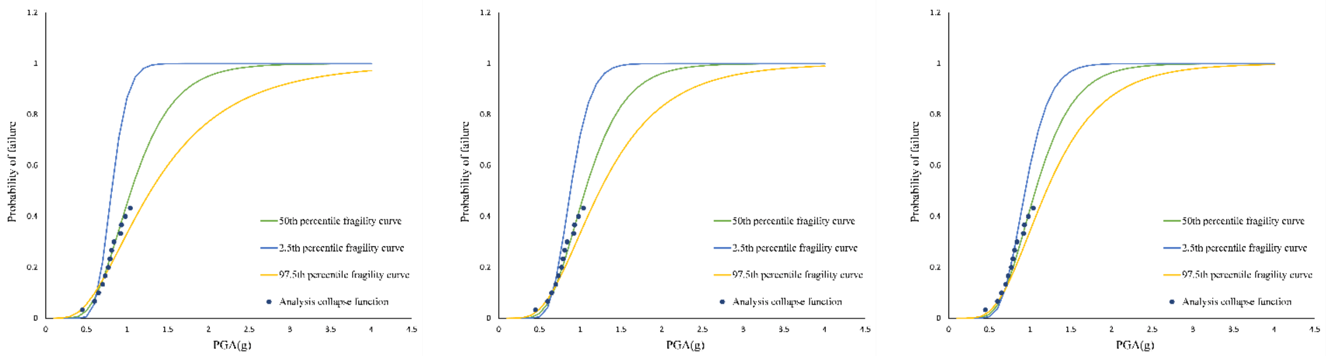


(a) Density curve for 100 MCMC simulation

(b) Density curve for 1,000 MCMC simulation

(c) Density curve for 1,000 MCMC simulation

Fig. 5 Updated density curves using Bayesian Inference and MCMC simulation



(a) Fragility curves for 100 MCMC simulation

(b) Fragility curves for 1000 MCMC simulation

(c) Fragility curves for 10000 MCMC simulation

Fig. 6 95% confidence interval of updated fragility curves using Bayesian Inference and MCMC simulation

bound of fragility curve at 2nd standard deviation respectively.

The IDA provides a complete picture of the nonlinear response of the structure. 30 number of dynamic analysis is performed on the intake tower model and 13 number of collapses are experienced on the basis top tower design displacement. Exercising the IDA method mentioned in Eqs. (5) and (6), the lognormal fragility parameters are found having median collapse parameter 1.02 g and dispersion 0.42 which is depending on the failure number. Fig. 4 mentions the fragility curve with 95% confidence bound and density function respectively.

The figures from both analyses result noticed the wide confidence interval which indicates large uncertainty of the median fragility curve. A large number of data is required for reducing the uncertainty using these conventional fragility model which increases the computational time and cost. The Bayesian Inference method can integrate different kinds of seismic risk data and can update fragility parameters also. Updating the fragility parameters from prior to posterior is accomplished by different MCMC simulation as we need posterior distribution. In this study, Bayesian Inference is employed for integrating data from static pushover analysis and time history analysis with the help of the special type of algorithm called MCMC. Table 1 demonstrates the updated parameters corresponding 100, 1000 and 10000 MCMC simulation for 2.5, 50 and 97.5% of confidence band which shows the gradual decreasing of dispersion, eventually the decreasing of the confidence interval. Fig. 5 explains the density function of updated distribution which reveals that dispersion of the data is gradually decreasing, and Fig. 6 illustrates the 95% confidence band of fragility curve for different MCMC simulation which expresses the reduction of uncertainty of median fragility curve.

One of the important objectives of this work is to improve the confidence associated with the median fragility curves. As we can see, the Bayesian inference methodology can be quite instrumental in the significant reduction of the 95% confidence band region upon incorporating the data from the time-history analysis and the nonlinear static pushover analysis.

7. Conclusions

This research proposes the Bayesian Inference for evaluating seismic fragility of the intake water tower with the help of a special class of computational algorithms called Markov Chain Monte Carlo. The method provides a worthy way to embody the different types of seismic risk data and to update the fragility parameters when new information become available. The intake tower is significantly used as for controlling the release of water of reservoir and for maintaining the hydropower plant. The seismic risk assessment of the intake tower is one of the crucial factors for assessing the risk of reservoir or hydropower plant system. One of the important objective of this study is to decrease the uncertainty associated with the median fragility curve of the intake tower. The uncertainty associated with the median damage estimates for both static pushover analysis as well as time history analysis is shown using the confidence bound associated with it. The confidence bounds generated with the fragility estimates appear quite wide indicating the large uncertainty associated with these fragility estimates. The huge number of additional information is necessary for getting the higher level of confidence which leads to computationally prohibitive. The Bayesian Inference method is used to integrate the fragility parameters from static pushover analysis and a small number of time history analyses. Updating fragility estimation using Bayesian Inference and MCMC simulation is observed to be a notable reduction in computational demand for the probabilistic failure risk assessment of the intake tower and significantly improved statistical efficiency. The uncertainty of the median fragility is decreased from prior information to posterior as well as the number MCCM simulation increased. The Bayesian Inference methodology using MCMC simulation can be an auxiliary tool for significant reduction of the 95 percent confidence band region upon incorporating the small number numerical analysis data.

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References

Ang, A.H.S. and Tang, W.H. (2006), *Probability concepts in Engineering*, Vol. I, John Wiley & Sons, New York, NY, USA.

Baker, J.W. (2013), “Efficient analytical fragility function fitting using dynamic structural analysis”, *Earthq. Spectra*, **31**(1), 579-599.

Casella, G. and George, E.I. (1992), “Explaining the Gibbs Sampler”, *Am. Statistician*, **46**(3), 167-174.

Cocco, L., Suarez, L.E. and Matheu, E.E. (2010), “Development of a nonlinear seismic response capacity spectrum method for intake towers of dams”, *Struct. Eng. Mech.*, **36**(3), 321-341.

Congdom, P. (2006), *Bayesian Statistical Modelling*, Second Edition, John Wiley & Sons, New York, NY, USA.

Ellingwood, B. and Kinali, K. (2009), “Quantifying and communicating uncertainty in seismic risk assessment”, *Struct. Safe.*, **31**(2), 179-187.

Gamerman,D. and Lopes, H.F. (2006), *Markov Chain Monte Carlo: Stochastic Simulation for Bayesian Inference*, Second Edition, Chapman and Hall/CRC, Florida, USA.

Gokkaya, B.U., Baker, J.W. and Deierlein, G.G. (2015), “Illustrating a bayesian approach to seismic collapse risk”, *12th Interantional Conference on Application of Statistics and Probability in Civil Engineering, ICASP12*, Vancouver, Canada, July.

Ibarra, L. F., and Krawinkler, H. (2005). “Global collapse of frame structures under seismic excitations”, Report No. 152; John A. Blume Earthquake Engineering Center, Stanford, CA, 324.

Ioannis Ntzoufras (2009), *Bayesian Modeling using WinBUGS*, John Wiley & Sons, Inc., Hoboken, New Jersey.

Kennedy, R.P., Cornell, C.A., Campbell, R.D., Kaplan, S., Perla, H.F. (1980), “Probabilistic seismic safety of an existing nuclear power plant”, *Nuclear Eng. Des.*, **59**(2), 315-338.

Kim, Dookie, Yi, Jin-Hak, Seo, Hyeong-Yeol and Chang, Chunho (2008), “Earthquake risk assessment of seismically isolated extradosed bridges with lead rubber bearings”, *Struct. Eng. Mech.*, **29**(6), 689-707.

Koutsourelakis, P.S. (2010), “Assessing structural Vulnerability against earthquake using multi-dimensional fragility surface: A Bayesian framework”, *Prob. Eng. Mech.*, **25**(1), 49-60.

Lagarosa, N.D., Tsompanakisb, Y., Psarropoulosb, P.N. and Georgopoulosb, E.C. (2009), “Computationally efficient seismic fragility analysis of geostructures”, *Comput. Struct.*, **87**(19), 1195-1203.

Mehani, Y., Bechtoula, H., Kibboua, A. and Naili, M. (2013), “Assessment of seismic fragility curves for existing RC buildings in Algiers after the 2003 Boumerdes earthquake”, *Struct. Eng. Mech.*, **46**(6), 791-808.

Ng, Iok-Tong, Yuen, Ka-Veng and Dong, Le (2015), “Probabilistic real-time updating for geotechnical properties evaluation”, *Struct. Eng. Mech.*, **54**(2), 363-378.

Nielson, B.G. and DesRoches, R. (2007), “Seismic fragility methodology for highway bridges using a component level approach”, *Earthq. Eng. Struct. D.*, **36**(6), 823-839.

Pei, S. and Van de Lindt, J.W. (2009), “Methodology for long-term seismic loss estimation: An application to Woodframe buildings”, *Struct. Safe.*, **31**, 31-42.

Sashi Kanth Tadinada (2012), “A Bayesian framework for probabilistic seismic fragility assessment of structure”, Ph.D. Dissertation; Dept. of Civil Engineering, North Carolina State University, Raleigh, North Carolina.

Shinozuka, M., Feng, M., Lee, J. and Naganuma, T. (2000), “Statistical analysis of fragility curves”, *J. Eng. Mech.*, **126**(12),1224-1231.

Singhal, A. and Kiremudjian, A. (1998), “Bayesian updating of fragility with application to RC frames”, *J. Struct. Eng.*, **124**(8), 922-929.

USACE (2003), Structural Design and Evaluation of Outlet Works, EM 1110-2-2400, US Army Corps of Engineers, June 2, 2003.

USACE (2007), Structural Earthquake Design and Evaluation of Concrete Hydraulic Structures, Engineering Manual EM 1110-2-6053.

Vamvatsikos, D. and Cornell, C.A. (2002), “Incremental Dynamic Analysis”, *Earthq. Eng. Struct. D.*, **31**(3), 491-514.

Vimvatsikos, D. and Cornell, C.A. (2005), “Direct estimation of seismic demand and capacity of MDOF systems through incremental dynamic analysis of an SDOF approximation”, *J. Struct. Eng.*, **131**(4), 589-599.

Vimvatsikos, D. and Cornell, C.A. (2006), “Direct estimation of the seismic demand and capacity of oscillators with multi-linear static pushovers through IDA”, *Earthq. Eng. Struct. Dyn.*, doi:10.1002/eqe.573.

Zhang, L., Wu, Z., Ye, S. and Zhang, H. (2008), “Seismic response analysis of the underwater high-rise independent intake tower”, *The 14th World Conference on Earthquake Engineering*, Beijing, China, October.

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