CONDIONAL SPECTRUM BASED RECORD SELECTION FOR NONLINEAR DYNAMIC ANALYSIS OF 3D STRUCTURAL MODELS

Mohsen KOHRANGI¹, Paolo BAZZURRO¹, Dimitrios VAMVATSIKOS³

ABSTRACT

Nonlinear dynamic analysis is commonly used in seismic risk assessment. Record selection is the tool to connect the ground motion to the structural response through a ground motion intensity measure (IM). Naturally, appropriate record selection techniques as well as a good choice of IM have been two important research topics in the last decade. Recent studies have shown the necessity of record selection that thoroughly represents the seismicity at the site of interest. Similarly, many studies have focused on the best choice of IMs capable of estimating the response of specific buildings with the least scatter. The advances put forward by this body of research are geared mostly to structural analysis of buildings modeled in 2D. Few are the specific record selection approaches and IMs suggested expressly for nonlinear dynamic analysis of 3D structural models. Herein, we explore several proposals for conditional spectrum-based record selection for 3D structural models using different IMs. Especially, we present a vector-based conditional spectrum record selection that conveys information from two orthogonal horizontal components of the ground motion. We further explore the application of the newly presented approaches for 3D analysis of several building examples and consequently provide suggestions for their use in seismic risk assessment.

Keywords: Hazard consistent record selection; Conditional Spectrum; 3D nonlinear dynamic analysis

1. INTRODUCTION

Dynamic analysis is a common approach in performance-based earthquake engineering (PBEE) to predict the seismic response of structures. One fundamental step in dynamic analysis is the selection of input ground motions. A smart record selection is the tool used in PBEE to justify connecting the seismic hazard at a site to the structural response via a single ground motion Intensity Measure (IM). In recent years, different techniques have been developed for selection of input ground motions for structural analysis. We can classify them into two main categories: “Scenario-based selection” and “target-based selection” (Beyer and Bommer 2007). In the first category, the selected records fall in bins around central values of seismic parameters, such as magnitude, source-to-site distance, site class and epsilon (e.g., Stewart et al. 2007; Bommer and Acevedo 2004; Baker and Cornell 2005; Jayaram and Baker 2010). If probabilistic seismic hazard analysis is performed, the scenario parameters are identified via hazard disaggregation analysis as those corresponding to the earthquakes that contribute the most to the hazard at the site. In the second method, a set of records are selected to match a target spectrum or a target distribution of ground motion intensity measures (e.g., Naeim et al. 2004; Shantz 2006; Watson-Lamprey 2006; Beyer and Bommer 2007; Youngs et al. 2007; Kottke and Rathje 2008; Bradley 2010; Baker 2011; Jayaram et al. 2011). Such a target could be the uniform hazard spectrum (UHS) (adopted mainly by seismic design codes, such as the Eurocode 8), a conditional mean spectrum (CMS) (Baker 2011), or a conditional spectrum (CS) that accounts for both mean and variance of the spectral accelerations (Jayaram et al. 2011). The GCIM approach (Bradley 2010) goes one step forward and accounts for any ground motion parameter of interest for structural analysis, assuming that such parameters are known to the analyst beforehand and that they can be predicted for ground motions caused by future earthquakes.

¹Research assistant, University School for Advanced Studies IUSS Pavia, Pavia, Italy, mohsen.kohrangi@gmail.com
²Professor, University School for Advanced Studies IUSS Pavia, Pavia, Italy, paolo.bazzurro@iusspavia.it
³Professor, National technical university of Athens, Athens, Greece, divamva@mail.ntua.gr
The main scope of CS and GCIM, among other methods, is providing suites of records that are compatible with the hazard at the site. In other words, these methods try to select the records that are most representative of the seismicity of the region. As such, at any single IM level, a set of records are selected (or artificially simulated) and scaled to retain the conditioning IM value. The remaining parameters, such as spectral accelerations at other ordinates of the spectrum (or when using GCIM other parameters like duration) are then matched with their appropriate conditional distribution. Within the boundaries of these record selection schemes, the adoption of a single conditioning IM is unavoidable although this practice accepts some limitations due to the representation of the entire seismic hazard with a single parameter. Given the application, the IM commonly adopted are structure-dependent quantities, such as the spectral acceleration at the first mode period of the structure, $Sa(T_1)$. Therefore, not only the chosen IM should represent well the site seismic hazard (i.e., it should be “sufficient”) but also should be a good predictor of the structural response (i.e., it should be “efficient”). $Sa(T_1)$ is the most common and perhaps simplest solution but it is appropriate for none but simple structures. Many studies in the past (Shome and Cornell 1999; Luco 2002; Bradley et al. 2009; Faggella et al. 2013) have addressed its relative lack of efficiency and sufficiency (see Luco and Cornell (2007) for definitions) for building response prediction. The deficiencies of $Sa(T_1)$ in response prediction spawned many proposals for advanced scalar and vector-valued IMs (Cordova et al. 2000; Baker and Cornell 2008; Tothong and Cornell 2008, Bianchini et al. 2009, Bojórquez and Jervolino 2011). Specifically, when predicting the response of 3D structural models under bi-directional excitations, the IM should intuitively contain information at least about both horizontal components of the ground motion to improve the resolution of the response prediction (Kohrangi et al. 2016a; 2016b; 2016c).

Despite these advances in record selection, there is still little insight about record selection schemes for 3D structural models. To date, the focus of most (if not all) of the record selection proposals concerns 2D structural models (Bradley 2013; Lin et al. 2013a; Lin 2013b). Among the few suggestions to account in record selection for the effect of bi-directional excitations for 3D structural analysis, Beyer and Bommer (2007) suggested using as a scalar IM the geometric mean of spectral accelerations from the two horizontal orthogonal components of the ground motion at the first frequencies of vibration in the transversal and longitudinal direction of the building and to treat this IM using a CMS approach. Lin et al. (2013) based on the results obtained from application of CS record selection and 2D structural analysis, used intuitive arguments to state that the CS method conditioned on scalar IMs (regardless of whether the geometric mean of two components or extracted from an arbitrary component or the largest of the two components) should be applicable to 3D buildings as well. The latter study also pointed out that ensuring hazard consistency in record selection for 3D models requires that ground motions maintain conditional $Sa$ distributions consistent with hazard at all periods and orientations of interest. To our knowledge, no other proposals for record selection geared to 3D structures are available in the literature.

The main scope of the study presented here is on exploring several proposals for record selection devised especially for nonlinear dynamic analysis of 3D structural models. As such, we investigate different CS based record selection approaches that account for the hazard consistency of either one or both horizontal components of the ground motion, or of their geometric mean. Additionally, we extend the concepts of the CS based record selection conditioned on scalar IMs to CS conditioned on a vector of IMs, herein called CS(vector). Such vector IM, for the sake of this study, is defined such that it conveys information about the two main orthogonal axes of the building and the corresponding excitations. In the following, we first describe the mathematics of the CS(vector) method; consequently, we provide illustrative examples for record selection, based on the new proposal. Finally, we compare the results obtained from the new and the other currently available methods and provide recommendations regarding the application of scalar- and vector-based CS methods.

2. CS(VECTOR) TARGET SPECTRUM

In this section, we describe the methodology for CS record selection conditioned on a vector of IMs. Note that here we explain only the mathematical formulations for generating target spectra (i.e., mean and variance in a set of spectral ordinates), whereas the record selection and scaling algorithm are adopted from the approach provided by Jayaram et al. (2011) with the exception of the minor modifications described in the following. Since the focus here is on record selection for 3D structural
models, we based our description of the method on CS conditioned on a two–component vector made of two IMs extracted from the two orthogonal components of the ground motion. However, the method is general and can be extended to more than two-component conditioning vectors and for various IMs according to the needs of the structural analysis. We call the conditioning vector, \( \mathbf{IM}^*\)={\( IM_1^*, IM_2^* \)} in which the bold character represents matrix variables. \( \mathbf{IM}^* \) could be the combination of any two IMs such as \{\( Sa(T_{i1}), Sa(T_{i2}) \), \( Sa_g(T_1), Sa_g(mT_1) \), or \{\( \text{Avg}SA_x, \text{Avg}SA_y \); in which \( Sa(T_{i1}) \) and \( Sa(T_{i2}) \) are the spectral accelerations of \( x \) and \( y \) components of the ground motion at the period of the first mode of vibration of the building in \( x \) and \( y \) axes, respectively. \( Sa_g(T_1) \) and \( Sa_g(mT_1) \) are the geometric mean of the spectral accelerations at \( T_1 \) and \( 1.5 \cdot T_1 \), respectively, extracted from both horizontal components; finally, \( \text{Avg}SA_x \) and \( \text{Avg}SA_y \), are the average spectral accelerations in a period range extracted from the \( x \) and \( y \) components of the ground motion, e.g., the geometric mean of uniformly spaced \( Sa(T) \) ordinates over a range of periods for each component. For more details about \( \text{Avg}SA \) see Kohrangi et al. (2016a and 2016b). The CS target spectrum for \( \text{Avg}SA \) is defined by a vector of mean values in a range of periods defined by the user (e.g., 0s to 4.0s) together with a covariance matrix defined for the spectral accelerations in the selected period range. The mean vector and covariance matrix are then used to perform Monte Carlo simulation to generate potential target response spectra of individual records. The main steps in generation of the mean and covariance matrix are explained below.

The logarithmic mean (\( \mu \)) of the vector \( \mathbf{SA}=\{\ln Sa(T_1), \ln Sa(T_2),…,\ln Sa(T_n)\} \) conditioned on the joint occurrence of \( \ln \mathbf{IM}_1^*=x_1 \) and \( \ln \mathbf{IM}_2^*=x_2 \) for given \( M \), \( R \) and “site” values is computed as

\[
\mu = \begin{bmatrix}
\mu_{\ln Sa(T_1) | \ln \mathbf{IM}_1^*=x_1, \ln \mathbf{IM}_2^*=x_2, m, r} \\
\mu_{\ln Sa(T_2) | \ln \mathbf{IM}_1^*=x_1, \ln \mathbf{IM}_2^*=x_2, m, r} \\
\vdots \\
\mu_{\ln Sa(T_n) | \ln \mathbf{IM}_1^*=x_1, \ln \mathbf{IM}_2^*=x_2, m, r}
\end{bmatrix}
\]

\[
\mathbf{H}_{|T_n}^* = \begin{bmatrix}
\mathbf{H}_{11} & \mathbf{H}_{12}^T \\
\mathbf{H}_{21}^T & \mathbf{H}_{22}
\end{bmatrix},
\]

Note that \( \mathbf{H}_{11} \) in Equation (2) depends only on the vector \( \mathbf{IM}^* \) but is independent of \( T_n \), whereas \( \mathbf{H}_{21} \), \( \mathbf{H}_{12} \) and \( \mathbf{H}_{22} \) are functions of the spectral accelerations at period \( T_n \). The elements of the matrix \( \mathbf{H} \) are defined in Equations (3)-(5):

\[
\mathbf{H}_{11} = \begin{bmatrix}
\sigma^2_{\ln \mathbf{IM}_1 | m, r} & \rho_{\ln \mathbf{IM}_1, \ln \mathbf{IM}_2 | m, r} & \rho_{\ln \mathbf{IM}_1, \ln \mathbf{IM}_2 | m, r} & \rho_{\ln \mathbf{IM}_1, \ln \mathbf{IM}_2 | m, r} \\
\rho_{\ln \mathbf{IM}_1, \ln \mathbf{IM}_2 | m, r} & \sigma^2_{\ln \mathbf{IM}_1 | m, r} & \rho_{\ln \mathbf{IM}_1, \ln \mathbf{IM}_2 | m, r} & \rho_{\ln \mathbf{IM}_1, \ln \mathbf{IM}_2 | m, r} \\
\rho_{\ln \mathbf{IM}_1, \ln \mathbf{IM}_2 | m, r} & \rho_{\ln \mathbf{IM}_1, \ln \mathbf{IM}_2 | m, r} & \sigma^2_{\ln \mathbf{IM}_1 | m, r} & \rho_{\ln \mathbf{IM}_1, \ln \mathbf{IM}_2 | m, r} \\
\rho_{\ln \mathbf{IM}_1, \ln \mathbf{IM}_2 | m, r} & \rho_{\ln \mathbf{IM}_1, \ln \mathbf{IM}_2 | m, r} & \rho_{\ln \mathbf{IM}_1, \ln \mathbf{IM}_2 | m, r} & \sigma^2_{\ln \mathbf{IM}_1 | m, r}
\end{bmatrix},
\]

\[
\mathbf{H}_{21}^T = \begin{bmatrix}
\rho_{\ln \mathbf{Sa}(T_1), \ln \mathbf{IM}_1 | m, r} & \rho_{\ln \mathbf{Sa}(T_1), \ln \mathbf{IM}_2 | m, r} & \rho_{\ln \mathbf{Sa}(T_2), \ln \mathbf{IM}_1 | m, r} & \rho_{\ln \mathbf{Sa}(T_2), \ln \mathbf{IM}_2 | m, r}
\end{bmatrix},
\]

\[
\mathbf{H}_{22} = \begin{bmatrix}
\sigma^2_{\ln \mathbf{Sa}(T_1) | m, r} & \rho_{\ln \mathbf{Sa}(T_1), \ln \mathbf{IM}_1 | m, r} & \rho_{\ln \mathbf{Sa}(T_1), \ln \mathbf{IM}_2 | m, r} \\
\rho_{\ln \mathbf{Sa}(T_1), \ln \mathbf{IM}_1 | m, r} & \sigma^2_{\ln \mathbf{IM}_1 | m, r} & \rho_{\ln \mathbf{IM}_1, \ln \mathbf{IM}_2 | m, r} \\
\rho_{\ln \mathbf{Sa}(T_1), \ln \mathbf{IM}_2 | m, r} & \rho_{\ln \mathbf{IM}_1, \ln \mathbf{IM}_2 | m, r} & \sigma^2_{\ln \mathbf{IM}_1 | m, r}
\end{bmatrix},
\]

3
In these equations $\sigma_{ln IM_1 | w, r}^2$ and $\sigma_{ln IM_2 | w, r}^2$ are the variance of $\ln IM_1$ and $\ln IM_2$, respectively; and $\rho_{ln IM_1, ln IM_2}$ is their correlation coefficient. The quantity $\rho_{ln Sa(T), ln IM}$ is the correlation coefficient between $\ln Sa(T)$ and $\ln IM$. The covariance of $\text{SA}$ conditioned on the joint occurrence of $\ln IM_1 = \chi_1$ and $\ln IM_2 = \chi_2$ (here is referred to as $\Sigma$) is then obtained based on the following steps.

Let $\Sigma_0$ denote the (unconditional) covariance matrix of the vector $\text{SA}$.

$$
\Sigma_0 = \begin{bmatrix}
\sigma_{ln Sa(T_1)}^2 & ... & \rho_{ln Sa(T_1), ln Sa(T_2)} & \sigma_{ln Sa(T_1)} \cdot \sigma_{ln Sa(T_2)} \\
\vdots & \ddots & \vdots & \vdots \\
\rho_{ln Sa(T_n), ln Sa(T_1)} & \sigma_{ln Sa(T_n)} \cdot \sigma_{ln Sa(T_1)} & \cdots & \sigma_{ln Sa(T_n)}^2 \\
\end{bmatrix},
$$

(6)

Let $\Sigma_1$ denote the covariance matrix of the two vectors of $\text{SA}$ and $\text{IM}^* = \{IM_1^*, IM_2^*\}$:

$$
\Sigma_1 = \begin{bmatrix}
H_{11}^{T_1} \cdot H_{11}^{-1} & H_{11}^{T_2} \cdot H_{11}^{-1} & H_{12}^{T_1} \cdot H_{12}^{-1} & H_{12}^{T_2} \cdot H_{12}^{-1} & \cdots & H_{11}^{T_1} \cdot H_{11}^{-1} \cdot H_{12}^{T_2} \cdot H_{12}^{-1} \\
\vdots & \ddots & \vdots & \vdots & \ddots & \vdots \\
H_{11}^{T_1} \cdot H_{11}^{-1} & H_{11}^{T_2} \cdot H_{11}^{-1} & H_{12}^{T_1} \cdot H_{12}^{-1} & H_{12}^{T_2} \cdot H_{12}^{-1} & \cdots & H_{12}^{T_1} \cdot H_{12}^{-1} \cdot H_{12}^{T_2} \cdot H_{12}^{-1} \\
\end{bmatrix},
$$

(7)

Finally, the covariance matrix of $\text{SA}$ conditioned on $\text{IM}^*$ is obtained as follows:

$$
\Sigma = \Sigma_0 - \Sigma_1.
$$

(8)

Finally, using the $\mu$ and $\Sigma$ generated as described above, we can construct the conditional spectrum and perform the record selection following the method discussed by Jayaram et al. (2011). Figure 1 shows an illustrative example of the application of this method for a vector $\text{IM}^*=[Sa_{g,w}(T_1=1.0s)=0.5g, Sa_{g,w}(T_2=3.0s)=0.1g]$ and a scenario with $M_s=7.0$, $R=30km$ and strike slip fault type, based on the GMPE of Boore and Atkinson (2008). Figure 1(a) shows the target spectra (median and 2.5/97.5 percentile response spectra) along with the response spectra of 20 individual records. Straight form its definition, the target CS-vector spectra are hinged at two spectral ordinates corresponding to the spectral accelerations adopted here (i.e. $T_1=1.0s$ and $T_2=3.0s$).

Figure 1. Illustration of the CS(vector)-based record selection for geometric mean of spectral accelerations for vector $\text{IM}^*=[Sa_{g,w}(T_1=1.0s)=0.5g, Sa_{g,w}(T_2=3.0s)=0.1g]$ and a scenario with $M_s=7.0$, $R=30km$ and strike slip fault type based on the GMPE of Boore and Atkinson (2008): (a) target spectra (blue lines) and 20 selected individual records (grey lines), (b) mean target spectrum (black line) and the mean of the selected records (blue line), (c) conditional standard deviation of the target (black line) and selected record set (blue line).

It should be noted, however, that, finding actual records that (after scaling) exactly pass through the conditioning points is not an easy task. Hence, depending on the conditioning values, there might be a lack of records in the selection. Herein, we considered the mean of the scale factors related to the two hinge points; in addition, we considered only the records for which the ratio of the scale factors falls
between a tolerance of 0.95 and 1.05. Figure 1(b) and Figure 1(c) show the comparison between the target and selected ground motions in terms of the logarithmic mean and conditional dispersion, respectively. Note also that similar developments for a mean spectral target for two different spectral ordinates have also appeared in Kwong and Chopra (2017) while a formulation for the covariance has also appeared in Kishida (2017) although none has been able to apply it for record selection as done here.

3. APPLICATION OF CS(VECTOR) IN NONLINEAR DYNAMIC ANALYSIS

Three building examples are considered in this study. The examples include 3-, 5- and 8-story infilled RC buildings representative of typical Southern Europe design and construction practice, designed without provisions for earthquake resistance (Figure 2). More details about the properties of these buildings, their structural modeling, and their modal, static and dynamic responses can be found in Kohrangi et al. (2016b). In this study we selected a site on the coast of the southern Marmara Sea in Turkey with latitude and longitude of 29.1° and 41.0°, respectively (see Kohrangi et al., 2016a for more details of the hazard analysis). We used OpenQuake (Monelli et al., 2012) to perform the seismic hazard computations. These computations are based on the hazard model developed for the Seismic Hazard Harmonization in Europe (SHARE) Project (Giardini et al., 2013). We performed the vector PSHA (VPSHA) calculations (Bazzurro, 1998) via the “indirect” approach of VPSHA (Bazzurro et al., 2009). In this study, we utilized consistent definitions of spectral acceleration variables (i.e., arbitrary or geometric mean components (Baker and Cornell, 2006) by modifying the standard deviation of the applied GMPE, according to the definition of spectral acceleration considered. We considered four different definitions of IMs in our record selection and response prediction. The selected IMs and their application in record selection are explained in the subsequent section.

Figure 2. Plan view of building examples; left: 3-story building; middle: 5-story building; right: 8-story building).

4. GROUND MOTION DATABASE

4.1. Explanation of the adopted record selection variants

In order to provide a comparison between different record selection assumptions using the CS method, we considered the variants listed in Table 1, namely seven different cases for each building. Table 1 describes both the conditioning IM and assumptions considered in the record selection for each variant. The target spectra for each conditioning IM were based on the mean scenarios obtained from the disaggregation results of PSHA and VPSHA of the selected site. This approach is referred to as the approximate method versus the exact method in which all the causal events in the disaggregation analysis are considered in generating the target spectrum (Lin et al., 2013). Note that to ensure full consistency between hazard and record selection, we used the same GMPE of Boore and Atkinson (2008) in both tasks.

In the following, we briefly explain the selected IMs and the concept behind the choice of each one. FEMA P-58 (2012) proposes the use of the geometric mean of spectral accelerations at the average period, \( \bar{S}_g \), of the structure, where \( \bar{S}_g = (T_{1x} + T_{1y}) / 2 \) and \( T_{1x} \) and \( T_{1y} \) are the fundamental
periods of the structure in x and y axis, respectively. For comparison purposes, we also adopted this conditioning IM in one of our record selection cases. In this case, the records are selected and scaled to match the target spectrum of the geometric mean of the spectral accelerations of the two ground motion horizontal components. Another common approach is selecting records that match the target spectrum of one of the two components of the ground motion. This approach is mainly used in practice when engineers identify the most vulnerable axis of the building and therefore, they select their records based on one component only and apply them along the weakest building direction. In this case, the conditioning IM will be the spectral acceleration of an arbitrary component of the ground motion at the first mode period of the structure in its x or y axis, i.e., $S_a(T_{1x})$ or $S_a(T_{1y})$, respectively.

We split this approach into two categories. In the first approach, we select and scale the records to match a target spectrum for one of the two components of the ground motion. The other component in this case is adopted regardless of its consistency with the hazard. In the second and more robust approach, we consider both components of the ground motion in the target spectrum taking into account the correlation of the spectral accelerations in the two orthogonal directions. We label the former approach as “R” because one of the components will be chosen regardless of the hazard consistency, and the latter approach as “C” because of its compatibility with the hazard for both components of the ground motion. For all of the above-explained cases, we selected suites of records at six stripes corresponding with six IM levels with central bin values of 0.03, 0.1, 0.3, 0.5, 0.7 and 1.0g, including 50 pairs of records in each (total of 300 pairs). Note that the selected IMs’ return period range from 10 to 5000 years at the site of interest. For all above mentioned variants, we used the CS record selection algorithm of Jayaram et al. (2011), modified for the cases of $CS\{S_a(T_{1x})\}$-C and $CS\{S_a(T_{1y})\}$-C to consider the spectral ordinates at both orthogonal directions as well as their correlations.

<table>
<thead>
<tr>
<th>Index</th>
<th>Conditioning IM</th>
<th>Record selection description</th>
</tr>
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<tbody>
<tr>
<td>$CS{S_{a_m}(T)}$</td>
<td>Geometric mean of spectral accelerations at the average period, $S_{a_m}(T)$.</td>
<td>Records are selected and scaled to match with the target spectrum of the geometric mean of the spectral accelerations of two components.</td>
</tr>
<tr>
<td>$CS{S_a(T_{1x})}$-R or $CS{S_a(T_{1y})}$-R</td>
<td>Spectral acceleration of an arbitrary component of the ground motion at the first mode period of the structure in its x or y axis, i.e., $S_a(T_{1x})$ or $S_a(T_{1y})$, respectively.</td>
<td>Records are selected and scaled to match the target spectrum of one of the two components. The other component is inherited and used regardless of its spectral shape hazard consistency.</td>
</tr>
<tr>
<td>$CS{S_a(T_{1x})}$-C or $CS{S_a(T_{1y})}$-C</td>
<td>A vector IM, consisting of spectral acceleration of arbitrary components of the ground motion at the first mode period of the structure in x and y axes of the building, i.e. ${S_a(T_{1x}), S_a(T_{1y})}$.</td>
<td>Records are selected and scaled to match the target spectrum of both components considering the correlation of the spectral accelerations in two orthogonal directions. The spectral shapes at both components are, therefore, compatible with the hazard.</td>
</tr>
<tr>
<td>$CS{AvgSA_x, AvgSA_y}$</td>
<td>A vector IM, consisting of spectral accelerations averaged in a period range for arbitrary components of the ground motion, i.e. ${AvgSA_x, AvgSA_y}$.</td>
<td>Records are selected and scaled to match the target spectra of both components considering the correlation of the spectral accelerations in two orthogonal directions. The spectral shape at both components are, therefore, compatible with the hazard.</td>
</tr>
</tbody>
</table>

**Record selection method for this case is explained in section 3.**

† The average spectral acceleration is defined as the geometric mean of 10 equally and linearly spaced periods at a range of [0.8, 1.5] $T_1$ for the 3- story building and at a period range of [0.2, 1.5] $T_1$ for the other four examples. The reason for this choice is explained in Kohrangi et al. (2010b).

Finally, we defined two vector IMs consisting of two components representing the ground motion from the two orthogonal horizontal directions. The first vector IM includes spectral accelerations at the first modal period of vibration corresponding to the x and y axis of the building, $IM^* = \{S_a(T_{1x}),$
and finally, in the second vector IM, we considered the spectral accelerations averaged in a relative period range corresponding to the two orthogonal components of the ground motion, \( IM^* = \{ \text{Avg}SA_x, \text{Avg}SA_y \} \). For the vector conditioning IMs, we discretized the 2D IM domain into 6x6 cells centered at values of 0.03, 0.10, 0.30, 0.50, 0.70 and 1.0g per each IM. For each cell, we selected 10 pairs of records (total of 360 pairs) that best match with the target spectra. We selected the records from the NGA West ground motion database (Chiou et al., 2008). We emphasize that CS-c and CS(vector) cases could also be extended by considering the third ground motion (i.e., vertical) component for structures whose response is affected by the vertical excitation.

\[
\begin{align*}
CS[\text{Sa}_x(T_{1x}), \text{Sa}_y(T_{1y})] & \quad \text{CS}[\text{Sa}_x(T_{1x})]-\text{C} & \quad \text{CS}[\text{Sa}_x(T_{1x})]-\text{R} \\
\end{align*}
\]

Figure 3. Illustration of the CS record selection used for the nonlinear dynamic analysis of the 3-story building for various selection versions. Left column: CS(vector)-based record selection for a vector IM\(^*\)=\( \{\text{Sa}_x(T_{1x}), \text{Sa}_y(T_{1y})\} \) and the mean scenario of \( M_w=7.0, R=30\text{km} \) obtained from the disaggregation analysis of the joint occurrence of \( \text{Sa}_x(T_{1x})=0.57s=0.5g \), \( \text{Sa}_y(T_{1y})=0.66s=0.1g \); Middle column: CS[\text{Sa}_x(T_{1x})]-C for a scenario with \( M_w=6.5, R=28.4\text{ km} \) obtained from the disaggregation analysis of \( \text{Sa}_x(T_{1x})=0.57s=0.5g \); Right column: CS[\text{Sa}_x(T_{1x})]-R for a scenario with \( M_w=6.5, R=28.4\text{ km} \) obtained from the disaggregation analysis of \( \text{Sa}_x(T_{1x})=0.57s=0.5g \). (Note: the first row shows the target spectra in blue lines and the selected records in grey lines; the second row shows the target spectra in red and median spectra of the selected records in blue; the last row shows the target spectra in red and conditional standard deviation of the spectra for the selected records in blue).

Figure 3 shows the results of record selection, in terms of individual selected records, the target spectra and the quality of matching for the mean and variance of the selected and target spectra, for three variants corresponding to CS[\text{Sa}_x(T_{1x}), \text{Sa}_y(T_{1y})], CS[\text{Sa}_x(T_{1x})]-\text{C} and CS[\text{Sa}_x(T_{1x})]-\text{R}, in the left, middle and right columns of this figure, respectively. The first row shows the target spectra (i.e.
median and 2.5/97.5 percentile spectral accelerations) and the pairs of selected records (for both horizontal components). The second and third rows show (visually) the goodness of match between the spectra of the selected records and the target spectra for the logarithmic mean and conditional dispersion, respectively, for both of the orthogonal components. This figure helps explaining the differences between different record selection assumptions. In these examples, the CS(vector) is hinged at two conditioning scalar IMs at \( Sa_x(T_{1x}=0.57s)=0.5g, \) \( Sa_y(T_{1y}=0.66s)=0.1g. \) As explained earlier, in CS[\( Sa_x(T_{1x}) \)-C, the spectra are hinged at \( Sa_x(T_{1x}=0.57s)=0.5g \) only, however, the records are selected in a way to respect the conditional distribution of the spectral accelerations at other spectral ordinates in both the \( x \) and \( y \) components. CS[\( Sa_x(T_{1x}) \)]=R, on the other hand, selects the records conditioned on \( Sa_x(T_{1x}=0.57s)=0.5g \) and respects the spectral distribution of other spectral ordinates only for the \( x \) component of the ground motion. The right column of Figure 3 shows for this variant the natural mismatch of mean and variance between the target and selected records in the \( y \) direction.

5. RESULTS

5.1. Nonlinear dynamic analysis

We performed nonlinear dynamic analyses for all three building examples and record selection variants. The amount of results and figures to present are beyond the limited space of this paper, therefore, we try to address some of the most important findings and support our arguments with selected results and figures. As engineering demand parameter (EDP) for gauging the response severity, we considered the maximum interstory drift ratio (MIDR) along the height of the buildings in either the \( x \) or the \( y \) axis of the buildings. Figure 4, which illustrates the results of MIDRx and MIDRy for the 5-story building, shows the data points obtained from the seven different record selection variants. Note that for the vector IMs, the marginal data points that represent equivalent stripes similar to the scalar IMs are all plotted in the same figure for illustration purposes. However, for \( IM \) vectors, the data points are distributed within cells (i.e., within the limits from both \( x \) and \( y \) directions) rather than stripes (i.e., within the limits only on one direction). In addition, in Figure 4, the results are plotted in terms of IM=\( Sa_x(T_{1x}) \) versus MIDRx; and IM=\( Sa_y(T_{1y}) \) versus MIDRy. As such, the data points hold the fixed values of the pre-defined stripes, only if the conditioning \( IM \) corresponds with the axis label of the Figure, e.g. CS[\( Sa_x(T_{1x}) \)]=R, CS[\( Sa_x(T_{1x}) \)=C and CS[\( Sa_x(T_{1x}), Sa_y(T_{1y}) \)] for MIDRx. For other cases, the data points are plotted as scatter data because they have been conditioned on a different IM, e.g. CS[\( Sa_{g,w}(\bar{T}_{1}) \)], CS[\( Sa_y(T_{1y}) \)]=R, CS[\( Sa_y(T_{1y}) \)=C and CS[\( AvgSA_x, AvgSA_y \)] for MIDRx.

![Figure 4](image_url)

Figure 4. 5-story response data points obtained from the seven different record selection schemes of Table 1: a) \( Sa_x(T_{1x}) \) vs. MIDRx; b) \( Sa_y(T_{1y}) \)-MIDRy.

The response of the 5-story building along the \( y \) axis, at least at the linear elastic state of the response, is coupled with torsion whereas the response in the \( x \) direction is practically insensitive to torsion. This is the reason why Figure 4(a), for the case of vector IMs, MIDRx even at the low levels of \( Sa_x(T_{1x}) \), shows relatively high values compared with the other scalar counterparts. For instance, the first stripe
of Figure 4(a) corresponds to $S_a(T_{1x})=0.03g$, nevertheless, for vector IM of CS\{ $S_a(T_{1x})$, $S_a(T_{1y})$\}, there are cells with still $S_a(T_{1x})=0.03g$ but with $S_a(T_{1y})$ values up to 1.0g; as such, due to torsional behavior in Y direction, the response in the X direction is also affected. On the other hand, as can be seen in Figure 4(b), due to the non-torsional behavior of the X axis of this building, the response in the Y direction is not affected by the excitation of X direction. This trend is also observed in all other examples with respect to their torsional/non-torsional behavior. Even though such extreme cases (when excitation in X and Y are significantly different) are rare, as stated by the very low frequency of occurrence of these combinations at the site, their effect for the torsional buildings could be clearly observed in this example.

5.2. Response hazard curve

Following Shome and Cornell (1999), we compute the mean annual rate (MAR) of exceeding different values of an EDP, $\lambda(EDP \geq edp)$, using the conditional complementary cumulative distribution function of $EDP|IM$ for the non-collapsed data, $P(EDP \geq edp \mid NC, IM)$, and the probability of collapse given IM, $P_{col|IM}$, along with the rate of occurrence of scalar or vector IMs of interest, $\lambda(IM)$, formally:

$$\lambda(EDP \geq edp) = \int IM \left[ P(EDP \geq edp \mid NC, IM) \cdot (1 - P_{col|IM}) + P_{col|IM} \right] d\lambda(IM)$$

(9)

We considered two collapse criteria. The first is the global side-sway collapse that we equated to non-convergence of the analysis after large lateral displacements were reached. In addition, we considered a local collapse criterion that can be associated to the loss of load bearing capacity of the columns. This was assumed at an IDR value of 0.04 for the 3-, 5- and 8-story buildings. We used simple interpolation between bins (for scalar cases) and cells (for vector cases) of the response to obtain the distribution of $EDP|IM$.

Figure 5. Comparison of response hazard curves using different record selection variants for: a) 8-story building, MIDRx; d) 8-story building, MIDRy.

Figure 5 shows the results in terms of response hazard curves for the 8-story building examples. In general, we observed that the spread for response exceedance MAR among different methods is low, especially for the regular buildings. This is because all of these cases are based on legitimate CS record selection schemes and, by definition, given their consistency with the hazard at the site, they all are expected to provide robust estimates of the actual MAR of exceeding for the analyzed buildings (Bradley 2013, Lin et al. 2013). By inspecting the data points obtained by nonlinear analysis of the 3D torsional building examples of this study (e.g. Figure 4), one would have expected to see larger differences in the response hazard curves between the vector and scalar IMs due to the effect of the corner cells of the CS(vector) cases. However, even though such an effect is clearly observable at the response level, when the response is weighted with the hazard (to obtain the response hazard curves), since the hazard MAR of observing vector IM values at those corner cells is practically zero, its convolution with fragility essentially cancels out the effect of the data points in the corner cells. Figure 5(a) and Figure 5(b) also illustrate that the choice of the conditioning axis of the building along
with the “regardless” record selection scheme can significantly influence the response hazard estimates. The 8-story building of this study is more flexible in the X-direction (with $T_{1x}=1.30s$) and relatively stiff in the Y-direction (with $T_{1y}=0.44s$). This building because of its significantly weak walls has a soft story in the first floor in its X-direction. As can be seen in Figure 5(a) and Figure 5(b), the collapse rates estimated by $CS[S_{a_y}(T_{1y})]-R$ (magenta line) are larger than other cases whereas $CS[S_{a_y}(T_{1y})]-R$ still provides collapse rates that are more consistent. Even though both latter schemes are based on the selection of one component regardless of the other orthogonal component, since the building is more vulnerable in its X direction, the choice of IM = $S_{a_y}(T_{1y})$ is not a good choice. It is interesting to note that the $CS[S_{a_y}(T_{1y})]-C$ despite using the same IM as $CS[S_{a_y}(T_{1y})]-R$ variant, due to maintaining the correlation of the spectral accelerations for the two orthogonal components of the ground motion, brings its corresponding response hazard curve closer to the most reliable $CS(\text{vector})$ cases.

6. CONCLUSIONS

This study aimed at investigating several record selection proposals for seismic risk assessment of 3D structural models. We considered several variations of the conditional spectrum-based record selection approach in our study by changing the conditioning IM and the corresponding target spectrum. Conditioning IMs include scalar and vector IMs that are related to the response of the structure, such as spectral acceleration (geometric mean or arbitrary) at the first modal period of the structure or spectral accelerations averaged in a range of periods. For the scalar IM cases, we generated the target spectra hazard consistent with both of the two horizontal orthogonal components of the ground motion based on scalar PSHA, i.e. $CS(IM)-C$, or with one of them, i.e. $CS(IM)-R$. For the vector IM cases, we generated target spectra consistent with the hazard for both horizontal orthogonal components based on vector PSHA and disaggregation analysis. We tested all these record selection variants for the response prediction and risk based assessment of three RC 3D building models. The results show that, in general, if CS-based record selection is conducted consistently with the IM used for fragility and for both the $x$ and $y$ axes of the building, then the results of risk based assessment for the CS(vector) and CS(scalar) are very close. Nevertheless, for structures having quite different responses in their two orthogonal axes, using an inconsistent selection between $x$ and $y$ components based on a scalar IM emphasizing one of the two axes, i.e. $CS(IM)-R$, can be problematic, especially if that axis is not the most critical one. Having said that, the results also showed that even an inconsistent selection with one of the axis, i.e. $CS(IM)-R$, but that emphasizes the weakest axis of the building will work well. Moreover, in a case with an inconsistent selection, using a different conditioning IM for CS than the predictor IM for fragility (not necessarily inconsistent with $x$ or $y$, just between fragility and hazard), vector IMs will still perform well whereas the scalar IMs will be most troubled. Observing the fairly low scatter in the response MAR using all considered proposals, besides the $CS(IM)-R$ for extreme examples, will rise the question if one would still suggest the use of CS(Vector) that separates the two orthogonal horizontal components. With the results we obtained here, we may not recommend CS(Vector) at least for the structural buildings and for the far-field seismicity prevalent in our example as it is computationally more complex. Nevertheless, it might be useful for other structural types or seismicity conditions (e.g., forward directivity). What we can currently suggest as the simplest and at the same time reliable approaches are $CS[S_{g,m}(\bar{T})]$, $CS[S_{a_x}(T_{1x})]-C$, $CS[S_{a_y}(T_{1y})]-C$ or similar options for AvgSA, i.e., $CS[AvgSA_{g,m.}]$, $CS[AvgSA_x]-C$ and $CS[AvgSA_y]-C$ with CS compatible selection. In all of these cases one only needs scalar PSHA.

7. REFERENCES


