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DEMAND-ORIENTED GROUND MOTION SELECTION USING NONLINEAR PREDICTORS OF RESPONSE

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Abstract

The purpose of performance-based earthquake engineering is to design structures for predictable and controlled seismic performance within established levels of risk. Rigorous quantification of seismic performance requires computing the seismic demand hazard, this is, the risk of incurring a certain level of seismic demand. However, risk-based assessments are not feasible in engineering practice because of the large number of nonlinear response history analyses required for such purpose. Alternatively, an estimate of the level of seismic demand for a specified risk can be obtained from an intensity-based assessment (IBA), i.e., from an ensemble of ground motions scaled to a fixed value of a single conditioning intensity measure (IM). Evidently, the accuracy of the estimate provided by an IBA depends on how well the conditioning IM can predict the response in terms of the demand measure of interest. The choice of the conditioning IM is limited among those for which a ground motion models are available. The reason for this is that the ground motion models are required to compute the seismic hazard at the site in terms of IM and select a hazard consistent ensemble of records that allows to obtain an unbiased estimate of the conditional response. As a result, practical IMs usually consist of spectral accelerations, which obviously have a limited capability for predicting the response of complex nonlinear multi-degree-of-freedom structures. This paper presents a ground motion selection procedure that allows to conduct IBAs conditioned upon IMs or predictors of response for which ground motion models are not available. The procedure relies on the empirical characterization of the seismic hazard at the site in terms of the predictor by means of a large set of ground motions, and on the deaggregation of results to identify a reduced set of records to compute the conditional response. The procedure is demand-oriented in the sense that it provides, for each demand measure of interest, a unique ensemble of ground motions to obtain an accurate estimate of the level of demand for a specified risk at a reduced computational cost.

Keywords: seismic performance assessment, ground motion selection, predictors of response

1. Introduction

The purpose of performance-based earthquake engineering is to design structures for predictable and controlled seismic performance within established levels of risk. This implies the need for defining performance objectives (PO), which specify the acceptable risk of incurring a certain level of seismic demand. A general PO for a given measure of structural response or Engineering Demand Parameter EDP can be expressed as $\lambda_{EDP}(edp_a) < \nu_f$, where λ_{EDP} is the annual rate of exceedance of a certain level of demand for the parameter EDP, edp_a is the allowable level of seismic demand, and ν_f is the target rate of failure.[1] Alternatively, the same PO can be expressed more explicitly as

$$edp_f < edp_a \tag{1}$$

where edp_f is the level of demand for the target rate of failure, this is, $\lambda_{EDP}(edp_f) = \nu_f$ [1]. Both expressions are equivalent, and the difference lies only on the quantity that needs to be determined for conducting the design check. For example, suppose that the response measure of interest is the maximum floor acceleration MFA, and that the design is intended to ensure that the probability of MFA exceeding mfa_a = 1g is less than 2% in 50 years (equal to an annual exceedance rate of 0.0004yr^{-1}). In such case, the PO can be expressed either as $\lambda_{MFA}(1\text{g}) < 0.0004\text{yr}^{-1}$ or $mfa_f < 1\text{g}$, with $\lambda_{MFA}(mfa_f) = 0.0004\text{yr}^{-1}$.

Evaluation of such probabilistic POs requires conducting response history analyses (RHA) of a realistic (and therefore sophisticated) structural model to an ensemble of earthquake ground motions. This is necessary not only for deriving numerical values, but also for improving the understanding of the system so that performance can be potentially improved. Due to the great deal of uncertainties induced by the highly complex nature of earthquakes, rigorous quantification of seismic performance requires a probabilistic approach in which uncertainties can be explicitly accounted for. This type of assessment is referred to as a probabilistic seismic demand analysis (PSDA). Its primary output is the seismic demand hazard curve λ_{EDP}, which gives the rate of exceedance of all possible demand values, and therefore allows to verify immediately POs expressed in terms of equation (1). Despite the conceptual benefits, conducting a PSDA involves (at least) hundreds of RHAs, which hinders its application in engineering practice [2, 3]. For this reason, current practice of earthquake engineering [e.g. 4] relies on intensity based assessments (IBA), in which seismic performance criteria is prescribed on the basis of the seismic demand obtained from an ensemble of ground motions scaled to a specified level of intensity. Interestingly, the use of IBAs for probabilistic performance assessment can be justified on the fact that they provide an estimate of the level of demand corresponding to the target rate of failure, edp_f [1, 5–8], therefore allowing to conduct design checks as that in equation (1). In this context, we will refer to the quantity of interest edp_f as the target demand.

Even if the great reduction in the computational effort makes IBAs practical, their adequacy for estimating edp_f depends significantly on the intensity measure (IM) adopted for defining the conditioning intensity level. While it is well-known that the accuracy of the estimate of the target demand increases as the conditioning IM improves its ability to predict the response parameter EDP, practical IMs have very limited prediction capabilities, and therefore cannot always provide meaningful results for decision-making. The reason for this is that the choice of the conditioning IM is restricted to those for which ground motion models are available; this is, (i) a ground motion prediction equation (GMPE) to compute the seismic hazard at the site and define the conditioning intensity level, and (ii) the correlation coefficients between such IM and others that significantly contribute to the building's response. This is necessary to select an ensemble of records that is consistent with the conditional hazard of those other IMs and obtain an unbiased estimate of the conditional demand. As a result, the conditioning IM typically consists of the spectral acceleration at a given period $S_a(T)$, for which ground motion models are widely available [e.g. 9, 10]. There are two main problems with this approach. First, because it is usually not possible to identify the most convenient spectral period T before conducting the calculations, multiple IBAs may need to be conducted in order to obtain the best possible

[1] Uppercase symbols represent variables, and lowercase symbols denote realizations of their uppercase counterpart.

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estimate of edp_f [5, 6]. And second, since spectral accelerations are defined in terms of the maximum displacement of an elastic single-degree-of-freedom (SDOF) oscillator, they tend to be inefficient predictors for different measures of response of a complex nonlinear multi-degree-of-freedom (MDOF) system, particularly when damage concentration occurs. As a result, in some cases even a worst-case approach can result in considerable underestimation of the target demands [8].

This paper presents a ground motion selection procedure that allows to conduct IBAs conditioned upon advanced IMs or predictors of response for which the necessary ground motion models are not available. This enables to specifically develop such IM or predictor for the structure and response parameter of interest. The procedure relies on the empirical characterization of the seismic hazard at the site in terms of the predictor by means of a large set of ground motions, and on the deaggregation of results to identify a reduced set to compute the conditional response. The procedure is *demand-oriented* in the sense that it returns, for each demand measure of interest, a single ensemble of ground motions for obtaining an accurate estimate of the target demand and additional insight into understanding the system to support probabilistic performance assessment.

2. Conditional ground motion selection

In this paper, we will refer to the conditional intensity measure for conducting an IBA as X to highlight the fact that, theoretically, any type of measure can be considered for this purpose. The problem of estimating the level of demand with a specified rate of failure ν_f has been addressed by Loth and Baker [1, 7]. Using a structural reliability framework, it is showed that a *lower bound* estimate of edp_f is obtained from the median demand of an IBA conditioned upon X reaching its level of intensity associated to ν_f, this is, x^* such that $\lambda_X(x^*) = \nu_f$. The approach is justified on the fact that the seismic intensities considered in an IBA are an approximation to the checking (or design) point, i.e., the set of amplitudes most likely to cause failure of the system. Scalar IMs are always insufficient for EDP, meaning that the response is sensitive to other features of the ground motion. Therefore, in order to obtain an accurate or unbiased estimate of the response conditional on $X = x^*$, it is necessary to conduct RHAs for a set of ground motions that faithfully represents the conditional distribution of other IMs that have a significant effect on the response. When only the median response is of interest, as it is in this paper, the conditional mean spectrum (CMS) [11] is the most efficient target spectrum for ground motion selection [6, 12]. Also, the CMS is consistent with the concept of checking point, since it is the most likely response spectrum given the specified level of intensity.

In this section, we will present an approach to approximate the CMS and select the corresponding set of ground motions when the necessary ground motion models for X are not available. The proposed procedure relies on the empirical characterization of the seismic hazard at the site in terms of X by means of a large set of ground motions, and on the deaggregation of results to identify the reduced set of N_{gm} records with the largest contribution to X equaling the intensity level of interest x^*. Noting the analogy with the concept of checking point and considering that these records are specifically selected to conduct a specified design check, we will refer to them as the *checking ground motions* (CGM).

Next, we present a detailed description of the proposed procedure, illustrating and validating each step with the results obtained for an 'advanced' IM for which the corresponding ground motion models are available. The implementation of nonlinear predictors will be discussed in the following section. The IM considered for this purpose is the average spectral acceleration over a specified period range, defined as

$$\overline{S_a} = \sqrt[N_T]{\sum_{i=1}^{N_T} S_a(T_i)} \tag{2}$$

where T_i are $N_T = 13$ periods in the range between 0.7s and 3.0s. The site considered is Berkeley, CA, assuming 600m/s as the shear wave velocity. The conditional intensity level corresponds to a hazard level of $\nu_f = 0.001\text{yr}^{-1}$ (5% probability of exceedance in 50yr). The computation of the CMS conditioned upon the average spectral acceleration using ground motion models for single period spectral ordinates [9, 10] was first

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introduced by Baker and Cornell [13]. For the purposes of this example, the set of ground motions selected to fit the CMS consists of the 11 records that most closely match the target spectrum in the period range 0.4—4s.

2.1 Step 1: Compute the seismic hazard at the site in terms of X

The first step consists on conducting a PSDA to characterize X at the site of interest. Although alternative methods are available [3], we will focus on procedures that rely on a scalar conditioning intensity measure $IM^{\star}$ so that

$$\lambda_X(x) = \int_0^{\infty} G_{X|IM^{\star}}(x|im^{\star})\,|\mathrm{d}IM^{\star}| \quad (3)$$

where $G_{X|IM^{\star}}(x|im^{\star})$ is the complementary cumulative density function of X conditioned upon $IM^{\star}$, commonly described as lognormal. These approaches consist on computing (3) numerically by evaluating the integrand at a finite number of intensity levels. In order to do this, different ensembles of ground motions are selected using either the conditional spectra (CS) [14] or generalized conditional intensity measure (GCIM) [15] distributions at each of these intensity levels, and $G_{X|IM^{\star}}(x|im^{\star})$ is obtained from statistical inference. Evidently, using a finite number of ground motions introduces error in the computation of the seismic hazard. One approach that has been proposed to assess whether the estimate of λ_X is accurate or not consists of comparing the seismic hazard curves resulting from different conditioning IMs. If the estimates are close to each other, then they are unbiased. As will become apparent later, this method will also be useful in the process of ground motion selection.

Step 1 is summarized as follows: (a) adopt n conditioning scalar intensity measures $IM_i^{\star}$ for which their corresponding seismic hazard curves $\lambda_{IM_i^{\star}}$ are readily available, with $i = 1, 2, \ldots, n$; (b) specify the hazard levels at which the integrand of (3) will be evaluated for each conditioning intensity measure and select the corresponding ensembles of ground motions using either the CS or GCIM-based approaches; (c) compute the seismic hazard curve in terms of X as the arithmetic average of the hazard curves obtained for each conditioning intensity measure; and finally, (d) the intensity level corresponding to the target rate of interest ν_f is extracted from the curve, this is, x^* such that $\lambda_X(x^*) = \nu_f$.

Application example: Suppose that we are interested in applying this procedure for $X \equiv \overline{S_a}$. Three different conditioning periods are considered for conducting Step 1: $IM_1^{\star} \equiv S_a(0.4s)$, $IM_2^{\star} \equiv S_a(2s)$, and $IM_3^{\star} \equiv S_a(4s)$. The hazard curves at the site of interest for each conditioning IM are computed in OpenSHA [16] using the GMPE by Campbell and Bozorgnia [9]. For each seismic hazard curve, eleven different intensity levels with probabilities of exceedance of 99, 80, 50, 20, 10, 5, 2, 1, 0.5, 0.2 and 0.1% in 50 years are considered. The corresponding hazard curves and intensity levels are shown in Fig. 1a. At each intensity level, 30 ground motions are selected via the GCIM approach to ensure hazard consistency with respect to 12 other intensity measures: the 5-75 significant duration, and the spectral accelerations at 0.05, 0.1, 0.2, 0.3, 0.5, 0.75, 1, 1.5, 3, 5 and 10 seconds. GCIM distributions are derived employing appropriate ground motion prediction equations [9, 17] and correlation models [10, 18]. A total of $3 \times 11 \times 30 = 990$ ground motions are selected from the NGA-West1 database [19]. The estimate of the seismic demand hazard curve λ_X consists of the arithmetic average of the different curves obtained for each conditioning period. Fig. 1b shows the individual and average seismic hazard curves in terms of X, showing excellent agreement between the analytical and empirical results. The intensity level for the target rate of interest ν_f extracted from the average curve is $x^* = 0.42$g, which differs by only 2% with the analytical result obtained using the corresponding GMPE.

2.2 Step 2: Characterize the probability of $IM_i^{\star}$ given $X = x^*$

The CMS consists on the most likely target spectrum conditional upon $X = x^*$. For the problem in hand, we can only compute accurately the most likely realization of a very specific vector of intensity measures $\mathbf{IM}^{\star} =$

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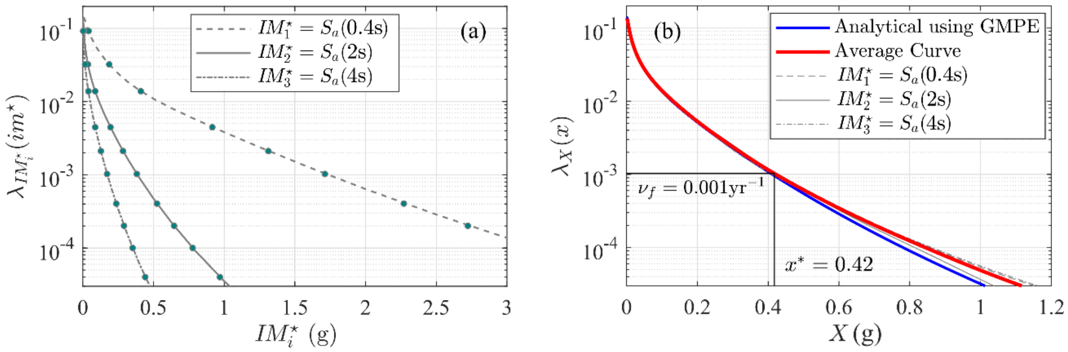

Fig. 1 – (a) Seismic hazard curves for each $IM_i^\star$, and (b) Seismic hazard curves for $X = \overline{S_a}$

$[IM_1^\star, \dots, IM_n^\star]$. In order to do this, we need to deaggregate the characterization of X conducted in Step 1. Recalling Bayes' Theorem, the marginal probability density function of each conditioning IM is

$$f_{IM_i^\star|X}(im_i^\star|x^*) = \frac{f_{X|IM_i^\star}(x^*|im_i^\star)\, f_{IM_i^\star}(im_i^\star)}{f_X(x^*)} \tag{4}$$

Noting that $f_{X|IM_i^\star}(x^*|im_i^\star)$ can be characterized with the ground motions selected in Step 1, equation (4) can be easily computed since $f_X(x^*)$ is a constant and, by definition, $f_{IM_i^\star}(im_i^\star) = |\mathrm{d}\lambda_{IM_i^\star}(im_i^\star)|/\lambda_{IM_i^\star}(0)$.

Application example: Fig. 2a—d illustrate the calculation of the marginal distribution $IM_1^\star|X = x^*$. First, the probability density function of the conditioning intensity measure is obtained by taking the derivative of the corresponding seismic hazard curve (Fig. 2a). Next, the distribution of $X|IM_1^\star$ is characterized using the $11 \times 30 = 330$ records selected in Step 1 with $IM_1^\star$ as the conditioning intensity measure. Black dots in Fig. 2b show the fraction of ground motions for which $X > x^*$ at each of the 11 intensity levels considered. With this data, the parameters of a lognormal are fitted using the maximum likelihood estimation. Fig. 2b shows the resulting cumulative density function $F_{X|IM_1^\star}(x^*|im_1^\star)$ and Fig. 2c the probability density function $f_{X|IM_1^\star}(x^*|im_1^\star)$. Finally, the marginal distribution $f_{IM_1^\star|X}(im_1^\star|x^*)$ is computed as in (4) and presented in Fig. 2d. The procedure is repeated for the remaining conditioning intensity measures $IM_2^\star$ and $IM_3^\star$. Their cumulative distributions are shown with solid lines in Fig. 2e. These are compared to the lognormal distributions obtained using the corresponding GMPE and correlation coefficients for the mean rupture scenario (dashed lines). The results obtained with the proposed procedure show excellent agreement with the theoretical distributions.

2.3 Step 3: Identify the checking ground motions

After characterizing the conditional hazard in terms of $\mathbf{IM}^\star$, the final step consists of identifying the CGM. Same as in the CMS-based approach, this set represents those ground motions with the largest contribution to $X = x^*$. When matching the CMS, however, prospective earthquake records are first amplitude scaled to reach the intensity level of interest. If this approach was followed herein, variable X would be constrained to IMs that increase linearly with the scale factor. Recalling that X is intended to be a structure-specific predictor of response, an alternative selection procedure that allows to consider nonlinear predictors is preferred.

Instead of looking into a database, prospective ground motions will be determined from the large set of records selected in Step 1. Since no further amplitude scaling can be applied to them, the set is first screened to identify those records for which $x^* - \epsilon < X < x^* + \epsilon$, where ϵ is the level of tolerance specified by the user. Prospective ground motions are then those included in that subset. Next, the selection of the CGM is conducted in the same way as done when matching a CMS; noting that each marginal distribution $IM_i^\star|X = x^*$ can be approximated as lognormal, its most likely realization $im_i^{\star,*}$ consists simply of the median value. Finally, the CGM are defined as the N_{gm} records that most closely match the vector of median intensities $\mathbf{im}^{\star,*}$. As in the

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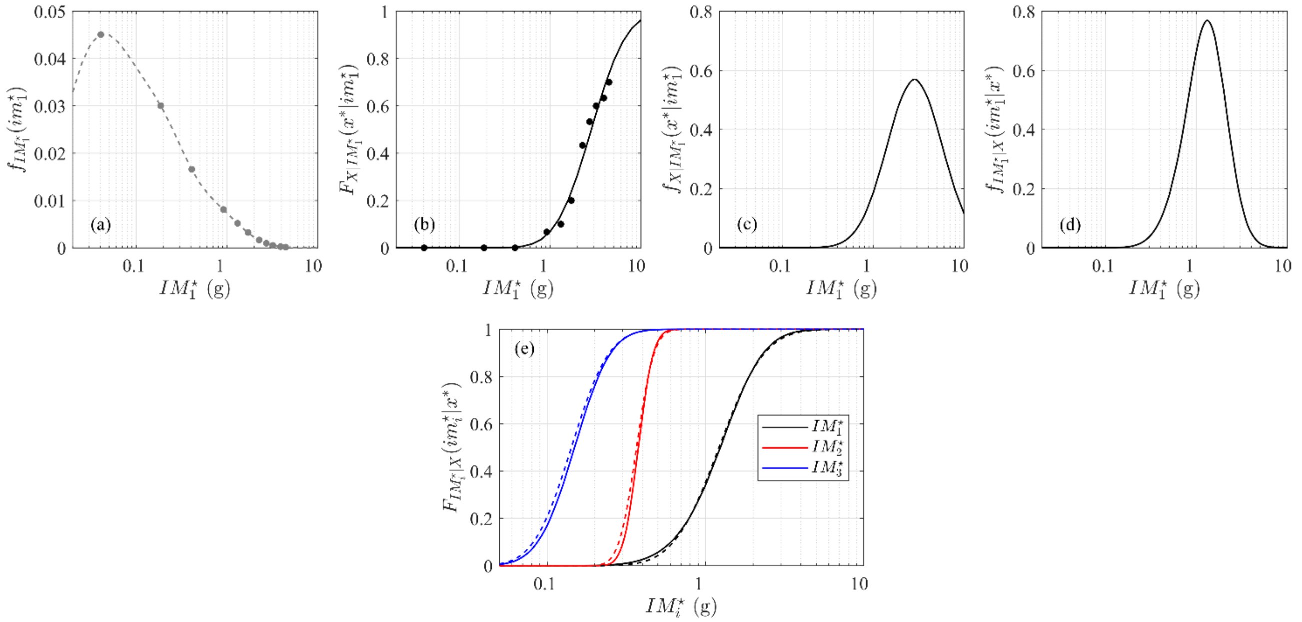

Fig. 2 – Calculations for computing the probabilities distributions $IM_i^{\star}|X = x^*$

case of the CMS, the similarity between a certain ground motion gm and the target intensities is evaluated in terms of the sum of squared errors SSE between the logarithm of the spectral ordinates of the ground motion $\mathbf{im}^{\star,gm}$ and the natural logarithm of the median conditional intensities

$$SSE = \sum_{i=1}^{n} \left[\ln im_i^{\star,gm} - \ln im_i^{\star,*}\right]^2 \quad (5)$$

As in traditional procedures, the number of ground motions to be considered as the CGM depends on the expected variability and the required accuracy.

Application example: Step 3 is now applied to identify the CGM for $X = 0.42$g. For the purposes of this example, the tolerance level is specified as $\epsilon = 0.03$g. Then, from the 990 records considered in Step 1, the number of prospective ground motions is reduced to just 53. Next, we compute the SSE for each of these and define the CGM as the $N_{gm} = 11$ records that present the lowest error. Both the prospective ground motions and the CGM are shown in Fig. 3a. The choice of 11 ground motions is justified on the intention of keeping consistency with the set adopted to match the CMS using the traditional approach.

The median and the standard deviation of the distribution of the CGM are presented in Fig. 3b and 3c, respectively. The results can be compared against those obtained with the traditional procedure. The median of the CGM shows excellent agreement with the analytical CMS in the range between $IM_1^{\star}$ and $IM_3^{\star}$. This implies that the choice of the conditioning intensity measures should consider the period range of interest, same as done when selecting ground motions using the CMS as the target spectrum. Compared to the set obtained using the CMS-based approach, the CGM present larger variability. This is reasonable considering that the number of prospective ground motions is significantly lower in this case. While the selection of the CGM was constrained to 53 records, in the CMS-based approach the reduced set of records was selected from a total of 1029.[2] Naturally, this implies that, when the implementation of traditional procedure is possible, the response to the CGM will present larger dispersion, and therefore the estimate of the median demand will be

[2] Prospective ground motions were those in the NGA-West1 database with magnitude greater than 5.5 and shear wave velocity between 300m/s and 900m/s. Also, the maximum scale factor was limited to 10.

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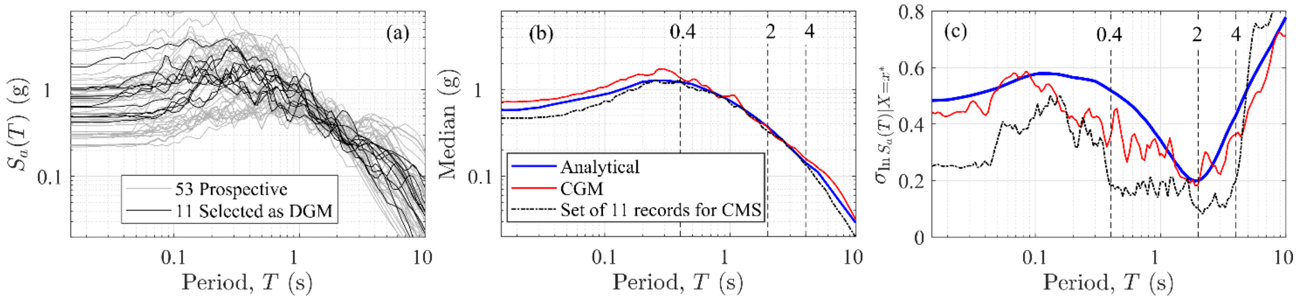

Fig. 3 – Selection of the CGM

less precise.

The previous example shows that hazard consistent ground motion selection conditional upon an advanced IM in the absence of the corresponding ground motion models is feasible. The proposed procedure requires only two main inputs from the user: the choice of the conditioning intensity measures $IM_i^\star$ for conducting the PSDA of X, and the tolerance level ϵ. The rest of the steps can be automatized. The input parameters will be further discussed in the next section, in which we will implement the procedure in the context of probabilistic performance assessment using nonlinear predictors of response.

3. Demand-oriented ground motion selection in a realistic case study

As previously discussed, an accurate estimate of the level of demand with a specified rate of failure can be obtained from the median response conditional upon X, where X is a variable that presents a strong correlation with the demand measure of interest EDP. The main benefit of the procedure introduced in the previous section is that it allows to consider any type of IM or predictor as the conditioning variable X, as it bypasses the need of ground motion models for record selection. Evidently, this approach is only practical if the computational effort for characterizing X is negligible compared to that required for characterizing EDP. Variable X can be therefore understood as a proxy variable; it is not itself relevant but becomes important as it is easily computed and serves as an approximation to the checking point for performance assessment in terms of equation (1).

Considering this constraint imposed to X, it is reasonable to think of it as the response of a structural model that is a simplified version of the one used for characterizing EDP. While most of the IMs adopted in engineering practice are in fact defined in terms of the response of a very simple structural model (spectral accelerations, for example), in this case we will specifically develop such model considering the properties of the structure and demand measure being assessed. In the following, we will refer to the complex model used to characterize EDP as the *reference model*; to the simplified version as the *predictor model*; and to its response X as the *predictor response*. Next, we will conduct a realistic case study comparing the results from a rigorous PSDA against the estimates of the target demands obtained by means of traditional IBAs, and alternative predictor models using the procedure introduced in this paper.

3.1 Building, reference model, site and PSDA

The structural system selected is an eight-story three-bay steel special moment frame with reduced beam section connections. This building was designed as part of a study on the NIST evaluation of the FEMA P695 methodology, where it was denoted with archetype ID number 4RSA [20]. Additional information on the geometry may be found in such reference. The reference structural model is drawn from Do's PhD Dissertation [21]. The inelasticity of the frame is modeled using damage-plasticity based beam and column elements, with a damage formulation that allows to describe the main characteristics of steel components, including the accumulation of plastic deformations, the cyclic strength hardening in early cycles, low-cycle fatigue behavior, and the distinct deterioration rates in primary and follower half cycles. The column element is specifically formulated to capture the response under significant axial forces. The first three modal periods are $T_{n1} = 2s$,

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$T_{n2} = 0.72s$ and $T_{n3} = 0.4s$. P-Δ effects from the gravity load that is not directly tributary to the column elements of the frame is captured by means of inflexible leaning columns adjacent to the frame. Rayleigh damping is used with the damping matrix proportional to the constant mass matrix and the tangent stiffness matrix for a damping ratio of 2.5%.

Again, the site considered is Berkeley, CA, and the PSDA is conducted using the same set of ground motions considered in the application example of Step 1 in Section 2.1. The estimate of the seismic demand hazard curve λ_{EDP} consists of the arithmetic average of the different curves obtained for each conditioning intensity measure. Here, we will focus on two measures of demand: the maximum story drift ratio $MSDR$, and the maximum floor acceleration MFA along the height of the building. Setting $\nu_f = 0.001\text{yr}^{-1}$ (5% probability of exceedance in 50 years), the corresponding target demands are $msdr_f = 2.57\%$ and $mfa_f = 0.80$g. In the following, we will intend to estimate these levels of demand by means of intensity based assessments using both the traditional approach and the proposed demand-oriented procedure.

3.2 Traditional IBAs

Previous research shows that if drift ratios are of interest, ground motions should be conditioned upon vibration periods that are close to or larger than the building's fundamental period; on the contrary, higher mode periods tend to capture better acceleration demands [6, 8]. Given that we are interested in both drifts and accelerations, and that it is not possible to determine *a priori* the best possible conditioning period in each case, we conduct a worst-case approach with the following periods: T_{n3} and T_{n2} for MFA, T_{n1} and $2T_{n1}$ for $MSDR$. For each conditioning period, a set of records is selected so that it matches the corresponding CMS associated to ν_f. In addition, we consider a fifth IBA in which the UHS associated to ν_f is the target spectrum adopted for ground motion selection. The UHS is not part of the worst-case approach. Instead, it is considered herein to test the hypothesis that it provides an upper bound estimate of the target demands. Based on the recommendations in ASCE 7-16 [4], 11 ground motions are adopted in each set. The estimate of the target demand provided by each IBA consists of the geometric mean of the response distribution. The use of the geometric mean as an estimator of the median demand is justified on the assumed lognormality of the response distribution.

Fig. 4 summarizes the results obtained with traditional IBAs. First, we solely focus on the numerical values. As expected, traditional IBAs conditioned upon scalar IMs always underestimate the target demands. For $MSDR$, the closest estimate is obtained from the IBA conditioned upon $S_a(T_{n1})$, which underestimates $msdr_f$ by 21%. On the other hand, the lower bound estimate of MFA is obtained with $S_a(T_{n2})$ as the conditioning intensity measure, with an underestimation of 13%. Note that this approach not only provided inaccurate estimates of the target demands, it also resulted in significant waste of computational effort, as the RHAs associated to CMS(T_{n3}) and CMS($2T_{n1}$) ended up being useless. Regarding the results from the UHS, for the target rate considered in this example, these are not 'overly' conservative as oftentimes stated.

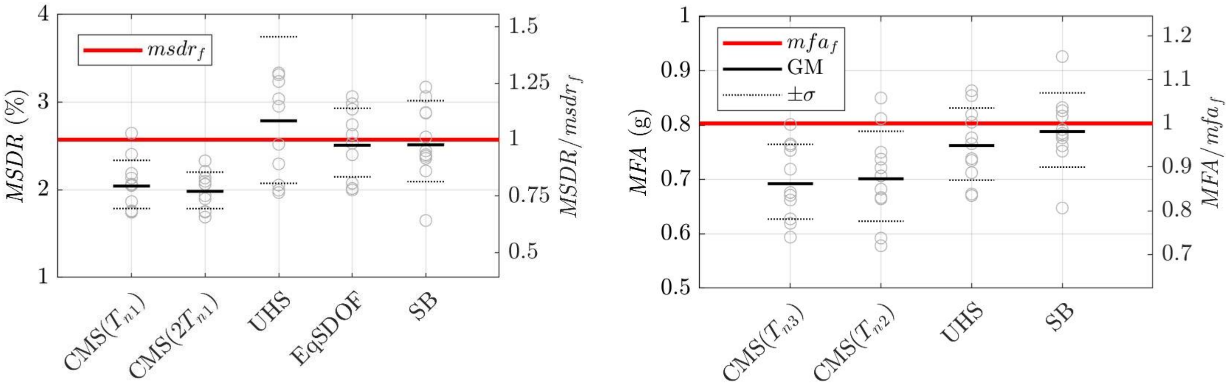

Fig. 4 – Comparison of results from PSDA and IBAs. GM: geometric mean. σ: standard deviation

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Interestingly, $MSDR$ is overestimated by just 8% and MFA is underestimated by 5%.

After analyzing the numerical values, one might conclude that the UHS is the most adequate target spectrum for performance assessment in terms of equation (1) considering a target rate of failure of 0.001yr^{-1}. However, it is important to recall that deriving numerical values is not the only purpose when conducting RHA, probably not even the main one. Performance quantification should also provide further information to understand the system so that performance can be potentially improved. Suppose, for example, that after conducting the IBAs described above it is determined that the maximum story drift ratio is larger than the allowable level of demand for the exceedance rate of interest. In order to decide how to modify the design, it is then crucial to identify which stories suffer the largest drift demands. One possible way to do this is to analyze the peak story drift ratios $PSDR$ along the height of the building for those ground motions for which $MSDR = msdr_f$. Fig. 5a shows the profiles that result from the 11 RHAs, among the 990 considered for conducting the PSDA, for which $MSDR$ is closest to $msdr_f$. By analyzing the distribution of demand, it is clear that the largest drifts tend to occur in the first or the second story, with only 3 out 11 profiles reaching their maximum drift in the upper stories. Fig. 5b presents the results obtained from UHS, the only target spectrum that provided an accurate estimate of $msdr_f$. These profiles, however, do not allow to capture where the largest drift occur. As a result, it is concluded that neither of the IBAs considered provide meaningful information to aid in the process of decision-making for assessing or improving the design, and therefore are unsuitable for performance assessment in terms of POs as that in equation (1).

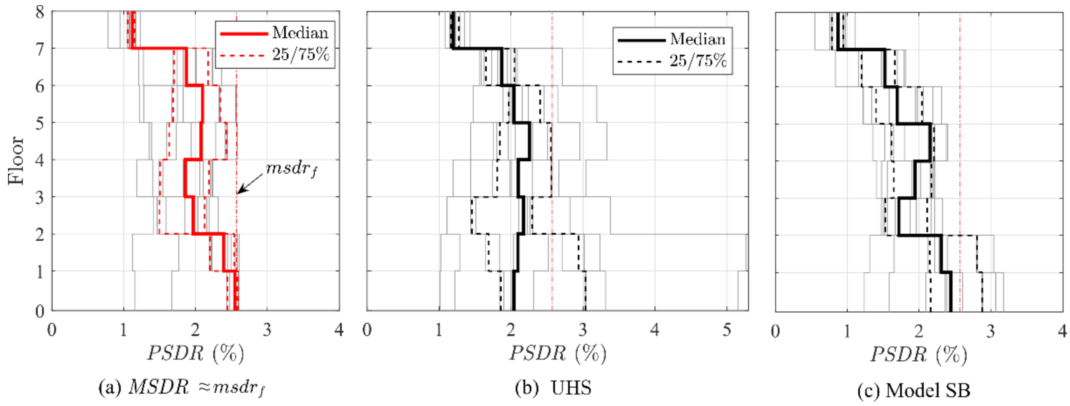

Fig. 5 – Peak story drift ratio profiles along the height of the building for different sets of ground motions

3.3 Demand-oriented procedure

The key step for obtaining an accurate estimate of the target demands is the development of the predictor model. Engineering judgment is required to decide which are the main features of the structure that need to be captured. Because the correlation between EDP and the predictor response X usually decreases as further simplifications are made to the reference model, it is important to strike the right balance between computational costs and prediction capabilities. Next, we will consider two different predictor models for implementing the demand-oriented procedure: an equivalent SDOF system and a simplified MDOF model. Note that the purpose of adopting different models is not to conduct a worst-case approach. Instead, multiple models are considered only to show that predictor responses that provide accurate estimates of the target demands can be obtained using models of different degree of complexity.

Equivalent SDOF systems determined from the nonlinear static response of the reference model have been widely adopted in previous research as predictors of structural response. However, the availability of GMPEs for describing the response of inelastic SDOF systems is limited to the special case of bilinear hysteretic behavior with post-yield stiffness equal to 5% of the initial stiffness [22]. With the purpose of further increasing the correlation with drift demands, we consider a SDOF system that is specifically developed considering the degrading hysteretic behavior of the reference model. This predictor model, denoted as

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EqSDOF, is then formulated using the damage model developed by Do and Filippou [23], with damage parameters established in accordance with the pushover response of the reference model. Its maximum inelastic displacement is adopted as the predictor response for $MSDR$.

The second predictor model considered consists of an eight-story shear building with bilinear story shear–drift relationship. This model, denoted as SB, is able to capture how initial strength and stiffness vary along the height of the building, and is therefore intended to provide predictor responses for both $MSDR$ and MFA. At each story, the initial stiffness is defined in terms of the total floor mass, the first modal period and first mode shape of the reference model. The yield shear force and tangent stiffness for each story is obtained from the pushover response of the reference model to lateral forces proportional to the first-mode inertia forces. P–Δ effects are considered as the first order approximation by computing the geometric stiffness of each floor.

The demand-oriented ground motion selection procedure is now conducted using different measures of response of the predictor models to estimate the target demands for $MSDR$ and MFA. The first input that needs to be specified is the choice of the conditioning intensity measures $IM_i^\star$ for selecting the large ensemble of records for conducting PSDA with the predictor models. When following the traditional approach, ground motions are selected so that they match the target spectrum over a period range corresponding to the vibration periods that significantly contribute to the building's dynamic response. ASCE 7-16, for example, specifies this range as $0.2T_{n1}$ to $2T_{n1}$ (in this case, 0.4—4s). With the purpose of ensuring hazard consistency within that range, the conditioning IMs are specified as $IM_1^\star \equiv S_a(0.4s)$, $IM_2^\star \equiv S_a(2s)$, and $IM_3^\star \equiv S_a(4s)$. The large ensemble of records used for characterizing the predictor responses X at the site of interest is then identical to that considered for conducting the PSDA with the reference model. However, the time required to complete the 990 RHAs using the simplified models described above is about three orders of magnitude smaller. In other words, for models EqSDOF and SB, the PSDA is completed in an amount of time that is similar to that required for obtaining a single realization of EDP. This is the key fact that makes the proposed procedure practical.

Fig. 6a and 6b illustrates the steps followed to compute the median drift demand of the reference model conditional upon the maximum displacement of EqSDOF. The level of predictor response associated to ν_f is $x^* = 15.9$in, and the 40 prospective records in Fig. 6a are a result of specifying a tolerance level $\epsilon = 0.9$in. Then, after computing equation (5) to the prospective records, the $N_{gm} = 11$ ground motions with the lowest SSE are adopted as the CGM. The choice of $N_{gm} = 11$ records is justified on keeping consistency with the traditional procedures previously considered. The CGM are then used to conduct RHAs with the reference model and estimate the median conditional response as shown in Fig. 6b, which in this case is 2.51%.

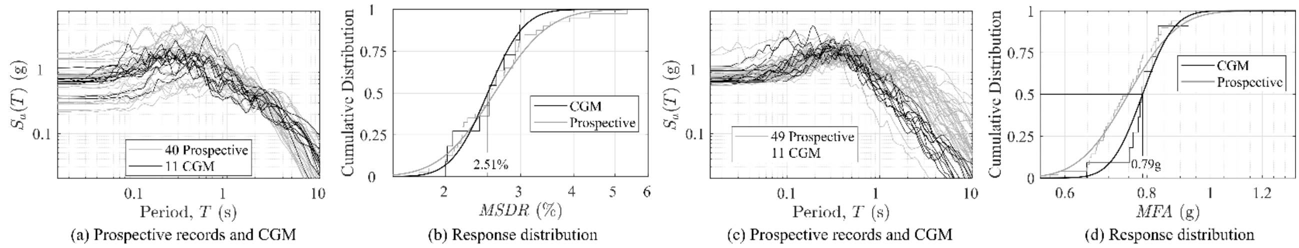

Fig. 6 – Computation of response conditional upon nonlinear predictors

The choice of the tolerance level ϵ should strike the right balance between the main purpose of the procedure (the fact that X should be approximately equal to x^*) and the convenience of increasing the number of prospective ground motions. This last matter is necessary to ensure that the CGM fit the median of the conditional distribution and reduce the variability of spectral accelerations as much as possible. In this case study, at least $3 \times N_{gm}$ prospective ground motions were necessary for such purpose, and the maximum tolerance level required was $0.08x^*$. To further illustrate the importance of matching the target intensities, Fig. 6c and 6d summarize the implementation of the demand-oriented procedure for estimating MFA using the maximum floor acceleration of SB as the predictor response. The comparison of the response distribution for the CGM and the prospective records in Fig. 6b and Fig. 6d shows that the structural demand conditioned upon

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$X = x^*$ is not independent of spectral shape. Therefore, the fact that the CGM allow to match the median of $IM_i^* \mid X = x^*$ and reduce the variability of the distribution of spectral ordinates is important for obtaining an unbiased estimate of the median demand conditioned upon X at a reduced computational effort.

The results obtained with the demand-oriented procedure are shown in Fig. 4 together with those for traditional IBAs. The proposed procedure not only provides very accurate estimates; more importantly, it allows to obtain such estimates at a reduced computational cost, since the procedure returns a single set of records for each EDP considered. Comparing the standard deviations of the response distributions, it is noted that the dispersion of results obtained with the CGM is similar to that resulting from ground motions selected to match a traditional CMS. This implies that, for the same number of records, both methods are equally precise. Evidently, the key point is the identification of an adequate predictor response for the demand measure of interest. As an example, Fig. 7 shows the correlation between the predictor responses and the $MSDR$. Clearly, compared to single period spectral ordinates, the prediction capabilities of the predictor responses considered is significantly stronger, which explains why the results are improved compared to the multiple-IBA approach.

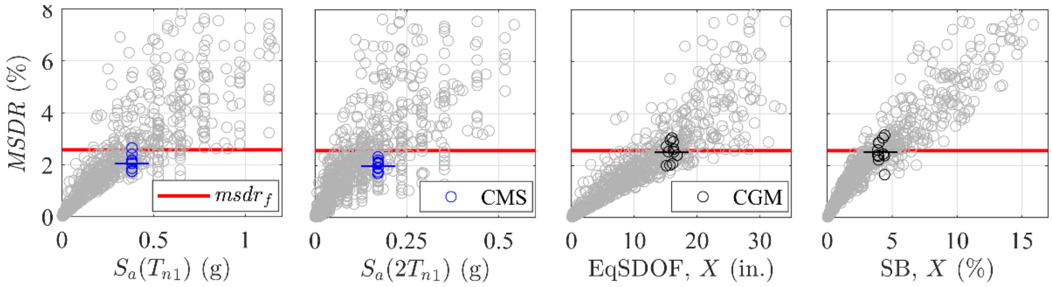

Fig. 7 - Relation between $MSDR$, and different response predictors for the eight-story special moment frame

In order to further evaluate the adequacy of the proposed procedure for the purpose of performance assessment, it is necessary to check whether the CGM provide additional insight into understanding the system at the demand level of interest. Fig. 5c shows the profiles of $PSDR$ along the height of building obtained with the maximum story drift ratio of SB as the predictor response for $MSDR$. In this case, the results allow to conclude that the maximum drifts are more likely to occur in the lower stories, as was demonstrated in Fig. 5a, providing valuable information for decision-making.

4. Conclusions

This paper deals with ground motion selection with the purpose of conducting probabilistic performance assessment. In this sense, the reduced set of records should provide an accurate estimate of the level of demand with a specified rate of exceedance, and additional insight into understanding the system so that performance can be potentially improved. An existing solution consists on conducting multiple IBAs, each conditioned upon a different IM and take the maximum response as the estimate of the target demand. This approach has two main problems. First, since it is usually not possible to determine beforehand the most convenient IM, multiple IBAs are sometimes required. Second, if none of the IMs considered is an efficient predictor of the demand measure of interest, even the worst-case approach will result in inaccurate estimates of the target demand. With the purpose of increasing the correlation with the response, we propose an alternative ground motion selection that bypasses the need for ground motion models for the conditioning IM. This allows to specifically develop such IM as predictor for the response measure of interest, and therefore ensuring that a single IBA will provide valuable information for conducting the design check.

Using an eight-story building at a realistic site as a case study, the proposed procedure is shown to provide demand estimates that are more accurate and as precise as those obtained from analyzing the building with multiple IBAs. Also, since the predictor models considered allow to characterize the predictor response in an amount of time that is similar to that required for conducting a single RHA of the reference model, the proposed

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procedure requires less computational effort than the multiple-IBA approach.

5. References

[1] Loth C, Baker JW (2015). Rational design spectra for structural reliability assessment using the response spectrum method, *Earthquake Spectra*, **31** (4), 2007–2026.

[2] Bradley BA (2012). The seismic demand hazard and importance of the conditioning intensity measure, *Earthquake Engineering and Structural Dynamics*, **41** (11), 1417–1437.

[3] Kwong NS, Chopra AK, McGuire RK (2015). A ground motion selection procedure for enforcing hazard consistency and estimating seismic demand hazard curves, *Earthquake Engineering and Structural Dynamics*, **44** (14), 2467–2487.

[4] ASCE/SEI Minimum Design Loads and Associated Criteria for Buildings and Other Structures (ASCE/SEI 7-16), *Minimum Design Loads and Associated Criteria for Buildings and Other Structures*. Reston, VA.

[5] Bradley BA (2013). A comparison of intensity-based demand distributions and the seismic demand hazard for seismic performance assessment, *Earthquake Engineering and Structural Dynamics*, **42** (15), 2235–2253.

[6] Lin T, Haselton CB, Baker JW (2013). Conditional spectrum-based ground motion selection. Part II: Intensity-based assessments and evaluation of alternative target spectra, *Earthquake Engineering and Structural Dynamics*, **42** (12), 1867–1884.

[7] Loth C (2014). Multivariate ground motion intensity measure models, and implications for structural reliability assessment, Stanford University.

[8] Kwong NS, Chopra AK (2017). A Generalized Conditional Mean Spectrum and Its Application for Intensity-Based Assessments of Seismic Demands, *Earthquake Spectra*, **33** (1), 123–143.

[9] Campbell KW, Bozorgnia Y (2008). NGA Ground Motion Model for the Geometric Mean Horizontal Component of PGA, PGV, PGD and 5% Damped Linear Elastic Response Spectra for Periods Ranging from 0.01 to 10 s, *Earthquake Spectra*, **24** (1), 139–171.

[10] Baker JW, Jayaram N (2008). Correlation of spectral acceleration values from NGA ground motion models, *Earthquake Spectra*, **24** (1), 299–317.

[11] Baker JW (2011). Conditional Mean Spectrum: Tool for Ground-Motion Selection, *Journal of Structural Engineering*, **137** (3), 322–331.

[12] NEHRP Consultants Joint Venture (2011). Selecting and Scaling Earthquake Ground Motions for Performing Response-History Analyses, Washington, DC.

[13] Baker JW, Cornell CA (2006). Spectral shape, epsilon and record selection, *Earthquake Engineering and Structural Dynamics*, **35** (9), 1077–1095.

[14] Baker JW, Lee C (2018). An Improved Algorithm for Selecting Ground Motions to Match a Conditional Spectrum, *Journal of Earthquake Engineering*, **22** (4), 708–723.

[15] Bradley BA (2010). A generalized conditional intensity measure approach and holistic ground-motion selection, *Earthquake Engineering and Structural Dynamics*, **39** (12), 1321–1342.

[16] Field EH, Jordan TH, Cornell CA (2003). OpenSHA: A Developing Community-modeling Environment for Seismic Hazard Analysis, *Seismological Research Letters*, **74** (4), 406–419.

[17] Bommer JJ, Stafford PJ, Alarcon JE (2009). Empirical Equations for the Prediction of the Significant, Bracketed, and Uniform Duration of Earthquake Ground Motion, *Bulletin of the Seismological Society of America*, **99** (6), 3217–3233.

[18] Bradley BA (2011). Correlation of Significant Duration with Amplitude and Cumulative Intensity Measures and Its Use in Ground Motion Selection, *Journal of Earthquake Engineering*, **15** (6), 809–832.

[19] Chiou B, Darragh R, Gregor N, Silva W (2008). NGA Project Strong-Motion Database, *Earthquake Spectra*, **24** (1), 23–44.

[20] NIST (2010). Evaluation of the FEMA P-695 Methodology for Quantification of Building Seismic Performance Factors.

[21] Do TN (2018). Damage assessment and collapse simulations of structures under extreme loading conditions, University of California, Berkeley.

[22] Tothong P, Cornell CA (2006). An Empirical Ground-Motion Attenuation Relation for Inelastic Spectral Displacement, *Bulletin of the Seismological Society of America*, **96** (6), 2146–2164.

[23] Do TN, Filippou FC (2018). A damage model for structures with degrading response, *Earthquake Engineering and Structural Dynamics*, **47** (2), 311–332.

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