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Division V

SEISMIC FRAGILITY ASSESSMENTS OF APR-1400 CONTAINMENT BUILDING USING BAYESIAN INFERENCE FRAMEWORK

Md Samdani Azad[1], Duan Nguyen[2], Bidhek Thusa[1], Tae-Hyung Lee[1]

[1] Ph.D. Student, Department of Civil and Environmental Engineering, Konkuk University, Seoul, Korea (samdaniazad@konkuk.ac.kr)
[2] Lecturer, Department of Civil Engineering, Vinh University, Vietnam (duyduankxd@vinhuni.edu.vn)
[1] Ph.D. Student, Department of Civil and Environmental Engineering, Konkuk University, Seoul, Korea (bdhek@konkuk.ac.kr)
[1] Professor, Department of Civil and Environmental Engineering, Konkuk University, Seoul, Korea (thlee@konkuk.ac.kr)

Abstract

The purpose of this study is to perform seismic fragility assessments of the reactor containment building (RCB) in the Advanced Power Reactor 1400 (APR-1400) nuclear power plants (NPPs) with the aid of Bayesian-Markov Chain Monte Carlo (MCMC) simulation. Fragility is a pivotal component of seismic performance that expresses the relationship between a ground motion intensity and the engineering demand parameter. The accurate estimation of fragility normally requires a large number of nonlinear time history analyses that spend inevitably significant computational time. The current study employed Bayesian inference combined with MCMC simulations to overcome this issue for RCB structures. The framework requires a prior belief (e.g., fragility curve) that can be obtained from engineering judgment, experiences, previous studies, or simplified linear models. After that, a few nonlinear time history analyses are performed to update the prior belief and then achieve posterior fragility curves. The findings show that Bayesian inference and MCMC simulation can significantly improve the fragility curves of various damage states.

INTRODUCTION

In probabilistic seismic evaluations, a fragility curve represents the probability of failure in relation to an intensity measure such as peak ground acceleration (PGA). It is widely used in many standards as well as the Nuclear Regulatory Commission of the United States (NRC). Several approaches for developing seismic fragility curves have been proposed. Shinozuka et al. (2000) presented a maximum likelihood estimate approach, while Elingwood et al. (2002) proposed an incremental dynamic analysis method. Multiple-strip (Iervolino et al. 2010) and cloud methods (Jalayer et al, 2014) were also employed to derive the seismic fragility curves of structures. These approaches, however, are computationally expensive and necessitate extensive time-history research. For a simplified lumped mass stick model (LMSM), performing a large number of time history analysis is convenient. In the case of full three-dimentional finite element model (3D FEM) or multilayer shell element model (MSLM) of the reactor containment building (RCB) in nuclear power plants (NPPs), however, it is quite impractical to perform numerous time history analyses. Nguyen et al. (2021) recently recommended the beam-truss model (BTM) for containment building of NPPs, which is a simplified yet adequately detailed model. In comparison to the full 3D FEM model, the BTM is efficient enough in terms of simplification and capturing nonlinear behaviours. The RCB model is still expensive when undertaking a large number of nonlinear time-history analyses for developing fragility curves. To address these challenges, several researchers attempted to estimate the parameters of seismic fragility curves using Bayesian inference techniques. It is possible to anticipate the accurate estimation of different parameters using Bayesian inference with a smaller amount of data. Based on Bayesian inference, Alam et al. (2017) developed seismic fragility curves for intake towers. Tadinada and Gupta (2020) applied the technique to a box-shaped concrete wall. Pujari and Ghosh (2014) performed seismic fragility tests on nuclear containment buildings. However, those researches were confined to the development of fragility curves for a specific damage state, namely collapse. However, fragility curves for other damage states such as cracking, yielding, and so on must be developed to have proper inspection and maintenance planning. In this study, we apply the Bayesian inference with Markov Chain Monte Carlo (MCMC) technique to estimate the fragility parameters for four different damage states, including cracking, yielding, extensive cracking, and crushing, of the Advanced Power Reactor 1400 (APR-1400) containment building. Prior fragility curves of different damage states are required for Bayesian inference, and these are approximated by the RCB's LMSM. Following that, 50-time history analyses are performed, with the BTM used to capture nonlinearity of the structure. The prior fragility curves are updated, and the posterior fragility curve are constructed, using this 50-time history analysis. The posterior fragility curves are the final fragility curves that take into account the RCB structure's nonlinearity as well.

DESCRIPTION OF THE MODEL

For the numerical studies in this work, the reinforced concrete (RC) containment building of the APR 1400 NPPs is used. The RCB structure is a cylinder building with a radius of 23.5 m, a height of 54 m, and a thickness of 1.22 m. The dome's radius is 23.2 m, as well as its average thickness is 1.07 m. Figure 1 (a) depicts the RCB structure and the wall reinforcement detailing.

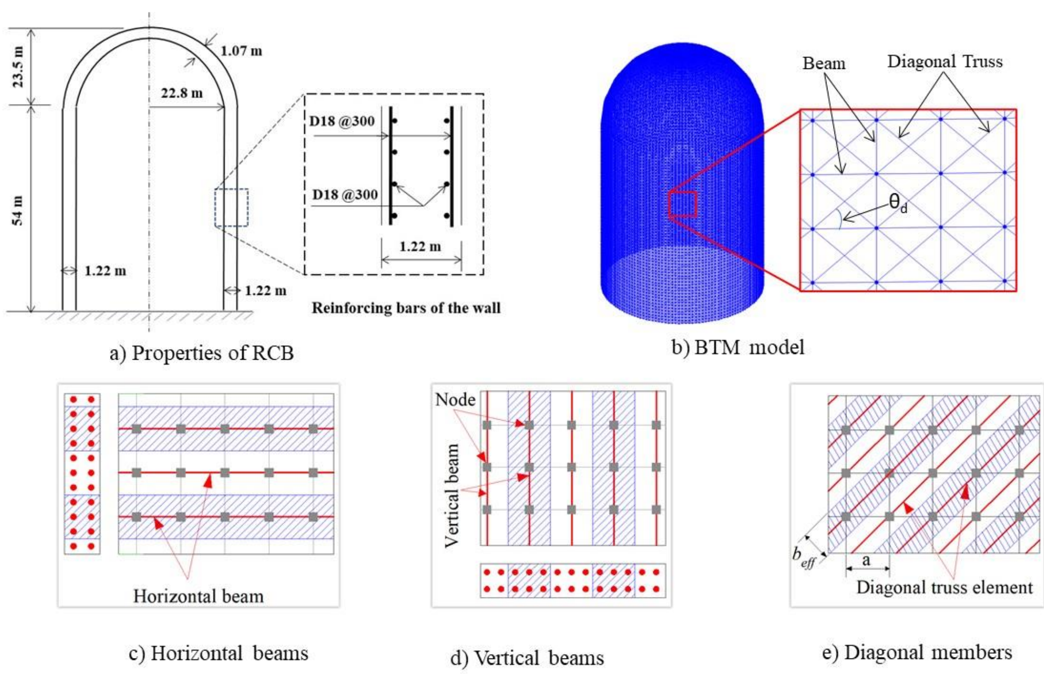

Figure 1. a) Dimension of RCB, b) BTM of RCB, c) horizontal beams, d) vertical beams, e) diagonal truss members

It was noted that LMSM is a simplified method that is insufficient for nonlinear analysis, whereas 3D FEM and MLSM need extremely expensive computations (Nguyen et al., 2021). Therefore, BTM is a reasonably simple and efficient model for performing nonlinear analysis when compared to these models, and it is used in this study to develop a numerical model of RCB. The detailed advantages of BTM were discussed in Nguyen et al. (2021). The dimension of the panel is determined by the mesh convergence test, which determines the dimensions of the beam and truss elements. The horizontal and vertical elements are both 1.0 m long. The diagonal members are modelled as truss elements, whereas the horizontal and vertical elements are modelled as nonlinear beam elements. The width of the beam elements is equal to the wall thickness, i.e., 1.22 m, whereas the height of the beams is determined by the panel size. Besides, the width of the diagonal truss elements (b) is computed as the product of the length of the panel (a) and sin(θ_d), as shown in Equation (1).

$$b = a \times \sin(\theta_d) \tag{1}$$

where θ_d is the angle between the diagonal and the horizontal elements. The BTM of RCB is modeled using OpenSees (Mazzoni et al., 2006), as shown in Figure 1(b). The *forceBeamColumn* elements are used to construct the beam elements. The diagonal truss members are built using the *corotTruss* elements. The vertical and horizontal beam elements are modelled with concrete and reinforcements included, while the diagonal truss elements exhibit purely concrete behaviour. Nonlinear material models are employed to develop beam and truss elements. Concrete and reinforcing bars are modelled using the *concrete02* and *steel02* models, respectively. The approach described above is also consistent with the study of Lu and Panagiotou (2014). The illustrated modelling of the RCB wall using BTM is shown in Figures 1 (b-e). Figure 2 depicts the *concrete02* and *steel02* models. The relevant properties of concrete and steel are taken from Nguyen et al. (2021).

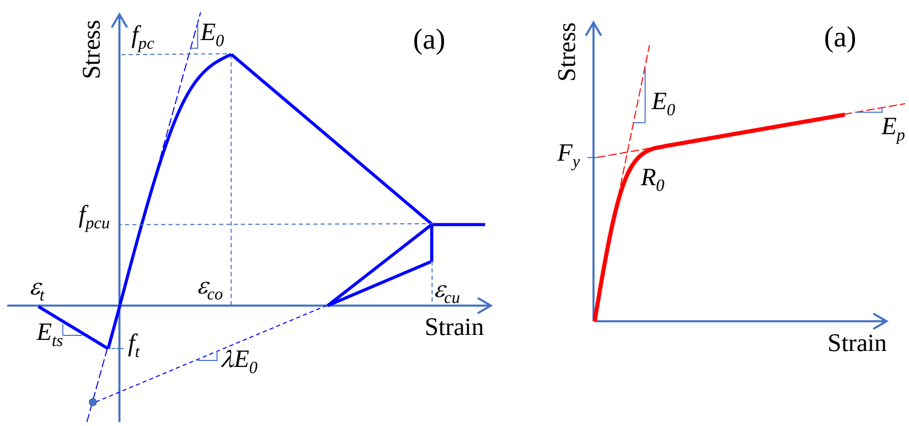

Figure 2. (a) *Concrete02* and (b) *steel02* models

SEISMIC FRAGILITY

The fragility curve is a practical tool to assess the probabilistic vulnerability of structures subjected to seismic loadings. Damage states should be defined to develop the fragility curves. The damages states are estimated following the methodology of Nguyen et al. (2021) in this study. Four damage states are considered, which are minor (i.e., concrete cracking, referred to as DS1), moderate (i.e., rebar yielding, referred to as DS2), extensive (i.e., extensive cracking and yielding at the bottom, referred to as DS3), and collapse (i.e., crushing, referred as DS4). For a particular damage state, the fragility curves can be estimated following Equation (2).

$$F(x; \mu, \sigma_R) = \phi[\frac{\ln(x/\mu)}{\sigma_R}] \tag{2}$$

where $\phi(.)$ denotes the standard normal cumulative distribution function (CDF), x is intensity measure (IM), μ is the median value of the distribution function, and σ_R denotes the logarithmic standard deviation or dispersion of $ln(IM)$.

BAYESIAN INFERENCE

Bayesian inference is an effective way to accurately estimate parameters by updating prior information with newly observed data. The seismic fragility of any structure can be updated through updating its parameters, $\theta(\mu, \sigma_R)$ employing Bayesian inference. The seismic fragility can be updated following Equation (3), as shown below

$$f''_{\boldsymbol{\theta}}(\theta|Y) = \frac{P(Y|\theta)f'_{\boldsymbol{\theta}}(\theta)}{P(Y)} \tag{3}$$

where $f'_{\boldsymbol{\theta}}(\theta)$ is the prior information/ Belief that is approximated from the LMSM model of the RCB;
$P(Y|\theta)$ is the likelihood of the observation Y that can be obtained by performing nonlinear time history analysis of the BTM of the RCB;
$P(Y)$ is the marginal likelihood.
$f''_{\boldsymbol{\theta}}(\theta|Y)$ is the updated/posterior fragility curve.

At first, the prior parameters are derived from the LMSM model employing cloud analysis method (Jalayer et al., 2014) following the procedure of Figure 3. The LMSM model is developed and 90 ground motions are chosen based NRC spectra, as described in Nguyen et al. (2021). A regression analysis is done to estimate the parameters of the prior fragility curve and the fragility curves are plotted for four damage states. From the analysis using LMSM, μ and σ_R are computed.

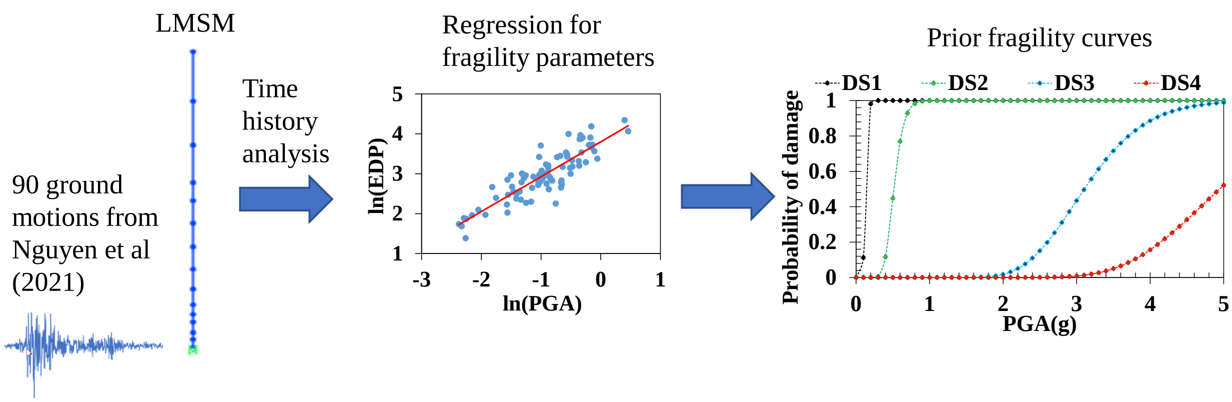

Figure 3. Prior fragility curves of RCB

As the seismic fragility is a function that includes the median (μ) and the standard deviation (σ_R), both parameters are needed to be updated through the inference. We can assign θ_1 for median acceleration (μ) and θ_2 for the standard deviation (σ_R). θ_1 has a prior normal distribution with mean, *log*(μ) and standard deviation, σ_U (i.e., epistemic uncertainty). In addition, θ_2 is considered as uniformly distributed within ±15% of its mean value σ_R according to Tadinada and Gupta (2020). The observations (Y) can be obtained as the engineering demand parameter from the nonlinear time history analysis of the RCB. Hence, the Bayesian inference is incorporated following the Equations (4-6). The value of the prior parameters are illustrated in Table 1.

$$p(Y|\theta_1, \theta_2) \sim Normal(\theta_1, \theta_2) \tag{4}$$
$$p(\theta_1; \mu, \sigma_U) \sim Normal(log\,(\mu), \sigma_U) \tag{5}$$
$$p(\theta_2) \sim Uniform(0.85\sigma_R, 1.15\sigma_R) \tag{6}$$

Table 1: Values of different parameters of the prior fragility curve.

Parameters	Value	Source
Mean of the median capacity, μ	DS-1: 0.129g	Estimated from LMSM model of RCB
	DS-2: 0.514g	
	DS-3: 3.106g	
	DS-4: 4.945	
Standard deviation of the median capacity, σ_U	0.27	Pujari and Ghosh (2014)
Standard deviation of the fragility curve, σ_R	0.21	Estimated from LMSM model of RCB

The observations (Y) are obtained from the 50-time history analyses of RCB. The selected ground motions are scaled considering NRC spectra, as shown in Figure 4. The posterior fragility curves $f''_{\boldsymbol{\Theta}}(\theta|Y)$ are estimated through numerical simulations generating a large number of samples by employing MCMC simulation (Congdon, 2006). The application of MCMC is necessary since we didn't use a conjugate prior for θ_2. In addition, the posterior distribution is not always tractable by analytical solution. Sampling the distribution enables easeness to find the value of parameter with highest frequency. Markov Chain provides a transition from one state to other state in such a way that the current state depends on the previous state. Metropolis-Hastings (MH) algorithm is one of the widely used types of MCMC method that draw samples from a target distribution. While there is more than one parameter, the sampling process is incorporated through Gibbs sampling which is a special case of MH algorithm. The steps of posterior sampings are briefly presented below.

1. At initial stage (t=0), set (θ_1^0 or θ_2^0) with some starting value.
2. At iteration 1 (t=1)
    a. Sample $\theta_1^1 \sim p(\theta_1|\theta_2^0)$, that is from the condition distribution $(\theta_1|\theta_2) = \theta_2^0$; Hence the current state is (θ_1^1, θ_2^0).
    b. Sample $\theta_2^1 \sim p(\theta_2|\theta_1^1)$, that is from the condition distribution $(\theta_2|\theta_1) = \theta_1^1$; Hence the current state is (θ_1^1, θ_2^1).

3. At iteration 1 (t=2)
    a. Sample $\theta_1^2 \sim p(\theta_1|\theta_2^1)$, that is from the condition distribution $(\theta_1|\theta_2) = \theta_2^1$; Hence the current state is (θ_1^2, θ_2^1).
    b. Sample $\theta_2^2 \sim p(\theta_2|\theta_1^2)$, that is from the condition distribution $(\theta_2|\theta_1) = \theta_1^2$; Hence the current state is (θ_1^2, θ_2^2).
4. We have to repeat it for 50000 times (t=50000) and the final stage will be (θ_1^t, θ_2^t).

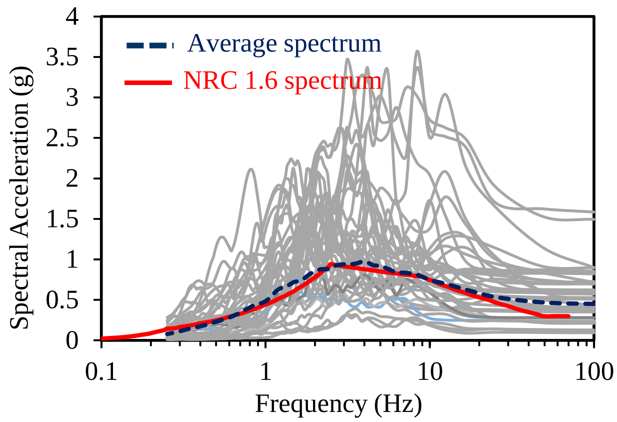

Figure 4. Response spectra of ground motions to update the prior fragility curve

RESULTS AND DISCUSSION

In the nonlinear RCB model, 50-time history analyses are employed to update the previous fragility parameters (μ, σ_R). Figure 5 shows the updated distributions of parameters obtained by running 50,000 MCMC simulations with a burn-in of 1,000 to eliminate the influence of autocorrelation. The prior and posterior parameters have a considerable difference. The distribution of μ is shifted to a higher value for DS-1. After updating DS-2, there is a slight difference from the previous version. However, there is a major shift for DS-3 and DS-4. Based on the definition of the damage states, DS-1, DS-3 and DS-4 are governed by the concrete characteristics. DS-2 is dominated by reinforcing steel behaviour. It's understandable that the nonlinear characteristic of concrete and steel is reflected in the update of the fragility curves. The update of σ_R can also be seen in the figure.

Using the updated fragility parameters, Figure 6 compares the prior and posterior fragility curves. The fragility curve for DS-1 shows a minor change and the fragility curve for DS-2 shows a small change. However, there is a significant difference in the fragility curves of DS-3 and DS-4. Because extensive cracking and crushing occur within the nonlinear region of the stress-strain behaviour of concrete, the changes in DS-3 and DS-4 demonstrate the inclusion of highly nonlinear concrete behaviour in the RCB structure. Furthermore, concrete cracking causes nonlinear behaviour in the material, resulting in a minor shift in the updated fragility curve. DS-2 is characterized by the yielding of reinforcement steel and a slight update in the fragility curve for DS-2 is reported.

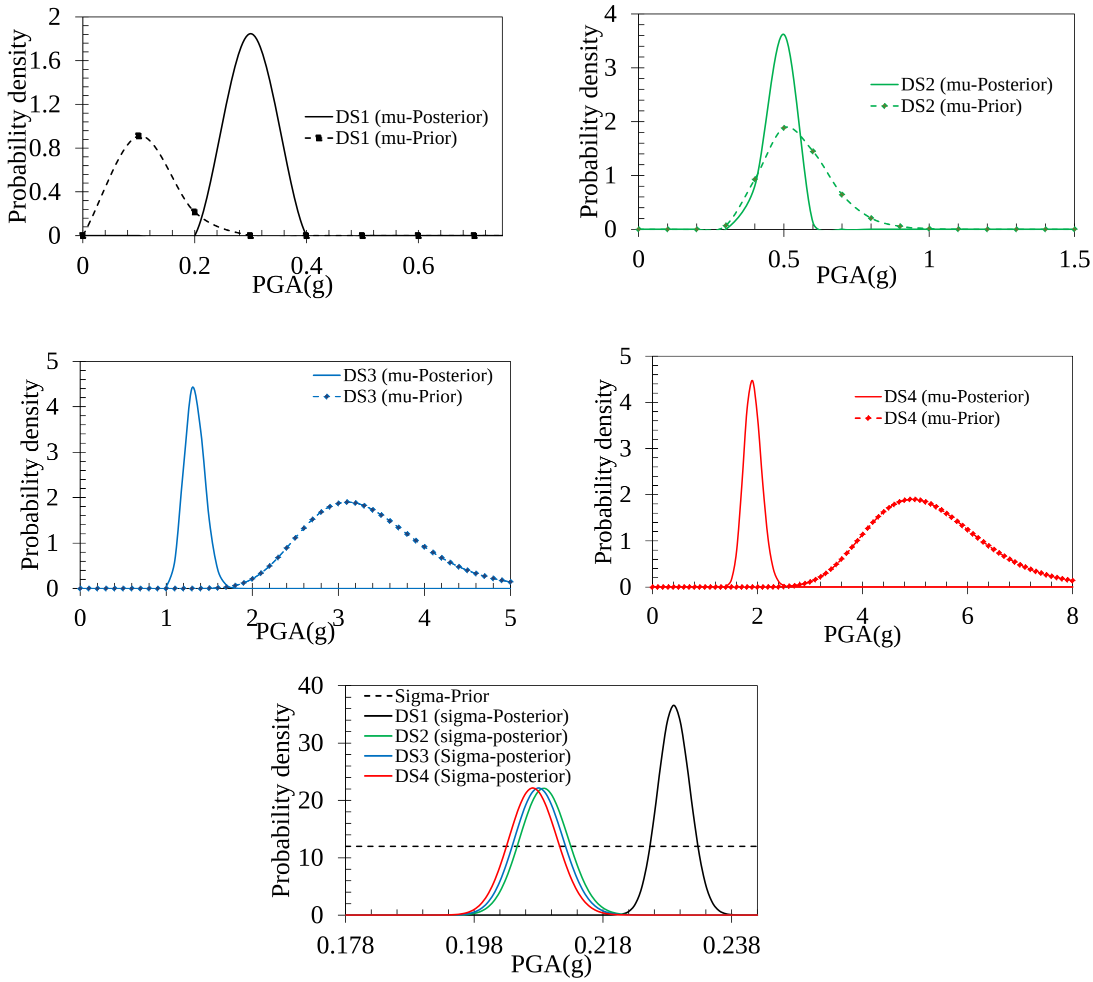

Figure 5. Updated distributions of parameters (μ and σ_R) at different damage states

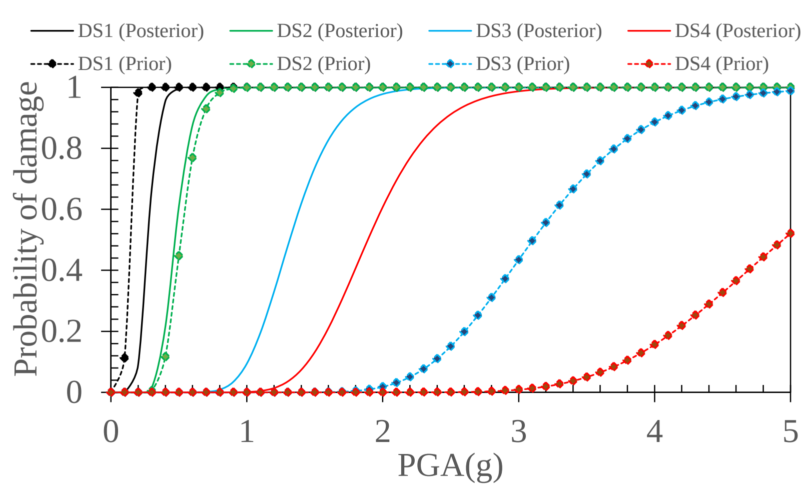

Figure 6. Prior and posterior fragility curves

CONCLUSION

Bayesian inference with MCMC simulation is employed to construct fragility curves of the RCB structure. Initially, prior fragility curves are developed using LMSM and updated it using nonlinear time history analyses in BTM of RCB. The following conclusions can be drawn:

1. Bayesian inference with MCMC simulations is proposed to develop fragility curves with reduced number of time history analyses. Fragility curves for four different damage states are constructed through the framework.
2. The updated fragility curves reflect the nonlinear characteristics of concrete and steel.

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