

EFFECTIVE UPDATING PROCESS OF SEISMIC FRAGILITIES USING BAYESIAN METHOD AND INFORMATION ENTROPY

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ABSTRACT

Seismic probabilistic safety assessment (SPSA) is an effective method for evaluating overall performance of seismic safety of a plant. Seismic fragilities are estimated to quantify the seismically induced accident sequences. It is a great concern that the SPSA results involve uncertainties, a part of which comes from the uncertainty in the seismic fragility of equipment and systems. A straightforward approach to reduce the uncertainty is to perform a seismic qualification test and to reflect the results on the seismic fragility estimate.

In this paper, we propose a figure-of-merit to find the most cost-effective condition of the seismic qualification tests about the acceleration level and number of components tested. Then a mathematical method to reflect the test results on the fragility update is developed.

A Bayesian method is used for the fragility update procedure. Since a lognormal distribution that is used for the fragility model does not have a Bayes conjugate function, a parameterization method is proposed so that the posterior distribution expresses the characteristics of the fragility. The information entropy is used as the figure-of-merit to express importance of obtained evidence. It is found that the information entropy is strongly associated with the uncertainty of the fragility.

1. INTRODUCTION

Seismic probabilistic safety assessment (SPSA) is an effective method for evaluating the overall performance of seismic safety of a nuclear power plant (NPP). The SPSA requires seismic fragility estimations of all safety components. Seismic fragilities that are defined as failure probabilities on condition that an earthquake occurs are estimated to quantify the seismically induced accident sequences. It is a great concern that the SPSA results involve uncertainties, a part of which comes from the uncertainty in the seismic fragility of equipment and systems.

The uncertainty of the seismic fragility derives from the lack of knowledge concerning the failure mechanism. When the uncertainties are significant, we would be willing to make efforts to reduce the uncertainty to an acceptable level from the viewpoint of usage of the risk information. A straightforward approach to reduce the uncertainty is to perform a seismic qualification test and to reflect the results on the seismic fragility estimate.

One needs to find out the cost-effective seismic qualification tests in terms of acceleration level and number of tested components in the vibration tests. Thus, a mathematical method to optimize the test condition and to reflect the test results on the fragility update and to optimize the test conditions is important.

In the present paper, we propose the method to reflect the seismic qualification test results on the fragility mathematical method by the Bayesian update and the method to express a

figure-of-merit of the test by the information entropy. We find out the most cost-effective condition of the test.

In section 2, the seismic fragility model is described and features of the uncertainty in the seismic fragility are discussed. In section 3, we develop a mathematical method, i.e. the Bayesian approach to reflect the tests results on the fragility update. In section 4, the information entropy is proposed as the figure-of-merit to express importance of obtained evidence.

2. SEISMIC FRAGILITY

The SPSA requires seismic fragilities of all safety equipments of NPP. The seismic fragility is defined as the component failure probability of the equipments on condition that peak ground acceleration (PGA) α occurs by an earthquake. The PGA is the intensity parameter of an earthquake. A cumulative lognormal distribution is commonly used to describe the seismic fragility curves. The fragility function $F(\alpha)$ is expressed as:

$$F(\alpha) = \Phi \left[\frac{\ln(\alpha/C)}{\beta_R} \right] \quad \text{or} \quad \frac{F(\alpha)}{d\alpha} = \frac{1}{\sqrt{2\pi}\beta_R} \exp \left[-\frac{1}{2} \left\{ \frac{\ln(\alpha/C)}{\beta_R} \right\}^2 \right] \quad (1)$$

The graphic expression of the fragility function is shown in Figure 1. β_R and C are parameters of the fragility function associated with the randomness and the seismic capacity of the component, respectively. $\Phi(-)$ is the cumulative standard

normal distribution function.

The parameter C corresponds to the PGA level at which the seismic fragility equals 0.5. The slope of the seismic failure probability curve corresponds to the randomness β_R of the magnitude and the component response. If β_R equals zero, the failure is deterministic, that is it definitely finds beyond the point alee the PGA level equals the parameter C .

The seismic capacity has uncertainty and is expressed by probability density function (PDF). In general, a lognormal distribution is used to describe the PDF $f(C)$.

$$f(C) = \frac{1}{\sqrt{2\pi}\beta_U C} \exp\left[-\frac{1}{2}\left\{\frac{\ln(C/A_m)}{\beta_U}\right\}^2\right] \quad (2)$$

Here A_m and β_U are the median value and the logarithmic standard deviation of the PDF, respectively. The parameter β_U corresponds to uncertainty of the seismic capacity. The uncertainty is attributed to the inadequateness of our knowledge concerning the seismic capacity. The PDF of the seismic capacity is shown in Figure 2.

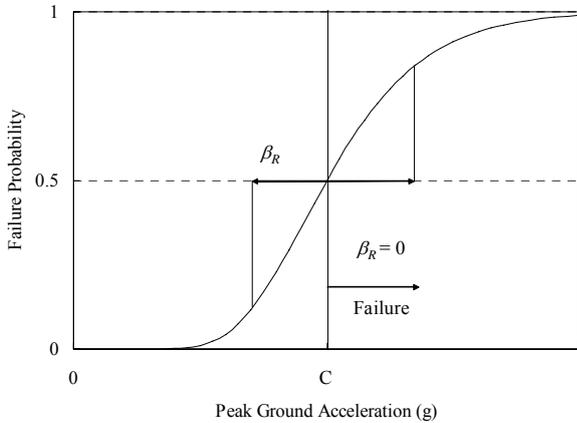


Fig. 1 Failure probability on condition that the seismic capacity is C

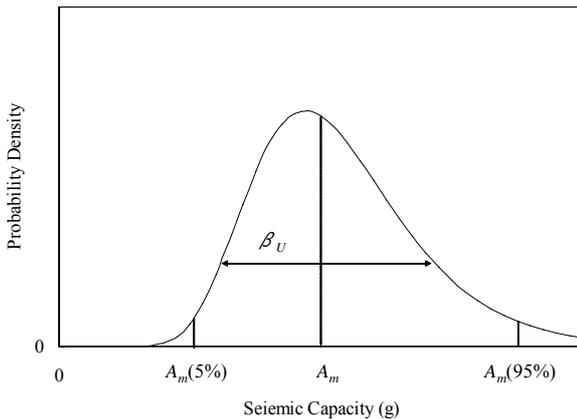


Fig. 2 Probability density of the seismic capacity

If we use various confidence levels of the seismic capacity, we can draw many fragility curves. Figure 3 shows the fragility curves for three confidence levels which equal median (50% confidence safety), 5% confidence, and 95% confidence of seismic capacity as a function of the PGA. Because the seismic capacity has uncertainty, the fragility curves are drawn with various confidence levels. When fragility curves are not believed because of large uncertainty, it is important to reduce the uncertainty. Thus, to reduce uncertainty of the seismic capacity, we perform a seismic

qualification test and reflect the test results in the seismic capacity.

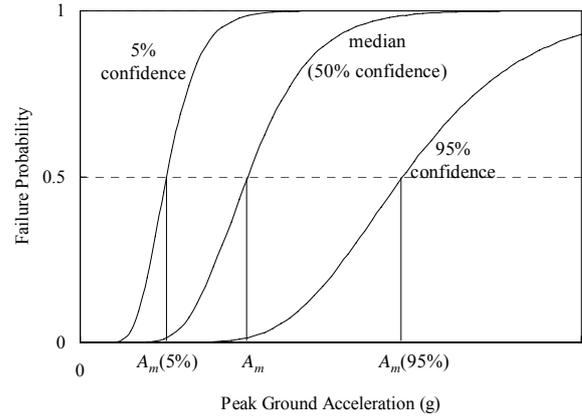


Fig. 3 Seismic fragility curve (median, 5% and 95% bounding with median of A_m)

3. BAYESIAN UPDATE

3.1 Bayesian Update Procedures

Our knowledge on the seismic-induced failure is imperfect and its uncertainty is expressed by a PDF of seismic capacity as in Eq. (2). When we have a new evidence E , it is reasonable that we update the function based on the new information. Let $L(E|C)$ be the likelihood of the evidence E on condition that we have a subsection judged regarding the seismic capacity that is expressed as the prior PDF $f(C)$, the posterior PDF $f(C|E)$ of the seismic capacity after we obtain the evidence E is expressed as:

$$f(C|E) = \frac{f(C)L(E|C)}{\int_0^{\infty} f(C)L(E|C)dC} \quad (3)$$

This is the Bayesian method and the process is called “Bayesian Update”.

We assume that a seismic qualification test at acceleration level α is performed on condition that the seismic capacity is C and its subject probability is $f(C)$. The failure probability of the test component is given by Eq. (1), i.e. $F(\alpha|C)$. The likelihood L that the test result is “failure” equals $F(\alpha|C)$. The likelihood that the test result is “success” equals $1 - F(\alpha|C)$. When N components are tested at the same acceleration level α , the likelihood L_k is the probability that k components fail out of N components and is calculated by the binomial distribution:

$$L_k = \binom{N}{k} F(\alpha|C)^k \{1 - F(\alpha|C)\}^{N-k} \quad (4)$$

Substituting Eqs. (2) and (4) into Eq. (3), the posterior PDF $f(C|E)$ is calculated from the prior PDF $f(C|E)$.

As an example, let us consider a seismic qualification test is performed at the median capacity level. The prior seismic fragility parameters in Eqs.(1) and (2) are assumed to be $A_m = 2.0g$, $\beta_R = 0.3$, $\beta_U = 0.4$. In this case, the likelihood parameters in Eq. (4) are $N = 1$ and $k = 0$ “success” or $k = 1$ “failure”. The likelihood is expressed as:

$$\begin{aligned} L_{k=0} &= 1 - F(\alpha|C) \quad (\text{Success}) \\ L_{k=1} &= F(\alpha|C) \quad (\text{failure}) \end{aligned} \quad (5)$$

Figure 4 shows the results of the Bayesian update of the seismic capacity. If the component does not fail, the posterior distribution of the PDF shifts towards larger seismic capacity from the prior distribution and when the test result is failure, the posterior distribution shifts towards smaller seismic capacity from the prior distribution.

In the SPSA, a lognormal distribution of seismic capacity model is commonly used because of simplicity and mathematical convenience. However the posterior distribution is not a lognormal because the fragility model does not have a Bayes conjugate function and the posterior distribution is calculated from the prior distribution and the likelihood function. Therefore, the posterior distribution is approximated to a lognormal distribution.

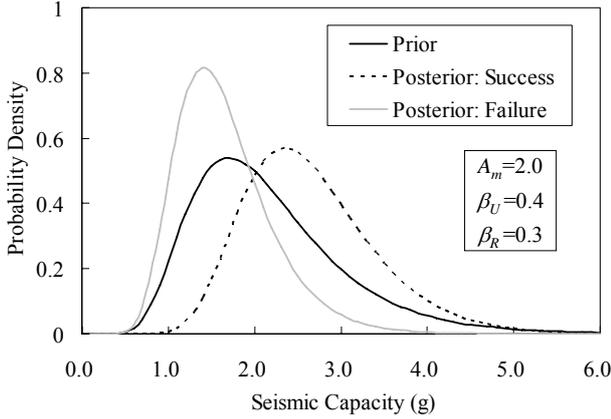


Fig. 4 Bayesian update: prior and posterior PDFs of the seismic capacity

3.2 Posterior Distribution of Seismic Capacity

A lognormal distribution has two parameters, for example, the seismic capacity has A_m and β_U . The technique that is to select two points from the posterior distribution of the seismic capacity and substituting the points into lognormal distribution Eq. (2) to estimate two parameters is simply and easy to approximate the posterior distribution. In this paper, the approximation technique is to select the two points from median (50% confidence), 5% confidence, and 95% confidence of the posterior distribution.

Figure 5 shows the results of the two approximated posterior distribution at the success shown in Figure 4. The technique of Approximation 1 is to select 5% confidence and median of the distribution. The technique of Approximation 2 is to select 5% confidence and 95% confidence of the distribution.

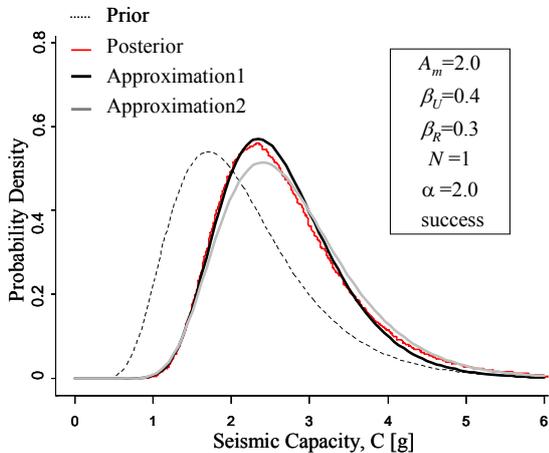


Fig. 5 Approximated distributions of the posterior PDFs of the seismic capacity

The fragility parameters A_m and β_U can be estimated from the approximated distribution. Comparing the prior fragility parameter with the approximated parameter from the posterior distribution, we can compare the prior distribution of the seismic capacity with the posterior distribution.

Here let us consider the most effective acceleration level of the seismic qualification test if we plan a single test. One test result has two possibilities, i.e. “success” or “failure”. When the test acceleration level is very low, it is possible that the component is success. On the other hand, the component will fail if the test acceleration level is very high. The test results are indefinite according to the test acceleration level. However, we can estimate the expected values of the posterior fragility parameters from the two possibility test results using the Bayesian update and the approximation technique:

$$\begin{aligned} \bar{A}_m(\alpha) &= F(\alpha) \times A_m(\alpha, 1) + (1 - F(\alpha)) \times A_m(\alpha, 0) \\ \bar{\beta}_U(\alpha) &= F(\alpha) \times \beta_U(\alpha, 1) + (1 - F(\alpha)) \times \beta_U(\alpha, 0) \end{aligned} \quad (6)$$

The expected values of the posterior two fragility parameters A_m and β_U are calculated by Eq. (6). $F(\alpha)$ and $1 - F(\alpha)$ are the failure probability and the success probability of the component at the acceleration level α , respectively. When the test result is failure on condition that the test acceleration level is α , the posterior parameter A_m estimated by the Bayesian update is expressed as $A_m(\alpha, 1)$. When the test result is success on condition that the test acceleration level is α , the posterior parameter A_m estimated by the Bayesian update is expressed as $A_m(\alpha, 0)$. Where $\bar{A}_m(\alpha)$ is expected value of the posterior A_m estimated by the Bayesian update at the test acceleration level α . By the same token, where $\beta_U(\alpha, 1)$ is the posterior β_U estimated by the Bayesian update on condition that the test result is failure and $\beta_U(\alpha, 0)$ is the posterior β_U on condition that the test result is success. $\bar{\beta}_U(\alpha)$ is expected value of the posterior β_U estimated by the Bayesian update at the test acceleration level α .

Figure 6 shows the posterior median value $A_m(\alpha, 1)$ estimated by the Bayesian update when the test result is failure, the posterior median value $A_m(\alpha, 0)$ when the test result is success and the expect median value $\bar{A}_m(\alpha)$ of the posterior A_m as a function of the test acceleration, respectively. The prior fragility parameters of a test component are assumed to be $A_m = 2.0g$, $\beta_U = 0.4$ and $\beta_R = 0.3$ and the approximation technique used for the posterior distribution is Approximation 2 shown in Figure 5. The small change of the expected A_m ($=\bar{A}_m(\alpha)$) from the prior $A_m(=2.0g)$ is the result of the Bayesian update. The expected A_m of the low test acceleration level is near the $A_m(\alpha, 0)$ and the value is higher than the prior A_m . On the other hand, the expected A_m of the high test acceleration level is near the $A_m(\alpha, 1)$ and the value is lower than the prior A_m . The expected A_m doesn't change greatly from the prior A_m because the expected A_m is reflected in the expected value by the failure probability of the component.

Figure 7 shows the posterior logarithmic standard deviation $\beta_U(\alpha, 1)$ estimated by the Bayesian update when the test result is failure, the posterior logarithmic standard deviation $\beta_U(\alpha, 0)$ estimated by the Bayesian update when the test result is success and the expected value $\bar{\beta}_U(\alpha)$ of the posterior β_U as a function of the test acceleration, respectively. The expected β_U gets the smallest value on condition that the test acceleration level is the prior A_m . The result means that the prior A_m acceleration level test is effective because the parameter β_U express the uncertainty of the seismic capacity. We consider that the test on condition that the test level is the

prior A_m is effective from the test results in Figure 6 and Figure 7.

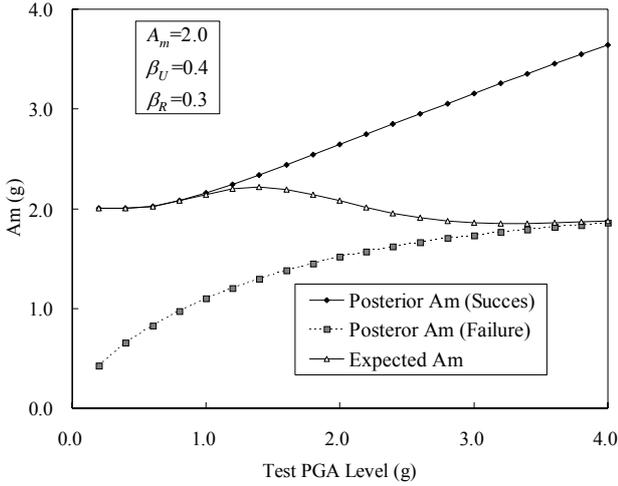


Fig. 6 Expected value of A_m performing a test as a function of test acceleration level

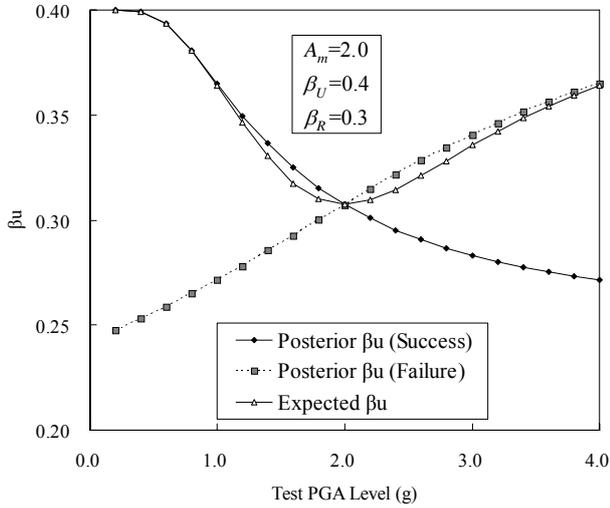


Fig. 7 Expected value of β_U performing a test as a function of test acceleration level

4. INFORMATION ENTROPY

4.1 Estimation of Test Importance Using Information Entropy

In the section 3, we propose the technique to reflect information on the seismic fragility update using Bayesian update and to approximate the posterior distribution. The effective acceleration level of the seismic qualification test is the level that is the prior median value of the capacity. In this section, we propose importance of the test and estimate the importance. To estimate the importance of the test, we use the logarithmic likelihood and the information entropy.

It is interesting to know the importance or worth of new information from the seismic qualification test. The importance of the new information can be estimated by the logarithmic likelihood V_k :

$$V_k(E|C) = -\ln L_k(E|C) \quad (7)$$

where L_k is the likelihood. The likelihood L_k is the probability that the evidence is observed and is given by Eq. (4) in the present case.

The range of the logarithmic likelihood is from zero to

infinity. If seismic capacity of a component is small and a significant earthquake occurs, the component will definitely fail. In this case, we take the failure for granted and the value of the new information is little. Accordingly, the logarithmic likelihood is nearly zero. On the other hand, if seismic capacity is large and a small earthquake occurs, the component will definitely success. In this case, we take the success for granted. If the component is failure in this case, the value of the new information is importance. Accordingly, the logarithmic likelihood is infinite. Thus, the logarithmic likelihood is defined as quantity of information of an event (result of a seismic qualification test).

Since we do not know the test results in advance, the expected value of the logarithmic likelihood with respect to all the possibilities is a point of concern. It is defined as the information entropy; E . we assume the test result is either fail or success. The information entropy $E(\alpha|C)$, test acceleration level is α and seismic capacity of the test component is C , is expressed as:

$$E(\alpha|C) = -F(\alpha|C)\ln F(\alpha|C) - \{1-F(\alpha|C)\}\ln\{1-F(\alpha|C)\} \quad (8)$$

When N components are tested at the same acceleration level, there are $N + 1$ possibilities. Thus the general expression of the entropy is $E(\alpha, N|C)$:

$$E(\alpha, N|C) = -\sum_{k=0}^N L_k \ln L_k \quad (9)$$

Quantity of information entropy is expected quantity of information when a seismic qualification test performs, therefore, quantity of information entropy is defined as an importance of performing a test.

4.2 Information Entropy with Respect to the Seismic Capacity

On the seismic fragility model, the seismic capacity is updated as a result of seismic qualification test. To perform the test to reduce uncertainty of the seismic capacity, we estimate the information entropy with respect to the seismic capacity. Because the seismic capacity is expressed by PDF in Eq. (2), we estimate the expected value of the distribution of the seismic capacity:

$$\bar{E}(\alpha, N) = \int_0^{\infty} E(\alpha, N) f(C) dC = -\int_0^{\infty} f(C) \sum_{k=0}^N L_k \ln L_k dc \quad (10)$$

Where $E(\alpha, N)$ and $\bar{E}(\alpha, N)$ are the information entropy to perform the test of acceleration level α and N components and the expected information entropy, respectively. The expected entropy is estimated by integrating distribution of seismic capacity and entropy over the whole acceleration level of the seismic capacity.

Figure 8 shows the expected information entropy for the seismic qualification test of a component and the reduction of β_U as a result of the Bayesian update, respectively. The reduction of β_U from the prior β_U is described as $\Delta\beta_U$. The prior fragility parameter is $A_m = 2.0g$, $\beta_U = 0.4$ and $\beta_R = 0.3$ (The parameters are used in the following example). The horizontal axis indicates the acceleration level at which the test is performed. When the expected entropy is compared with $\Delta\beta_U$, the acceleration level of the entropy value is strongly associated with the level of $\Delta\beta_U$ and the level of the maximum entropy value ($=2.0g$) is consistent with the level of the maximum value of $\Delta\beta_U$. Because the parameter β_U

express uncertainty of the seismic capacity, the test acceleration level to reduce the uncertainty of the seismic capacity can be judge from the expected information entropy with respect to the seismic capacity. 2.0 g is mordantly that the reduction of the uncertainty and importance of the mew information coincident is in good.

Here, let us consider multiple components test. Figure 9 shows the results of the expected entropy and the $\Delta\beta_U$ as a result of the Bayesian update for the number of tested components, that is $N=1$ and 4. It is found that the four components test is the same relationship in the case of the one component test by expected entropy and $\Delta\beta_U$. Thus, the entropy value is correlated with $\Delta\beta_U$ from the prior regardless of the number of tested component. The fact remains that the uncertainty can be described with the entropy, even if the number of component increases. Knowing expect entropy distribution and the prior fragility parameters, we can expect the posterior β_U of the test as a function of the test acceleration level.

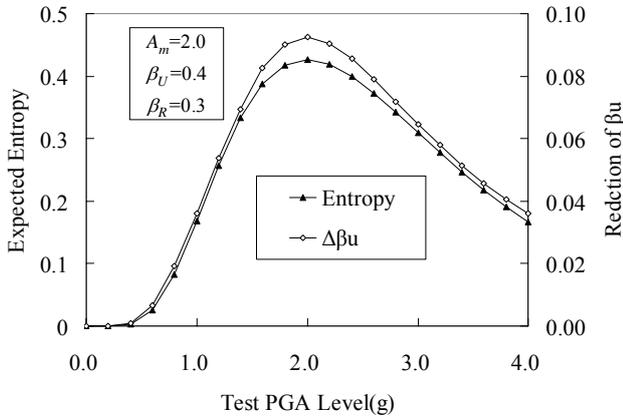


Fig. 8 Expected entropy and $\Delta\beta_U$ as a result of the Bayesian update as a function of test acceleration level

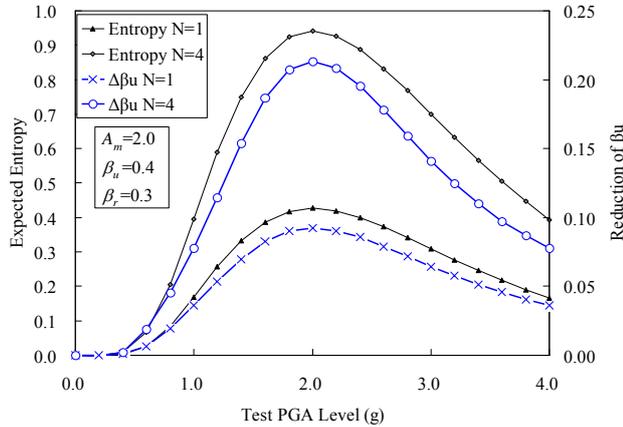


Fig. 9 Expected entropy and $\Delta\beta_U$ as a result of the Bayesian update by N components test

4.3 Information Entropy with Respect to the Seismic Capacity and the Seismic Hazard

It is a reasonable that the value of new information is different by analysts on seismicity of the plant. In this section, an example is given to explain how the conclusion is influence by the seismicity of N.P.P, i.e. the seismic hazard.

In seismic risk assessment of components in NPP, we need to assess seismic hazard at the plant with the component's seismic fragility. The seismic hazard is assessed as an annual frequency of earthquake happening on condition that acceleration level exceeds α on the site of the plant.

An example of the seismic hazard curves is shown in Figure 10. There are eight hazard curves. Four of them shown by solid lines have 0.10 weight factor ($\omega_i=0.1$) and the other have 0.15 ($\omega_i=0.15$). M is the number of difference hazard curve. With the fragility curves of the seismic components in the plant, the seismic hazard curves of the site are estimated, and the annual frequencies of failure of the components on the site are calculated as:

$$F_r = - \int_0^{\infty} \sum_{i=1}^M \omega_i \frac{dh_i(\alpha)}{d\alpha} F(\alpha) d\alpha \quad (11)$$

where $h_i(\alpha)$ and ω_i are i -th hazard curves and its weight factor or relative credibility, respectively.

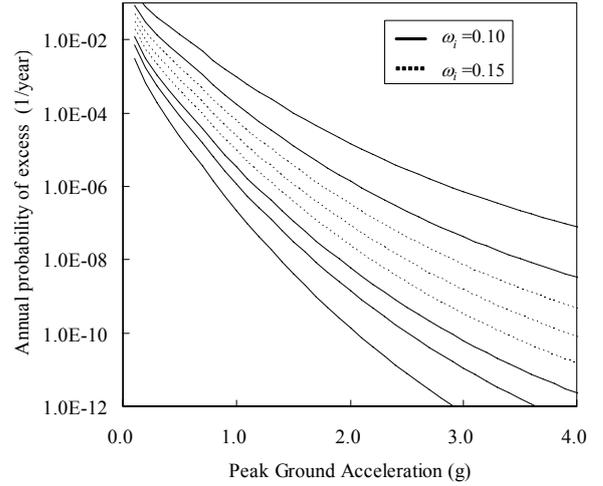


Fig. 10 Example of seismic hazard curves

When the seismic hazards are considered with the fragility of the components in the assessment the effective test level is most likely changed from only considering the fragility. For example, comparing the plant site of large seismic hazard with small seismic hazard, we expect that the effective test level is different. Thus, the information entropy model with respect to the seismic hazard and the seismic capacity is necessary to estimate the effective test level for the component from the site of the plant.

$\bar{E}(\alpha, N)$ in Eq. (10) is the expression of the expected information entropy with respect to the seismic capacity. The expected information entropy with respect to the seismic hazard and seismic capacity is defined as $\tilde{E}(\alpha)$:

$$\tilde{E}(\alpha, N) = - \int_0^{\infty} \omega_i \frac{dh_i(\alpha)}{d\alpha} E(\alpha | C) f(C) dC \quad (12).$$

The expected entropy is the importance of a seismic qualification test of N components at acceleration level α for a analyst who believe that the seismic capacity PDF is $f(C)$ and the seismic hazard is $h(\alpha)$.

The solid line in Figure 11 shows the expected information entropy with respect to the seismic hazard and the seismic capacity for the seismic qualification test of a component. The fragility parameter is $A_m = 2.0g$, $\beta_U = 0.4$ and $\beta_R = 0.3$ and the seismic hazard is the curves shown in Figure 10 (The parameters and the hazard are used in the following example). The horizontal axis indicates the acceleration level at which the test is performed. It is seen the acceleration level at which the expected entropy become maximum is 1.2g. The two dotted lines in Figure 11 show the normalized expected information entropy with respect to the seismic capacity and

the normalized $\Delta\beta_U$ for the seismic qualification test of the component, respectively. The normalized values mean that the expected entropy and the $\Delta\beta_U$ in Figure 8 are normalized with respect to the maximum value ($=2.0g$ value). Thus when the test acceleration level equals $2.0g$, the normalized expected entropy and the normalized $\Delta\beta_U$ equal 1. The right vertical axis indicates the normalized value. Figure 11 shows that the test acceleration level of the maximum expected entropy ($=1.2g$) is smaller than the level of the maximum expected entropy ($=2.0g$) with respect to only the seismic capacity. The effective test acceleration level judged by the expected entropy with respect to the seismic hazard and the seismic capacity is not A_m , and even if the effective level test judged by the seismic hazard and the seismic capacity is performed, $\Delta\beta_U$ not becomes the maximum value. As a result, the effective test level using the expected entropy with respect to the seismic hazard and the seismic capacity is not judged by the fragility parameters of the component. We propose that the effective test level is judged by the annual frequency of failure of the component as well as the seismic hazard assessed as the annual frequency.

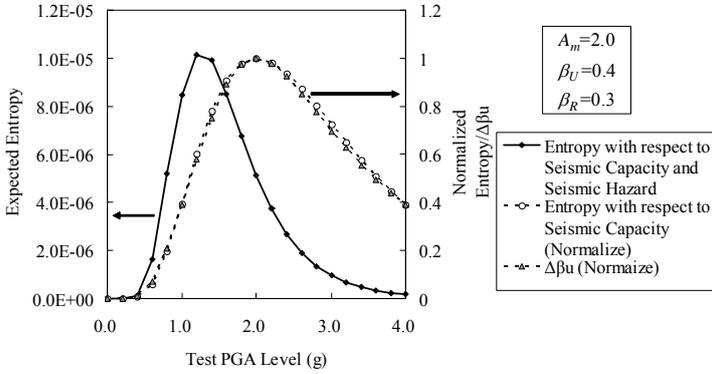


Fig. 11 Expected entropy with respect to the seismic hazard and the seismic capacity (The dotted lines are the normalized expected entropy with respect to the capacity and normalized $\Delta\beta_U$)

Figure 12 shows the expected annual frequency of failure estimated for the posterior fragilities as a function of the test acceleration. The horizontal axis indicates the acceleration level at which the test is performed and the three solid line curves indicate the frequency when the fragility curve of confidence level is believed to be median (50% confidence), 5% confidence, and 95% confidence, respectively. The left vertical axis indicates the expected annual frequency of failure per year. The dotted line in Figure 12 shows the interval of the expected annual frequency from the 5% confidence level fragility to the 95%. The right vertical axis indicates the interval value of annual frequency per year. The linear interval of the expected annual frequency is the narrowest when the test acceleration level equals $1.2g$. An interval of expected annual frequency narrowness means that reduction of the uncertainty of the frequency is small. Thus, performing the test at $1.2g$ level, the analyst can expect that the uncertainty of the annual frequency of failure become smallest.

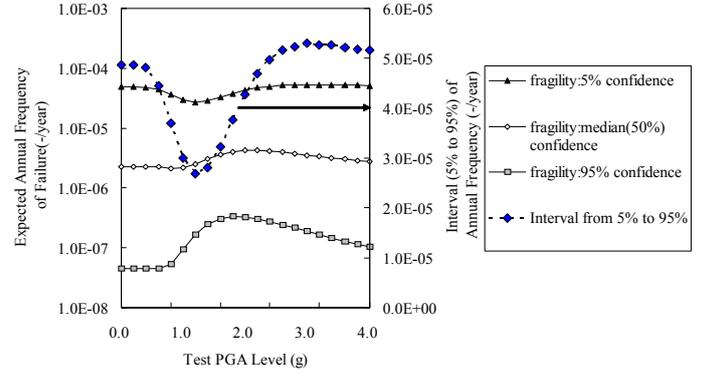


Fig. 12 Expected annual frequency of failure estimated for posterior fragilities at a test (The dotted line is linear interval value of expected annual frequency of failure between 5% and 95% confidence)

Figure 13 shows the expected information entropy with respect to the seismic hazard and the seismic capacity and the linear interval of the expected annual frequency from the 5% confidence level fragility to the 95%. The horizontal axis indicates the acceleration level at which the test is performed. The left vertical axis indicates the expected entropy and the right vertical axis indicates the interval of annual frequency per year. The acceleration level of the maximum expected entropy agrees with the level of the minimum value of the interval. In addition, the expected entropy is strongly associated with the interval of the expected annual frequency narrowness. Accordingly, the test acceleration level to reduce the uncertainty of the annual frequency of failure can be judged by the expected information entropy with respect to the seismic capacity and the seismic hazard.

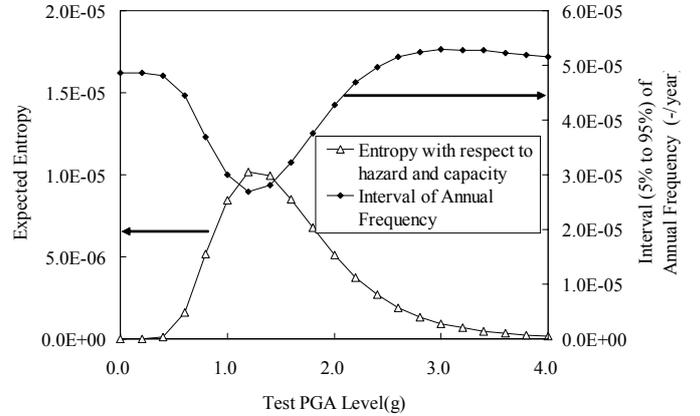


Fig. 13 Expected entropy with respect to hazard and capacity of a test and interval value of expected annual frequency of failure estimated for posterior fragilities between 5% and 95% confidence

5. CONCLUSION

The Bayesian method and the information entropy are effective in the fragility update and the uncertainty reduction.

When the distribution of the seismic capacity is logarithmic normal distribution, the posterior fragility curve is not lognormal function in the Bayesian update process. However, the posterior distribution of the seismic capacity can be approximated by selecting two points. In the comparison of the approximated fragility parameters with the prior parameters, the posterior distribution of the seismic capacity can be compared with the prior distribution. As a result of comparing the expected posterior β_U with the prior β_U , it is found that the effective acceleration level of the test is the prior A_m .

Estimating the expected entropy with respect to the seismic capacity, it is found that the reduction of β_U is related to the expected entropy. Accordingly, the test acceleration level to reduce the uncertainty of the seismic capacity can be judge from the expected entropy with respect to the seismic capacity.

Estimating frequency of components failure in NPP is needed to the fragility model of the components and the seismic hazard at the plant. Because of estimating the seismic hazard, the entropy mathematical method is changed and the acceleration level of the maximum expected entropy changes from the estimation with only respect to the seismic capacity. The test acceleration level to reduce the uncertainty of frequency of failure can be judge from the maximum expected entropy with respect to the seismic capacity and the seismic hazard.

As a result of the analyses, when an analyst wants to know test acceleration level of components to reduce the uncertainty of the components fragilities, the analyst estimate expected entropy with respect to the seismic capacity of the components. And when an analyst wants to know test acceleration level of components to reduce the uncertainty of the frequency of the components failure, the analyst estimate expected entropy with respect to the seismic capacity and the seismic hazard. It is found that the test level to reduce uncertainty is correlated with the expected entropy.

NOMENCLATURE

A_m	median value of seismic capacity [m/s ²]
C	seismic capacity [m/s ²]
E	evidence
$E(-)$	information entropy
$\bar{E}(-)$	expected information entropy with respect to seismic capacity
$\tilde{E}(-)$	expected information entropy with respect to seismic capacity and seismic hazard
$F(-)$	failure probability

$f(-)$	PDF of seismic capacity
$h(-)$	seismic hazard
L	likelihood
M	number of seismic hazard curves
N	number of test components
V	logarithmic likelihood

Greek Letters

α	peak ground acceleration level [m/s ²]
β_R	randomness of the seismic magnitude and component response
β_U	uncertainty of seismic capacity
$\Delta\beta_U$	reduction of β_U from the prior β_U
Φ	cumulative standard normal distribution function
ω	weight factor of seismic hazard

Subscripts

i	i-th hazard curves
k	number of failure components

REFERENCES

- Atwood, C.L. et al., (2003). "Handbook of Parameter Estimation for Probabilistic Risk Assessment," NUREG/CR-6823.
- Robert, J. B. (1998). "Current status of methodologies for seismic probabilistic safety analysis," *Reliability engineering and system safety.*, **62**, pp.71-88.
- Yamaguchi, A. (1991). "Bayesian Methodology for Generic Seismic Fragility Evaluation of Components in Nuclear Power Plants," *SMiRT 11 Transaction Vol.M*, Tokyo, JAPAN, Aug. 18-23.
- Yamaguchi, A. (2006). "Usage of Information Entropy in Updating Seismic Fragilities" OECD, Jeju Island, KOREA, Nov. 6-8.