Validating IM-based methods for probabilistic seismic performance assessment with higher-level non-conditional simulation

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SUMMARY:
Probabilistic seismic performance assessment consists of evaluating the probability that a structure exceeds a limit state at least once within a given time interval (risk). Classical methods to evaluate it are those of structural reliability. For dynamic problems such as the seismic one, recourse to simulation methods is the most common choice. So far, the main obstacles to their widespread adoption have been the limitations of stochastic ground motion models and the computational cost. The last fifteen years have seen a considerable amount of research devoted to the development of approximate affordable alternatives, employing some assumptions to dramatically reduce the effort and requiring only accessible tools and notions in probability/statistics. These methods can be collectively denoted as "IM-based", since they rely on the hazard-fragility split of risk, which are expressed in terms of an Intensity Measure (IM). The paper critically compares results of the two classes of methods.

Keywords: Monte Carlo, Importance Sampling, Synthetic records, IDA, RC frame

1. INTRODUCTION

This paper presents a comparison of the results of probabilistic seismic performance assessments carried out with reliability methods and with so-called IM-based methods. The latter methods, emerged in the last years as affordable alternatives to the former ones (Cornell, 1996, Deierlein et al, 2003), derive their name from the main assumption employed to reduce the computational cost associated with simulation. The assumption is that the probability of exceeding a limit state, conditional on a measure of the local ground motion intensity (the IM) at the site of the structure, is independent of other earthquake properties such as, notably, magnitude, source-to-site distance, faulting style, etc. For the same reason the reliability methods are called herein non-conditional, to underline the fact that they do not rely on the above assumption. In both classes of methods there is a spectrum of alternatives. The paper considers two such alternatives for the IM-based methods, and three for the non-conditional methods.

It is important to highlight the complementary criticalities of the two classes. Whereas the non-conditional methods can claim to explore in a probabilistically consistent manner the whole random space and thus lead to unbiased estimates of the probabilities of interest, the IM-based ones cannot and, further, the validity of their main assumption (conditional independence) is structure- and IM-dependent. On the other hand, IM-based methods employ real recorded ground motions while non-conditional methods require stochastic models that simulate synthetic motions starting from basic random variables. The capability of the latter to represent real motions has been under scrutiny and the "final" satisfactory model has not emerged yet. Also, uncertainty in hazard prediction, i.e. due to imperfect knowledge in the source characterization (source boundaries, source activity parameters) as well as in the source-to-site portion of the ground motion generation (different ground motion prediction equations), can be easily/economically accounted for in IM-based methods (usually through a logic tree on alternative models and assumptions), while it may represent a challenge for non-conditional methods.

In conclusion, apart from the computational aspects, the main difference between the two classes is in

the probabilistic representation of the ground motion. A first critical comparison of the results obtained with the two alternatives was presented in (Jalayer and Beck, 2008). Therein the authors compared the results of subset simulation (Au and Beck, 2003) with the Atkinson and Silva (2000) stochastic ground motion model, with those obtained from so-called multiple-stripe analysis (an IM-based method). Due to the limitations of the employed stochastic ground motion model a (scalar and structure-dependent) correction term to inflate ground motion variability needed to be introduced.
Recently, a new model for synthetic motions has been presented (Rezaeian and Der Kiureghian, 2010). The model claims to correctly represent not only the median of natural ground motions, but also their total variability. This paper therefore employs this new model to perform a comparison, without introducing any correction term. The results thus serve the double purpose of validating the IM-based methods and the synthetic ground motion model.

2. SIMULATION METHODS

Among reliability methods, simulation ones represent a robust way to explore the behaviour of systems of any complexity. They are simply based on the observation of system response to input. Simulation of a set of inputs from the joint density $f(\mathbf{x})$ of the random input parameters and evaluation of corresponding outputs allows to determine through statistical post-processing the distribution of the output (in this respect, the IM-based methods can be seen as "small-sample simulations", where the small sample size is achieved by conditioning). This section introduces the three methods employed in the comparison.
Monte Carlo (MC) simulation (Rubinstein, 1981) is the crudest possible way of estimating the "failure probability" p_f, i.e. the probability that the structure violates the limit state. MC method amounts to estimating an unbiased estimator of p_f, here denoted as $\hat{p}_f$, as an arithmetic average over a sufficiently large number N of samples. It can be shown that the variability (variance) of $\hat{p}_f$ around p_f is proportional to p_f itself and decreases with increasing number N of samples. A basic result that follows is that the minimum number of samples required for a specified confidence in the estimate (in particular to have 30% probability that $\hat{p}_f \in [0.67,1.33]p_f$) is given by $N \geq 10(1-p_f)/p_f \cong 10/p_f$. Such result (which holds for sufficiently small p_f's, say, in the order of 10^{-3} or lower) implies that an exorbitant number N of trials is needed to get a correct estimate of failure probability. It also follows that in order to reduce the minimum required N one must act on the variance of $\hat{p}_f$. This is why the wide range of enhanced simulation methods that have been advanced to improve performance fall under the name of "variance reduction techniques".
One such technique is *Importance Sampling* (IS), which is based on the idea that, when values of $\mathbf{x}$ that fall into the failure domain F (set of points corresponding to limit state violations) are rare and difficult to sample, they can be conveniently sampled according to a more favourable distribution, somehow shifted towards F. Of course the different way $\mathbf{x}$ values are sampled must be accounted for in estimating p_f through so-called IS weights. The difficulty associated with the IS method is to devise a good sampling density $h(\mathbf{x})$, since it requires some knowledge of the failure domain F.
A second, effective variance reduction technique, denoted IS-K in the following, starts from the IS method and enhances it with a statistical technique called *clustering* in order to further decrease the required number N of simulation runs. IS is first used to preferentially sample "important" events, then "K-Means Clustering" is employed to identify and combine redundant events in order to obtain a small catalogue. The effects of sampling and clustering are accounted for through a weighting on each remaining event, so that the resulting catalogue is still a probabilistically correct representation of $f(\mathbf{x})$. The method has been recently proposed by Jayaram and Baker (2010) for developing a small but stochastically representative catalogue of earthquake ground motion intensity *maps*, i.e. events, that can be used for risk assessment of spatially distributed systems. Nothing prevents the method from being employed for the risk assessment at a single site. The required modification is minor and concerns the criterion for clustering events. The remainder of this section describes the modified single-site version of the method, and the reader interested in the details of the differences can refer to Jayaram and Baker (2010).
The method uses an importance sampling density h on the random magnitude M. The original density

for M is defined as a weighted average of the densities $f_i(m)$ specified for each of the n_f active faults/sources, weighted through their corresponding activation frequencies λ_i (the mean annual rate of all events on the source, i.e. events with magnitude larger than the lower bound magnitude for that source). If m_{min} is the minimum magnitude of events on all sources, i.e. the minimum of the lower bound magnitudes of all considered sources, and m_{max} is the corresponding maximum magnitude, the range $[m_{min},m_{max}]$ contains all possible magnitudes of events affecting the site. The original probability density is much larger near m_{min} than towards m_{max}. The range $[m_{min},m_{max}]$ can be partitioned (stratified) into n_m disjoint intervals, chosen so as to be small at large magnitudes and large at smaller magnitudes. The procedure, also referred to as *stratified sampling*, then requires sampling a magnitude value from each partition using within each partition the original density. These leads to a sample of n_m magnitude values that span the range of interest, and adequately cover important large magnitude values. The IS density $h(m)$ for m lying in the k-th partition is then:

$$h(m) = \frac{1}{n_m} \frac{f(m)}{\int_{m_k}^{m_{k+1}} f(m)\,dm} \tag{2.1}$$

Once the magnitudes are sampled using IS, the rupture locations can be obtained by sampling faults using their conditional probabilities (if m is sampled outside the bounds of a source, the source cannot have generated the event).

Once magnitude M and location, and hence source to site distance R, have been sampled for an event, a ground motion time-series model (see section 3) can be used to generate an input motion to be used for structural performance assessment. Given the uncertainty affecting the motion at a site for a given (M, R) pair, repeated calls to the ground motion time-series model will yield different input motions. Often time-series coming from different events present similar spectral content. Repeating structural performance evaluation for such similar motions is not going to add much valuable additional information for the risk assessment. This is where the statistical technique of clustering plays its role. K-means clustering groups a set of observations into K clusters such that the dissimilarity between the observations within a cluster is minimized (MacQueen, 1967).

Let $\mathbf{S}_1,\ldots,\mathbf{S}_r$ denote the response spectra of r motions, generated using IS, to be clustered. Each spectrum $\mathbf{S}_j = \left[s_{1j},\ldots,s_{ij},\ldots,s_{pj}\right]$ is a p-dimensional vector (p being the number of considered vibration periods), where $s_{ij} = s_j\left(T_i\right)$ is the spectral ordinate at the i-th period for the j-th motion. The K-means method groups these events into clusters by minimizing V, which is defined as follows:

$$V = \sum_{i=1}^{K} \sum_{\mathbf{S}_j \in S_i} \left\| \mathbf{S}_j - \mathbf{C}_i \right\|^2 = \sum_{i=1}^{K} \sum_{\mathbf{S}_j \in S_i} \sum_{q=1}^{p} \left(s_{qj} - C_{qi}\right)^2 \tag{2.2}$$

where K denotes the number of clusters, S_i denotes the set of events in cluster i, $\mathbf{C}_i = \left[C_{1i},\ldots,C_{qi},\ldots,C_{pi}\right]$ is the cluster centroid obtained as the mean of all the spectra in cluster i, and $\left\| \mathbf{S}_j - \mathbf{C}_i \right\|^2 = \sum_{q=1}^{p} \left(s_{1qj} - C_{qi}\right)^2$ denotes the distance between the j-th event and the cluster centroid, evaluated as the Euclidean distance and adopted to measure dissimilarity.

Once all the events are clustered, the final catalogue can be developed by randomly selecting a single event from each cluster (accounting for the relative weight of each event), which is used to represent all events in that cluster on account of the similarity of the events within a cluster. In other words, if the event selected from a cluster produces a given structural response value, it is assumed that all other events in the cluster produce the same value by virtue of similarity. The events in this smaller catalogue can then be used in place of those generated using IS for the risk assessment, which results in a dramatic improvement in the computational efficiency. This procedure allows selecting K strongly dissimilar input motions as part of the catalogue, but will ensure that the catalogue is *stochastically representative*.

3. SYNTHETIC GROUND MOTION MODEL

3.1. Available models

Probabilistic models of ground motion can be roughly classified in two groups: seismologically-based models, and random or stochastic process models.

The development of the former models, which are based on the physical process of earthquake generation and propagation, is a success story whose beginnings date back not earlier than the late sixties. Today, these models have reached a stage of maturity whereby nature and consequences of the underlying assumptions are well understood, and hence they have started to be applied systematically in geographical regions where data are not sufficient for a statistical approach to seismic hazard, as, for example, in some North-American regions, or Australia, but also in several regions of the world whose seismic activity is well-known, for the double purpose of checking their field of validity and supplementing existing information. A list of applications of this latter type is contained in (Boore, 2003). The number of different models that have been proposed in the literature in the last two decades is vast: a recent survey with about two hundreds references is contained in (Papageorgiou, 1997); additional references can be found in (Boore, 2003).

One such model is described briefly here since it is widely used in applications and in particular it was employed in Jalayer and Beck (2008). It is the so-called *stochastic ground motion model* described by Atkinson and Silva (2000), whose origin is due to Brune (1971), Hanks and McGuire (1981) and Boore (1983). Generation of a realization of ground motion acceleration starts with the sampling of a sequence $\mathbf{w}$ of independent identically distributed (i.i.d.) variables representing a train of discrete acceleration values in time $w(t)$ (what is called a *white noise* sequence). This signal is then multiplied by an envelope function $e(t; M,R)$ that modulates its amplitude in time and is a function of the event magnitude M and source to site distance R (Iwan and Hou, 1989). A Discrete Fourier Transform (DFT) is then applied to the modulated signal and the resulting spectrum is multiplied with the so-called Radiation spectrum, which is the expected Fourier amplitude spectrum of the site motion. Inverse Fourier Transform yields back in the time-domain the generated non-stationary non-white sample of acceleration $a(t; M,R,\mathbf{w})$.

A comment is in order. In a study directed towards risk assessment, the uncertainties introduced at each step of the analysis need to be quantified. The variability introduced by multiplying the spectrum of the semi-empirical seismological model by that of a windowed white noise, although certainly reasonable, is just one component of the total variability. It is quite obvious that all parameters needed to get the radiation spectrum and not mentioned here must be affected by uncertainty, but this kind of epistemic uncertainty is disregarded altogether in the model. In this respect, the attribute *stochastic* attached to the model name is misleading. The only randomness is that introduced by the random white noise sequence $\mathbf{w}$. The resulting synthetic ground motions are thus expected to exhibit a lower variability than that characterising recorded ground motions. This was the reason for the introduction of a correction term in Jalayer and Beck (2008). Finally, the DFT-multiplication-IFT procedure inevitably introduces some distortion in the spectral content of the simulated samples.

Random process models started being developed in answer to a basic need of the earthquake engineering community: defining realistic models of the seismic action for design purposes. Without seismological models yet available, engineers started to look at the records that were rapidly accumulating, in search of ground motion properties possessing a stable statistical nature (given earthquake and site characteristics such as magnitude, distance and site soil type). This empirical approach focussed mainly on the frequency content of the motion, with due attention also paid to the modulation in time of the motion and, to a much lesser extent, to the modulation with time of the frequency content. It was the observed statistical stability of the frequency content of the motions under similar conditions of M, R and site conditions that led to the idea of considering the ground motion acceleration time-series as samples of random processes, i.e. random scalar functions of the scalar parameter t.

The simplest way to obtain a random function of time is as a linear combination of deterministic basis functions of time $h_i(t)$ with random coefficients $\mathbf{x}$. One class of such processes is that of *filtered white noise processes*, where the independent identically distributed random coefficients represent a train of discrete values in time $w(t)$ (the already introduced white noise sequence), and the functions $h_i(t)$

represent the impulse response function (IRF) of a linear filter. The well-known Kanai-Tajimi (Kanai, 1957) (Tajimi, 1960) process is one such process and the filter IRF is the acceleration IRF of a linear SDOF oscillator of natural frequency ω_g and damping ratio ξ_g. The next section introduces the model employed in this paper, which can be regarded as a very advanced version of the Kanai-Tajimi one.

3.2. The employed model

The model by Rezaeian and Der Kiureghian (2010), denoted R-ADK in the following, has been used in this work to sample synthetic ground motions. In order to introduce frequency non-stationarity it makes the filter parameters time-dependent: $\omega_g(t)$ and $\xi_g(t)$, collectively denoted as $\boldsymbol{\lambda}(t)$. The output of the filter (the filtered white noise) is then normalised to make it unit-variance and modulated in time. Finally, the process is high-pass filtered to ensure zero residual velocity and displacement and accuracy for long-period spectral ordinates of the synthetically generated motions.
The strength of the model rests in the predictive equations that the authors have developed, through statistical regression, for the model parameters as functions of earthquake and site characteristics such as magnitude M, distance R, faulting style F and average shear wave velocity V_{s30}.
The model parameters have been identified within the selected set of recorded motions, which is targeted at "strong" shaking, and includes only $M \geq 6$ and $R \geq 10$km records, specifically excluding motions with near-fault features. The authors have worked with a reduced set of recorded ground motions taken from the so-called NGA (Next Generation Attenuation) data base (PEER-NGA).
This empirical model has been only briefly recalled here; a detailed description can be found in Rezaeian and Der Kiureghian (2010). **Figure 1** shows some sample motions generated for four different (M,R) pairs (two motions for each pair).

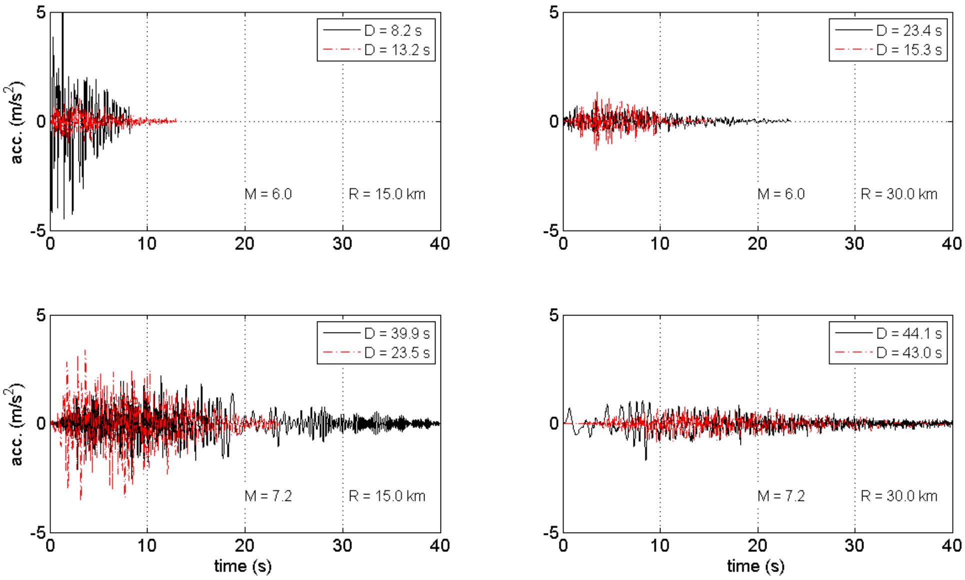

Figure 1. Acceleration time-series obtained from the R-ADK model for different (M,R) pairs.

4. EXAMPLE APPLICATION

The MC, IS and IS-K methods described in §2, jointly with the R-ADK time-series model described in §3.2, are applied to the determination of the Mean Annual Frequency (MAF) of exceedance of a structural limit state, λ_{LS}, for the fifteen storeys RC plane frame shown in **Figure 2**. Results show how MAFs in the order of 10^{-3} can be obtained with a few hundreds of analyses when the more effective method is employed.
Given that, subject to the quality of the ground motion time-series model, this approach is more general than the IM-based one, the example offers a term of comparison for the results obtained with the conditional probability approach. Within the limits of the considered example, the outcome of this

comparison provides a cross-validation, of the IM-based methods versus the non-conditional ones, and of the employed synthetic ground motion model versus real records.
Figure 2 shows the frame overall dimensions and the reinforcement (with layout shown in the same figure, all bars same diameter), in terms of geometric reinforcement ratio (percent), of the total longitudinal reinforcement for columns and of the top longitudinal reinforcement for beams (at column-beam joints). Beams have all the same cross-section dimensions, 0.30m wide by 0.68m deep, across all floors. Columns taper every five floors. Exterior columns, with a constant 0.50m width, have 0.73m height for the base and middle columns, 0.63m for top columns. Interior columns, with a constant 0.40m width, have 0.76m, 0.73m and 0.62m height, for the base, middle and top columns, respectively.

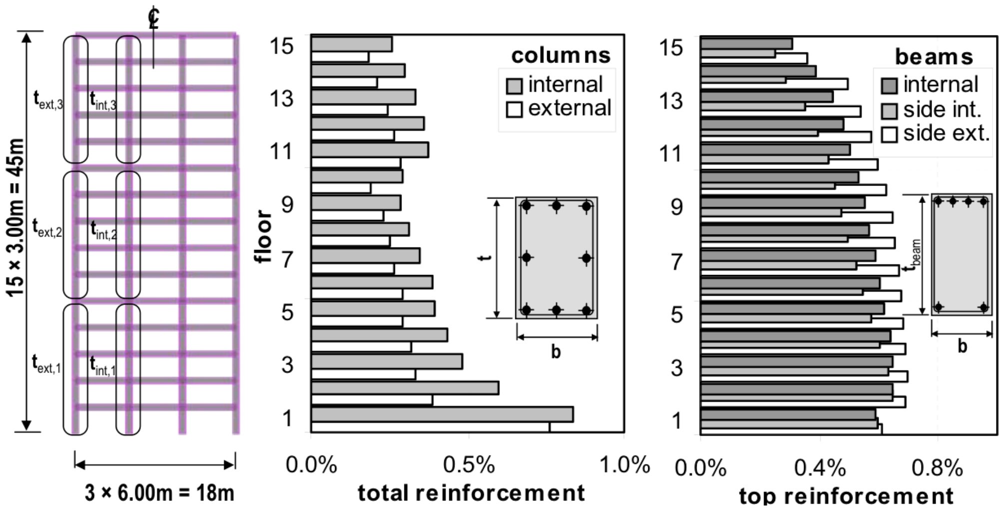

Figure 2. The 15-storeys RC plane frame.

The frame is located at a site affected by two active seismo-genetic sources, whose probabilistic model for the activity rate is the truncated Gutenberg-Richter one, which gives the mean annual rate of events with magnitude $M \geq m$ on source i as the product of the mean annual rate of all events λ_i on the source, and the probability that given an event, it has $M \geq m$. The values here assigned to the activity parameters are: source #1, $\lambda = 0.43$, magnitude slope $\beta = 1.96$, lower and upper magnitude limits M_L = 6 and M_U = 7; source #2, $\lambda = 0.11$, $\beta = 2$, M_L = 6.5 and M_U = 7.3.
For all methods (IM-based and non-conditional) structural response has been evaluated with an inelastic model set up in the analysis package OpenSEES. The model consists of standard nonlinear beam-column elements with fibre discretised sections (Scott-Kent-Park concrete and Menegotto-Pinto steel models). Gravity loads are applied prior to time-history analysis. The structural performance measure adopted is the peak inter-storey drift ratio θ_{max}.

4.1. Results of MC, IS and IS-K methods

The results shown in the following are obtained by means of three independent simulations: a reference case consisting of a plain Monte Carlo simulation (MCS) with 10,000 runs, an Importance Sampling simulation (ISS) on magnitude with 1,000 runs, and the IS-K method where the 1,000 ground motions previously sampled with IS are clustered into 150 events. In all cases, given a (*M,R*) pair (together with values for V_{s30} and fault mechanism), the R-ADK model is employed to produce an acceleration time-series at the site of the frame.
For the IS-K method, the clustering follows an iterative procedure, whose final result is usually obtained in less than 10 iterations. For the sake of illustration, **Figure 3** shows the first nine clusters obtained from the procedure. The motions are represented by their displacement response spectra. The spectrum of the time-series sampled to represent the whole cluster is shown in solid black. Notice how cluster size is not constant (e.g. compare clusters #2 and #5, the latter having only two time-series).
Figure 4, left, shows the histogram of the relative frequency of the θ_{max} samples from the MC. Similar

histograms, with a lower number of bins reflecting the smaller sample size, are obtained for the IS and IS-K methods. These histograms are used to obtain the cumulative distribution function $F_{\theta max}(x)$.

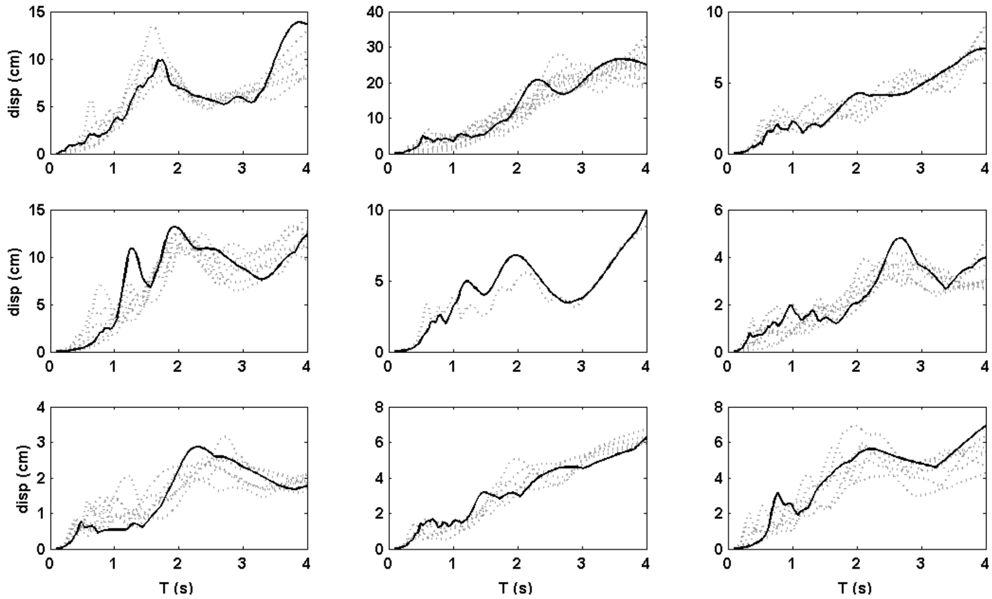

Figure 3. Nine of the 150 clusters employed in the IS-K method: displacement spectra of the time-series in each cluster (dashed grey) and spectrum of the randomly selected record representative of the cluster (solid black).

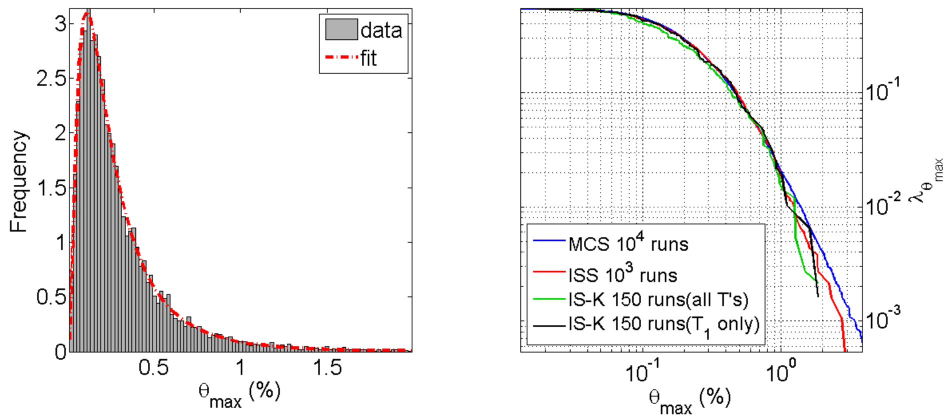

Figure 4. Histogram of the relative frequency of the θ_{max} samples from the MCS (left) and MAF of exceedance of θ_{max}, obtained from different simulation methods (right).

Figure 4, right, shows the MAF curves for θ_{max} obtained by the three simulation methods according to the expression:

$$\lambda_{\theta max}(x) = \lambda_0 G_{\theta max}(x) = (\lambda_1 + \lambda_2)\left[1 - F_{\theta max}(x)\right] \tag{3.1}$$

The curves are remarkably close to each other, down to rates in the order of 10^{-3}, which is also as far as one can trust an MCS result with 10,000 runs. In the figure there are two curves for IS-K method. They correspond to two clustering criteria: the first (green line) determines similarity of the time-series based on their full response spectrum, while the second criterion uses only the spectral ordinate at the fundamental period of the structure. The closeness of the two curves is expected due to the dynamic properties of the considered structure which has only a weak second mode contribution to response.

In conclusion, the IS-K method is shown to yield results equivalent to those obtained with plain MC, for an effort which is two orders of magnitude lower, making the approach affordable in practice.

4.2. Comparison with the IM-based approach

As already mentioned, the cornerstone of the IM-based approach is the split between the work of the seismologist, that characterises the seismic hazard at the site with a MAF of an intensity measure, and that of the structural engineer, whose task is to produce the conditional distribution of the limit state given the IM.
In order to be able to compare the two approaches, it is first necessary to investigate differences in the hazard, as obtained through attenuation laws during a PSHA, and as implied by the employed ground motion model in the non-conditional simulation approach. Large differences in the intensity measure at the site, based on the same regional seismicity characterisation, would directly translate into different MAFs of structural response.
Figure 5 shows the MAF of the spectral acceleration, at the first mode period of the frame, T_1=2.2s (left) and at T=1.0s (right), evaluated through PSHA, employing six distinct attenuation laws, five of which developed as part of NGA effort (PEER, 2005) and, thus, sharing the same experimental base (recorded ground motions) as the Rezaeian and Der Kiureghian synthetic motion model. The figure shows also the MAF of S_a obtained from the synthetic motions sampled for the MCS and ISS cases.
As shown by the figure, the hazard obtained employing the synthetic motions falls within the range of variability of the attenuation laws. Comparing **Figure 5**, left and right, one can see how the performance of the synthetic ground motion model is not uniform over the range of vibration periods. In any case, the quality of its predictions should be judged in light of the differences exhibited by the GMPEs themselves. The GMPE by Idriss shows a closer match at both periods and is used in the comparison of MAFs of structural response (addressed below).

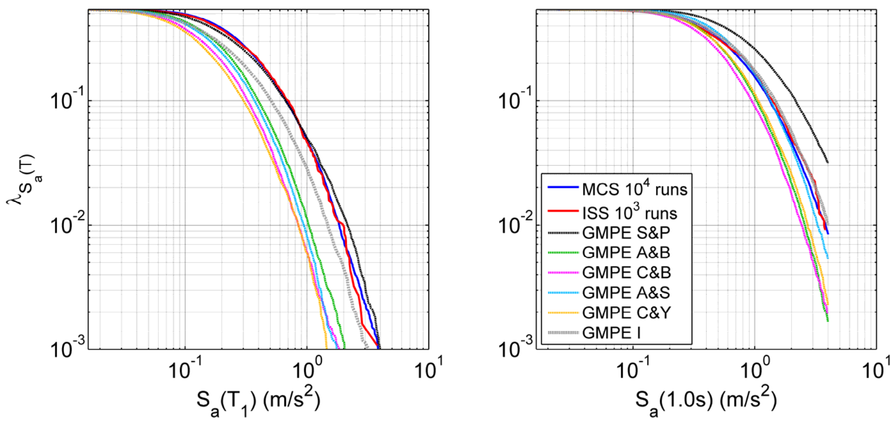

Figure 5. Mean annual frequency of exceedance of the spectral acceleration (hazard curve), at the first mode period T_1 = 2.2s (left) and at T = 1.0s, as obtained by PSHA with different attenuation laws (S&P: Sabetta and Pugliese 1996, A&B: Atkinson and Boore, C&B: Campbell and Bozorgnia, A&S: Abrahamson and Silva, C&Y: Chiou and Youngs, I: Idriss) and by postprocessing the spectral ordinates of the synthetic motion samples.

In the IM-based or conditional probability approach structural analysis for recorded ground motions are employed to establish the distribution of maximum response conditional on intensity measure. This can be done in essentially two different ways, through an Incremental Dynamic Analysis (IDA) (Vamvatsikos and Cornell, 2002), which involve scaling of records, and a Cloud Analysis, which employs unscaled records. In the former case motions are scaled to increasing levels of the IM to produce samples of the engineering demand parameter (EDP) from which a distribution, commonly assumed lognormal, is established at each level. In the latter case, additional assumptions are made, two of which are related to the distribution of EDP given the IM: the median EDP-IM relationship is approximated with a power-law, and the EDP dispersion is considered independent of the IM. **Figure 6** shows the IDA curves that relate the chosen EDP = θ_{max} with the IM = $S_a(T_1)$. Two sets of curves are shown, one obtained with 30 motions taken randomly from those sampled for the MCS using the R-ADK model, labelled “Synthetic”, on the left, and the other obtained with 30 recorded ground motions taken randomly from the same set of records (PEER, 2005) used as a basis to develop the R-ADK model. The figure shows with black dots the structural analyses results (S_a- θ_{max} pairs) employed to draw the IDA curves, and with red dots the values of θ_{max} interpolated at one value of $S_a = y$, to establish the complementary distribution $G_{\theta_{max}}\left(x \middle| S_a = y\right)$ (basically estimating $\mu_{ln\,\theta_{max}}\left(y\right)$ and $\beta_{\theta_{max}}\left(y\right)$ - the figure reports the estimates of median and dispersion at the same intensity for the two cases). Notice that the number of analyses is not the same for the synthetic and natural motions. This is due to the algorithm used to trace the curves which requires a number of analyses that is record-dependent (see Vamvatsikos and Cornell, 2002).

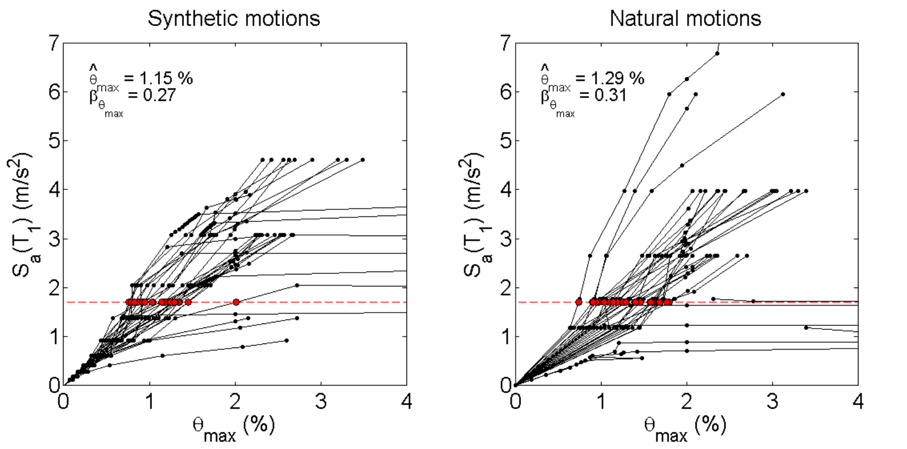

Figure 6. IDA curves obtained with 30 motions (synthetic on the left, natural recorded motions on the right).

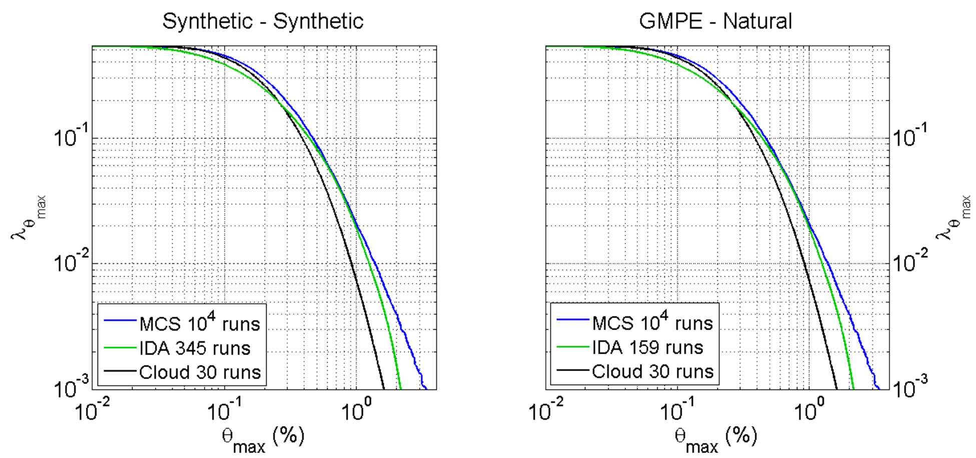

Figure 7. Mean annual frequency of exceedance curves of the peak inter-storey drift ratio, obtained from non-conditional and conditional approaches.

The final results can be condensed in the two MAF plots shown in **Figure 7**. The left plot shows the MAF of structural response obtained using synthetic motions also for the conditional probability approach, i.e. for deriving the hazard curve and the distribution of response. This plot provides a comparison of the probabilistic approaches "all other factors being the same", and the results show that, at least for the considered structure, the approximation associated with the IM-based method is completely acceptable. The right plot shows analogous results where now the IM-based curves are obtained with the Idriss hazard curve and recorded ground motions. The match is still quite good for the IDA-based case, while the Cloud with its fewer runs and constrained median response predicts lower values. The good match constitutes a measure of the quality of the synthetic ground motion model, which, as claimed by its authors, simulates with an acceptable accuracy both the median intensity of natural motions and their total variability. As a final comment, it appears from the above analyses that IS-K and IDA yield similar results with comparable efforts (150 vs 159 runs in this particular case), suggesting that the choice between these methods may become in a not so distant future a matter of personal preference.

5. CONCLUSIONS

Probabilistic assessment of seismic performance of a fifteen storeys RC plane frame, in terms of mean annual frequency of the peak inter-storey drift ratio θ_{max}, is carried out employing two classes of methods, i.e. the reliability (or non-conditional) methods and the so-called IM-based (or conditional) ones. Among the different alternatives comprised by both classes, this work considers two IM-based alternatives, and three non-conditional ones. First, a comparison between the MAF curves obtained with the three non-conditional methods, i.e. Monte Carlo, Importance Sampling and IS with K-means clustering, clearly shows that the latter cheaper method yields results practically equivalent to those obtained with plain MC making the approach affordable in practice. Then, the good match of the simulation-based MAF curves with those obtained with IM-based methods using the same synthetic motions to compute hazard and fragility, provides a validation of the IM-based methods, whose associated approximation is shown to be completely acceptable. Finally, analogous results obtained by comparing simulation-based MAF curves with IM-based ones retrieved with regular GMPE and real records provide a measure the quality of the synthetic ground motion model and hint at a future where methods will converge in terms of results and effort.

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