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PROBABILISTIC SEISMIC DEMAND MODEL FOR RC FRAME BUILDINGS USING CLOUD ANALYSIS AND INCREMENTAL DYNAMIC ANALYSIS

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ABSTRACT

Incremental dynamic analysis (IDA) is developed for accurate estimation of seismic demand and capacity of structures. IDA requires nonlinear time history analysis of the structure for a selected ground monition scaled to many intensity levels to capture the entire range of structural response ranging from elastic to collapse. Recognising that IDA is computationally intensive, the cloud analysis is generally preferred in practice to develop a probabilistic seismic demand model of structures. The accuracy of the demand model estimated using cloud analysis, however, is believed to strongly depend on the selection of ground motion records. In this paper, the seismic demand estimated from the IDA and cloud analysis with a careful selection of ground motion records is compared with reference to two RC frames (four-, and eight- storey) representative of code conforming buildings. Use of static pushover analysis and its approximate relation with fractile IDA curves are proposed to estimate the collapse capacity (i.e., median and dispersion of spectral acceleration) of each structure and guide the selection of ground motion records for the cloud analysis to cover the full range of the structural response. Finally, the seismic demand model accounting for collapse is developed and the model parameters and probability of collapse are determined. These models represent a fundamental tool in portfolio loss assessment.

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ABSTRACT

Incremental dynamic analysis (IDA) is developed for accurate estimation of seismic demand and capacity of structures. IDA requires nonlinear time history analysis of the structure for a selected ground monition scaled to many intensity levels to capture the entire range of structural response ranging from elastic to collapse. Recognising that IDA is computationally intensive, the cloud analysis is generally preferred in practice to develop a probabilistic seismic demand model of structures. The accuracy of the demand model estimated using cloud analysis, however, **is** believed to strongly depend on the selection of ground motion records. In this paper, the seismic demand estimated from the IDA and cloud analysis with a careful selection of ground motion records is compared with reference to two RC frames (four-, and eight- storey) representative of code conforming buildings. Use of static pushover analysis and its approximate relation with fractile IDA curves are proposed to estimate the collapse capacity (i.e., median and dispersion of spectral acceleration) of each structure and guide the selection of ground motion records for the cloud analysis to cover the full range of the structural response. Finally, the seismic demand model accounting for collapse is developed and the model parameters and probability of collapse are determined. These models represent a fundamental tool in portfolio loss assessment.

Introduction

Performance-based earthquake engineering (PBEE), almost two decades after Cornell presented his seminal paper [1], is approaching maturity. The PBEE entails estimation of performance through explicit consideration of uncertainty (aleatoric and epistemic) in both demand and capacity, and use of nonlinear structural response. The turning point in the field was the introduction of the so-called "IM-based" methods [2] (where IM stands for intensity measure) for evaluating the probability distribution of performance measures, and the large concerted effort led mainly by the Pacific Earthquake Engineering Research Center (PEER) to promote the new paradigm [3].

IM-based methods utilize the theorem of total probability to split the computation of the probability, or of the rate, of a performance measure exceeding any given threshold, into those of evaluating the rate of the action (seismic hazard) and of evaluating the probability of its effect (structural demand given the intensity):

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$$\lambda_D(d) = \int_0^\infty p(D > d | S = s) \left| \frac{d\lambda_S(s)}{ds} \right| \quad (1)$$

where λ is the rate of exceedance, D is the demand, S the seismic intensity measure, and $p(D>d|S=s)$ is the probability of the demand exceeding the threshold d given that the intensity equals the level s.

Eq. (1) and IM-based methods have been the subject of a considerable body of research. Closed-form solutions of Eq. (1) have been proposed [4][5][6]. Various studies have been devoted at checking the approximation made [7][8] and reaching the conclusion that the main source of error is in the linear fit (in log-log space) of the seismic hazard curve. The latter limitation, on the other hand, is relaxed with consideration of second-order logarithm formulation [5][6][9].

While the issue of approximation of closed-form solutions is of great relevance to the adoption of the PBEE paradigm by the practicing engineers, other issues raise greater concerns. The first is the accuracy of IM-based methods in a wider sense. Eq. (1) rests on the assumption that, given S, the demand D is independent of all other ground motion properties, which is called the *sufficiency* property of the IM [10]. While it is obvious that $\lambda_D(d)$ is theoretically unique, multiple studies have highlighted how estimations obtained by Eq. (1) exhibit a non-negligible dependence upon the chosen IM, i.e.:

$$\lambda_D^{(1)}(d) = \int_0^\infty p(D > d | S_1 = s_1) \left| \frac{d\lambda_{S1}(s_1)}{ds_1} \right| \neq \lambda_D^{(2)}(d) = \int_0^\infty p(D > d | S_2 = s_2) \left| \frac{d\lambda_{S2}(s_2)}{ds_2} \right| \quad (2)$$

This is of course due to the lack of sufficiency of the chosen IMs. The solution to this problem can be sought by careful selection of ground motion records used to estimate $p(D>d|S=s)$. It is well known that, in order to compensate for what is missing in the chosen IM (in terms of characterization of the ground motion at the site), records should be chosen so as to reflect as closely as possible the causative events dominating seismic hazard at the site. Proposals for such informed and targeted records selection include simple spectrum-matching with records from a magnitude and distance bin chosen by hazard de-aggregation [11], conditional mean spectrum matching [12][13] with consideration of "epsilon", to selection of records to match the full conditional probability distribution (not just the conditional mean) of ground motion given the intensity measure [14]. Bradley [15] has recently confirmed that $\lambda^{(1)}_D = \lambda^{(2)}_D$ in a formal manner, provided that the set of records are different and appropriately selected.

A second important issue, which is also relevant to adoption of the PBEE paradigm in practice, but becomes of really paramount importance in urban/regional loss assessment studies [16][17], is that of *efficiency* of the IM. Efficiency is directly related to the computational cost of evaluating $p(D>d|S=s)$. A more efficient IM is better related to the response and requires a smaller number of analyses to characterize the demand distribution. The problem with efficiency, however, is that there is no optimally efficient IM for all different types of response measures of interest, or even for the same response measure at different locations.

Computational cost also depends on the type of IM-based approach adopted [18]. Basically there are three approaches. The most accurate is the Multiple Stripe Analysis (MSA), which consists of performing structural analysis for a number of records scaled all to the same $S=s$ level, and estimating the parameters of an assumed demand distribution (the lognormal one being by now confirmed to be an appropriate model in almost all cases, for both displacement and acceleration responses). This is repeated for as many levels of S as desired, to cover the full range of response from linear elastic to collapse. The accuracy of this approach is due to the fact that at each $S=s$ level the employed records can (and should) be changed to reflect the change in causative events and in particular in the distribution of motion given S. Optimal application of MSA would require the use of different suits of records at each intensity level, as well as selection to minimize scaling to the desired intensity. Whether scaling of records is allowed, and in case to what extent, has been the subject of much speculation. Luco and Bazzurro [19] have produced evidence that indeed scaling introduces a bias in the response and have also provided a preliminary estimation of the dependence of this bias upon the amount of scaling. Nonetheless, in practice, MSA is seldom if ever carried out with different suites of records and, thus, scaling is used and results do not differ much from what is obtained by the second IM-based approach, the Incremental Dynamic Analysis (IDA) [20]. Scaling is indeed at the very heart of IDA. Both MSA and IDA are extremely intensive from a computational point of view, even though ‘economic’ variants of MSA with one, two or three stripes have been considered [18][21].

At the other end of the spectrum, one finds the so-called ‘cloud’ analysis. This third IM-based approach consists of performing structural analysis for a number of motions at their unscaled recorded intensity, to collect a ‘cloud’ of intensity-response data points, and then using regression analysis to evaluate the parameters of the conditional demand distribution. Cloud analysis being by far the most cost-effective one, it is very attractive as a means to establish probabilistic seismic demand models for large number of buildings, such as those needed in a loss assessment study [16][17]. Further advantage, with respect to the MSA method, is that based on the same analyses different demand models can be established with different regressions, choosing the best IM for each demand quantity.

For the above reasons, this paper explores how to maximize accuracy of the cloud analysis and evaluates its’ effectiveness by comparison with IDA results for two RC plane frame buildings.

Methodology

Cloud analysis has been originally used by Cornell et al. [4] to support a lognormal demand model with constant ‘dispersion’ β_D (or σ_{lnD}) and conditional median given by:

$$D_{50\%}\left(S=s\right)=a\cdot s^{b} \quad (3)$$

This particularly simple model was chosen because it allowed closed-form solution of the risk integral. More elaborate analytical forms have been proposed thereafter, for both the median and the dispersion, and shown to offer a better fit to numerical response results. For instance, Aslani and Miranda [7] propose conditional median and dispersion *vs* intensity relationships in the form:

$$D_{50\%}\left(S=s\right)=a\cdot s^{b}\cdot c^{s} \quad (4)$$

$$\beta_D\left(S=s\right)=\beta_1+\beta_2 s+\beta_3 s^2 \quad (5)$$

They also suggest that the fit should be performed by excluding outliers, i.e. collapse data points.

The approach in [7], however, is meant for structure-specific loss estimation, while the goal of this paper is to provide a tool appropriate for introducing elements of structure-specific analysis in the context of large-scale urban loss assessment, as a replacement for generic fragility curves. Thus, while it is possible to adopt Eq. (4) for the conditional median, it is not possible to fit Eq. (5) to cloud analysis results (indeed, MSA, with quite a large number of records per level, was used in [7] for that purpose).

One important issue in deriving the conditional demand distribution is that, with increasing seismic intensity, the likelihood of collapse increases and collapse tends to dominate and distort the demand distribution. To correct this, a three parameters (lognormal) distribution (TPD) was proposed in [22]:

$$p\left(D>d\middle|S\right)=p\left(D>d\middle|S,NC\right)p\left(NC\middle|S\right)+p\left(C\middle|S\right) \tag{6}$$

where $p(D>d|S,NC)$, assumed to be lognormal with parameters estimated based on non-collapse data only, is the probability of demand conditional on the non occurrence of collapse (*NC*), while $p(C|S)=1-p(NC|S)$ is the collapse fragility, estimated by a binary regression model [22]. Alternative approximate choices for the collapse fragility have been also proposed. For example, [23] suggest using, even if within their method it is used as a first approximation, a lognormal collapse fragility with estimated parameters. Finally, a general advice about the need to select records to cover the range of required intensities was also given in [22].

Based on the above, herein we propose the following approximate procedure:

1. Estimate fractile IDA curves of the structure by means of pushover analysis, using a tool such as ‘SPO2IDA’ [24]. This requires a piece-wise linear fit of the pushover curve (Fig. 2, left).
2. Use these approximate IDA (Fig. 2, right) to get an estimate of the upper bound collapse intensity (s_C). Select records to span in an approximately uniform manner the intensity range [s=0, $s=s_C$]. Records should also be selected at least with reference to the causative events (magnitude and distance bins) from PSHA of each sub-interval in which [s=0, $s=s_C$] is divided (these need not to be large in number).
3. Perform cloud analysis and collect intensity-response data points for all responses of interest, as shown in Fig. 3.
4. Identify outliers and carry out regression analysis to fit the median model in Eq. (4) with a *constant* dispersion to non-collapse points.
5. Use the approximate IDA from step 1 to evaluate median and dispersion of the collapse intensity, $s_{C,50\%}$ and β_{sc}, parameters of the approximate lognormal collapse fragility.

The above steps allow establishing a demand model in the form:

$$p\left(D>d\middle|S=s\right)=\Phi\left(\frac{\ln\left(as^{b}c^{s}/d\right)}{\beta_D}\right)\Phi\left(\frac{\ln\left(s_{C,50\%}/s\right)}{\beta_{s_C}}\right)+\Phi\left(\frac{\ln\left(s/s_{C,50\%}\right)}{\beta_{s_C}}\right) \tag{7}$$

Application

Reinforced concrete (RC) frames considered

Two reinforced concrete (RC) (four- and eight-storey) special moment frame (SMF) buildings designed according to ASCE7-02 and ACI318-02 (see [25][26] for details) are selected to illustrate the proposed methodology. The SMF designs were controlled primarily by the strength demands to achieve the target seismic design coefficient, the strong column weak-beam requirement, joint shear capacity provisions, and drift limitations. Additional details on the structural design variants can be found in [25].

Modeling choices

A two-dimensional nonlinear finite element analysis model was set up in OpenSEES for time-history analysis [25][26]. In order for the structural models to accurately predict the response for low (i.e., elastic response) -to high (i.e., collapse)- intensity ground motions, the frames are modelled using the plastic-hinge model, which lumps the bond-slip and beam-column yielding response into one concentrated hinge, to capture the strength and stiffness deterioration and collapse behaviour. For the hinges a trilinear backbone curve developed by Ibarra et al. [27] is used [25]. P-Δ effects are accounted for using a combination of gravity loads on the lateral resisting frame and gravity loads on a leaning column element. The first mode period T_1 is computed to be 1.0 s and 1.8 s for four- and eight- storey frame, respectively.

Seismic hazard

The building is assumed to be located in Los Angeles [118.250 ^{o} W, 34.050 ^{o} N], and the seismic hazard for two fundamental periods, T_1 = 1.0 s (Figure 1, left) and T_1 = 2 s (Figure 1, right), are computed from the USGS (https://geohazards.usgs.gov). The PSH Deaggregation on NEHRP BC rock is considered and 30 ground motion records were selected from the representative (M_w, r) pairs at the site to cover the spectral acceleration at first mode period from low intensity to collapse. The M_w ranges from 5.4 to 7.2 and r ranges from 0.5 km to 30 km.

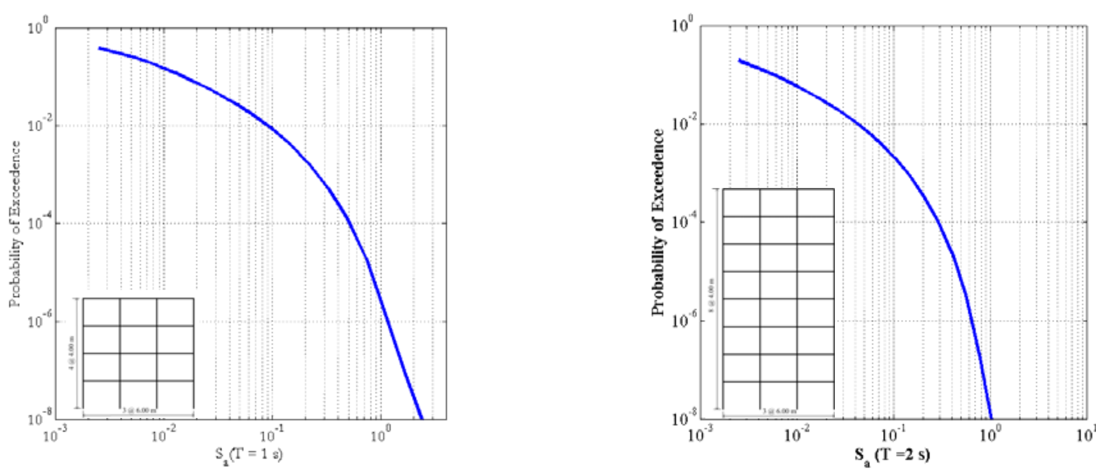

Figure 1. Seismic hazard at the site

Results and discussion

Fig. 2 (left) shows the static pushover curves (SPO) and their piecewise linear approximation. Fig. 2 (right) shows the approximate IDA curves computed using "SPO2IDA" software. The median collapse spectral capacity ($S_{C,50\%}$) is around 2g and 1g, for 4- and 8-storey frame respectively. The approximate 16, 50, and 84% fractile IDA curves computed by SPO2IDA tool, are used to determine the collapse distribution parameters (i.e., $S_{C,50\%}$ and β_C).

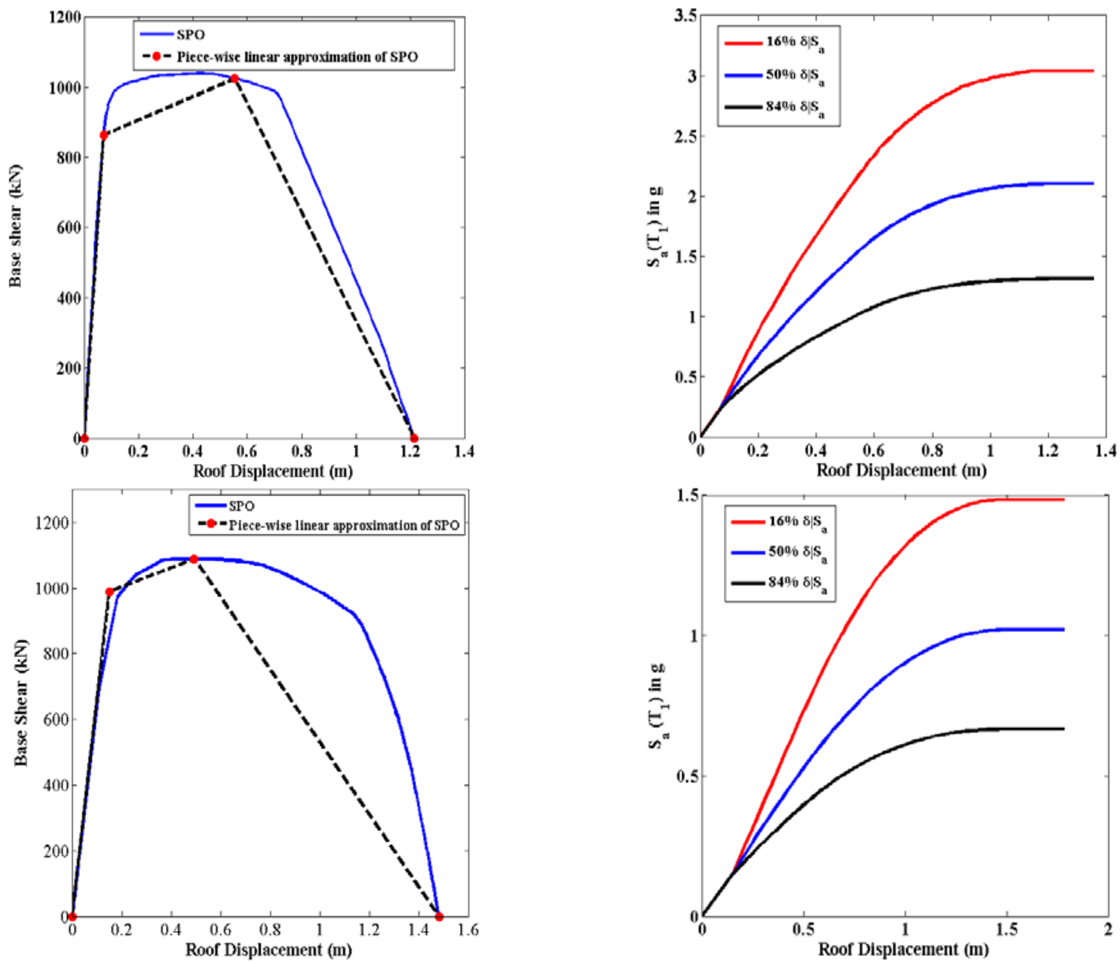

Figure 2. Pushover curves, piece-wise linear approximations and approximate IDA from SPO2IDA for the considered frames 4- (top) and 8- storey (bottom)

As stated above a set of 30 records was selected to cover up to maximum collapse spectral capacity (i.e., 16% percentile IDA). The nonlinear time-history analysis was performed and maximum interstory drift ratio (θ_{max}) is obtained. Fig. 3 (left, 4 storey) shows intensity-response scatter plot for uninformed (UI) and informed (I) ground motion record selection. The cloud analysis is performed, and median non-collapse, 16^{th} and 84^{th} percentile demand model are computed using Eqs. 3 and 4. The median demand model developed according to Eq. 3 for (I) record set differs only slightly from the (UI) record set (Fig. 3, left). Moreover, use of Eq.(4) over (3) results in a negligible improvement in the quality of the fit.

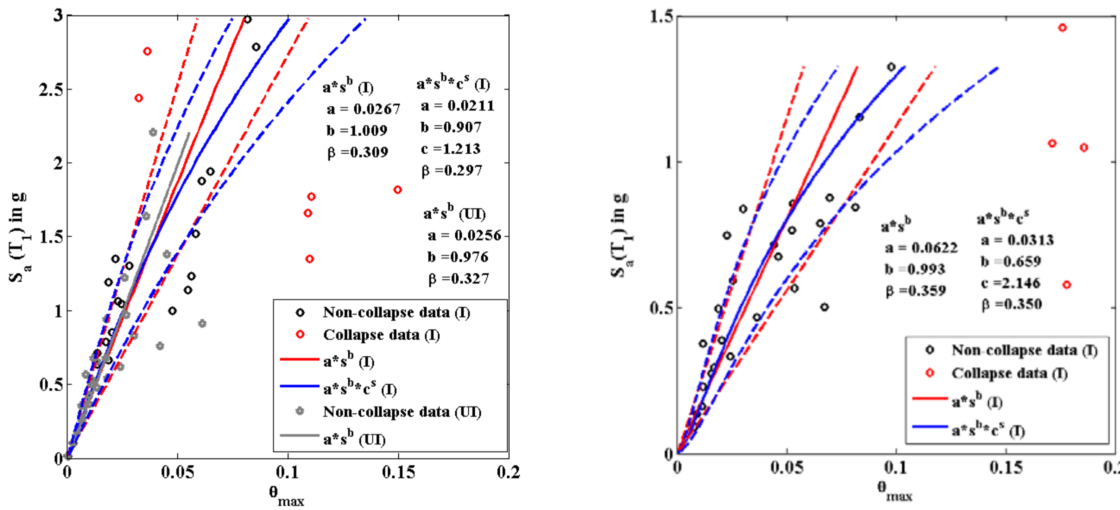

Figure 3. Cloud analysis and the median non-collapse demand model fit (solid line) together with the 16th and 84th percentile (dash line) for the considered frames: 4-storey (left) and 8-storey (right) [Collapse points are plotted but not used in the model].

Next, IDA was performed (see Fig. 4) and used to determine the collapse distribution parameters, which is identical to the one computed from the approximate IDA (Table 1). The informed cloud data points, together with IDA curve, are also shown in Fig. 4. The points are distributed satisfactorily to cover the IDA results up to collapse range.

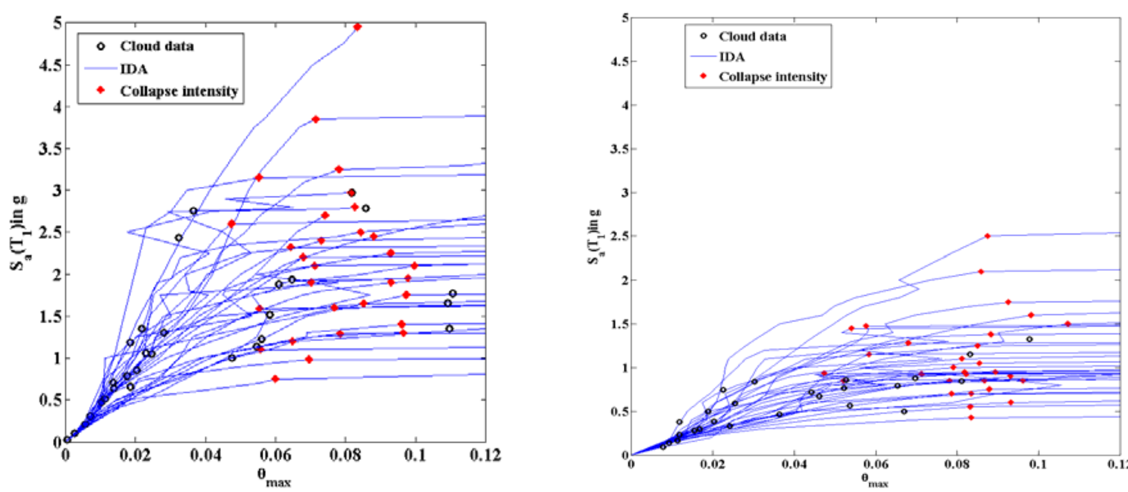

Figure 4. IDA curves and identification of the collapse intensity for 4-storey frame (left) and 8-storey (right).

Table 1. Collapse distribution parameters

Building	From approximate IDA		From full IDA	
	$S_{C,50\%}$ (g)	β_C	$S_{C,50\%}$ (g)	β_C
4-storey	2.02	0.423	2.00	0.411
8-storey	1.02	0.403	1.03	0.391

Finally, the drift hazard curves are developed by integrating the Eq. 7 and seismic hazard for both frames using the demand models fitted according to Eqs. 3 and 4, and IDA (Fig. 5). A good match in all three curves, for both building, confirms validity of proposed method. The mean annual frequency of exceeding collapse computed using both approximate fragility from spo2IDA and full IDA results is, respectively, 1.221e-6 and 1.208e-6 for 4-storey frame, and 1.557e-6 and 1.362e-6 for 8-storey frame.

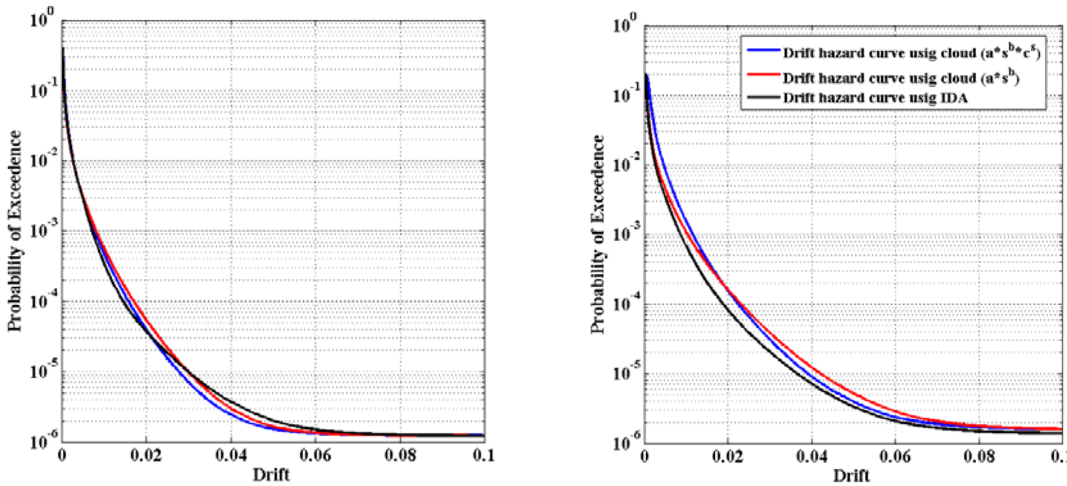

Figure 5. Drift hazard curve computed with IDA and cloud: 4-storey (left) and 8-storey (right).

Conclusions

The paper proposes a method to effectively use "Cloud analysis" to capture structural response up to collapse. The method is computationally cheaper than IDA/MSA and employs dynamic analysis as opposed to other approximate methods that rely on nonlinear static one, thus accounting for record-to-record variability and cyclic degradation, which are very important for non code-conforming structures. Concerns about the method are that it uses an approximate collapse fragility and retains the constant demand dispersion assumption and a fixed median response model. Numerical tests on two frames, however, have shown that the drift hazard curve obtained is a good approximation of that from a full IDA, owing to good performance of the approximate collapse fragility from spo2IDA, and the fact that, excluding collapse points, power laws for the median and a constant dispersion are acceptable. The method can be thus employed in urban loss estimation as a replacement for generic fragility curves to improve confidence.

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