A Bayesian Formulation of Seismic Fragility Analysis of Safety Related Equipment

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Abstract

A Bayesian approach to seismic fragility analysis of safety-related equipment is formulated. Unlike treating two sources of uncertainty of in the parameter estimation in two steps separately using the classical statistics, a Bayesian hierarchical model is advocated for interpreting and combining the various uncertainties more clearly in this article. In addition, with the availability of additional earthquake experience data and shaking table test results, a Bayesian approach to updating the fragility model of safety-related equipments is formulated by incorporating acquired failure and survivor evidence. Numerical results show the significance in fragility analysis using the Bayesian approach.

1. Introduction

Seismic equipment fragility, representing the seismic capacity of the equipment and the associated uncertainties, is a fundamental ingredient in seismic probabilistic risk assessment (SPRA) for nuclear power plants (NPP) [1]. To ensure adequate seismic capacity of NPP facilities, seismic design criteria have been specified by different organizations. American Society of Civil Engineers (ASCE) (2005) laid down a performance-goal based approach for NPP structures, i.e., to satisfy the performance goal, a mean frequency of 10^{-5}/yr for seismic-induced onset of significant inelastic deformation (FOSID), sufficient conservatism shall be introduced at the component-level to achieve both of the following: (1) less than 1% of unacceptable performance for the Design Basis Earthquake (DBE) ground motion, (2) less than 10% of unacceptable performance for the 150% DBE ground motion. US Nuclear Regulatory Commission (USNRC) [3] prescribed a plant-level requirement that all new plant designs must demonstrate a seismic margin of 1.67 corresponding to 1% probability of failure on “core damage” fragility curve. Nevertheless, plan-level seismic risk or margin depends on the fragility (capacity and the associated uncertainties) of individual component, thus the accuracy in fragility evaluation of safety-related equipment is of fundamental importance.

The current lognormal fragility model that has been used in nuclear energy industry since the late 1970s, involves the estimation of two key parameters: median seismic capacity of a Structure, System, and Component (SSC) and its variability [2,4,5]. These parameters are estimated semi-empirically based on limited industry data from seismic safety studies of 26 nuclear power plants, resorting to some engineering judgments. Two sources of uncertainty, i.e., aleatory uncertainty (due to inherent randomness) and epistemic uncertainty (due to lack of knowledge) [9], are introduced in determining the best estimate of median seismic capacity. Conservative estimates are often made, leading to wide confidence bands associated with the median fragility curve. How to better estimate the median seismic capacity and reduce its epistemic uncertainty is a challenging yet rewarding task. Earthquake experience data and shaking table test results are believed to be valuable evidence for validating the model assumption, incorporating useful information, and updating empirical fragility estimate. Electric Power Research Institute (EPRI) has maintained an electronic earthquake experience database for evaluating the seismic adequacy of a wide variety of equipments since 1981 [6]. USNRC has made efforts in evaluating the Japanese Nuclear Energy Safety (JNES) equipment fragility test data for use in SPRA for US NPPs [1].

With the availability of newly acquired data, a brain draining task is how to incorporate the evidence into the empirical model. Bayesian approach is a proper mathematical tool for combining and updating the available information given in statistical form [7]. Some efforts have been made in developing the Bayesian approach to fragility analysis. Singhal and Kiremidjian [8] performed a Bayesian statistical analysis for updating earthquake ground motion versus damage relationships, where only the median damage index was assumed to be random and needed updating. Igusa *et al.* [9] proposed a Bayesian approach to analyze the two types of uncertainty for structural engineering applications. He employed the hierarchical Bayesian model to treat separately the aleatory and epistemic uncertainties before aggregation and developed insight into the different effects due to each uncertainty. Straub and Kiureghian [10] proposed an improved seismic fragility modelling from empirical data by explicitly considering the statistical dependence among empirical observations of the same equipment items mounted at various locations and endured multiple earthquakes. These efforts, however, either resorted to only the failure data or failure rate without handling survivor data, or employed complicated numerical simulations, thus are not immediately applicable to fragility analysis of nuclear facilities. Efforts in Bayesian fragility analysis of safety-related equipments in nuclear industry are still needed.

In this article, a Bayesian formulation of seismic fragility analysis of safety-related equipment is proposed. In the following, after a brief introduction on seismic fragility analysis used in nuclear industry, a Bayesian interpretation of seismic fragility is presented, which employs the hierarchical Bayesian model. Next, a Bayesian updating process of seismic fragility is formulated. Finally numerical examples are presented to illustrate how Bayesian updating significantly affects the fragility results.

2. Background on seismic fragility

Seismic fragility of a structure, system, or component (SSC) of interest is usually defined as the conditional probability of failure (e.g., structural failure, functional failure) for a given ground motion parameter such as peak ground acceleration (PGA) or spectral acceleration at fundamental period. Such probability of failure is further represented by the ground motion capacity X of a SSC less than the ground motion level x (demand) as

$$p_f = P\{X < x\}\,. \tag{1}$$

Ground motion capacity X is the ground motion level at which the seismic response of the SSC results in its failure, and is often modelled as the product of three variables

$$X = X_m \cdot \varepsilon_R \cdot \varepsilon_U \, , \tag{2}$$

where X_m is the best estimate of median ground motion capacity, ε_R is the random variable representing *aleatory* uncertainty about the median, and ε_U is the random variable representing the *epistemic* uncertainty in estimating X_m due to lack of knowledge. ε_R and ε_U are usually taken to be lognormal random variables with unit median and logarithmic standard deviations of β_R and β_U , respectively. A major task of seismic fragility analysis is to estimate the median capacity X_m and the two logarithmic standard deviations β_R and β_U .

Taking logarithmic of equation (2), and letting $Y = \ln X$, one has

$$Y = \mu_Y + \ln \varepsilon_R + \ln \varepsilon_U \, , \tag{3}$$

where $\mu_Y = \ln X_m$, $\ln \varepsilon_R \sim N(0, \beta_R^2)$, and $\ln \varepsilon_U \sim N(0, \beta_U^2)$.

Seismic fragility for a ground motion level *x*, non-exceedance level *Q*, can be derived as [4,5]

$$p_f = P\{X < x \,|\, Q\} = P\{Y < y \,|\, Q\} = \Phi\left[\frac{y - \mu_Y + \beta_U \Phi^{-1}(Q)}{\beta_R}\right], \tag{4}$$

where $\Phi(\cdot)$ is the standard Gaussian cumulative distribution function, and for Q = 5%, 50%, and 95%, equation (4) gives a family of fragility curves.

Fragility can also be expressed in terms of the composite uncertainty, β_C , without separating aleatory and epistemic uncertainties, as

$$p_f = P\{X \le x\} = P\{Y \le y\} = \Phi\left[\frac{y - \mu_Y}{\beta_C}\right], \qquad \beta_C = \sqrt{\beta_R^2 + \beta_U^2} \, , \tag{5}$$

which gives a single composite fragility curve or mean fragility curve.

As an example, assuming the fragility parameters for a component are X_m =0.87g, β_R =0.25, and β_U =0.35, a family of fragility curves with Q = 5%, 50%, and 95% and a composite fragility curve are determined using equations (4) and (5) as shown in Figure 1.

3. Bayesian interpretation of seismic fragility

When parameter estimation involves multiple levels of uncertainty, hierarchical Bayesian model can be applied for combining all sources of uncertainty [11]. In fragility analysis, the median seismic capacity of a SSC is estimated based on some generic quantities common to

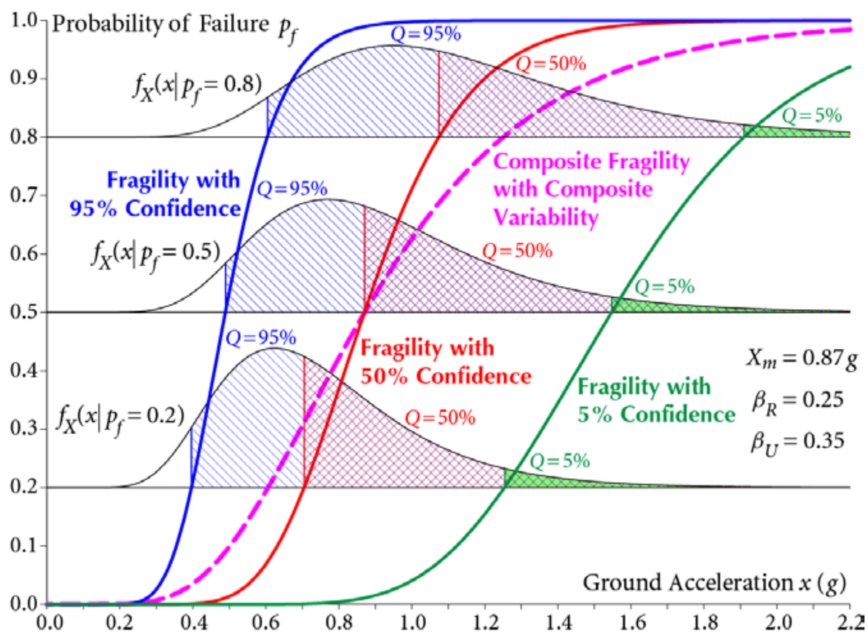

Figure 1: Fragility curves

this SSC in similar plants. The quantities of a SSC in a specific power plant thus carry aleatory uncertainty, controlled by irreducible chance or randomness. Yet another level of epistemic uncertainty exists, reflecting our lack of knowledge or information, and is reducible given newly acquired information. In the following, a hierarchical Bayesian model is applied for combining clearly these two types of uncertainty.

Given the lognormal distribution of ground motion capacity X of a SSC: $X \sim LN(\mu, \sigma^2)$, and letting $Y = \ln X$, one has

$$Y \sim N(\mu, \sigma^2), \quad \text{or} \quad Y = \mu + R, \text{ where } R \sim N(0, \sigma_R^2), \tag{6}$$

where μ is also uncertain, and has its own distribution

$$\mu = \mu_Y + U, \text{ where } U \sim N(0, \sigma_U^2). \tag{7}$$

Combining equations (6) and (7), one has

$$Y = \mu_Y + U + R \sim N(\mu_Y, \sigma_U^2 + \sigma_R^2), \tag{8}$$

which corresponds to the composite fragility case.

If more than the composite fragility is of interest, from equation (7) one also has

$$\mu = \mu_Y + \sigma_U \cdot s, \tag{9}$$

where $s \sim N(0,1)$ is a standard normal random variable characterizing the epistemic uncertainty in estimating μ_Y. Associating s with non-exceedance level Q in the sense that $s_q = \Phi(1-Q) = -\Phi(Q)$, one has

$$Y \mid \sigma_R \sim N(\mu_Y + \sigma_U \cdot s_q,\ \sigma_R^2) = N(\mu_Y - \sigma_U \cdot \Phi^{-1}(Q),\ \sigma_R^2) \tag{10}$$

and corresponding to equation (4), one has

$$\begin{aligned} p_f &= P(Y < y) = P(\mu_Y + \sigma_U \cdot s_q < y) = P(\mu_Y < y - \sigma_U \cdot s_q) \\ &= \Phi\left[\frac{y - \mu_Y - \sigma_U \cdot s_q}{\sigma_R}\right], \end{aligned} \tag{11}$$

where aleatory and epistemic uncertainties are separated. It is seen that the Bayesian method provides a sound provision for combining different sources of uncertainty in a mathematically rigorous manner.

Solving from the above equation, one has

$$\begin{aligned} &y = \mu_Y + \sigma_U \cdot s_q + \sigma_R \cdot s_p, \quad \text{or} \\ &x = X_m \cdot \exp(\sigma_U \cdot s_q + \sigma_R \cdot s_p), \end{aligned} \tag{12}$$

where $s_p = \Phi^{-1}(p_f)$. Equation (12) shows how two types of uncertainty are propagated in estimating the ground acceleration level x for a failure probability p_f and non-exceedance level Q, as shown in Figure 1 for p_f = 0.2, 0.5, 0.8. Substituting p_f = 0.05 and Q = 0.95 into equation (12) or reading the ground acceleration level corresponding to p_f = 0.01 from the composite fragility curve, yields the so called "*High Confidence, Low Probability of Failure*" (HCLPF) capacity

$$\begin{aligned} &Y_{HCLPF} = \mu_Y + \sigma_R \cdot \Phi^{-1}(0.95) - \sigma_U \cdot \Phi^{-1}(0.05) = \mu_Y - 1.645(\sigma_R + \sigma_U), \\ \Rightarrow\ &X_{HCLPF} = X_m \exp[-1.645(\sigma_U + \sigma_R)]; \end{aligned} \tag{13}$$

$$\begin{aligned} &Y_{HCLPF} = \mu_Y + \sigma_C \cdot \Phi^{-1}(0.01) = \mu_Y - 2.326 \cdot \sigma_C, \\ \Rightarrow\ &X_{HCLPF} = X_m \exp[-2.326 \cdot \sigma_C]. \end{aligned} \tag{14}$$

4. Bayesian updating of seismic fragility

Besides providing a clearer interpretation of combining various types of uncertainty in parameter estimation, the Bayesian approach has significance in updating the model parameter as additional evidence or data becomes available. Subjective judgments based on experience or indirect information can be combined systematically with observed data to obtain a balanced, informed, thus more convincing estimation using the Bayes' Theorem.

For Bayesian fragility analysis, the interest lies in updating the probability distribution of Y given observed evidence E, which may include a number of equipment failures and survivors for a level of ground shaking. To do so, prior distribution of μ must be updated first based on the observed evidence, and then combines with the conditional probability distribution of Y given μ to give the posterior Y.

4.1 Prior distribution of μ

The distribution of μ reflects our state-of-knowledge of parameter estimation, which is the epistemic uncertainty part, and is given as

$$f_U^{'}(\mu) = \frac{1}{\sqrt{2\pi}\sigma_U} \exp\left[-\frac{1}{2}\left(\frac{\mu - \mu_Y}{\sigma_U} \right)^2 \right] \sim N_U(\mu_Y, \sigma_U^2)\,. \qquad (15)$$

4.2 Likelihood function

Our state-of-knowledge of μ can be improved by combining the observed evidence E through the likelihood function.

4.2.1 Failure data

Given evidence of n observed failures $\boldsymbol{y} = [y_1, y_2, ..., y_n] = \mathrm{E}$, the likelihood function is

$$L(\mathrm{E} \mid \mu) = L(\mu) = \prod_{i=1}^{n} f_U(y_i, \sigma_U^2)\,. \qquad (16)$$

Since the product of n normal cumulative density functions is also normal, one has

$$L(\mu) \sim N_U(\bar{y},\ \frac{\sigma_U^2}{n}), \quad \bar{y} = \frac{1}{n}\sum_{i=1}^{n} y_i\,. \qquad (17)$$

4.2.2 Survivor data

For survivor data, the likelihood is given in the form of cumulative distribution function

$$L(\mathrm{E} \mid \mu) = L(\mu) = \prod_{i=1}^{n} P(Y - y_i > 0) = \prod_{i=1}^{n} \Phi\left[-\frac{y_i - \mu}{\sigma_U} \right] = \prod_{i=1}^{n} R_U(y_i, \mu, \sigma_U^2)\,, \qquad (18)$$

where $R_U(y_i, \mu, \sigma_U^2)$ is the complementary cumulative density function of μ.

4.3 Posterior function of μ

4.3.1 Failure data

$$f_U^{''}(\mu) = k \cdot L(\mu) \cdot f_U^{'}(\mu) = \prod_{i=1}^{n} f_U(y_i, \sigma_U^2) \cdot f_U^{'}(\mu)\,, \qquad (19)$$

where $k = [\int L(\mu) \cdot f_U^{'}(\mu)\, \mathrm{d}\mu]^{-1}$ is the normalizing constant. It can be shown that $f_U^{''}(\mu)$ is also normal, with posterior mean and posterior standard deviation given, respectively, as

$$\mu^{''} = \frac{\dfrac{\bar{y}}{(n/\sigma_U^2)} + \dfrac{\mu_Y}{1/\sigma_U^2}}{\dfrac{1}{(\sigma_U^2/n)} + \dfrac{1}{\sigma_U^2}} = \frac{n\bar{y} + \mu_Y}{n+1}, \qquad \sigma_U^{''} = \sqrt{\frac{\sigma_U^2 \cdot (\sigma_U^2/n)}{\sigma_U^2 + (\sigma_U^2/n)}} = \frac{\sigma_U}{\sqrt{n+1}}.$$

4.3.2 Survivor data

$$f_U^{''}(\mu) = k \cdot L(\mu) \cdot f_U^{'}(\mu) = k \cdot \prod_{i=1}^{n} R_U(y_i, \mu, \sigma_U^2) \cdot f_U^{'}(\mu), \tag{20}$$

where $k = [\int L(\mu) \cdot f_U^{'}(\mu)\, \mathrm{d}\mu]^{-1}$ is the normalizing constant that can be solved only numerically for evidence of survivor data.

4.4 Posterior function of *Y*

Since the interest is to update *Y* given evidence E, posterior *Y* need to be evaluated by

$$f_Y^{''}(y) = f_Y(y\,|\,\mathrm{E}) = \int_{-\infty}^{\infty} f_Y(y\,|\,\mu) \cdot f_U^{''}(\mu)\, \mathrm{d}\mu, \tag{21}$$

where $f_Y(y\,|\,\mu) \sim N_Y(\mu, \sigma_R^2)$. For failure data, $f_U^{''}(\mu) \sim N_U(\mu^{''}, \sigma_U^{''2})$ can be expressed analytically. It can be derived from equation (21) that the posterior *Y* is given as

$$f_Y^{''}(y) = \frac{1}{\sqrt{2\pi}\sqrt{\sigma_R^2 + \sigma_U^{''2}}} \cdot \exp\left[-\frac{1}{2}\left(\frac{y-\mu^{''}}{\sqrt{\sigma_R^2 + \sigma_U^{''2}}}\right)^2\right]. \tag{22}$$

However, for survivor data, $f_U^{''}(\mu)$ can only be given numerically. Posterior *Y* needs to be determined numerically using equations (20) and (21).

5. Numerical example

Equipments for nuclear installations are relatively stiff, and often have substantial margin against the prescribed seismic design criteria. Equipment fragilities are usually conservatively estimated. Through Bayesian updating, empirical acceleration capacities of equipments, recorded from either earthquake experience or shaking table tests, can be applied to obtain a balanced, informed, thus more convincing fragility analysis for safety-related equipment.

5.1 Example 1 using assumed data

As an initial estimation, the fragility parameters of an equipment item are given as: median acceleration capacity X_m =1.75*g*, uncertainty β_R = 0.26, and β_U = 0.27.

1. Failure data: in a shaking table test, 3 identical equipments were recorded to fail respectively at acceleration levels x_1=2.8*g*, x_2=3.0*g*, x_3=3.1*g*. Using Bayesian updating

process given in Section 4, the prior and posterior Y and fragility curves plotted against ln(X) are shown in Figure 2, where X denotes the shaking acceleration level.

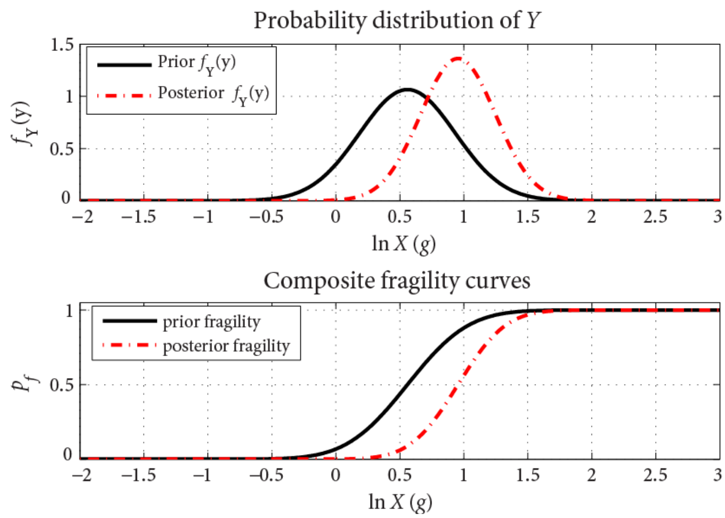

Figure 2: Prior and posterior Y and fragility curves for failure evidence

2. Survivor data: in a shaking table test, 3 identical equipments were recorded to withstand x_1=2.8g, x_2=3.0g, x_3=3.1g (identical with the above) without failure. Using Bayesian updating process, the prior and posterior Y and fragility curves plotted against ln(X) are shown in Figure 3.

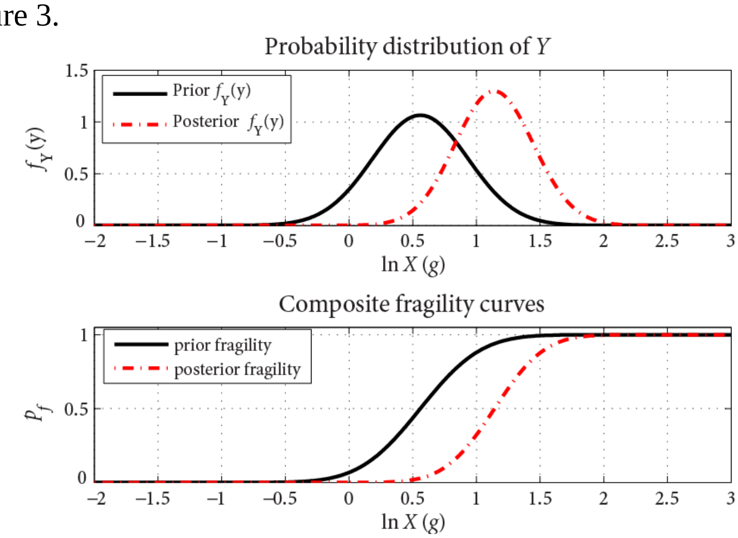

Figure 3: Prior and posterior Y and fragility curves for survivor evidence

Observed in Figures 2 and 3 are that the posterior probability density functions of Y, $f_Y''(y)$, differ significantly from the prior, and the fragility curves, i.e., the cumulative density functions of Y, change substantially.

In seismic margin assessment, the HCLPF capacity needs to be calculated according to equation (13) or (14), and is required to be greater than the Review Level Earthquake (RLE) ground motion, typically defined as PGA = 0.3g with a reference spectrum shape given by NUREG/CR-0098. Failure probability of the equipment under shaking table test is evaluated for the RLE ground motion, in which the peak response spectrum value equal to 0.65g from the reference spectrum should be used instead of PGA. Given in Table 1 are the prior and posterior parameters for evidence of both failures and survivors.

Table 1: HCLPF capacity and failure probability for RLE

prior	X_m	β_c	HCLPF	$p_{f,RLE}$
	1.75 g	0.375	0.73 g	0.0041
Evidence of 3 failures for $\boldsymbol{x}$ = 2.8 g, 3.0 g, 3.1 g				
posterior	X_m	β_c	HCLPF	$p_{f,RLE}$
	2.60 g	0.293	1.31 g	1.1×10^{-6}
Evidence of 3 survivors for $\boldsymbol{x}$ = 2.8 g, 3.0 g, 3.1 g				
posterior	X_m	β_c	HCLPF	$p_{f,RLE}$
	3.13 g	0.308	1.53 g	1.6×10^{-7}

It is seen that all parameters are updated substantially. X_m and HCLPF are increased, while β_c and $p_{f,RLE}$ are decreased. Notice should be given that the lower probability portion (fragility tail part) is very sensitive to the estimated fragility parameters, based on which the estimated HCLPF capacity can be quite different.

5.2 Example 2 using earthquake experience data

Diesel generator is one of the dominant risk contributors for NPPs and one of the governing components for plant level HCLPF capacity. An example generator is shown in Figure 4.

Figure 4: Example diesel generator in NPP

Earthquake experience data for standby generators at a number of industrial sites subjected to strong ground motions are selected from the well-maintained earthquake experience database sponsored by the Seismic Qualification Utility Group (SQUG) and the Electric Power Research Institute (EPRI). The selected data given in Appendix A was summarized by Swan

[12], grouped according to Modified Mercalli Intensity (MMI) scale, and is confined to only MMI VIII (roughly 0.34-0.65g PGA, representing strong ground motion) and MMI VIII+ (roughly 0.50-0.95g PGA, representing severe ground motion). After eliminating failures due to factors other than seismic capacity of the diesel generators such as the ground base settlement, damage to connections, and failures due to components not mounted on the generators, yields a total of 2 failures out of 65 diesel or gas generators.

Based on the assessment result of Zion plant, for typical diesel generators it is estimated that $X_m = 1.1g$, $\beta_R = 0.26$, $\beta_U = 0.27$ (thus $\beta_C = 0.375$). Using Bayesian updating process, where the likelihood function should be determined using equations (16) and (18) together, the prior and posterior Y and fragility are shown in Figures 5 and 6. In Figure 5, evidence of only 2/6 (two out of six) failures at Southern California Edison Headqauaters in 1987 Whittier earthquake is used only, featuring plant-specific characteristics of diesel generators, such as ages and specifications. From Table 2, it is observed that compared to moderate decrease of uncertainty β_C, significant reduction is induced for median capacity X_m from 1.1g to 0.62g, and HCLPF from 0.46g to 0.31g. Failure probability for RLE $p_{f,RLE}$ is increased significantly to 0.0067 (RLE here is the PGA= 0.3g).

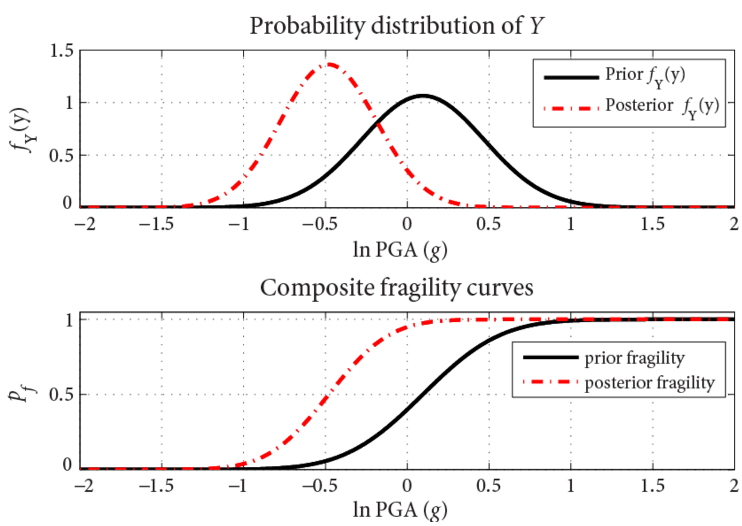

Figure 5: Prior and posterior Y and fragility curves for evidence of 2/6 failures at Southern California Edison Headqauaters in 1987 Whittier earthquake only

The posterior based on the plant-specific 2/6 failure data may not be generally applicable for other plants, which is a practical concern. Thus evidence of 2/65 failures from the entire selected data set is used for Bayesian updating. Its results are given in Figure 6 and Table 2. The posterior Y and fragility curve are not significantly different from the prior. X_m decreases slightly from 1.1g to 0.98g. The combined effect of decrease in X_m and β_C is to increase the fragility or risk in a wide PGA range (i.e., ln PGA = 0.7-1.0 g). However, the decrease in β_C greatly influences the tail of fragility curve, giving an increase in HCLPF from 0.46g to 0.52g, i.e., the posterior shows a greater seismic margin. This contradiction implies that fragility analysis method and seismic margin analysis method sometimes do not support each other.

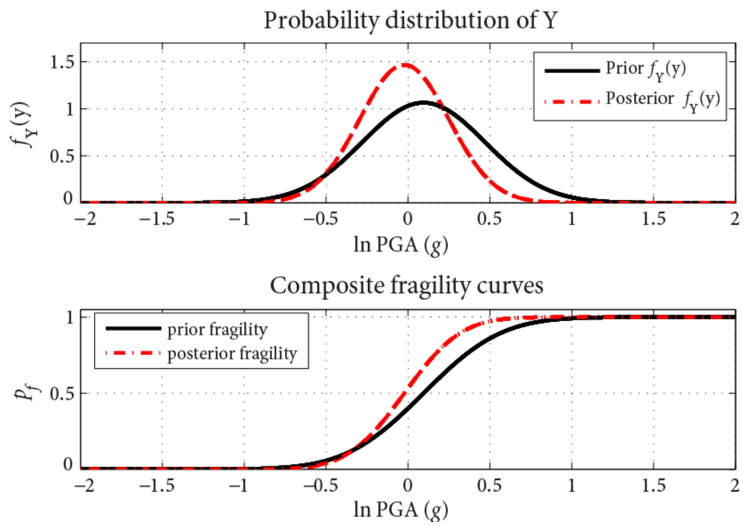

Figure 6: Prior and posterior *Y* and fragility curves for evidence of 2/65 failures

Table 2: HCLPF capacity and failure probability for RLE

prior	X_m	β_c	HCLPF	$p_{f,RLE}$
	1.1 *g*	0.375	0.46 *g*	2.6×10^{-4}
Evidence of 2/6 failure data				
posterior	X_m	β_c	HCLPF	$p_{f,RLE}$
	0.62 *g*	0.293	**0.31** *g*	0.0067
Evidence of 2/65 failure data				
posterior	X_m	β_c	HCLPF	$p_{f,RLE}$
	0.98 *g*	0.272	**0.52** *g*	6.9×10^{-6}

6. Conclusions and discussions

Safety-related equipments for nuclear installations are supposed to be seismically robust. However, their seismic capacities and fragilities are often conservatively estimated. Actual seismic capacities of these equipments need to be better evaluated, because they fundamentally influence the plant-level risk. A Bayesian formulation of seismic fragility analysis of safety-related equipment is developed, which incorporates empirical capacity evidence acquired from either earthquake experience or shaking table tests. Numerical results show that the prior distribution of capacity and fragility curve can be substantially updated using the Bayesian formulation.

It is also noticed that both the type of evidence (i.e., failures or survivors) and the size of selected data will influence the posterior. To give a reasonable and convincing updating, the evidence needs to be selected carefully and properly, which deserves further study.

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Appendix A:

Inventory of Diesel and Gas Turbine Generators from the SQUG/EPRI Database

Earthquake	**Site**	**Duration** (sec)	**PGA** (*g*)	**MMI**	**Portion of Generators Failed**
2011 Japan	Onagawa Nuclear Plant	90	0.68	VIII+	0/8
1985 Chilean	Llolleo Water Treatment Plant	40	0.75	VIII+	0/1
1994 Northridge	Olive View Hospital Cogeneration Plant	10	0.73	VIII+	0/4
	Great Western Data Center	10	0.50	VIII+	0/3
1983 Coalinga	Union Oil Propane/Butane Refinery	10	0.62	VIII+	0/18
1986 Palm Springs	Devers Substation	5	0.81	VIII	0/1
1994 Northridge	Placerita Cogeneration Plant	10	0.59	VIII	0/2
	Arco Cogeneration Plant	10	0.60	VIII	0/2
	Pitchess Cogeneration Plant	10	0.50	VIII	0/1
1992 Mendocino	Pacific Lumber Cogeneration Plant	10	0.46	VIII	0/1
	Centerville Naval Station	10	0.40	VIII	0/2
1989 Loma Prieta	UC Santa Cruz Campus	10	0.43	VIII	0/5
	Santa Cruz Water Treatment Plant	10	0.43	VIII	0/1
	Santa Cruz Telecom Central Office	10	0.43	VIII	0/1
	Watsonville Telecom Central Office	10	0.40	VIII	0/1
	Watsonville Water Treatment Plant	10	0.40	VIII	0/2
	National Refractory Brick Plant	10	0.30	VIII	0/2
1987 Whittier	Southern California Edison Headquarters	5	0.42	VIII	**2**/6
	California Federal Data Center	5	0.40	VIII	0/4