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A SAMPLING METHODOLOGY FOR ACCOUNTING MULTI-SOURCE DATA IN SEISMIC REGIONAL FRAGILITY OF EXISTING RC BUILDINGS

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Abstract

The paper presents a sampling approach tailored for deriving seismic regional fragility of existing reinforced concrete (RC) buildings. The methodology is proposed on the basis of two main aspects: (a) at regional level, the data to elaborate for computing seismic fragility can be of different nature; (b) to perform this study, a large number of numerical models can be generated thanks to the availability of computing power given by the Italian National Centre of High Performance Computing (HPC). Regarding point (a), data at the base of the study present different levels of accuracy, considering that both aggregate and detailed information represent the critical mass for the fragility evaluation. In addition, from the statistical perspective, the available data could be represented through both discrete and continuous distributions, which discourages the use of the common sampling approaches. Therefore, the proposed approach exploits the concepts at the base of Gibbs sampling, for which sample selection is performed by iteratively sampling each variable conditioned on the other ones and then creating a Markov chain that converges to an approximated high-dimensional joint distribution with sufficient accuracy. To establish the number of representative samples, the divergence of Kullback-Leibler was used, in order to compare the target and empirical distributions. The proposed methodology was tested on the available data about RC buildings in the region of origin of the authors, Puglia region, showing for a category of old structures (i.e., designed before 1980) the number of necessary data samples. Using the obtained data, regional seismic fragility curves were derived through a common modelling-analysis duo approach.

Keywords: Regional Level, Seismic Fragility, Sampling Method, Existing RC Buildings, High Performance Computing

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1 INTRODUCTION

The high vulnerability of existing reinforced concrete (RC) buildings to seismic action is a main concern that scientific community and public institutions continuously face by proposing and developing efficient methods for quantifying seismic fragility of the built stock. The first step of this process consists of providing measures to quantify the fragility of buildings at regional level, considering that a first screening can drive the decision-making processes. Concerning fragility analysis, different approaches can be mentioned, such as the ones based on empirical and observational data [1-2] and the ones based on mechanical simulation of the building stock [3-5], usually investigated accounting for different building typologies. When dealing with fragility analysis based on mechanical approaches, three main factors, with the related uncertainties influence the outcome of the investigation:

1. The quality and quantity of input data.
2. The type of analytical model.
3. The type of analysis to perform.

Concerning the modelling approach, the mechanical vulnerability depends on the type and number of models used. Generally, two main extremes can be mentioned [6], i.e., single-degree-of-freedoms (SDOFs) models (see for example [7-8]), which allow to provide the global response of different building typologies, and complex multi-degree-of-freedoms (MDOFs) models, which allow to simulate both local and global behavior of structures. Moving within the extremes, different observations can be provided with reference to large scale fragility analysis. In fact, using simple models like SDOFs, a broad coverage of the entire building portfolio can be achieved, emphasizing inter-building variability and neglecting the importance of specific structures. Instead, using MDOFs require precise definition of archetypes, to represent the building typology to investigate.

With regard to analysis methods, different approaches could be exploited, mainly oriented to static (e.g., [9]) and dynamic (e.g., [10]) analyses. For the purpose of fragility assessments, dynamic analysis is preferred, especially for the capacity to account for uncertainty, in terms of record-by-record variability. To this end, different aspects should be managed, such as the number of ground motion records, the ground motion record selection criteria, and the intensity measure.

Concerning input data, different observations can be drawn. First, at regional level, data creating exposure models are typically available in various formats and require adequate processing for mechanical-based fragility estimation. In addition, the distributions of input data are characterized by two main features: (a) multimodality; (b) multidimensionality. Regarding point (a), multimodality implies that the use of continuous probability distributions for describing the trend of data could not be accurate. In fact, the definition of an overall mean could lead to neglecting the modes, conditioning than the fragility results. Concerning point (b), multidimensionality should be considered for accounting the effective distribution of available data and their dependencies. In fact, when simulating candidates to represent fragility, the selection of data through a sampling approach should be set to follow both multimodality and multidimensionality criteria, ensuring a sufficient number of samples to reproduce the features of the entire space. Different examples exist about exposure models presenting the above features, such as [11] for Turkey, [12] for Portugal, [7] for an Iranian region, [13] for Italy. Nevertheless, the common trend is to represent data through continuous distributions, such as normal or lognormal, enabling the common sampling techniques, such as Monte Carlo Methods (e.g., [14]), Latin Hypercube Sampling (e.g., [15]), Gaussian processes (e.g., [16]), and Bayesian models (e.g., [17]).

This paper aims to provide an alternative method to select samples, given an exposure model. In particular, the main challenge is to perform sampling accounting for the effective multimodality and multidimensionality of the available parameters. To this scope, the proposed approach extracts data directly from a multidimensional discrete space characterized by discrete distributions of the parameters, considered as statistically independent random variables. The approach was based on the concepts of Gibbs Sampling [18], which allows sampling by a complex space of discrete distributions by generating a Markov Chain from the conditional distributions of each parameter over the other ones characterizing the space itself. The approach was coded and developed to be efficient towards different types of data and for ensuring the achievement of the convergence between the observed (target joint distribution) and the simulated (empirical joint distribution) data. To assess the convergence, the Kullback-Leibler divergence [19] was used. The proposed procedure was tested on the existing RC building stock of the Puglia Region, Southern Italy, for which some data of buildings designed without seismic details are available. After performing sampling, data were used to generate three-dimensional (3D) numerical models, which were investigated through nonlinear time history analyses (NTHAs) to derive fragility curves. As already reported, the main advantage of this method is its ability to faithfully represent available data without relying on enforced distributional assumptions. However, a notable drawback is the increased computational cost associated with the need for a larger number of samples to achieve convergence, limit exceeded through the availability of sufficient computational resources at the base of this study.

2 AVAILABLE DATA FOR EXISTING RC BUILDINGS DESIGNED WITHOUT SEISMIC DETAILS

The proposed approach was applied to the existing RC building portfolio designed without seismic details (i.e., before 1980) of Puglia Region, Southern Italy. As highlighted by Tosto et al. [20], the region is characterized by 257 municipalities and presents an increasing seismicity going from the Southern to the Northen part of the region. For the case at hand, typological data were retrieved from the application of the CARTIS methodology [21], developed within the Reluis project, for which information for 14 municipalities were collected, as representative of the existing building stock. In fact, the 14 municipalities cover about the 10% of the regional RC building stock. From the available data, five main typological parameters were considered among the available ones:

- number of storeys, N_{st}.
- base area, A.
- year of construction.
- presence of higher ground floor, H_{gf}.
- presence of pilotis, P_{il}.

From the available data, only the ones related to buildings designed before 1980 were used, using the year of construction as discriminant parameter. Hence, the remaining four parameters were considered in the exposure model.

Another source of data was considered at the base of this study, which is a database of concrete compression strength, f_{cm}, values derived by concrete specimens of real existing RC buildings. From these data obtained by a materials testing laboratory, only the values of f_{cm} were considered, although other features are present, such as height and diameter of the concrete specimens. Also in this case, given the year of construction of the buildings, only data for buildings designed before 1980 were considered.

To create the exposure model, data were clustered in three main spaces, according to the number of storeys: (a) low-rise buildings, considering N_{st} ranging from 1 to 3; mid-rise buildings, considering N_{st} ranging from 4 to 6; high-rise buildings, considering N_{st} ranging from 7 to 9. Hence, Figure 1 reports data in terms of probability mass functions, PMFs, showing each considered parameter, subdivided in the three spaces. It is worth noting that, to reduce the number of states within each space, a simplification was considered on the values of f_{cm}, which were approximated to the closer integer, with considered steps of 5 MPa.

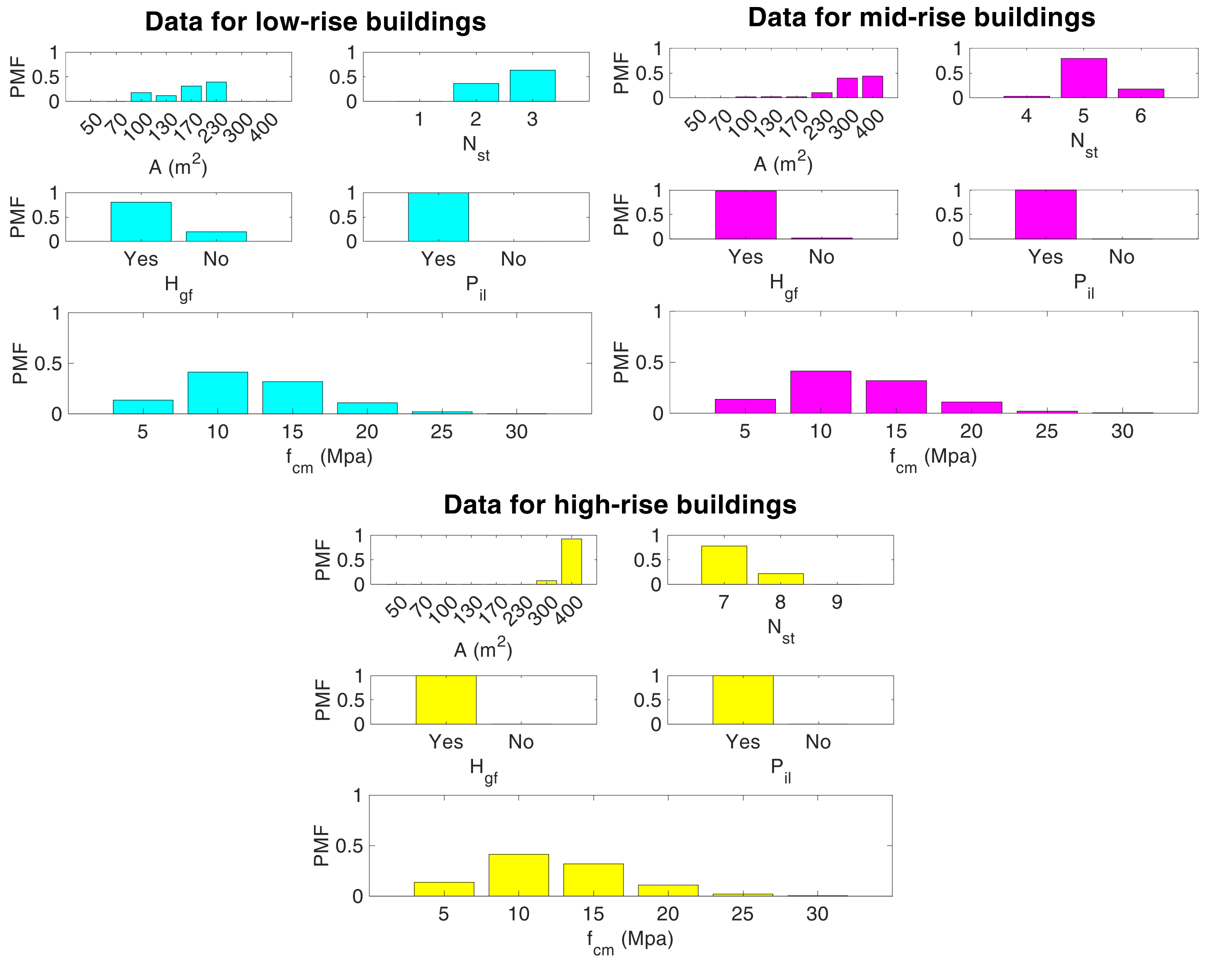

Figure 1: PMF of the considered parameters within the three spaces defined, i.e., low-, mid-, and high-rise buildings.

3 PROPOSED SAMPLING APPROACH

Once exposure is available, the proposed sampling approach was applied. In particular, given the space $\mathbf{X} = (X_1, X_2, \dots, X_n)$, characterized by a vector of statistically independent and uncorrelated discrete random variables X_i, each one assuming values $v_{1,}\ \dots, v_k$, the discrete joint distribution is named $p(\mathbf{X})$. It is worth noting that n indicates the number of parameters within the space, while k indicates the number of states for each parameter. In case of discrete distributions, $p(\mathbf{X})$ cannot be directly sampled, but if we consider the distribution of each variable, X_i, conditioned by the remaining variables, the sampling can be performed by the latter, according to the following expression:

$$p\left(X_i = v_j \left|\mathbf{X}_{-1}\right.\right) = \frac{p(X_1, X_2, \dots, X_n)}{\sum_{j=1}^{k} p(X_1, X_2, \dots, X_n)} \tag{1}$$

in which $\mathbf{X}_{-1}$ is the discrete multidimensional space except the variable X_i. This form allows to express the target joint distribution in tabular form, from which simply performing the sampling. In particular, a starting point should be defined, $\mathbf{X}^{(0)} = \left(X_1{}^{(0)}, X_2{}^{(0)}, \dots, X_n{}^{0}\right)$, where $X_i{}^{(0)} \in \left(v_{1,}\, v_{2,}\, \dots, v_k\right)$. After, a number of iterations, *I*, and a first part to discard named burn-in, *B*, are defined. *B* was assumed equal to 20% of *I*. For each value of *I* and each variable X_i, one parameter varied while the other ones were retained as fixed. The conditioned joint probability of each parameter can be computed at the time *t* as:

$$p\left(X_i = k \middle| \mathbf{X}_{-1}{}^{(t)}\right) \propto p(X_1{}^{(t)}, \dots, X_{i-1}{}^{(t)}, X_i = v_j, X_{i+1}{}^{(t-1)}, \dots, X_n{}^{(t-1)}) \tag{2}$$

The application of Equation (2) allows to select the value of the parameters directly from $p(X_i|\mathbf{X}_{-1})$, and repeating this approach for each variable, a number *I* - *B* of samples is obtained. To define the value of *I*, the operation can be repeated at increasing values of *I*, until achieving convergence, i.e., matching target and empirical joint distributions. To this end, the Kullback-Leibler divergence, D_{KL}, was used. It is worth noting that if the resulting number of samples is lower than the total number of states within the space, the number of models to consider are the ones sampled. On the other hand, if the number of samples is higher than the total number of states, it would be enough to consider the simple combinations of the number of states and compute, for each configuration of the parameters, the frequency within the sampled data, i.e., $f_{\chi(\mathbf{X})}$, where χ represents one configuration. In the second case, to define $f_{\chi(\mathbf{X})}$, the following expression can be employed

$$f_{\chi(\mathbf{X})} = \frac{count(\chi)}{I-B} \tag{3}$$

The above procedure was applied to data in Figure 1 and the results can be observed in the graphs of D_{KL} reported in Figure 2. As can be observed, for each space, the number of sampled data (around 5000 combinations) is greater than the combination of the total number of states (equal to 576), which implies the computation of $f_{\chi(\mathbf{X})}$ for each configuration χ. Still, the achievement of the convergence was set in the graphs in Figure 2 when a value of $D_{KL} = 0.01$ was achieved.

4 ARCHETYPE GENERATION, MODELLING AND ANALYSIS

Once the number of combinations was assessed, sampled data can be used to generate archetype buildings, for which processing modelling and analysis phases. To generate archetype buildings, an automated simulated design process was created, according to the procedure proposed in [4]. In particular, the algorithm was set to design beams and columns of moment-frame 3D structures, only for gravity loads. To design columns, a simple axial stress was used, while for beams, a fixed end scheme was employed. To account for different loadings, a partializing coefficient was used, to consider central, side, and corner elements. To design steel reinforcement, an iterative algorithm was predisposed, aimed at increasing steel diameters and reducing steel spacing (both for longitudinal and transversal reinforcement). The local checks were performed by comparing capacity and demand in terms of admissible stresses, as typical of buildings designed before 1980.

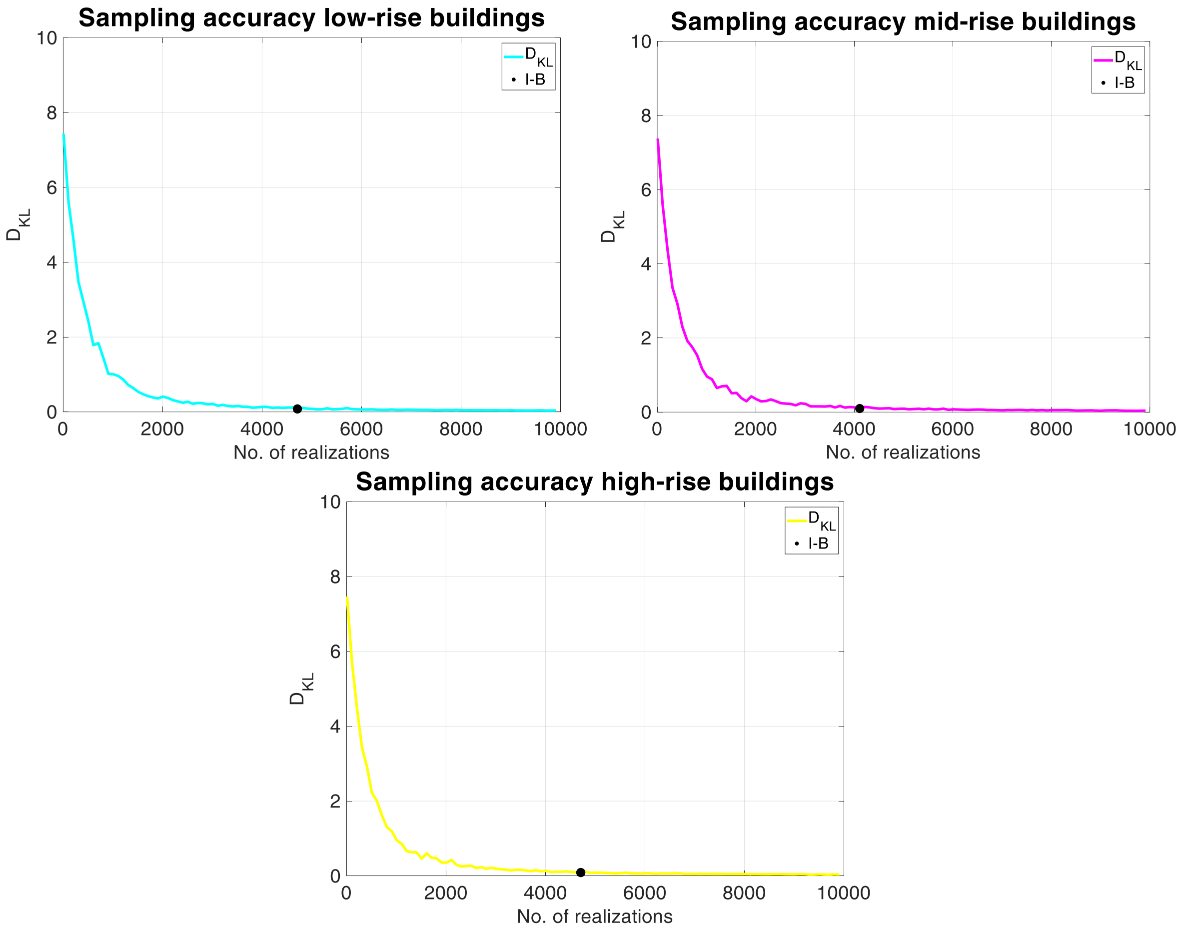

Figure 2: Sampling accuracy in terms of D_{KL} and value of $I - B$ for the three spaces defined, i.e., low-, mid-, and high-rise buildings.

Regarding numerical models, the simulated archetypes were modelled in Opensees [22]. Beams and columns were modelled as frame elements. External restraints were used, as well as internal ones for simulating rigid diaphragms. Fixed values of gravity and dead loads were used, according to the current code prescriptions. The nonlinearity was simulated through a lumped plasticity approach placing hinges at the end of the frames through *beamWithHinges* command. The inelastic behaviour was considered by combining ductile and brittle mechanisms within a unique moment-rotation law, by using *Pinching4* material. Considering the generation of 3D models, plastic hinges in the columns accounted for a bi-directional behaviour, while beams accounted for only a mono-directional behaviour. Cyclic behaviour was considered according to the deterioration model proposed by [23]. Regarding masonry infill panels, a macro strut modelling approach was used, by defining two cross braces in each frame by using the *corotationalTruss* element. Finally, local effects on beam-columns joints were neglected.

Concerning seismic analysis, a cloud approach was used, according to available literature for regional level fragility assessment [16,24]. Record selection was not performed, since a set of 30 ground motion records was adopted directly from the two sets of ground motion records released by Kohrangi and Vamvatsikos [25] for different European cities (the records were randomly selected from the available sets, 15 for medium seismicity and 15 for high seismicity). Regarding the choice of the intensity measure, IM, and the engineering demand parameter, EDP, the choice was the average spectral acceleration, *AvgSa* as IM, and the interstorey drift ratio, θ_{max}, as EDP.

5 FRAGILITY ANALYSIS

According to the above information, NTHAs analyses were performed, and fragility curves were derived. In particular, an IM-basis approach was employed, by employing two main occurrences: (a) few collapses; (b) many collapses. In the first case, fragility curves were derived through the classical power-low approximation, while in the second case, fragility curves were derived by juxtaposing the results of the power-low approximation with the one given by the probability of having collapses or not, i.e., by employing the logistic regression [26]. The results, were derived for different damage states (DSs), by using as threshold in terms of interstorey drift ratio, $\theta_{max,DS}$, the values provided by [3]. In particular, the following values were considered for the five DSs:

- DS1: negligible to slight damage, $\theta_{max,DS}$ = 0.10%.
- DS2: moderate damage, $\theta_{max,DS}$ = 0.25%.
- DS3: substantial to heavy damage, $\theta_{max,DS}$ = 0.50%.
- DS4: very heavy damage, $\theta_{max,DS}$ = 1.00%.
- DS5: collapse, $\theta_{max,DS}$ = 1.50%.

The results obtained for each DS and for each configuration χ were combined by resuming the laws of total expectation and total variance, for which the values of medians and dispersions of each configuration were combined according to the frequency $f_{\chi(\mathbf{X})}$. The results of the analyses are reported in Figure 3, in which the patches identify the range of fragility curves derived from the sample of generated and investigated archetypes, while the main fragility curves are the overall ones for the region.

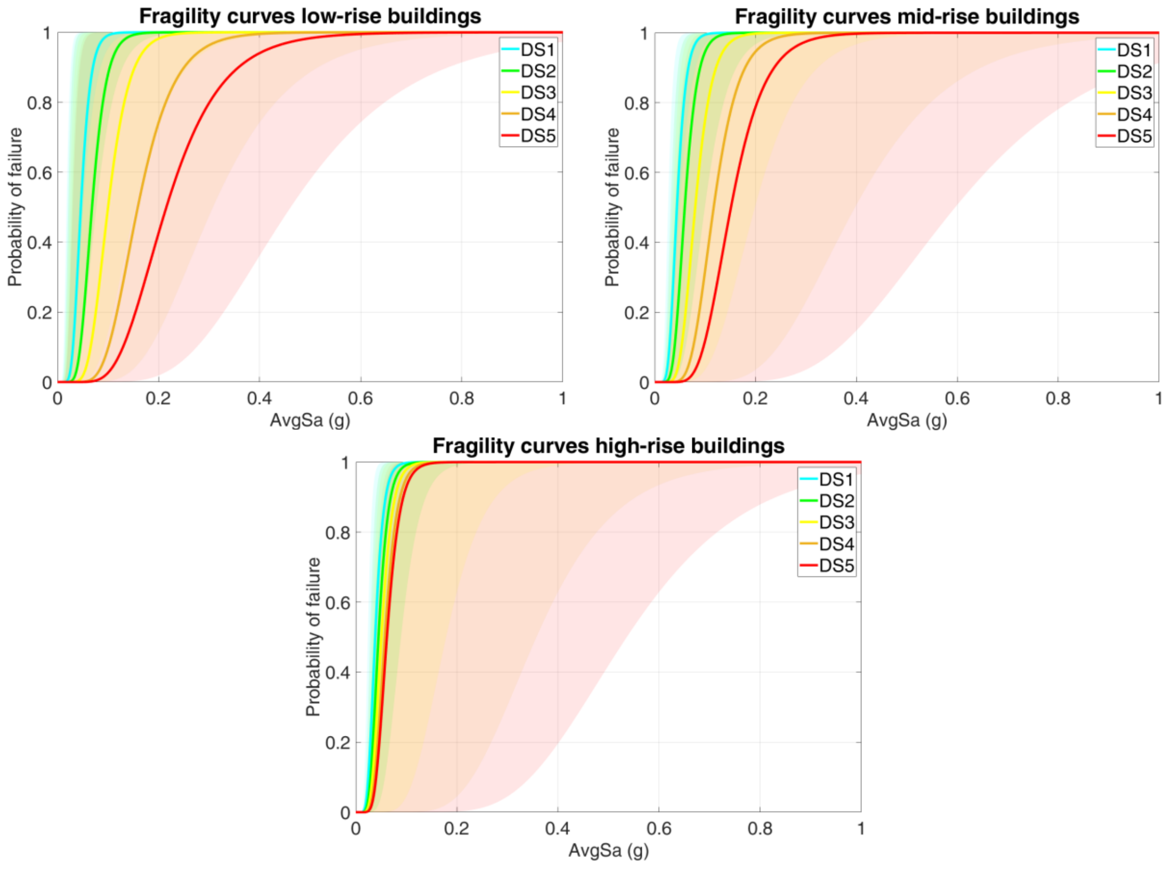

Figure 3: Fragility curves for the three spaces defined, i.e., low-, mid-, and high-rise buildings.

As can be observed in Figure 3, the most fragile buildings are the high-rise ones, while when reducing the number of storeys, the medians of fragility curves increase and then, the low-rise buildings present the lower fragility. This trend is also confirmed by the state-of-the-art, which provides similar results, as reported in the empirical fragility curves by [1].

6 CONCLUSIONS AND FUTURE DEVELOPMENTS

The paper presents a new sampling methodology aimed at elaborating data for fragility analysis of existing RC buildings at regional level, accounting for two main aspects of exposure data, that is, multimodality and multidimensionality. The method was set to perform sampling for spaces constituted by more probability mass functions, i.e., discrete distribution of parameters, also deriving from different sources. The algorithm was based on the Gibbs Sampling method, which allows to sample from a complex joint probability distribution, such as the one characterized by discrete distributions. For the case at hand, the sampling is performed by the distribution of each parameter conditioned by the others, which provides information in tabular form and then, facilitating data selection and extraction. To assess the number of necessary iterations and to achieve the convergence between the observed (i.e., target joint distribution) and the generated (i.e., empirical distribution) data, the Kullback-Leibler divergence was used.

The method was tested to the exposure model of the RC building portfolio of Puglia region, Southern Italy, considering only buildings designed without seismic details, i.e., before 1980. The sampled data were processed to generate archetype buildings, which were after modelled and analysed under seismic actions. The results were expressed in terms of fragility curves, providing overall results for different damage states by combining the output of each configuration according to the related frequency within the sampled data.

The main advantage of the proposed procedure is surely a certain fidelity of the simulation to the available data, ensuring multimodality and multidimensionality of the exposure and avoiding of adapting data to continuous distributions. On the other hand, as main disadvantage, an increasing computational effort is required, especially for achieving convergence between target and empirical distributions.

Future developments will aim to apply the same procedure to different types of data, i.e., other building typologies, realized with seismic details, also according to different building codes. In addition, the procedure could be used to provide risk measures (e.g., loss curves, expected annual losses) for different building typologies, in order to drive the decision-making processes.

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