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HOW TO MAKE BEST USE OF NUMERICAL SIMULATION, EXPERIENCE FEEDBACK AND EXPERT JUDGEMENT IN SEISMIC FRAGILITY ANALYSIS FOR NUCLEAR INSTALLATIONS

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Abstract:

The general framework of seismic risk assessment are due to the pioneering work of Cornell and co-workers. In nuclear engineering practice, the so-called safety factor (or separation of variables) approach is generally used to develop fragility curves due to its systematic applicability and the possibility to deal with many Structure, Systems and Components. In the recent decades, there have been significant advances in nuclear engineering regarding modelling and tools for dynamic structural and mechanical analyses. With increasing computational capabilities, it becomes now feasible and more and more common to develop numerical models representing complex and possibly nonlinear behaviour. We show how different sources of information such as expert judgement, numerical simulation, qualification tests and experience feedback can be combined in a Bayesian framework to develop best-informed fragility curves. We present an approach that allows for the consideration of generic fragility parameters and simulation to develop priors and update fragility curves using experience feedback considering both epistemic and aleatory uncertainty. In particular, we use a database that contains failure data collected in industrial plants that have experienced an earthquake. We discuss opportunities and difficulties of this approach, related to the lack of specific data for nuclear equipment despite growing experience feedback and awareness. Further advances such as vector fragility and hazard consistent definition of seismic load are discussed as perspectives of this work.

Introduction

The general concepts of seismic risk assessment are due to the pioneering work of Cornell and co-workers (Kennedy, Cornell et al.1980, EPRI 1994). In nuclear engineering practice, the so-called safety factor (or separation of variables) approach is generally used to develop fragility curves due to its systematic applicability and the possibility to deal with many SSCs (Structure, Systems and Components). With increasing computational capabilities, it becomes now feasible and more and more common to develop numerical models representing complex and possibly nonlinear behavior for components at stake.

There is an opportunity to combine efforts and to progress in current practice by supporting simulation results with experimental data and experience feedback in the framework of Bayesian approaches and machine learning.

Here, we focus on different aspects related to the numerical evaluation of fragility curves, including the choice of intensity measures, uncertainty propagation, reliability of numerical models, possible surrogates and the introduction of knowledge through expert judgement and in-situ experience data.

Different sources of information such as expert judgement, numerical simulation, qualification tests and experience feedback can be combined in a Bayesian framework to develop best-informed fragility curves. Bayesian approaches are becoming more and more popular. Here, we present an approach that allows for the consideration of generic fragility parameters and simulation to develop priors and update fragility curves using experience feedback considering both epistemic and aleatory uncertainty. This is illustrated in **figure 1**. In particular, we use a

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database that contains failure data collected in industrial plants that have experienced an earthquake. We discuss opportunities and difficulties of this approach, related to the lack of specific data for nuclear equipment despite growing experience feedback and awareness.

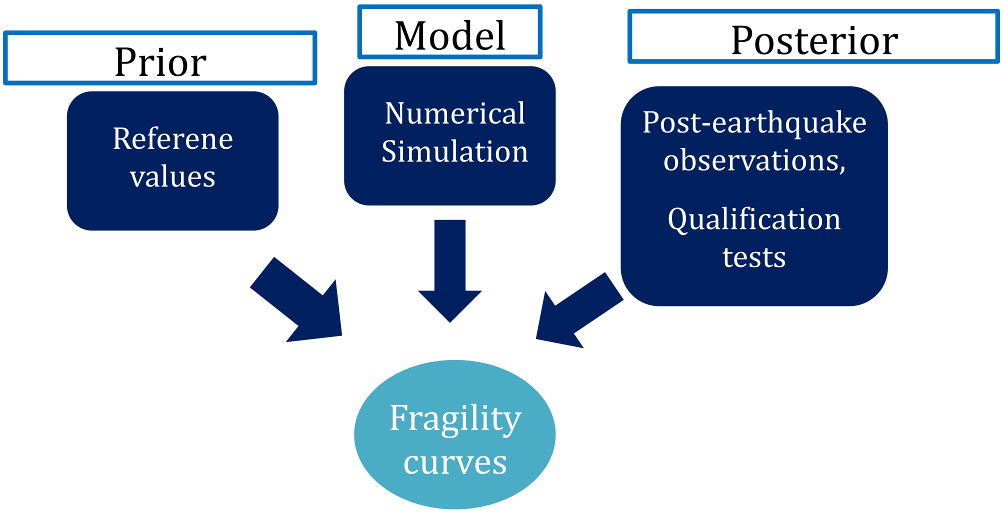


***Figure 1**. Illustration of Bayesian assessment process for fragility curves.*

The PGA (Peak Ground Acceleration) is generally used as intensity measure when developing fragility and hazard curves while a few equipment might be more sensitive to low frequency content of seismic ground motion and thus specific Pseudo-Spectral Acceleration (PSA). This can be addresses by considering vector hazard and vector fragility curves, the benefits for seismic risk assessment of nuclear plants still needs to be quantified. Other advancements with the development of the PBEE approaches that could be beneficial for nuclear safety assessment a related to more realistic definition of seismic load. This will be discussed as a perspective of this work.

Fragility curves

Fragility curves are computed as conditional probabilities of failure of structures, or critical components, for given values of a seismic intensity measure (IM), such as the peak ground acceleration (PGA). The computation of fragility curves requires a realistic estimation of the structure performance subject to seismic excitations via the quantification and the propagation of uncertainties existing in earthquake ground motions, structural material properties, damage variable.

The fragility curve is defined as the conditional failure probability of a structure, system or component (SSC), given the seismic load intensity α. Failure is not necessarily the collapse of the structure. When the performance of the structure or component is described by a pertinent damage measure (DM), then "failure" can be expressed by means of a threshold Ds. According to the second definition, failure occurs when the demand exceeds a defined limit capacity. The most general expression of a fragility curve as a conditional probability reads:

$$P_f(\alpha) = P(DM > Ds | IM = \alpha) \qquad (1)$$

In practice, the fragility curve is generally expressed as a lognormal distribution function. In this framework, the structural capacity is lognormally distributed with median A_m and lognormal standard deviation (log-std) β_C. This allows writing the fragility curves as the Cumulative Distribution Function (CDF):

$$P_f(\alpha) = \Phi\left(\frac{\ln \alpha - \ln A_m}{\beta_C}\right), \tag{2}$$

where $\Phi(u)$ designs the CDF of a normalized Gaussian random variable u. The uncertainties, expressed by β_C are categorized into two groups (Kennedy et al, 1980): aleatory uncertainties, which reveal the inherent randomness of variables or stochastic processes, and epistemic uncertainties, which originate from the lack of knowledge about the model and provide a family of confidence interval curves for the fragility estimation.

Considering lognormal distributions, the log std β_C can be decomposed in its aleatory and epistemic contributions, respectively β_R and β_U as

$$\beta_C = \sqrt{\beta_U^2 + \beta_R^2} \tag{3}.$$

The fragility curve is then expressed as a function of confidence level Q, which represents the epistemic uncertainties, as follows:

$$P_f(\alpha) = \Phi\left(\frac{\ln\left(\frac{\alpha}{A_m}\right) + \beta_U\, \Phi^{-1}(Q)}{\beta_R}\right) \tag{4}$$

This is illustrated in **Figure 1** with the mean, median and 5% and 95% confidence interval curves. Of course, in the case were only mean hazard and fragility curves are considered in the risk assessment, distinguishing epistemic and aleatory uncertainties is not useful. However, the distinction of the two gives a more complete picture of plant failure probabilities and acceptance criteria and allows to assess the impact of nuclear Improvement of prediction through the reduction of epistemic uncertainties

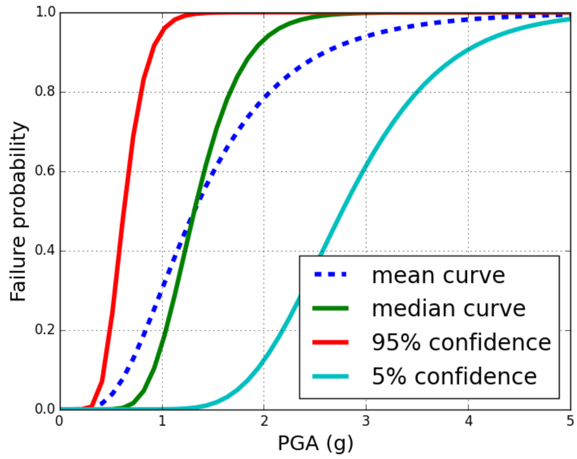


Figure 1: Family of fragility curves, lognormal model

The conditional probabilities can be evaluated pointwise for different IM values with the Monte Carlo method, as well as with methods based on the log-normal hypothesis such as currently used in nuclear engineering practice, see for example EPRI (1994), EPRI (2013). The adequateness of the lognormal model can and should be assessed by statistical tests when possible. In many cases, the consideration of PGA as well the assumption of lognormal prove to be very reasonable modelling choices (e.g. Zentner, 2016, Zentner et al, 2016, Wang et al 2018).

The trade between statistical precision of simpler parametric model fitting and improved data adjustment by nonparametric empirical models is generally in favour of the lognormal assumption. Indeed, considering nonparametric models means more degrees of freedom and in consequence requires larger samples to obtain convergence to an acceptable small statistical error.

Methods to evaluate fragility curves

Different popular approaches to compute fragility curves include (Baker, 2015, Zentner et al 2016):

- Multiple stripes to evaluate conditional failure probabilities

- Incremental dynamic analysis (IDA, Vamvatsikos & Cornell, 2004) to estimate parameters of capacity distribution or evaluate conditional failure probabilities
- Maximum likelihood approach or linear regression (known as “cloud” approach) for fitting parameters of the lognormal fragility curve – depending on the failure mode and damage variable (continuous or binary)
- Safety factor method (EPRI 1994)

An overview with an example application of a set of methods is given in the reference Zentner et al (2016). For the latter (certainly limited) case study, it could be shown that similar results are obtained with the different methods when applied based on the same assumptions. The choice of the best approach depends on envisaged application and should be guided by the kind of failure mode (binary or continuous damage variable), the kind of ground motion data, the available numerical resources and analysis framework (margin-based, advanced integrated simulation).

Also, it is useful to keep in mind particularities that need to be faced in reliability engineering and risk assessments in nuclear. Firstly, as opposed to regular buildings or even other industrial installation, structures, systems and components (SSC) in nuclear installations are in general very robust and well maintained. For obvious safety reasons of NPP, there is continuous inspection and repair or replacement of SSCs. In consequence, relevant ground motion, likely to damage SSCs, corresponds to very high return periods (for example up to 100 000 years for France) which is why databases do generally not contain recorded ground motion for such extreme events. This one reason why to date, in contrast to non-nuclear structures, synthetic ground motion are often preferred for seismic response analysis. In addition, a large frequency range up to 30 Hz (or more) has to be considered for the structural analysis and numerical simulations and many equipment are rather stiff structures.

Classification of SSCs for detailed and generic fragility assessment

In seismic PRA (Probabilistic Risk Assessment) practice the structures, systems and components (SSCs) are grouped with respect to their ruggedness and their importance in risk analysis. (or more precisely on the event under analysis - such as Core Damage Frequency). The following general steps of the definition process should be performed for identification of SSCs for fragility analysis:

1. Development of seismic equipment list (SEL);
2. Screening of SSCs based on ruggedness, impact on risk estimates, seismic capacity (IAEA 2009)
3. Selection of SSCs for detailed and generic fragility analysis.

Even after screening, the seismic equipment list is usually very large. Therefore the SSC from SEL are further classified into two groups

Tier 2: Generic fragility (generic parameters are proposed in EPRI 2013)

Tier 1: specific fragility (unique/critical items)

A graded approach is adopted. Only for SSCs that are in the detailed fragility list, the fragility parameters are derived on the basis of plant and site-specific information. The approach adopted is the EPRI safety factor approach. Then, it can be of interest to develop more detailed simulation-based models for a subset of the tier 1 SSCs with both significant impact on the risk estimates and featuring more complex structural behavior.

In what follows, we are only dealing with the case where more detailed analysis are required or where simulation based site specific analysis are carried out. It is recalled that the latter constitute a small subset of the tier 1 specific fragility list.

Table H-2 (continued)
Recommended representative values for structure, system, and component seismic fragilities [1, 2]

System, Structure, or Component	A_m [3]	β_r	β_u	Failure Mode [4]	Comment
Electrical Supply / Distribution Equipment					
Relay Chatter Failure (After Seismic Event)[5]	2.5	0.30	0.35	Loss of function	This failure mode indicates the relay is not functional after the event
Emergency Diesel Generator (EDG)	1.5	0.30	0.35	Loss of function	
Batteries[5]	1.5	0.30	0.35	Loss of function	
Battery Charger[5]	1.6	0.30	0.35	Loss of function	
Inverter[5]	1.6	0.30	0.35	Loss of function	
Cable tray[5]	2.5	0.35	0.50	Support failure	
Transformer (Indoor)[5]	1.5	0.30	0.35	Loss of function	
Pumps and Compressors					
Reactor coolant pump / Recirculation pump	2.5	0.30	0.40	Support failure	
Large vertical, centrifugal pump (motor-driven, Safety)[5]	2.0	0.30	0.35	Loss of function	
Large vertical, centrifugal pump (motor-driven, non-safety)[5]	1.0	0.30	0.35	Loss of function	
Compressor[5]	1.5	0.30	0.35	Loss of function	
Motor-driven pump[5]	2.0	0.30	0.35	Loss of function	
Turbine-driven pump[5]	2.5	0.30	0.35	Loss of function	

Figure 2 Example of generic fragility parameters from EPRI (2013)

Numerical simulation and metamodels to evaluate fragility curves and check model assumptions

The numerical simulation benefits from sustained progress in numerical modelling and HPC capabilities. Time history analysis are becoming the state of the art for assessing the behavior of particular SSC under seismic loads. In addition to containment building models to compute floor spectra, one can cite numerical models of overhead cranes (www.Socrat-benchmark.org), piping or fuel assembly grids (Pellisetti et al 2021, Zentner et al 2011).

The numerical simulation offers the opportunity to decrease biais or conservatism in the analysis introduced by the separation of modeling steps (such as interface between site response, structural response and equipment response). The separation of analysis steps instead of an integrated chain generally introduces additional conservatisms in the analysis chain and prevents from properly propagating uncertainties.

When combined with metamodeling, the numerical simulation also offers the possibility, to perform sensitivity analysis and assess model assumptions such as the assumption of a lognormal fragility model. The artificial neural network (ANN) based metamodel implemented in Wang et al (2018a) proved to be a versatile and efficient approach to reduce/optimize the number of numerical analyses required to develop meaningful fragility curves. In this framework, the most relevant IMs can be selected based on a filter feature selection approach with semi-partial correlation coefficient. The ANN is trained with the selected IMs. Fragility curves are computed with both parametric (lognormal hypothesis) and non-parametric methods. The overall workflow is illustrated in **Figure 3**.

The analysis conducted by the authors generally showed good approximations by the lognormal fragility model, this is illustrated in **Figure 4**.

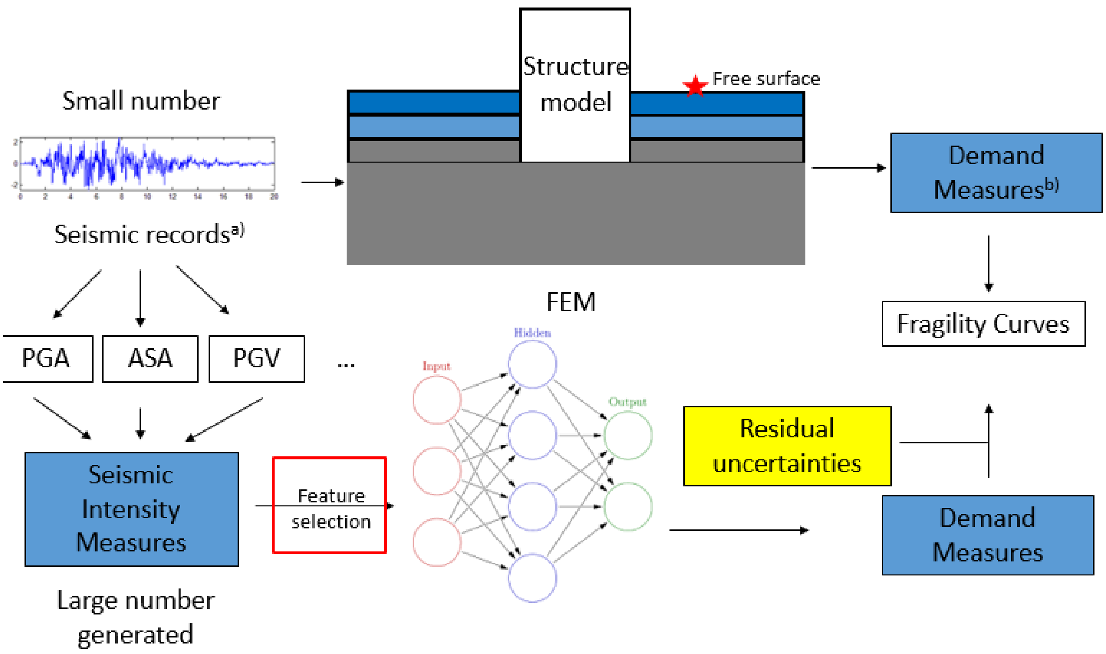


Figure 3: Workflow for fragility evaluation through the development of ANN metamodel to represent the link between seismic input at free surface and floor response from Wang et al 2018.

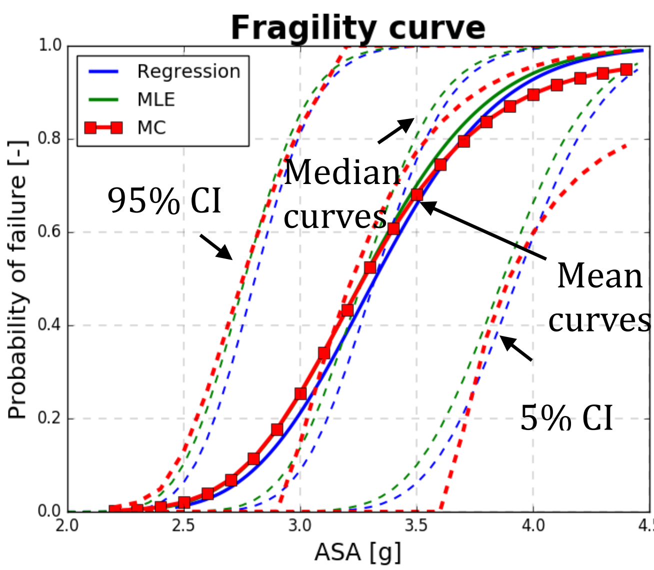


Figure 4: Comparison of fragility curves calculated with direct Monte Carlo (MC) simulation compared to lognormal fragility curves determined by Maximum Likelihood Estimation (MLE) and the cloud approach (Regression).

Usually, it is not obvious or even impossible to introduce all epistemic uncertainty in numerical models. In particular, part of the epistemic uncertainties are linked to the modeling options and assumptions themselves. Then, it is possible to introduce the missing part of epistemic uncertainty by using generic values for example from the EPRI safety factor method and introducing them in the fragility curves thanks to the lognormal assumptions by virtue of equation (3). In addition, the statistical uncertainty, arising from the finite number of numerical simulations, can be considered as epistemic (since reducible) and added to the final fragility curves.

In the framework of Bayesian updating the numerical simulation can be used to develop the prior model, if a sufficient number of analyses is affordable and feasible, or, in case of very complex and expensive numerical simulations, to inform a given prior obtained based on generic assumptions or simpler engineering models. This is detailed in what follows.

Bayesian updating of fragility curves

Methodology for updating with experience feedback data

The Bayesian updating approach provides a perfect framework for introducing supplementary information in the fragility evaluations. It is possible to account for few data and to introduce “positive feedback” or no observation, that is an equipment has not failed during a significant event.

The double log-normal fragility model distinguishing epistemic and aleatory uncertainty provides a natural environment to implement the Bayesian updating of fragility curves (Yamaguchi 2006, Wang et al 2018b). By definition, the epistemic uncertainty is due to lack of knowledge and can be reduced when more information or better models become available. So, it is expected that the β_U reduced while the estimation of median capacity is improved by shifting the value to the right or the left.

The double lognormal model of equation (4) is obtained by introducing epistemic uncertainty to a simple fragility model accounting only for aleatory uncertainty:

$$P_f(\alpha) = \Phi\left(\frac{\ln\alpha - \ln\,\hat{A}_m}{\beta_R}\right) \tag{5}$$

Considering now that the median structural capacity is itself a lognormal random variable with

$$\hat{A}_m \sim LogN(A_m,\, \beta_U) \tag{6}$$

yields the family of fragility curves of expression (4). Then, the likelihood function, expressing the likelihood of observations **z** $= (\boldsymbol{\alpha}, \boldsymbol{x})$ given the model reads:

$$L(\boldsymbol{z}|\hat{A}_m) = L(\boldsymbol{\alpha}, \boldsymbol{x}|\hat{A}_m) = \prod_{i=1,Nobs}[P_f(\alpha^i)]^{x^i}[1 - P_f(\alpha^i)]^{1-x^i} \tag{7}$$

Where x^i is 1 in the case of failure and 0 for survival (or no damage) for a given event *i* with PGA α^i . The posterior estimation of the pdf is:

$$f_{post}(\hat{A}_m|\boldsymbol{z}) \propto L(\boldsymbol{z}|\hat{A}_m)LogN(A_m, \beta_U) \tag{8}$$

where $LogN(A_m, \beta_U)$ is the (lognormal) prior distribution of the median capacity.

The damage data z used in this study are taken from the seismic qualification utility group (SQUG) database. The SQUG database (EPRI, 2016), built by the EPRI, gathers seismic experience data related to seismic capacity of equipment in industrial facilities (not limited to NPPs). It is expected that in the future new databases and more data will be available to the seismic engineering community so as to facilitate the implementation and increase meaningfulness of Bayesian updating approaches.

One key issue in the Bayesian updating approach is the location/definition of the control point. Indeed, the SSCs fragility curves are developed for ground motion intensity on soil surface where the plant is located while the database provides ground motion intensities referring to the database structure. In general PGA is the intensity measure (IM) which is why we will in what follows only use PGA or IM. In addition, the equipment considered for fragility updating might be located on a different floor level than the one with observations ion the database. This is illustrated in **Figure 4**. For the target equipment under study, the finite element model for the containment building is available and can be used for developing transfer functions between the ground surface motion and floor acceleration while for the database equipment only its height is known.

This means that we need to

1. Transfer the free field database PGA to the location of database equipment using the information on heights, this is the floor PGA used to update the target equipment fragility

$$PGA_{Floor} = \widehat{AF} \times PGA_{db}$$

$$\widehat{AF} = AF \times \epsilon_{SF}\,, \quad \epsilon_{FS} \sim LogN(1,\, \beta_{SF^2})$$

2. Transfer the floor PGA of the target equipment to free field at the studied site using the transfer function from the known FEM model

The uncertainty introduced by the transformation, evaluated as β_{trans} , needs to be introduced in the updated fragility:

$$P_f(\alpha) = \Phi\left(\frac{\ln\alpha - \ln\hat{A}_m}{\sqrt{\beta_R^2 + \beta_{trans}^2}}\right) \tag{9}$$

More details on this procedure can be found in Wang et al (2018b). A similar but simpler approach is also reported in EPRI (2018).

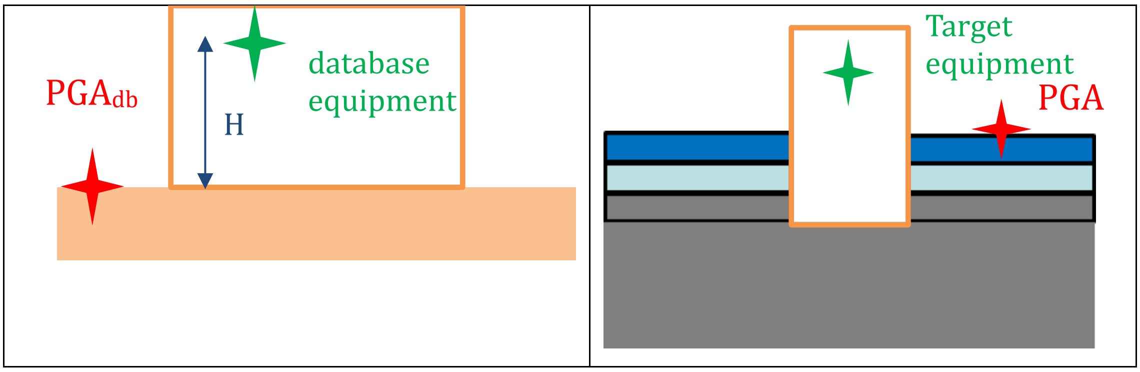


Figure 4: PGA control point and equipment location (height) for (left): database building and equipment (right): studied building and equipment, FEM model is available for the target structure.

Computational efficiency by updating generic or simple fragility curves with nonlinear analysis

The Bayesian updating approach can also be used to minimize the total amount of effort required to develop detailed fragility curves, see for example Kwag and Gupta (2018). The rationale here is to take advantage of existing studies and conventional/simplified approaches and update them by means of a few nonlinear FE simulations, 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. This approach is very promising but not further explored her.

Bayesian Updating with experience feedback – application to Karisma benchmark case study

The results shown in this section are reported in Wang et al (2018b). We consider a hypothetic equipment located in the Kashiwazaki-Kariwa NPP (K-K NPP) building. This model has been studied extensively by several teams in the framework of the Karisma benchmark organised by the IAEA (2013). A numerical model has been built in code_aster opensource FEM software for the containment building. An artificial neural network (ANN) metamodel is built from 100 finite element analyses accounting for soil-structure interaction (SSI). The inputs of the ANN are IMs representing the characteristics of the seismic time histories.

The equipment of interest is a low-voltage switchgear (LVSG), a combination of electrical control units such as circuit breaks and relays, etc., whose function is to ensure and protect the performance of 480V-AC (alternative current) electrical systems. The low-voltage switchgear is supposed to be situated on the -1 floor and we assume that failure occurs if floor spectral acceleration determined as the mean over the frequency range of interest for the equipment,

$$y = \frac{1}{9.-5.}\int_5^9 Sa^{floor}(f)df \tag{10}$$

exceeds the failure threshold 1.8g following EPRI (1991).

The prior fragility curve parameters are determined based on the results of numerical simulations completed by generic values from the EPRI safety factor method to fully account for epistemic uncertainty (not all of the epistemic uncertainty can be represented in the numerical model). The numerical model of the containment is shown in **Figure 5** (right) together with the overall configuration (left). In the simulations, the seismic record-to-record variability is considered as the only source of aleatory uncertainty.

Then, damage data, collected from the in-situ observation and the database of the seismic qualification utility group (SQUG), are used to construct the likelihood function for the Bayesian updating. The LVSG damage data can be divided into two groups: one in-situ observation for K-K NPP and 78 post-earthquake inspection data for the LVSG in the SQUG structures shown in **Figure 6**. Only one failure was reported in the SQUG database, but it was not sure whether it is earthquake related. This is accounted for by considering 50% confidence for the failure data, x=0.5 and by performing sensitivity studies reported in **Figure 7** (right).

The posterior equipment capacity is evaluated by Markov chain Monte Carlo simulation and posterior fragility curves are, then, obtained. The prior and posterior curves are shown in **Figure 7** (left).

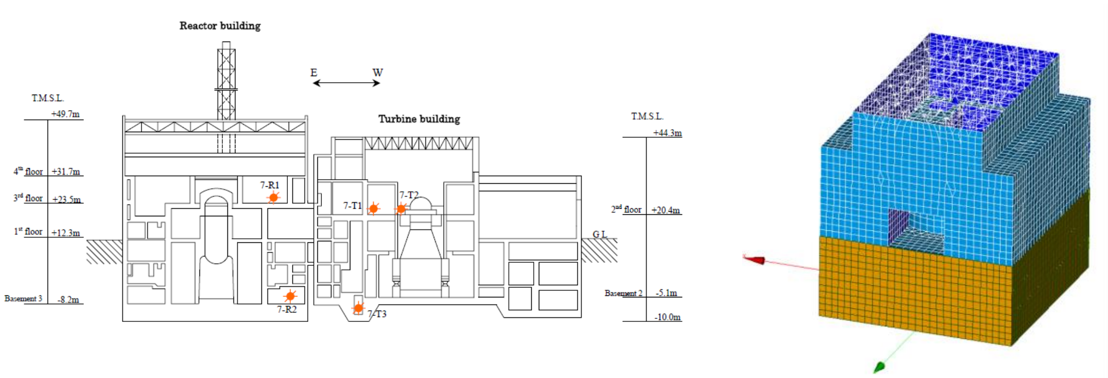


Figure 5: KK NPP buildings configuration (left) and FEM model for RB (right)

Earthquake	Number of the inspected LVSGs	Number of failures
1971 San Fernando Earthquake	9	0
1973 Point Mugu Earthquake	1	0
1975 Ferndale Earthquake	1	0
1979 Imperial Valley Earthquake	5	0.5
1983 Coalinga Earthquake	1	0
1984 Morgan Hill Earthquake	1	0
1985 Chile Earthquake	4	0
1985 Mexico Earthquake	1	0
1986 Adak Earthquake	2	0
1986 Chalfant Valley Earthquake	1	0
1987 Bay of Plenty Earthquake	3	0
1987 Superstition Hills Earthquake	1	0
1987 Whitter Earthquake	7	0
1989 Loma Prieta Earthquake	7	0
1992 Cape Mendocino Earthquake	2	0
1992 Landers/Big Bear Earthquake	3	0
1993 Guam Earthquake	3	0
1994 Northridge Earthquake	19	0
1995 Manzanillo Earthquake	4	0
1999 Kocaeli Turkey Earthquake	1	0
2010 Baja California Earthquake	2	0

Figure 6: data considered for updating Low Voltage Switchgear fragility (LVG)

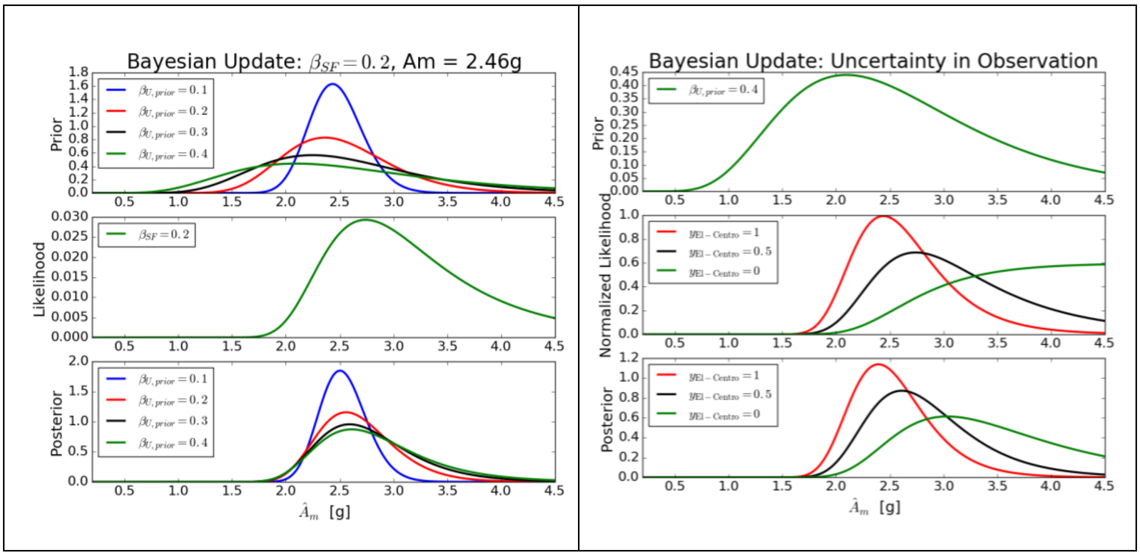
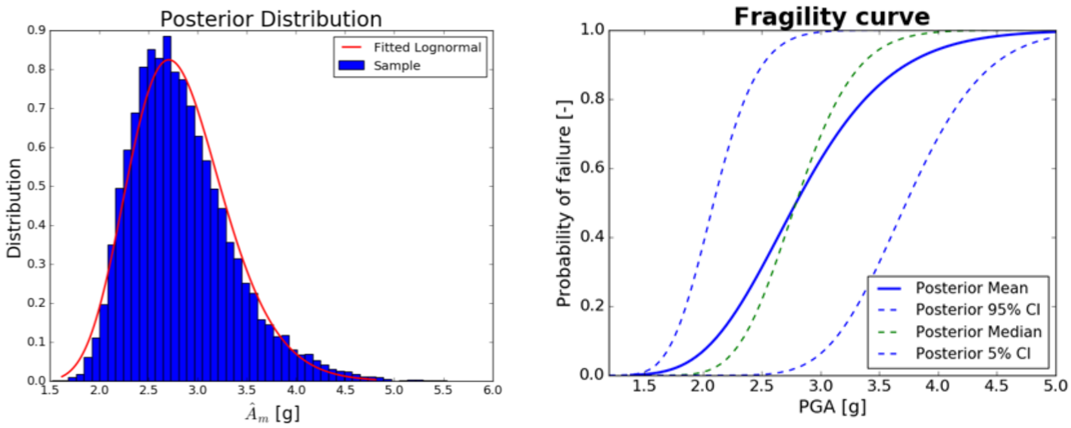


Figure 7: Prior, likelihood and posterior: updating of fragility parameters for case study data (left figures) and impact of uncertainty in observation by comparing results in x=0 (survival), x=1(failure) and x=0.5 (uncertain failure) (right figures)

The **Figure 8** shows the results of the updating with a clear decrease of epistemic uncertainty and refined estimation of median and HCLPF (High Confidence Low Probability of Failure) capacities.



β_R	A_m^{prior}	β_U^{prior}	A_{HCLPF}^{prior}	A_m^{post}	β_U^{post}	A_{HCLPF}^{post}
0.145	2.46g	0.4	1.00g	2.7g	0.176	1.59g

Figure 8: Results of the updating

Perspectives for further developments – ground motion & opportunity for vector fragility

The numerical simulation-based assessment of structures and their reliability also highlights new opportunities for improving practice in seismic risk assessment in nuclear.

For performing best estimate plus uncertainty numerical analyses and computing fragility curves, not only the seismic hazard curves, the classical output of PSHA, but also time histories are needed. In this work spectral matching and a stochastic simulation method have been applied. In the recent years, there have been significant advances in the physics-based simulation of ground motion, in particular stochastic physics-based methods. Accompanied by adequate record selection procedures these could be used together with to define sets of time histories for engineering purposes instead of the spectral matching and scaling. Indeed, the selection of a set of time histories from the larger databases, in agreement with seismic hazard, constitutes the link between seismic hazard assessment and structural engineering. In the recent decades, there have been advancements with the development of the PBEE approach including a more realistic definition of seismic load. The conditional spectra approach, Lin et al, (2013), Baker, (2011) allows for the decomposition of UHS into a series of scenario spectra corresponding to distinct magnitude, distance (M, D) earthquake scenarios and could be applied fragility assessment of SSC, cf Trevlopoulos et al (2020)

Eventually, the analysis showed that PGA performs well for multimodal and most regular stiff structures encountered in NPP although it might be outperformed by specific pseudo spectral acceleration -based IMs such as Average Spectral Acceleration (ASA, de Biasio et al, 2015) (see also Zentner et al 2016, Wang et al 2018, Pellisetti et al 2021a,). However, failure modes of particular SSCs such as dams are more correlated to low frequency PSA. Vector fragility and risk analysis is a tool to account for two complementary IMs such as PGA associated to low frequency PSA (Pellisetti et al 2021a). Recent advances in seismic hazard computations allow for the consideration of vector hazard (Pagani et al 2023, Zentner et al 2024).

Serval of these topics are currently addressed by EURATOM METIS (https://metis-h2020.eu/) project partners.

Conclusion and discussion

We have presented a Bayesian updating approach that allows to combine different sources of data and information and applied it to Karisma benchmark study:

- Use simulation and expert data to develop « initial » prior model
- Bayesian updating to improve estimation of median capacity and educe epistemic uncertainty
- Test/observation data: Both information on failure/survival can be used

The Bayesian updating methodology is very promising to introduce information from in-situ observation, given the increasing databases and shared experience feedback.

It is very versatile and can be useful in other configurations where a prior model is available and more detailed but rare additional information becomes available. Such a case could be the development of detailed non-linear numerical models with the possibility to conduct only few analyses at affordable cost or new test or experience feedback data. One drawback for the practical implementation of the experience feedback updating is the available data. Most databases, including SQUG, do contain only few data from NPP equipment but mainly feature experience feedback from non-nuclear industrial installations. This can induce a bias in the estimations since, in addition to differences in the equipment, it can be expected that nuclear installation are much more robust and well maintained than other installations. However, it is expected that international databases with experience feedback from nuclear will increase in the coming years.

In addition to databases and numerical capabilities, there is a constant increase in scientific knowledge, in the field of seismology and geophysics. The evolution of the state of the art in earthquake engineering, requires a continuous effort to introduce this knowledge in the seismic safety assessment procedures for design and periodic safety reviews. There is a need for comprehensive approaches and opensource tools to accelerate the transfer of approaches, that have achieved consensus, from research to (nuclear) engineering practice.

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