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THE EFFECT OF INTENSITY MEASURE SELECTION AND EPISTEMIC UNCERTAINTIES ON THE ESTIMATED SEISMIC PERFORMANCE FOR NON-STRUCTURAL COMPONENTS OF NUCLEAR POWERPLANTS

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Abstract: *The seismic performance of a structure/component is influenced by aleatory randomness and epistemic uncertainty, but also by the intensity measure (IM) selected for the assessment. Aleatory randomness results from natural ground motion record variability, while epistemic uncertainty corresponds to modelling assumptions, parameter variability, omissions or simplifications. IM selection, though, depends on the analyst and the data available. Potential candidate IMs are the peak ground acceleration (a nuclear industry standard), spectral acceleration at a fundamental period of the structure (the relative newcomer), and average spectral acceleration in the range of short periods (the novel option). Their performance in quantifying uncertainty for short-period nuclear powerplants is not given, nor is it necessarily obvious given the sizeable uncertainties involved. To provide a basis for discussion, a single-degree-of-freedom non-structural component in an AP1000 reactor building is used as case-study. Three alternative uncertainty propagation approaches are employed: (a) Monte Carlo simulation with classic Latin hypercube sampling, (b) Monte Carlo simulation with progressive Latin hypercube sampling and (c) a first-order second-moment method, representing different compromises between speed and accuracy. The resulting fragility curves of the non-structural component are compared in terms of efficiency for assessing its performance, offering evidence in support of optimizing IM selection.*

Introduction

Fragility assessment is a critical tool in the evaluation of the risk and resilience; by estimating the probability of a given level of damage or failure of the components exposed to levels of seismic intensity it forms the backbone of probabilistic safety assessment and helps maintain safe and resilient nuclear powerplants. Fragilities are uniquely parameterized by an intensity measure (IM). This is typically a single scalar that is meant to “fully” characterize a ground motion record. Its selection is crucial, as it is the only link between the seismic hazard and the structural response. Specifically, the IM must be general enough for its hazard to be computable, i.e., by virtue of having an appropriate ground motion prediction model, while it must also be specific enough to be closely related to the response of the powerplant's structures, systems, and components (SSCs).

Within such constraints, three candidate scalar IMs are considered. The first is Peak Ground Acceleration (PGA), which is a near-universal choice in the nuclear industry (Zentner *et al*., 2011). Also, the 5%-damped spectral acceleration at a given period *T*, or Sa(*T*), is examined as it is considered a good index for first-mode-dominated linear or nonlinear structures (Shome and Cornell, 1999; Tavakoli and Pezashk, 2005; Abrahamson and Silva, 2008). Finally, the average spectral acceleration (AvgSa) in alternative ranges of short periods, is used as it has been shown to offer good performance for a multitude of structures (Vamvatsikos and Cornell, 2005; Bojórquez and Iervolino, 2011; Eads *et al*., 2015; Kazantzi and Vamvatsikos, 2015; Kohrangi *et al.*, 2016a; Adam *et al.*, 2017).

Seismic performance is influenced by both aleatory randomness, and epistemic uncertainty. Aleatory randomness in seismic performance refers to the inherent variability or randomness in ground motion that occurs during an earthquake; basically, due to characteristics of the ground motion waveform that are not captured by the IM. Epistemic uncertainty refers to the uncertainty that arises from incomplete or imperfect knowledge about the behaviour of the structure. This can

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include uncertainties in the material properties of the structure, the design assumptions, and the analytical models used to predict the response. This type of uncertainty can be reduced by improving the knowledge of the system, such as through better understanding of the soil conditions or through more advanced analytical models.

Accounting for both aleatory randomness and epistemic uncertainty in the seismic performance of structures is important for ensuring that the structure is safe and resilient in the event of an earthquake. Various methods have been developed to account seismic performance uncertainty, such as Monte Carlo and simpler moment-estimation techniques. Three alternative methods are considered for the non-structural component under study; two of them are based on Monte Carlo simulations with the application of Latin hypercube sampling, while the latter is a first-order second-moment technique.

Model description

The nuclear powerplant under study is represented by a reduced-order “masses-and-sticks” model of the main containment/auxiliary building based on the AP 1000 advanced reactor design. The model is formed using the open-source structural analysis program OpenSees (OpenSees, 2006), employing a set of elastic beams and nodal masses. It consists of three concentric sticks, representing the Coupled Auxiliary and Shield Building (ASB), the Steel Containment Vessel (SCV), and the Containment Internal Structure (CIS). The three sticks are linked to each other by rigid elements at their base (Figure 1). The modelling data are taken from the Electrical Power Research Institute (EPRI, 2007).

The effect of the soil on the dynamic response is introduced via a simple cone model, also known as the Wolf model, a widely used approach for soil-structure interaction (SSI) analysis. The simple cone model is relatively easy to implement and computationally efficient compared to more complex models that incorporate more detailed soil properties. According to Wolf (1998), the halfspace under a structure is considered as a truncated semi-infinite rod with its area varying as a cone of the same material properties. However, the accuracy of the cone model is limited by the assumptions made regarding the soil behaviour and the representation of the foundation.

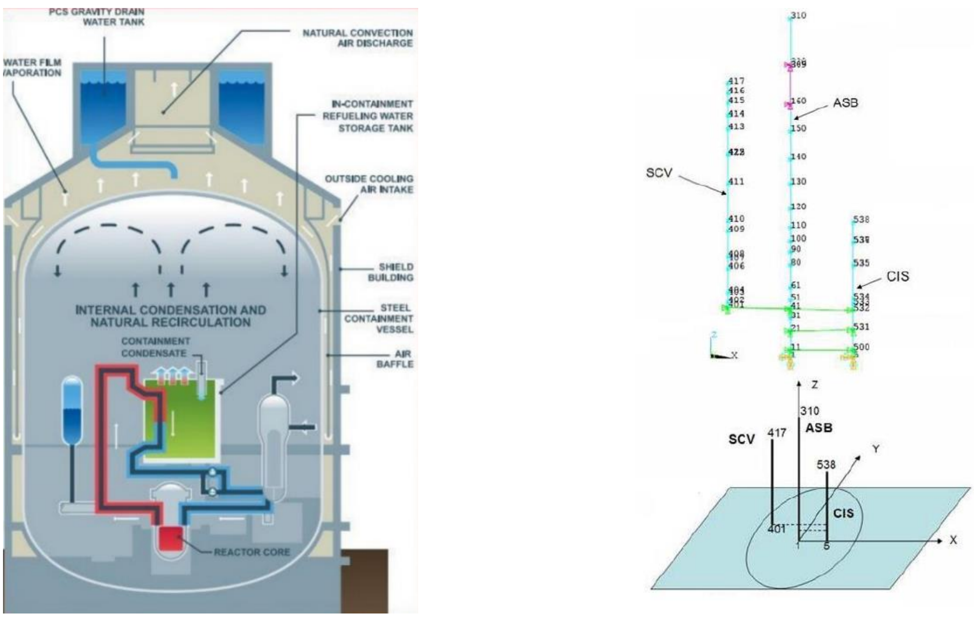


Figure 1. Original AP1000 reactor design (left) and simple stick model (right) per EPRI (2007)

From a modelling point of view, the cone is modelled as a lumped-parameter mass-spring-damper system. The model assumes that the soil can be approximated as a linear elastic medium with a uniform stiffness throughout its depth. The foundation of the structure is represented as a rigid mass that is connected to the soil through a spring and a dashpot. The spring represents the soil stiffness, while the dashpot represents the damping properties of the soil. The fundamental period of the powerplant, considering the mass-spring-damper system for the SSI, is equal to

$T_{1,bldg}$ = 0.46s. Each of the three substructures vibrates semi-independently, only connected to the others at the base, and having its own mode. The fundamental periods of the ASB, CIS, and SCV towers are $T_{1,bldg}$ = $T_{1,ASB}$ = 0.39s, $T_{1,CIS}$ = 0.29s, and $T_{1,SCV}$ = 0.15s, respectively.

Non-structural components, refer to equipment, systems, and components that are necessary for its operation and ultimately its safety. Examples of non-structural components include piping, electrical cables, control panels, and ventilation systems. The selected non-structural component is a service water pump used as an example in EPRI (2018). For the purposes of our study, it is considered as located at the top floor of CIS tower. The pump is modelled as a 3-dimensional stick with a single mass at its top. It is mildly nonlinear, having an elastic-perfectly-plastic force-deformation backbone, terminating at an ultimate ductility of 1.25 and sporting a moderately pinching hysteresis. When neglecting uncertainties, the pump is symmetrical in both principal axes X, Y, having a fundamental period of T_{pump} = 0.101s and yield strength V_{yield} = 37.37kN. Failure occurs at the reaching the ultimate ductility. As typical for mechanical equipment (per EPRI 2018), the median damping ratio of ζ = 5% is adopted. Failure is assumed to occur at a maximum displacement of d_u = 0.0029m for the pump, to be used as the capacity threshold for the fragility analysis.

Uncertainty analysis

According to EPRI (2018), when estimating the fragility of the water pump, important uncertainty should be considered not only in the parameters describing its behavior, i.e. the yield strength, the damping and period of vibration, but also in the parameters influencing the stiffness of the supporting understructure.

Regarding the pump model, five random variables are used to describe is structural characteristics: the damping ratio, the fundamental eigenperiods, and the yield strengths in the two principal axes (ζ_{pump}, $T_{pump,x}$, $T_{pump,y}$, $V_{yield,x}$, $V_{yield,y}$). Each of the parameters is assumed to follow a lognormal distribution with the median value described in the previous section. The dispersions of the yield capacity, the damping, and the period of the component are 0.16, 0.12, and 0.18, respectively.

For the understructure, only two uncorrelated stiffness-modifying parameters were employed: the first for the reactor building, used uniformly throughout all the structural elements assuming a perfect positive spatial correlation, the second for the cone model of the soil. Lognormal distributions are also assumed for both, employing a 0.20 dispersion. Their joint effect introduces a moderately high variability to the understructure period, influencing the potential for component-structure resonance. In total, a population of 12 possible instances of understructure stiffness was generated with classic Latin Hypercube Sampling (LHS, McKay *et al*. 1979). Compared to random sampling, LHS requires fewer samples to achieve similar accuracy, as it covers the parameter space more efficiently.

To propagate the parametric uncertainty from the understructure to the pump, three alternative methods were employed. The first is Monte Carlo simulation with classic LHS, as proposed, e.g., by Dolsek (2009), Vamvatsikos and Fragiadakis (2010). The second replaces LHS with the, arguably, more efficient approach of progressive LHS (Vamvatsikos 2014). Finally, a First-Order Second-Moment (FOSM) technique was applied (Melchers *et al*., 2002; Pinto *et al*., 2004).

Monte Carlo simulation with LHS involves generating random samples of the parameters under study, arranged within a latin hypercube. Replacing the crude random sampling, LHS generates random samples that are more evenly distributed across the parameter space. This method is widely used since it can provide accurate estimates at a relatively low cost, yet it can still suffer from inefficiencies as it is difficult to determine a proper sample size a priori, at least not without some prior experience with the problem. It can also be used inefficiently within the context of nonlinear response history analysis, as indiscriminate application may lead to repeating full performance assessment studies over multiple model samples. In our case, we take this naïve view of application, drawing 200 samples of pump model parameters (or alternative pump realizations), ensuring zero correlation among the five random variables.

On the other hand, Monte Carlo simulation with Progressive Latin Hypercube Sampling (PLHS) is an extension of LHS that allows for sequential refinement of the sample. PLHS starts with a small initial sample for each random variable, and then iteratively doubles its size in a progressive manner. Each new sample is added to the previous one in a way that maximizes the coverage of the parameter space and minimizes redundancy, by maintaining a latin hypercube design in each step. Thus, the advantage of PLHS is that it allows for a more efficient and effective exploration of the parameter space than classic LHS. In our case, the initial sample consists of 10 alternative pump realizations, whose performance is depicted from 10 samples of the five parameters. The size of this sample is doubled successively, until the median and dispersion of the fragilities is stabilized within the desired tolerance. For our case study a total of seven iterations was performed to reach comparable results as the classic LHS. In general, after N iterations, the size of the sample is $10 \times 2^{N-1}$. For $N = 7$ the final sample reaches a size of 640 models. Compared to the 200 models of classic LHS, this seems hardly efficient, yet in the context of record-wise PLHS, each model is paired with only one ground motion record at a time, rather than an entire set of them, heavily reducing the overall cost.

The FOSM method is a simplified method often used to estimate uncertainty. It is important to note that the FOSM method makes several simplifying assumptions, as its name implies, and its accuracy heavily depends on their validity. Specifically, a first-order (i.e., linear) approximation is employed for the overall model response, while only the first two statistical moments are propagated from input to output. FOSM requires $2 \times K + 1 = 11$ simulations, where $K = 5$ is the number of random variables. The first simulation corresponds to all random variables being set equal to their mean values. The next $i = 2, \ldots, 6$ simulations are obtained by shifting each parameter from its mean by plus one standard deviation, while all other variables remain equal to their mean values. For the remaining $i = 7,\ldots,11$) simulations the mean values minus one standard deviation are used instead.

Performance estimation

Dynamic analyses of the reactor building and the component were performed separately. Using this cascade approach, the computational time is dramatically reduced when the uncertainty analysis of the component's parameters is performed. At the first step, a dynamic analysis per each alternative model of the reactor building was implemented using a suite of 30 two-component ground motion records, selected to be consistent with the seismic hazard of a hypothetical site in Southern Europe. Assuming linearity, the floor acceleration timehistories resulting from these analyses can be scaled at will to derive the response at different scaled versions of the records. Using this shortcut, incremental dynamic analysis (IDA, Vamvatsikos and Cornell, 2002) was performed to evaluate the performance of the pump.

Initially, only a base case analysis was performed, setting all pump parameters at their median values. Thus, only the uncertainty in the understructure period was incorporated. Then, a different number of pump model realizations was selected for each uncertainty propagation method, based on its characteristics and limitations. For the application of Monte Carlo simulation with LHS a naïve application of the same suite of the 30 recorded two-component floor motion records was used per each model realization, resulting to a total of 12 × 200 × 30 = 72.000. The full ground set needs to be employed for FOSM, thus 12 × 11 × 30 = 3.960 IDAs were performed. When using Monte Carlo simulation with a record-wise application of PLHS, only a single two-component floor motion record was used per model realization. Specifically, for the first model, an IDA was run using only the first record of the set of thirty; for the second model, the second record was employed, cycling back to the first record after every 30 model realizations. This option results to a total of 12 × 640 × 1 = 7.680 IDAs, which is almost one-tenth of the classic LHS total, albeit about double the number needed for FOSM.

Analysis results and discussion

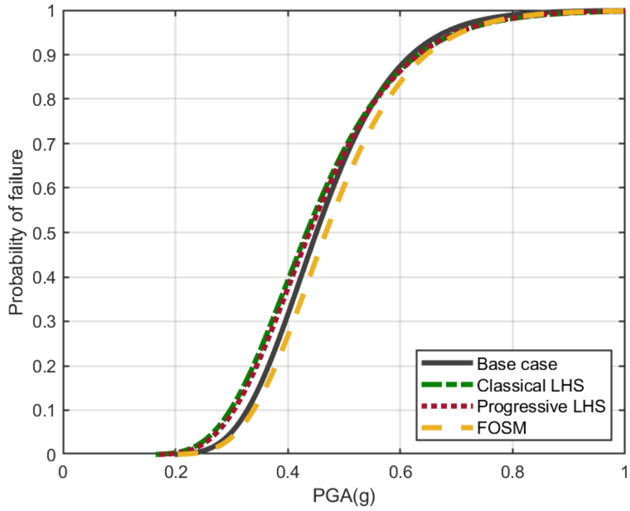
To achieve some parity between the three approaches, a lognormal fragility assumption was adopted. Thus, only the median and dispersion β (standard deviation of the log) of that characterize the fragility are estimated. To perform this calculation, for each single-record IDA curve and regardless of the propagation method employed, the IM value corresponding to the given (d_u = 0.0029m) limit-state threshold is estimated. For Monte Carlo based methods (classic LHS and PLHS), taking the median and dispersion of these IM values is all that is needed to determine the fragility parameters. For the FOSM method, we following the implementation described in Vamvatsikos and Fragiadakis (2010) to approximate the median IM and its dispersion due to parameter uncertainty. This is combined in a square-root-sum-of-squares manner with the record-to-record dispersion estimated by the base case.

This process was performed for three distinct classes of IMs, namely Sa(T, 5%), *PGA* and AvgSa; in all cases the geometric mean of both horizontal ground motion components was employed to define the IMs, ensuring compatibility with modern ground motion prediction equations. Figure 1 illustrates the fragility curves of the non-structural component for the three investigated IMs and the alternative uncertainty propagation methods against the base case. In Figure 2a, the results plotted correspond to PGA, followed by spectral acceleration at the fundamental period of the pump T_{pump} = 0.101s in Figure 2b. Fragility curves are estimated for three distinct period ranges for AvgSa, namely AvgSa(0.1-0.4s), AvgSa(0.1-0.2s) and AvgSa(0.05-0.15s). Figure 2c illustrates the results only for the latter. Table 1 contains the median (μ) and Table 2 the lognormal standard deviation (β) of each fragility analysis performed conditioned on the examined IMs.

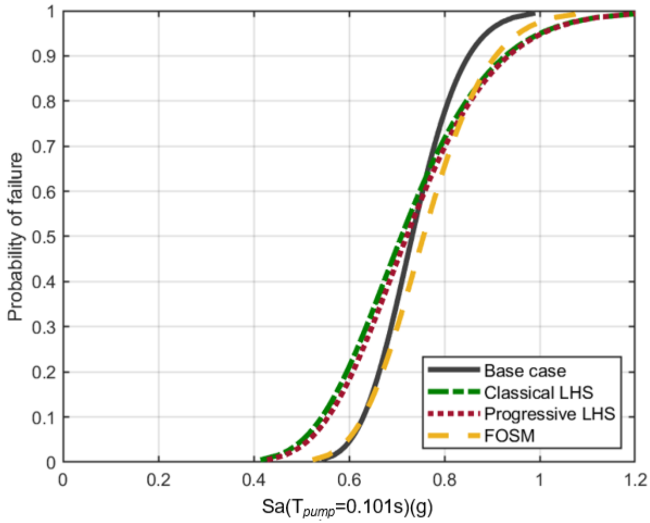
As expected, lacking the additional uncertainty of pump model parameters, the results of the base case analysis are clearly unconservative, especially for Sa(T_{pump},5%). They show lower dispersion and, in some cases, slightly higher medians. On the other hand, the results obtained from Monte Carlo with classic and progressive LHS are almost identical, as expected; this essentially supports the usage of the more efficient approach, showing that it can achieve similar results at a highly reduced budget. On the other hand, the FOSM method may be using only half of the runs of PLHS, but it does not manage to match it. It tends to underestimate the overall dispersion, an effect that is most visible in the case of Sa(T_{pump},5%).

At the end of the day, the key question that remains is which IM is the optimal for the fragility assessment of the pump. The dispersion is what is used to indicate the efficiency of an IM; the lower the dispersion of an IM, the higher the efficiency becomes, or in other words the fewer records needed to assess the response or the fragility. The comparison is done given the outputs from the classic LHS approach which is considered the more accurate. It is observed that both Sa(T_{pump} = 0.101s) and AvgSa(0.05s-0.15s) are highly efficient IMs, while PGA and AvgSa(0.1s-0.4s) lead to the highest dispersion values.

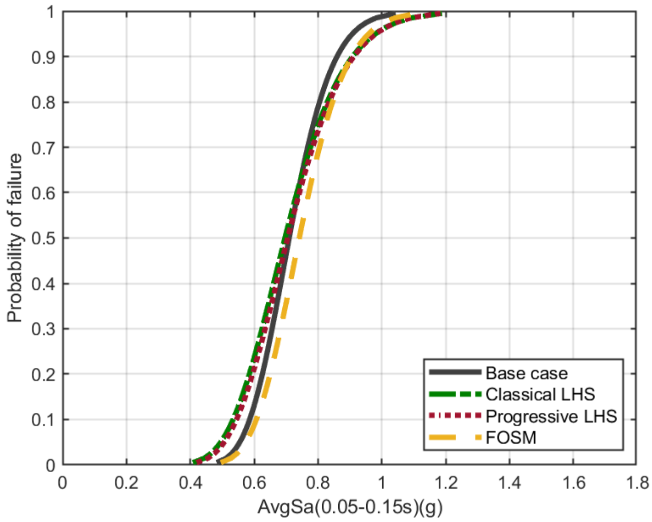
Is it correct though to examine spectral acceleration only at the fundamental period of one component? Where would that lead in the case of a different component? Figure 4 illustrates the distribution of dispersion for spectral acceleration values over a range of periods from 0 to 0.5s; dispersions for AvgSa(0.1-0.4s), AvgSa(0.1-0.2s) and AvgSa(0.05-0.15s) are also plotted as straight horizontal lines; all results correspond to Monte Carlo with classical LHS. The dispersion of the fragility curves conditioned on PGA and AvgSa(0.1-0.4s) are quite close as already mentioned. For a period, lower than 0.2s the results for spectral acceleration are comparatively lower and vice versa for higher periods. If you could only select a single IM for several different non-structural components, one could picture “lateral transpositions” of the SA(T,5%) curve to be centred at different component periods. Then, unless all components are very closely grouped together in terms of period, it is not difficult to imagine that selecting Sa at any period may be less efficient for the group than averaging over a period range.



(a) Fragility curves given PGA



(b) Fragility curves given Sa(T_{pump} = 0.101s, 5%)



(c) Fragility curves given AvgSa(0.05-0.15s)

Figure 2. Fragility curves of the pump for the base case analysis versus three uncertainty propagation methods given different IMs.

Analysis	PGA	Sa(0.101s)	AvgSa(0.1-0.4s)	AvgSa(0.1-0.2s)	AvgSa(0.05-0.15s)
Base case analysis	0.45	0.73	0.88	0.84	0.71
Monte Carlo Classical LHS	0.43	0.71	0.86	0.83	0.70
Monte Carlo Progressive LHS	0.44	0.72	0.88	0.84	0.71
FOSM	0.47	0.76	0.85	0.93	0.74

Table 1: Medians of fragility curves given the IM for the base case analysis versus the three uncertainty propagation methods. All values in units of g.

Analysis	PGA	Sa(0.101s)	AvgSa(0.1-0.4s)	AvgSa(0.1-0.2s)	AvgSa(0.05-0.15s)
Base case analysis	0.25	0.12	0.27	0.18	0.15
Monte Carlo Classical LHS	0.29	0.21	0.31	0.24	0.21
Monte Carlo Progressive LHS	0.29	0.20	0.31	0.24	0.20
FOSM	0.25	0.14	0.29	0.17	0.16

Table 2: Dispersions of fragility curves given the IM for the base case analysis versus the three uncertainty propagation methods.

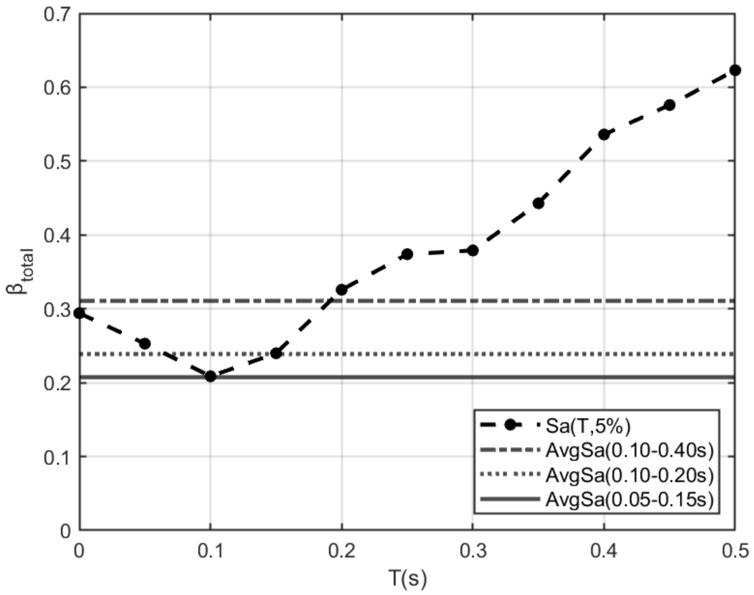


Figure 3. Distribution of dispersion for Sa over a range of periods from 0 to 0.5s. "Period-independent" dispersions for AvgSa(0.1-0.4s), AvgSa(0.1-0.2s) and AvgSa(0.05-0.15s) are also indicated with straight lines

Conclusions

Monte Carlo simulation with LHS and a first-order second-moment approach were used to estimate the effect of model parameter uncertainties on the seismic performance of a non-structural component of a nuclear powerplant. Monte Carlo simulation with progressive LHS is an alternative to Monte Carlo simulation with classic LHS and has been shown to provide results of the same precision at lower and controllable computational cost. The FOSM method on the other hand, provides less accurate results, especially given the examined IMs, while it may be harder to scale up when numerous parameters are involved.

The selection of the IM has a significant impact on the fragility curves of components. Spectral acceleration at the fundamental period of the component shows the lowest dispersion, and as a result, a good overall performance. Still, each non-structural component of the powerplant has its own eigenperiod, thus rendering the choice of a single “optimal” period rather difficult. If instead one tries to select an IM that is largely independent of the characteristics of each component, then AvgSa defined over a range of short periods leads to near-optimal and practically period-independent results.

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