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A BAYESIAN FRAMEWORK FOR ROBUST SEISMIC FRAGILITY ASSESSMENT BASED ON VARIOUS MODEL CLASSES

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Abstract

Seismic fragility is quantitatively expressed as the conditional probability that a structure will reach or exceed a specified level of damage (or damage state, DS) for a given value of a considered earthquake-induced ground-motion intensity measure (IM). Only limited/poor-quality historical damage/loss data, often associated to heterogeneous seismic regions, are generally available; hence, numerical (or simulation-based) fragility represents an attractive option in many practical risk-assessment applications. The numerical derivation of fragility curves requires a complex trade-off between the desired accuracy, the explicit consideration of uncertainties (both epistemic and aleatory) related to the numerical model, and the available computational performance. When high-performance computing is not available, simplified models are adopted and/or epistemic uncertainties related to the model variables neglected. The use of simplified models may lead to biased results, particularly when collapse fragility is of interest. In addition, quantifying the impact of modelling uncertainties on the seismic fragility results is a crucial issue for existing buildings, considering the limited available information in terms of material properties, structural detailing and the uncertainty in the considered capacity models.

This study presents a Bayesian framework for the derivation of numerical fragility curves based on multi-fidelity models, that can be thought as a modification of the well-known robust fragility framework. Different model classes, each characterised by an increasing refinement level, are used to surrogate fragility model parameters through the general Polynomial Chaos Expansion (gPCE) technique. Each analysis result is considered as a "new observation" in the Bayesian framework and used to update the gPCE coefficients. These latter are finally recombined considering the different degree of accuracy of each model class. The proposed approach allows a significant reduction of the computational burden while achieving a desired accuracy of the fragility estimates and without neglecting epistemic uncertainties.

The proposed procedure is demonstrated for an archetype reinforced concrete (RC) frame for which three model classes are provided. The lowest refinement level is based on the Simple Lateral Mechanism Analysis (SLaMA), which is a mechanics-based, analytical method. Whereas, the medium and the highest refinement levels are based on highly-refined numerical models simulated through non-linear static and dynamic analyses, respectively. Fragility curves are derived through a cloud-based approach employing unscaled real (i.e. recorded) ground motions and using the capacity spectrum method for SLaMA and non-linear static analysis. The fragility curves derived with the proposed procedure are compared with those calculated by using only the most refined model class, showing the good performance of the proposed approach.

Keywords: Bayesian Updating; Robust Fragility curves; SLaMA; general Polynomial Chaos Expansion

1. Introduction

The assessment of the structural fragility of buildings is a fundamental step in the modern performance-based earthquake engineering [1] and probabilistic seismic risk assessment. When only limited/poor-quality historical damage/loss data, often associated to heterogeneous seismic regions, are available, the derivation of numerical (or simulation-based) fragility curves is an attractive option in many practical risk-assessment applications. The numerical derivation of fragility curves requires a complex trade-off between the desired accuracy, the explicit consideration of uncertainties (both epistemic and aleatory) related to the numerical model, and the available computational performance. In particular, when high-performance computing is not available, simplified models are adopted and/or epistemic uncertainties related to the model variables neglected. The use of simplified models may lead to biased results, particularly when collapse fragility is of interest. In addition, quantifying the impact of modelling uncertainties on the seismic fragility assessment is a crucial issue for existing buildings, considering the limited available information in terms of material properties, structural detailing and the uncertainty in the considered capacity models [2].

Sampling-based approaches (e.g., plain Monte Carlo, Latin Hypercube Sampling) are the simplest way to derive seismic fragility curves considering both aleatory (i.e., record-to-record variability) and epistemic uncertainties (i.e., related to model parameters). In addition, several numerical approaches have been proposed in the scientific literature to reduce the computational burden required in the fragility curve derivation. Most of these approaches combine non-linear dynamic analysis (NLDA) procedures based on recorded ground motions (e.g., incremental dynamic analysis IDA [3], cloud analysis [4]) with reliability methods, such as first-order second-moment (FOSM) also referenced as mean value first-order second-moment (MVFOSM; e.g., [5]) or response surface methods [6]. Although these methods lead to a reduction of the computational cost for the derivation of fragility curves, they often tend to poorly approximate the limit state function for a given damage state (DS). In other words, these methods can be characterized by low accuracy when the structure under investigation is approaching a DS; this is particularly evident when the collapse DS is considered. The accuracy of the calculation can be clearly improved by increasing the number of samples or by applying more advanced computational strategies (e.g., subset simulation, importance sampling [7]).

An alternative way of dealing with fragility curve derivation is to consider the results of structural analyses related to a specific suite of ground-motion records and to a set of model parameter realizations as observations within a Bayesian framework [8]. In this approach, known as robust fragility [4], the parameters governing the fragility model are treated as random variables and updated through the application of the Bayes rule. The robust fragility curve method has been successfully applied in conjunction with cloud-based nonlinear dynamic analysis [9]. Cloud analysis can also account for the collapse cases (e.g., nonconvergence of the analysis, large values of the engineering demand parameter, EDP) [4]; this is particularly convenient from the computational viewpoint and represents a further improvement in this research field.

This paper presents a Bayesian framework for the derivation of numerical fragility curves based on multi-fidelity models; the proposed framework can be thought as a modification of the current robust fragility approach. The main idea behind the proposed framework is that high accuracy in the estimation of the structural performance is especially required in the proximity of the DSs of interest. Therefore, the computational burden related to the fragility curve derivation can be reduced by analysing refined models only when the structure is approaching the DS (i.e., when it is strictly necessary). Whereas, simplified or less-refined models can be used to evaluate the structural performance both in the safety and in the failure region of the probability space far enough from the DS thresholds. Different model classes, each characterised by an increasing refinement level, are used to surrogate the fragility model parameters through the general Polynomial Chaos Expansion (gPCE) technique [10]. Each analysis result is considered as a “new observation” in the Bayesian framework and used to update the gPCE coefficients. These latter are finally recombined considering the different degree of accuracy of each model class.

An illustrative application of the proposed framework is finally presented to show its feasibility in practice. In particular, three analysis refinement levels are considered for an archetype reinforced concrete (RC) frame building. The lowest refinement level is based on the Simple Lateral Mechanism Analysis (SLaMA) approach [11], which is a mechanics-based, analytical method allowing one to define the non-linear static force-displacement capacity and the plastic mechanism of RC structures. The medium and the highest refinement levels rely on detailed numerical models studied through non-linear static and dynamic analyses, respectively. Fragility curves are derived through a cloud-based approach employing unscaled real (i.e. recorded) ground motions and using the capacity spectrum method for both SLaMA and the non-linear static analysis of the refined model. The fragility curves derived with the proposed procedure are compared with those calculated by using only the most refined model class and the results of the comparison are critically discussed.

2. gPCE-based multi-fidelity model for fragility curve derivation

Given a set of structural analysis results collected in the vector **y** (i.e., the "new observations" in a Bayesian scheme), the robust fragility is defined as the expected value of a prescribed fragility model over the posterior distribution of the fragility model parameters, it reads as

$$P\left(EDP > EDP_{DS_i}|IM,\mathbf{y}\right) = \int_{\Omega_\chi} P\left(EDP > EDP_{DS_i}|IM,\boldsymbol{\chi}\right) f(\boldsymbol{\chi}|\mathbf{y})\, d\boldsymbol{\chi} = \mathbb{E}_{\boldsymbol{\chi}|\mathbf{y}}\left[P\left(EDP > EDP_{DS_i}|IM,\boldsymbol{\chi}\right)\right]. \quad (1)$$

In Eq. (1), EDP_{DS_i} is the EDP threshold related to the i-th DS, IM is the intensity measure considered in the fragility model, $\boldsymbol{\chi}$ is the vector of the fragility model parameters defined in the space Ω_χ, $P\left(EDP > EDP_{DS_i}|IM,\boldsymbol{\chi}\right)$ is the fragility function and $f(\boldsymbol{\chi}|\mathbf{y})$ is the posterior distribution of $\boldsymbol{\chi}$ conditioned on **y**. In this context, the fragility model parameters are considered random variables and updated once new analyses **y** are available. This leads to the reduction of the computational burden and to the possibility of calculating the confidence interval of a given fragility curve [4]. However, Eq. (1) has to be solved numerically (e.g., through Monte Carlo simulation), so the computational burden can be still high.

As mentioned before, the computational cost can be further reduced by using the robust fragility in conjunction with the cloud analysis that considers collapse cases [4]. In this case, the set of analysis results **y** is portioned into two groups: 1) NoC data for which the structure does not experience collapse; 2) C data corresponding to collapse inducing analysis results. By applying the total probability theorem, the structural fragility for the i-th DS can be written as,

$$P\left(EDP > EDP_{DS_i}|IM,\mathbf{y}\right) = P\left(EDP > EDP_{DS_i}|IM,NoC\right)\left(1 - P(C|IM)\right) + \\ + P\left(EDP > EDP_{DS_i}|IM,C\right)P(C|IM). \quad (2)$$

Assuming that $P\left(EDP > EDP_{DS_i}|IM,NoC\right)$ is described by a lognormal distribution and that the probability of collapse $P(C|IM)$ can be predicted by a logistic regression model (aka, logit) as a function of IM, then the fragility model $P\left(EDP > EDP_{DS_i}|IM,\boldsymbol{\chi}\right)$ can be written as,

$$P\left(EDP > EDP_{DS_i}|IM,\boldsymbol{\chi}\right) = \Phi\left(\frac{\ln\eta_{EDP>EDP_{DS_i}|IM,NoC}}{\beta_{EDP>EDP_{DS_i}|IM,NoC}}\right)\frac{\exp(-\alpha_0-\alpha_1\ln IM)}{1+\exp(-\alpha_0-\alpha_1\ln IM)} + \frac{1}{1+\exp(-\alpha_0-\alpha_1\ln IM)} \quad (3)$$

In Eq. (3), $\eta_{EDP>EDP_{DS_i}|IM,NoC}$ and $\beta_{EDP>EDP_{DS_i}|IM,NoC}$ are the conditional median and standard deviation of the natural logarithm of $EDP > EDP_{DS_i}$ for the NoC portion of **y**, $\Phi(\cdot)$ is a standard normal cumulative distribution function, while α_0 and α_1 are the parameters of the logistic regression. The variables of Eq. (3) are the fragility model parameters, that is $\boldsymbol{\chi} = \left[\ln\eta_{EDP>EDP_{DS_i}|IM,NoC}, \beta_{EDP>EDP_{DS_i}|IM,NoC}, \alpha_0, \alpha_1\right]$.

In this study, the parameters collected in $\boldsymbol{\chi}$ are surrogated through a multi-fidelity gPCE in order to implement in practice the idea of using structural models/analysis types with different refinement levels described in the previous section. The gPCE belongs to the family of spectral methods for the propagation of uncertainties through deterministic models. In the context of stochastic modelling, this approach relies on orthogonal basis functions for the construction of a response surface $\hat{u}_P^{\mathrm{gPCE}}$ of the uncertain model output $u(\boldsymbol{\theta})$, assuming that the uncertain parameters are collected in $\boldsymbol{\theta}$. Once a reliable gPCE is developed (i.e., gPCE leading to small errors), this technique allows one to directly solve the forward problem (i.e., to propagate epistemic uncertainties through the deterministic model, thus determining the output statistics) as well as performing a variance-based sensitivity analysis without any additional computational cost. The resulting response surface can be also used to surrogate the model output in optimization or reliability problems. The gPCE is an extension of the polynomial decomposition (PC, [12]) of $u(\boldsymbol{\theta})$,

$$u(\boldsymbol{\theta}) \approx \hat{u}_P^{\text{gPCE}}(\boldsymbol{\theta}) = \sum_{|\mathbf{i}|\leq P} \boldsymbol{u}_{\mathbf{i}}\, \boldsymbol{\Phi}_{\mathbf{i}}(\boldsymbol{\theta}). \tag{4}$$

where, P is the degree of the polynomial expansion, $\mathbf{i}$ is a finite multi-index set, $\boldsymbol{\Phi}_{\mathbf{i}}(\boldsymbol{\theta})$ is the matrix of the orthogonal basis functions, and $\boldsymbol{u}_{\mathbf{i}}$ is the matrix of the combination coefficients. The selection of the orthogonal basis function family is based on the probability density function (PDF) of the random parameters $\boldsymbol{\theta}$. Whereas, the combination coefficient calculation is based on some reference solutions of the deterministic model through interpolation, regression or the Bayesian approach [13]. This latter case, the Bayesian interpretation of the coefficient calibration, enable the coefficients $\boldsymbol{u}_{\mathbf{i}}$ of the PCE of $\boldsymbol{\chi}$ to be updated once the analyses collected in $\mathbf{y}$ are provided. Eq. (1) is then solved at the gPCE coefficient level, thus massively reducing the computational burden. In fact, conjugated Gaussian distributions or approximated hierarchical Laplace distributions can be used to solve the updating problem in a closed form or in a numerical way, respectively. It is worth noting that, the former approach is cheaper than the second one in terms of computational cost, but the latter promotes the sparsity of the basis [13].

This framework also enables different model classes to be considered in the fragility curve derivation. Let us assume that $\hat{u}_P^{\text{gPCE,HF}}(\boldsymbol{\theta})$ is the gPCE of a high-fidelity (HF) model which can be approximated through a multi-fidelity model $\hat{u}_P^{\text{gPCE,MF}}(\boldsymbol{\theta})$ composed of N model classes with a lower accuracy $\hat{u}_{P,j}^{\text{gPCE,LF}}(\boldsymbol{\theta})$, that is,

$$\hat{u}_P^{\text{gPCE,HF}}(\boldsymbol{\theta}) \approx \hat{u}_P^{\text{gPCE,MF}}(\boldsymbol{\theta}) = \sum_{j=1}^{N} \hat{u}_{P,j}^{\text{gPCE,LF}}(\boldsymbol{\theta})\ \hat{u}_{P,j}^{\text{gPCE,AC}}(\boldsymbol{\theta}). \tag{5}$$

where $\hat{u}_{P,j}^{\text{gPCE,AC}}(\boldsymbol{\theta})$ is the j-th additive correction (AC) factor (i.e., the difference between the j-th low refined structural model and the high-fidelity one). It is easy to prove that if the number of samples used to train the gPCE of the various model classes tends to infinite, then Eq. (5) tends to the solution of the high-fidelity model [14]. Eq. (5) is then transposed at the gPCE coefficients level to apply the optimal weights recombination methods [14],

$$\boldsymbol{u}_{\mathbf{i}}^{\text{MF}} = \sum_{j=1}^{N} \boldsymbol{u}_{\mathbf{i},j}^{\text{LF}} + \boldsymbol{w}_j \circ \left(\boldsymbol{u}_{\mathbf{i}}^{\text{HF}} - \boldsymbol{u}_{\mathbf{i},j}^{\text{LF}}\right). \tag{6}$$

In Eq. (6), $\circ$ is the Hadamard product, $\boldsymbol{u}_{\mathbf{i}}^{\text{MF}}$ are the gPCE coefficients of the multi fidelity model, while $\boldsymbol{u}_{\mathbf{i}}^{\text{HF}}$ and $\boldsymbol{u}_{\mathbf{i},j}^{\text{LF}}$ are those of the high-fidelity and the j-th low refined model, respectively. Whereas, $\boldsymbol{w}_j \in [0,1]^P$ is the weight vector which can be easily determined by performing a minimization procedure of the normalized empirical error ϵ_{emp} [15]. Combining the gPCE coefficients is particularly convenient because it enables the whole procedure presented in this paper to be defined at the gPCE coefficient level.

3. Case-study definition

3.1 Building definition

An archetype RC structures, representative of school buildings in Southeast Asia (such as Philippines, Indonesia), and defined based on a data-collection involving rapid visual surveys for over 200 school buildings [16], is analysed in this section to test the feasibility of the proposed procedure. The analysed structure is a two-storey rectangular-plan RC frame building (Fig. 1). The statistical analysis results of the data collected during the surveys [16] show that the number of longitudinal bays is the most variable parameters. Whereas, other geometrical features such as number of storeys, length of the transverse bays, dimension of the beams/columns show negligible variability within the surveyed sample.

Given that the data collection is based on a rapid visual survey, no direct information about the material properties is available. According to Southeast Asian statistics (e.g. [17]), the concrete cylindrical strength and steel yield stress in the region have average values of 24MPa and 400MPa, respectively. Coefficients of variation (CoV) values equal to 18% and 5% for the concrete cylindrical strength and steel yield stress respectively can be found in the scientific literature [18]. These values are used in this study for the definition of the distributions of the uncertain structural model parameters. By considering the same nominal value of material properties for all the buildings in the considered portfolio, it is implicitly assumed that the building-to-building variability coincides with the within-building variability.

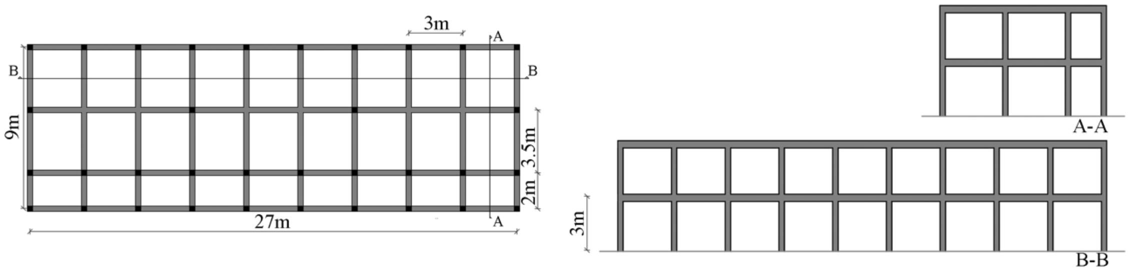

Fig. 1 – Archetype building under study [16].

The flexural and shear characterisation of beams, columns and beam-column joints of the analytical and numerical models adopted in this application are clearly affected by the variability of these parameters.

Structural detailing is key to define the numerical models for the fragility calculation. Therefore, the archetype building are simulated designed according to the Uniform Building Code, UBC [19] and the American Society of Civil Engineers (ASCE) 7-10 [20]. The use of these building codes is justified by the fact that most of Southeast Asia countries have adopted seismic provisions which are consistent with them. In particular, a low code target design, consistently with the HAZUS MH4, HAZard United States [21], is considered. The resulting detailing features are reported in Table 1.

Table 1 – Structural detailing of the archetype building [16].

	Typical beam	Typical column	Typical joint
Low Code	3 ϕ16 top layer 3 ϕ16 bottom layer ϕ10@150mm hooks	3 ϕ16 top layer 3 ϕ16 bottom layer ϕ10@100mm hooks	No stirrups

3.2 Model classes

Three model classes varying in refinement are adopted in this study. The lowest-refinement model class is based on SLaMa [11]. This method allows plastic mechanisms and capacity curve (i.e. a force-displacement curve) of RC frames, wall and dual-system buildings, to be estimated by means of a “by-hand” procedure (i.e., using an electronic spreadsheet). SLaMa is based on the calculation of the hierarchy of strength at sub-system level; the local results are then combined by adopting equilibrium and compatibility principles to obtain the global capacity curve. Many failure mechanisms (i.e. flexure, bar buckling, lap-splice failure, shear) are considered for each beam and column of the system. In this way, the weakest link drives the overall structural behaviour.

Refined numerical pushover analyses carried out with the finite element software Ruaumoko [22] are used to define the second (i.e., medium) refinement level. With this computational strategy, based on a lumped plasticity approach, the flexural capacity of the RC members is derived using moment-curvature analysis. Lap splice failure, flange effect, shear failure and bar buckling are modelled, as they can significantly modify the structural behaviour. P-Delta effects on the two-storey RC frame under study are clearly negligible and then not modelled. Finally, plane-rigid floor diaphragms are modelled, and fully fixed boundary conditions are considered at the base. A uniform force profile is adopted.

Non-linear time history analyses (NLTHAs) performed on the numerical model described above represent the last refinement level (i.e., the highest). The revised Takeda hysteretic model [23] is adopted for beams and columns, with the columns having a thinner loop. Whereas, the hysteretic behaviour of the beam-column joints is modelled using the Modified Sina model [23], which is able to capture their pinching phenomenon.

As discussed in the previous section, cloud analysis considering collapse cases is used for the fragility curve derivation. This can be directly applied in the case of NLTHAs (the highest refinement level), while for the other two cases, the capacity spectrum method (CSM) [24] is adopted. The equivalent viscous damping formulation is herein used to perform the CSM. The maximum inter-storey drift (chosen as EDP) is computed by using the displacement shapes provided in [11].

A set of 150 ground motion records is considered to have a statistically significant number of strong-motion records. They are a subset of the Selected Input Motions for displacement-Based Assessment and Design (SIMBAD [25]) database, which includes 467 tri-axial accelerograms, generated by 130 worldwide seismic events (shallow crustal earthquakes with moment magnitudes ranging from 5 to 7.3 and epicentral distances up to 35 km). The selected ground motion records are chosen by ranking the entire database in terms of peak ground acceleration (PGA) values (by using the geometric mean of the two horizontal components) and then keeping the component with the largest PGA value (for the 150 stations with highest mean PGA).

3.3 Fragility curve derivation

As discussed above, the EDP considered in this application is the maximum inter-storey drift, while the average spectral acceleration ($Avg\ S_a$) is the selected IM (Eq. (3)). $Avg\ S_a$ is defined as geometric mean of spectral-acceleration values in the range of period ($T_{1,min}$: 1.5 $T_{1,max}$), where $T_{1,min} = 0.38\ s$ is the minimum first-mode period for the entire database while $T_{1,max} = 0.53\ s$ is the maximum. Four structure-specific DS (Slight Damage, Moderate Damage, Extensive Damage, Complete Damage), which are based on the HAZUS definitions (but computed based on the actual pushover curve of the consider buildings), are investigated in this study. The corresponding drift limits, [0.25, 0.6, 1.5, 2] %, are assumed as representative of the entire building class.

The first step of the proposed approach is the construction of the gPCE of the fragility model parameters $\boldsymbol{\chi}$ for each model class. Assuming that the f_c and f_y are log-normally distributed, and that $N_{bays,x}$ follows an empirical distribution [16], Hermitian polynomials can be used as basis functions. A preliminary sensitivity analysis about the effect of the polynomial expansion cardinality variation on the normalized empirical error ϵ_{emp} allowed for the selection of the optimal polynomial expansion degrees. In particular, 5-th order polynomial expansions are used for the parameters related to the high-fidelity model while 3-th order polynomial expansions are adopted for those related to the medium and lowest refinement level.

The gPCE of the lowest and medium model classes are trained on the solution of 100 structural models (i.e., 100 realizations randomly sampled from the parameter distributions) for each considered ground motion record. While, only 50 analyses for each ground motion records are used for the high-fidelity model. The resulting gPCE coefficients are then combined to obtain a multi-fidelity gPCE of the parameters $\boldsymbol{\chi}$. Fig. 2 shows the normalized empirical error ϵ_{emp} of the multi-fidelity gPCE of $\ln\eta_{EDP>EDP_{DS_i}|IM,NoC}$ (Eq. (3)). Even with such a small number of high-fidelity model analyses, ϵ_{emp} is very small. This result can be achieved because of the sparsity of the gPCE basis promoted by the use of approximated hierarchical Laplace distributions, as previously discussed. It is worth noting that, the parametrization of the fragility derivation proposed in this study enables the evaluation of the ϵ_{emp} for each single ground motion records (or intervals of IM). This feature clearly paves the way for the development of an adaptive sampling procedure for a further reduction of the computational cost.

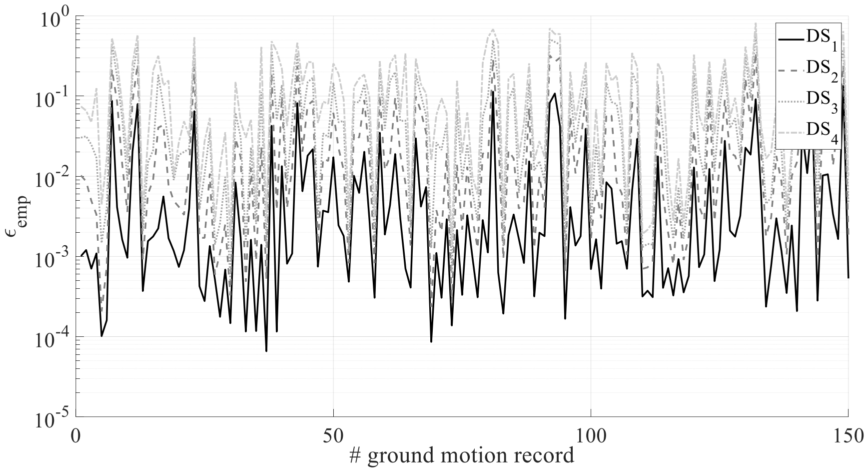

Fig. 2 – Normalized empirical error of the multi-fidelity mode of $\ln\eta_{EDP>EDP_{DS_i}|IM,NoC}$.

Finally, the fragility curves computed with the proposed multi-fidelity approach are compared with those derived with the application of the robust fragility method in its classical form (Fig. 3). In this latter case, 100 realization of the high-fidelity structural model for each ground motion record are used.

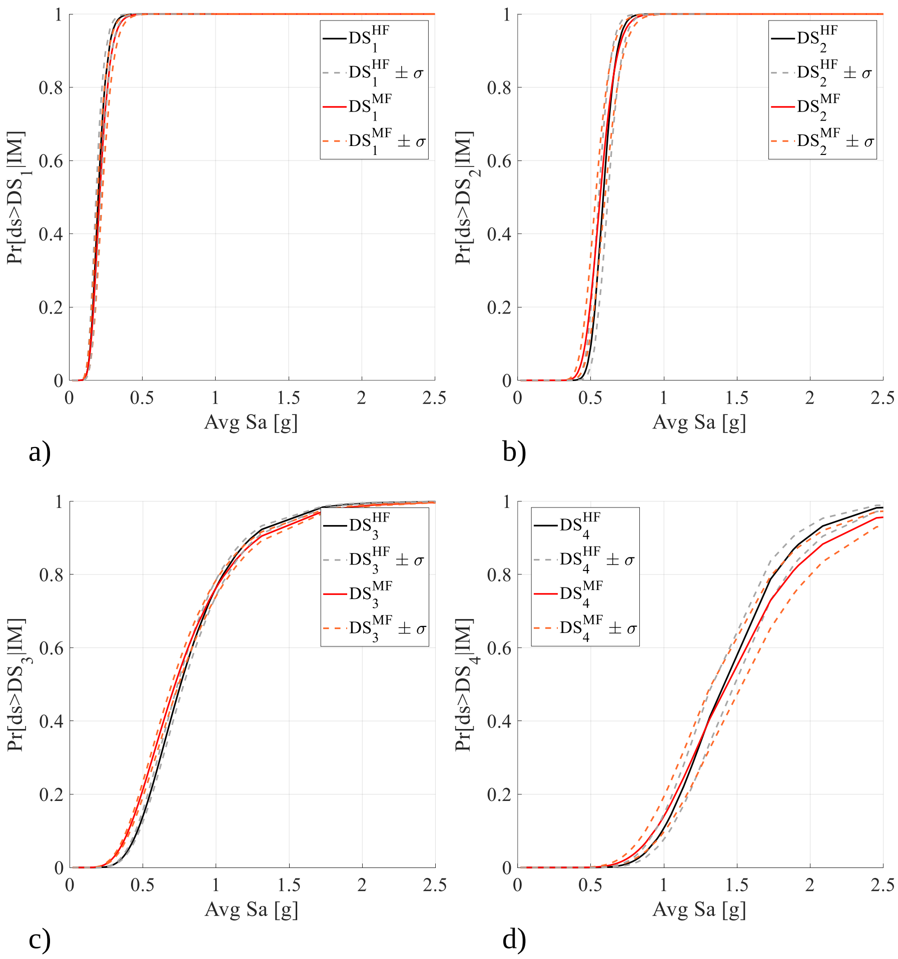

Fig. 3 – Fragility curves: a) DS_1; b) DS_2; c) DS_3 d) DS_4.

The fragility curves derived with the proposed multi-fidelity approach are very close to those calculated with the classical method for the case of DS_1 and DS_2. The relative errors in terms of $\ln\eta_{EDP>EDP_{DS_i}|IM,NoC}$ are equal to 3% and 6% for DS_1 and DS_2, respectively. Whereas those in terms of $\beta_{EDP>EDP_{DS_i}|IM,NoC}$ are equal to 10% and 12% again for DS_1 and DS_2, respectively. The mean multi-fidelity fragility curves are fully contained within the confidence interval of the high-fidelity one. In the case of DS_3 and DS_4, the proposed multi-fidelity model leads to an overestimation of the variability of the results. The relative errors in terms of $\ln\eta_{EDP>EDP_{DS_i}|IM,NoC}$ are in this case equal to 7% and 10% for DS_3 and DS_4. Those in terms of $\beta_{EDP>EDP_{DS_i}|IM,NoC}$ are equal to 18% and 20% again for DS_3 and DS_4, respectively. Also in these last two cases the results are comparable. These observations agree with the error reported in Fig. 2, that is higher in the case of DS_3 and DS_4.

4. Concluding remarks

The derivation of numerical seismic fragility curves is a challenging and computationally expensive task when both aleatory and epistemic uncertainties are considered. Several different methods aimed at reducing the computational cost related to the fragility curve derivation can be found in the scientific literature. In this context, particularly powerful is the use of the robust fragility approach in conjunction with the cloud analysis.

In this paper, a modification of the robust fragility approach is proposed to enable the use of different model classes in the computation of fragility curves. The main idea behind the proposed approach is to analyse refined numerical model only when strictly necessary (i.e., when the numerical output is approaching a selected damage state), and to use simplified models when the numerical results is far enough from the damage state.

A multi-fidelity general Polynomial Chaos Expansion of the fragility model parameters is then provided to combine different model classes. The Bayesian interpretation of the gPCE coefficient calibration allows further reducing the computational cost. In contrast to the classic robust fragility method, the proposed one do not require the use of numerical integration strategies to solve the inverse problem. In fact, conjugated gaussian and approximated Laplace distributions can be successfully adopted to model probabilistically the gPCE coefficients.

An illustrative case of study of an archetype reinforced concrete building is analysed to test the feasibility of the proposed approach. The results show a good agreement between fragility curves derived with the proposed approach and those derived with the classic robust fragility considering only the high-fidelity model. Future studies will aim at developing an adaptive sampling procedure to further reduce the computational burden.

5. Acknowledgements

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