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RAPID REGIONAL RESPONSE SIMULATION OF 3-D PROTOTYPE STRUCTURES FOR FRAGILITY CHARACTERIZATION

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SUMMARY

Estimation of structural responses of an ensemble of buildings is limited by the large amount of computational power required to run nonlinear time history analyses for structures of the building stock. In addition, lack of inventory data at regional levels prevents an adequate characterization of the built environment. Therefore, this study outlines a methodology with efficient computational procedures to construct fragility curves by using prototype 3-D structures, whose geometry is considered to be random, and consequently is able to capture regional variability. Randomness in earthquake incidence direction and signal are also accounted for in the methodology. Metamodels, first order reliability methods, and nonlinear constrained optimization are the key tools used to implement this study.

INTRODUCTION

Estimation of losses at regional levels due to either earthquake or other natural or man-made hazards must be simplified due to the sheer size of the problem. One of the first systematic attempts to codify building vulnerability to earthquakes came from the Applied Technology Council (ATC) in a report to the seismic safety commission for the state of California, ATC [1]. In that study, damage functions were derived by asking expert structural engineers, builders and researchers, to estimate the expected percentage of damage that would result to a typical building of specific construction type located in an area whit a given intensity scale, e.g., Modified Mercalli Intensity Scale (MMI). These damage curves were widely adopted until the 1994 Northridge earthquake stimulated the need for more accurate approaches. It is obvious that the main drawback of the ATC-13 approach is its subjectivity. Therefore, it became difficult to calibrate, modify or incorporate new data based on recent observations and modern technologies.

HAZUS is a major undertaking to improve earthquake vulnerability assessments lead by the National Institute of Building Sciences and first released in 1997. HAZUS has replaced ATC-13 as the state-of-the-art methodology. In HAZUS, spectral displacements (*Sd*) and spectral accelerations (*Sa*) are used

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instead of MMI's as the measure of seismic intensity. The focus shifted from ground motion to specific building type response to ground motion. This change allowed better calculation of structural damage. HAZUS still continues to rely on expert opinion and engineering judgment to estimate the state of the damage that would result from a given spectral displacement or acceleration. State of damage is assigned to objective structural responses (e.g., maximum interstory drift) obtained from analytical procedures such as nonlinear static analyses, NIBS [2]. Conditional probabilities of being in or exceeding a particular damage state, DS, are calculated by fitting the response of a population of structures, defined by simple sampling techniques, to lognormal distributions. This fitting process provides the parameters that characterize the probability law of the response.

Such an approach when used with a portfolio of buildings oversimplifies the problem because it uses fragility curves for classes of buildings but without accounting for any geometric variability within the class (i.e., variations in plan and elevation). Also, static nonlinear analysis provides an approximation of the structural response that can be more accurately calculated using nonlinear dynamic procedures. This study addresses these issues using efficient probabilistic and statistical tools, and it highlights the potential to include in fragility characterizations certain qualitative predictors such as age, maintenance, construction quality, etc.

REGIONAL INVENTORY DATA AND PREDICTOR VARIABLES

In order to determine the required data to construct a suitable finite element models for probabilistic simulation, existing databases such as tax assessment parcel data can be mapped with information from aerial photography, satellite imagery, and laser-based light detection and ranging (LIDAR) to infer the desired modeling inputs. These inputs include building height, building geometric configuration, structure type, location, total floor area, year of construction, land use/occupancy, and content value. Data-mining tools and knowledge-based systems can be used to fill in information gaps. This process permits establishing the variability of prototype structures so that parametric models can be constructed. Models are largely based on macro-level predictors (e.g., plan and elevation geometry). Complexity in plan configuration can be characterized by both absolute and relative dimensions, Arnold [3]. Figure 1 shows fundamental configurations which represent shapes that can be determined from pixel density of aerial images using pattern recognition algorithms but yet shapes that also allow parametric variations to account for regional inventories.

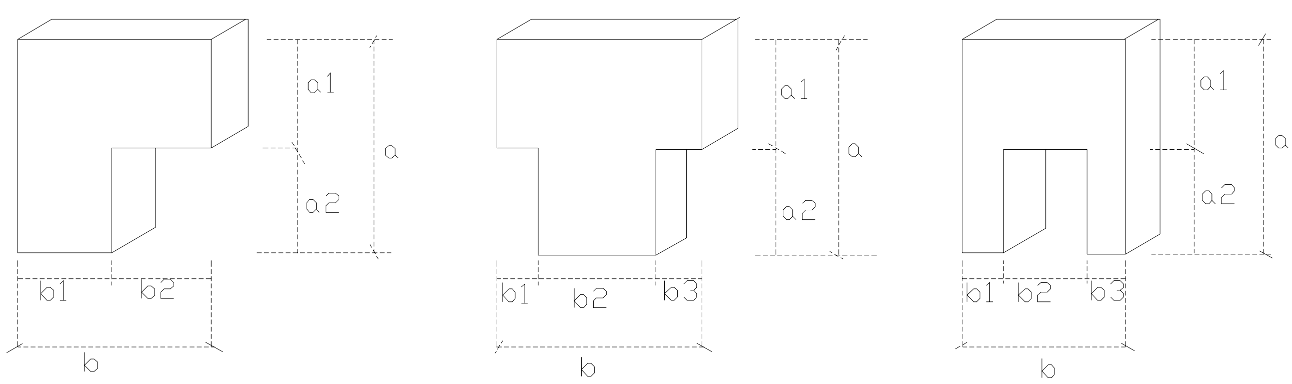

Figure 1. Fundamental plan shapes for pattern recognition and parametric variation.

This study focuses on buildings whose lateral force resisting system is a moment resisting steel frame. The buildings are designed for non-severe seismic areas, such as northeastern United States. Also, these structures are assumed to be low-rise and used for commercial purposes (i.e., offices). The proposed methodology starts with definition of the range of variability of the predictor parameters. In this study, L-shaped structures are characterized by the leg dimensions, *a*, and *b*. Earthquake direction is defined by the angle, α with respect to the horizontal X direction. Earthquake variability is included by utilizing ten different synthetic ground motions developed for Mid-America cities, Wen and Wu [4]. In addition, first-story height variability, *h*, is introduced to incorporate local effects induced by soft stories. Table 1 summarizes the variables used in the parametric models. Also a uniform probability law is assigned to the variables so that any value within the range is equally likely to occur. A parametric model for two-dimensional representation of buildings is introduced by Towashiraporn [5].

Table 1. Range of variation for predictor parameters.

Variable	Predictor levels						Probability Law
	1	2	3	4	5	6	
a [m]	9.1440	18.2880	27.4320	36.5760	45.7200	54.8640	Uniform
b [m]	9.1440	18.2880	27.4320	36.5760			Uniform
α [rad]	3.1416	0.7854	1.5708	2.3562			Uniform
h [m]	2.9718	3.9624	4.9530				Uniform

STRUCTURAL MODELING

The advanced system for inelastic analysis of structures, ZeusNL, is used to develop the 3D structural models. This finite element code has been developed by researchers of the Mid-America Earthquake Center, Elnashai [6]. Figure 2 shows a small sample of the structures used to characterize the response of a population of buildings for the low-rise steel moment resisting class.

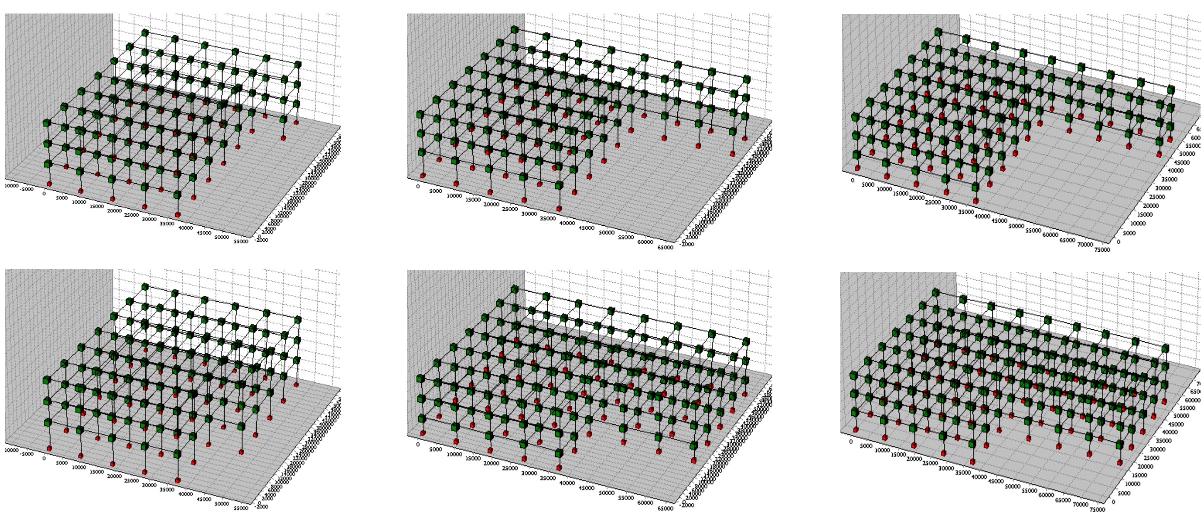

Figure 2. Sample of structures for response characterization increasing a ↓ and b→ (6 out of 14 cases).

ZeusNL explicitly models the spread of inelasticity along member length and across section depth, allowing for accurate estimation of damage accumulation. The code accounts for both material and geometric nonlinearities. Therefore, better predictions of building response are expected with nonlinear time history analyses (NTHA) when compared with the static nonlinear methods implemented in HAZUS.

In order to probabilistically characterize the response of reference building classes, it is necessary to randomly generate structures where each variable is a realization from its probability law. The variables considered in this study are assumed to be uniformly distributed, and at least 10,000 different structures are needed to have a manageable variance in the response characterization. The use of ZeusNL, or any other computational tool for dynamic analysis, can be very expensive computationally if all cases were to be explicitly run. Therefore, surrogate models, known as metamodels, are developed to provide practicality in heavily-computational problems and also to help uncover functional relationships between variables and responses.

EXPERIMENTAL DESIGN

The first step for metamodel development is defining an experimental design. An experimental design represents a sequence of experiments to be performed, expressed in terms of *factors* (i.e., design variables) set at specified *levels* (i.e., predefined ranges). The design is represented by a matrix **X** where the rows denote experiment runs, and the columns denote particular factor settings. A central composite design (CCD) is a two-level full or fractional factorial design (2^k or $2^{(k-f)}$), that has been augmented with a small number of carefully chosen treatments (i.e., combination of factor levels) to permit estimation of a second-order response surface model, Neter [7]. Additional points are center points (n_o), and star points positioned at $\pm\alpha$ for each factor. In this study variable a has six levels, variable b and α have four levels, and variable h has three levels. A full combinatorial design will be referred to as *grid* design and consists of 288 treatments. Provided that ten synthetic ground motions are being used to account for earthquake signal uncertainty, the number of cases becomes 2,880.

For vulnerability characterization, it is also required to scale the set of ground motions to different levels of an intensity measure. Spectral acceleration, *Sa*, has been chosen for that purpose, and all earthquakes are scaled so that the maximum spectral acceleration at the fundamental period of the structure corresponds to that of the scaling sequence (i.e., 0.1g, 0.2g, … , 2.0g). This requirement represents an increase in the number of NTHA's by a factor of ten if the range from 0.1g to 2.0g is divided in 10 levels. Consequently, a total of 28,800 analyses would need to be performed. This number would still be much smaller than the number of cases for a full Monte Carlo simulation, where the 10,000 cases to keep variance under control need to be multiplied by ten to account for the spectral acceleration levels resulting in 100,000 cases. These computational constraints demand an experimental design with reduced number of treatments that still allows estimation of first and second order effects (i.e., how predictor variables affect response in main and quadratic sense). Figure 3 summarizes the reduced experimental plan chosen for this study, where only 1,400 NTHA's are needed to estimate parameters of a second order predictive polynomial model (i.e., metamodel). This corresponds to 14 treatments, 10 earthquakes, and 10 *Sa* levels.

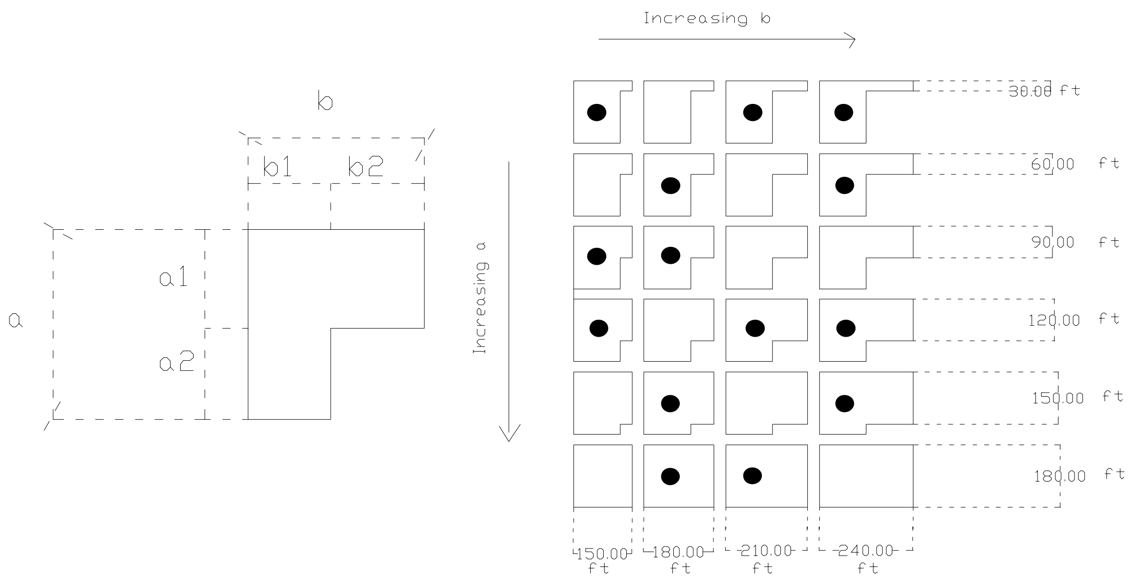

Figure 3. Treatments for experimental design used in metamodeling development.

METAMODELING PHASE

After performing the computer runs defined by the design of experiments (DOE), a predictive polynomial model of building response is required for each level of spectral acceleration, *Sa*. Polynomial regressions (PR) are low-order polynomials that relate a vector of independent input factors, **X**, influencing the response, **y**. For problems with low curvature (i.e., smooth response), a first order polynomial can be used:

$$\hat{y} = \beta_0 + \sum_{i=1}^{k} \beta_i x_i \tag{1}$$

For significant curvature (i.e., where more erratic response is expected), a second order polynomial which includes all two-factor interactions is more advisable. This model is the one chosen for the L-shaped buildings whose response is given in terms of the maximum interstory drift experienced by the structure in any direction:

$$\hat{y} = \beta_0 + \sum_{i=1}^{k} \beta_i x_i + \sum_{i=1}^{k} \beta_{ii} x_i^2 + \sum_{i=1}^{k} \sum_{j=1, i<j}^{k} \beta_{ij} x_i x_j \tag{2}$$

The process for constructing these PR models is generally called Response Surface Methodology (RSM), Khuri [8]. PR models have been applied in different science and engineering fields for designing complex systems. In particular, aerospace engineers have taken advantage of this methodology for technical feasibility and economical viability analyses of aircraft conceptual designs, DeLaurentis [9]; Mavris [10]. When creating PR models, it is possible to identify the significance of different input factors directly from the coefficients in a normalized regression model. In spite of this advantage, there are drawbacks when applying the methodology to highly nonlinear behaviors using higher order polynomials. Instabilities may arise, and estimation of all coefficients of the regression equation may require larger experimental samples, Hussain [11].

Since this study uses a suit of ten ground motion for each spectral acceleration level, it is assumed that each earthquake has the same probability of occurrence, and therefore, the mean response is used as response **y**. However, in order to account for the variability of the time history signal, another metamodel is fit to the variance of the response. Both metamodels are used to create a combined metamodel that accounts for the variability of the input parameters, and the variability of the ground motion. The predictive metamodel-based equations for each spectral acceleration level has the form:

$$\hat{Y}_i = \hat{y}_i \pm \hat{\sigma}_i \qquad (3)$$

where *i* represents each *Sa* level, and, y and σ, are predictive metamodels for the response and for the earthquake-induced variance of the response. Table 2 shows a sample of the regression coefficients for the mean and the variance of the response at *Sa* = 0.1g, and 0.2g. These values include the effect of 10 earthquakes and 14 different structures from the experimental design. First story height variation, *h*, is not included in the predictive response.

Table 2. Sample of coefficients for polynomial regression metamodels at Sa = 0.1g, and 0.2g.

	Sa	*Intercept*	*a*	*B*	*α*	*a^2*	*b^2*	*α^2*	*a * b*	*a * α*	*B * α*
Mean	**0.1**	-2.726	-0.041	-0.082	3.488	0.0017	0.0008	-0.787	-0.002	-0.005	0.038
	0.2	-31.84	-0.041	-0.103	26.29	0.011	0.006	-4.973	-0.016	-0.055	0.102
Std Dev	**Sa**	**Intercept**	**a**	**B**	**α**	**a^2**	**b^2**	**α^2**	**a * b**	**a * α**	**B * α**
	0.1	29.58	-0.076	-0.061	-20.06	-0.006	-0.005	3.549	0.013	0.044	-0.027
	0.2	23.38	-0.047	0.001	-16.08	-0.005	-0.004	2.945	0.011	0.033	-0.041

Metamodel Diagnostics

In order to validate the use of these metamodels, a series of diagnostics are preformed to assure no departures from the linear regression model with normally distributed error terms, which served as basis of the statistical analysis. Figure 4 shows that there are few evident outliers, error variance is constant, error terms are independent, and residuals tend to be normally distributed. Therefore, there is no need for data modification, transformation or implementation of remedial measures. However, more formal numerical tests can be performed to validate the model, when visual diagnostics evidence abnormal data behavior. Among these test, a modified Levene test for nonconstancy of error variance, studentized deleted residuals for outlying responses, or chi-square test for non-normality of residuals, are recommended, Neter [7]. These tests are beyond the scope of this study, but Figure 4 presents a residual and normal probability plot for the mean metamodel at *Sa* = 0.2g.

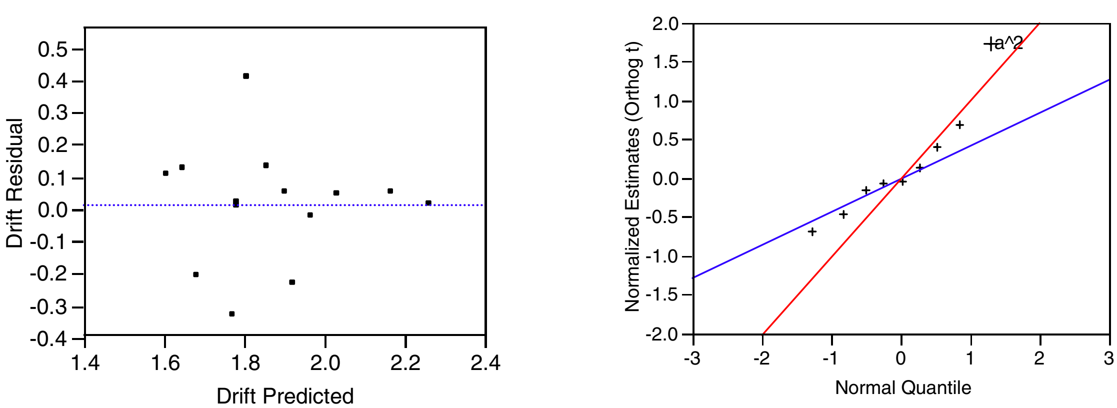

Figure 4. Diagnostics for polynomial-based predictive metamodels of building response.

DISCRETE FRAGILITY CHARACTERIZATION

Probabilistic approaches for fragility characterization can be based on two different theoretical developments: (1) numerical simulation, and (2) reliability theory. Metamodels play a key role in both groups since they are the enablers for implementing computationally unfeasible response calculations. This paper focuses on reliability-based fragilities. Rather than using numerical methods to determine the probability of failure of a particular class of structures, reliability methods rely on transforming limit state functions into linear or quadratic relationships. First order and second order reliability methods (FORM / SORM) are first-order or second-order Taylor series expansions of G(**x**) where this function expresses the difference between the available or desired performance response limit in terms of drift and the expected drift imposed by the earthquake. According to the guidelines for the seismic rehabilitation of buildings, FEMA 273, ATC[12], three levels of structural performance can be defined for the buildings under consideration: Immediate Occupancy (IO) ≤ 0.7% drift, Life Safety (LS) ≤ 2.5% drift, and Collapse Prevention (CP) ≤ 5% drift. Probability-based limit state design is the basis of most new structural design standards, Ellingwood [13]. The limit state equations, G(**x**), for calculating the probability of exceeding a performance level have the form:

$$G(\underline{x})_i = \text{Performance level Drift}_i \text{ - Metamodel Drift } [\%]_i \leq 0 \qquad (4)$$

The best choice for carrying out the Taylor expansion is the point of maximum likelihood on the limit state function. A useful step to find that point before FORM implementation is to transform all random variables into their standardized normal form, N(0,1). For uniform random variables the transformation is given by:

$$F(x) = \frac{x-\alpha}{\beta-\alpha} = \Phi(U_x) \qquad (5)$$

and

$$x = \Phi(U_x)*(\beta-\alpha)+\alpha \qquad (6)$$

Applying this transformations to each basic variable X_i, i = a, b, a, the unit of variance measurement in any direction in the uniform space is the same. The limit state equation now becomes, g(**U**) = 0. When using polynomial metamodel representations of the problem, all basic random variables appear in the equation and give a powerful tool for handling correlation. This is because even interacting random variables can be represented by their basic components (i.e., for any one of the terms, $X_i * X_j$, in the metamodel, there is no need to study another random variable, $Z = X_i * X_j$, but simply all transformations are introduced within X_i, and X_j independently). Therefore, transformations can be done at the basic resolution level, thus avoiding correlation transformation problems. In the extreme case where basic random variables are inherently correlated, transformations such as Rosenblatt and Nataf can be implemented, Melchers [14].

Once the transformed uncorrelated limit state equation, g(**U**) = 0, is available, the reliability index, β, is the shortest Euclidean distance from the origin (in the standard normal space) to the hyperplane, g(**U**) = 0, and this also defines the point for expanding the Taylor series. This means that FORM is a nonlinear constrained optimization problem, and such a problem can be solved using tools like Lagrange multipliers to create an unconstrained problem. The general formulation for this study is:

$$
\begin{array}{lll}
\text{Minimize} & \beta = (U_a^2+U_b^2+U_\alpha^2)^{1/2} & \text{(Reliability index)} \\
\text{subject to} & g(\mathbf{U}) = 0 & \text{(Assures maximum possible reliability)} \\
 & U_a \geq 0 & \text{(Nonnegative leg a)} \\
 & U_b \geq 0 & \text{(Nonnegative leg b)} \\
 & U_\alpha \geq 0 & \text{(Nonnegative leg Earthquake incidence angle)}
\end{array} \qquad (7)
$$

Minimizing the objective function, $\beta = (U_a^2+U_b^2+U_\alpha^2)^{1/2}$, is equivalent to finding the minimum distance from the origin to the plane, $g(\mathbf{U})=0$. The decision variables are U_a, U_b, and U_α. Minimizing $\beta = (U_a^2+U_b^2+U_\alpha^2)^{1/2}$ is equivalent to obtaining the maximum possible reliability index, β, for the structure under consideration. In other words β gives an estimate of how likely the structure will be on the failure side for a given earthquake intensity, *Sa*. The constraint, $g(\mathbf{U}) = 0$, assures that from all possible combinations of random structural parameters, a, b, and α, one gets the minimum distance to the origin of the reduced space as illustrated in Figure 5. This minimum distance, β, amounts to saying that desired performance drift of the building is equal to the imposed drift demanded by the earthquake. Non-negativity constraints assure that the physics of the model are kept consistent. Also, the U variables need to be nonnegative because the constraint, $g(\mathbf{U})$, contains the cumulative distribution function (CDF) of a standard normal variable. $\Phi(\ )$ does not have a closed-form solution, and it needs to be approximated by a polynomial sum in the optimization solver. Such an approximation contains the probability density function (PDF) of the standard normal, $\phi(\ )$, which has exponential terms of the form, $e^{-1/2*U}$, where U needs to be positive to assure convergence, Melchers [14].

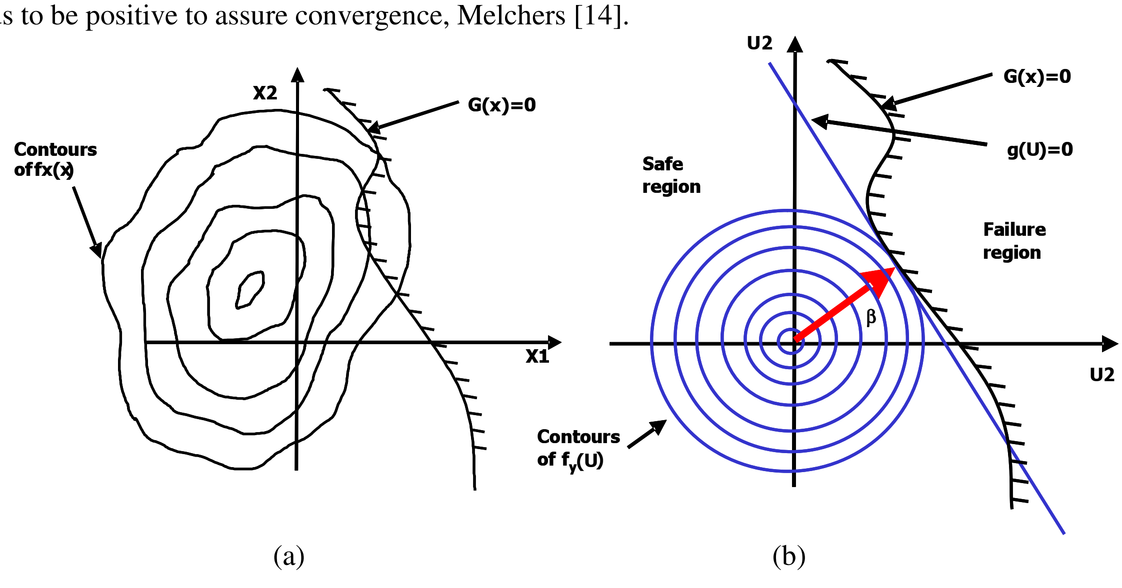

Figure 5. First order reliability method as a nonlinear constrained optimization problem: (a) equations in original space, and (b) in equations uniform variance space.

The polynomial approximation to include $\Phi(\mathbf{U})$ in the optimization solver is robust enough for values of any argument, $U \geq 0$. Approximated error when compared to numerical integration of $\Phi(\mathbf{U})$ is on the order of $\varepsilon < 5\text{x}10^{-5}$.

$$
\Phi(-\beta) \approx \left[\frac{\beta}{1+\beta^2} + \left(\sum_{i=0}^{5} a_i * \beta^i \right)^{-1} \right] \varphi(\beta) \qquad (8)
$$

where a_i ($i = 0, \ldots, 5$) have the following values: ($(2/\pi)^{1/2}$, 1.280, 1.560, 1.775, 0.584, 0.427). and $\phi(\ )$ corresponds to the standard normal PDF. As an illustration of metamodel use, equation (8) shows a truncated sample of the limit state equation used for the particular case of life safety (LS) at spectral acceleration, *Sa* = 0.2g. The highlighted coefficients correspond to the intercept and *a* terms of the model as shown in Table 2. The complete equation is one of the constraints of the optimization problem which is solved for each of the three performance levels at each of the ten spectral acceleration levels, *Sa*. Once the reliability indices, β, are determined, the nominal probabilities of being in or exceeding performance levels of the problem under analysis are calculated. They are simply computed as $P = \Phi(-\beta)$ or $P = \Phi(\beta)$, depending on the level of drift demand and the level of building performance under consideration. $\Phi(\,.\,)$ represents the cumulative density function for a standard normal random variable. Probabilities of exceeding each of the performance levels for *Sa* = 0.1 and 0.2g are shown in Table 3. Also, the reliability indices corresponding to those probabilities are included. For comparison purposes, Table 3 also shows the values obtained with a full Monte Carlo simulation using the metamodels under study.

$$g(U) = 2.50 - (\underline{\mathbf{-31.8455}} - \underline{\mathbf{0.04004}} * ((1 - 1/(2*Pi)^{1/2} * e^{(-0.5*Ua\hat{}2)} * (Ua/(1+Ua^2) + ((2/Pi)^{1/2} + \ldots \quad (9)$$

Table 3. Probabilities of being in or exceeding performance levels using FORM and Monte Carlo.

	Performance Level	0.1g	0.2g
FORM β Indices	I.O	0.2792	1.3401
	L.S.	1.0341	0.3919
	C.P.	2.4855	1.2761
	Performance Level	**0.1g**	**0.2g**
FORM Probabilities	I.O	0.3901	0.9098
	L.S.	0.1505	0.6524
	C.P.	0.0064	0.1009
	Performance Level	**0.1g**	**0.2g**
Monte Carlo	I.O	0.5291	0.7245
	L.S.	0.1733	0.4668
	C.P.	0.0029	0.2236

It can be observed that the probabilities depart, but not significantly, from the ones calculated using Monte Carlo simulation techniques. The trends are maintained. This suggests that the linearized limit state function resembles the response surface in shape and curvature in the neighborhood of the minimization points. However, far from the neighborhood of linearization, FORM overestimates the probabilities. It may be necessary to use Second Order Reliability Methods (SORM) to account for this phenomenon. Also, SORM is advisable to be used for metamodels with less smooth response surfaces, as the number of parameters and nonlinearities of the system increase (e.g., this might be appropriate for unreinforced masonry structures which behave in a rather fragile and unpredictable way as compared with the predictable behavior of ductile reinforced concrete or steel buildings).

VULNERABILITY CURVES

By fitting the discrete set of points obtained for each spectral acceleration level in lognormal probability paper, the parameters of the conditional probability distribution can be obtained. Figure 6 shows the relationship between spectral acceleration and probability of exceeding structural performance levels.

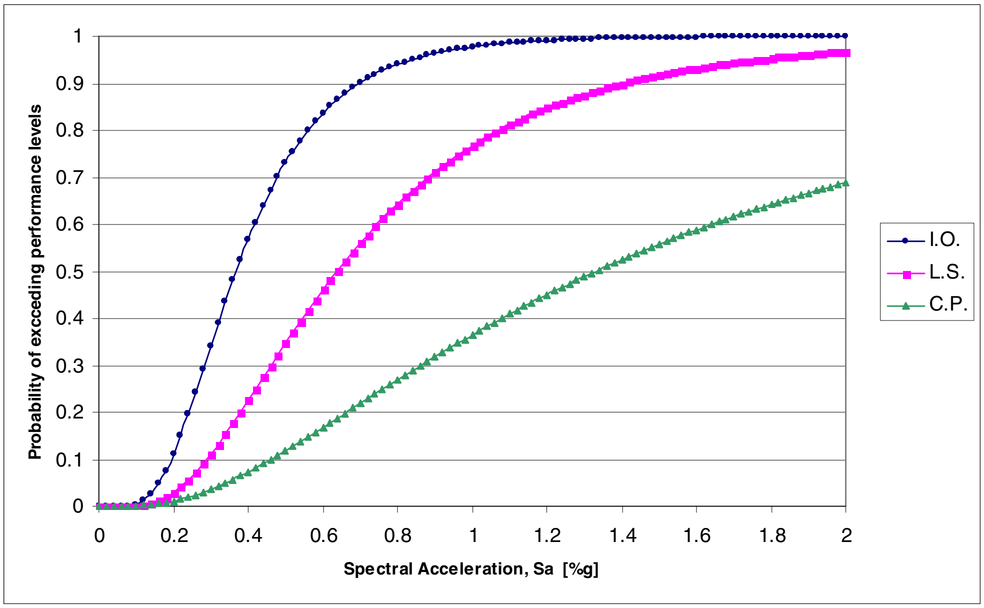

Figure 6. Conditional probabilities of exceeding performance levels given an earthquake intensity (case of L-shaped low-rise steel moment resisting frames).

ANALYSIS OF RESULTS

It is observed that for buildings with large geometry changes, the variability of the response increases at high spectral acceleration levels. This phenomenon is more likely attributed to the lateral resistance of the buildings as function of plan configuration, as well as the incidence direction of the earthquake.

Results from a sensitivity analysis of the optimization problem provide some insights to the problem at hand, as shown in Table 4. Within the neighborhood of optimality (i.e., $\beta = 0.3919$) a unit increment of transformed variables U, approximately represents in physical sense 18m (60 ft) of leg *a*, 9m (30ft) of leg *b*, and 45º angle α of earthquake incidence direction, respectively. The structure at optimality corresponds to the configuration that produced the worst performance, or the limit for maximum reliability. Based on the calculated optimizers such structure is similar to building (3, 2) in matrix of buildings of Figure 3.

Table 4. Data at optimality for sensitivity analysis in LS at 0.2g

Constraint	*Slack or Surplus*	*Dual Optima*
Maximum reliability g(U) = 0	0.0000	-0.6603
Nonnegative leg a	0.0000	-0.2665
Nonnegative leg b	0.0000	-0.0123
Nonnegative angle α	0.3919	0.0000

Dual variables approximately represent the rate of change in optimal value (i.e., β) for each additional unit of Right Hand Side, RHS, of each constraint, see equation (7). In this case one can say that an additional unit in building drift resistance, g(**U**) = 1%, will increase the Euclidian distance 0.66 units, or it will increase the reliability index, β, 0.66 units. This is an important increase in building reliability from β = 0.39, or 65% probability of exceeding LS, to β = 1.05, or 24.7% probability of exceeding LS drift. Physically this means that the structure would be stiffer, implying thicker columns and beams, plus the tendency of having symmetric L-shaped plan. Decreasing just the leg, *a,* in the reduced space one unit will improve the safety index, β, by 0.26. This means that β will pass from 0.39 to 0.55. This is equivalent to having a probability of exceeding a LS performance level for a 0.2g spectral acceleration of $P = \Phi(-0.55) = 29.1\%$ in comparison with the original 65% probability of exceeding the same LS level. Equivalently, a unit decrease or increase in leg, *b,* in the reduced space will produce a probability of exceeding the LS performance level of 64%. This value is almost the same at optimality. The reason is that a decrease in leg *b* produces a thinner leg *a*, which will not improve response. Also, increase of leg *b* will not improve response because orientation of internal columns in the original building design is with all of them in the *b* direction (i.e., X direction). Increase or decrease in earthquake direction, α, in the neighborhood of optimality (i.e., nearly symmetric L-shaped plan), does not change reliability. It is observed that the four directions included in this study (i.e., N-S, NW-SE, E-W, and NE-SW) induce similar response on this particular structure nearly symmetric L. Other more irregular leg-to-leg cases show opposite behavior.

CONCLUSIONS

This study presents a methodology for capturing seismic response of building classes that exhibit regional variation in geometric parameters like plan and elevation configuration. Such a methodology has the potential to be extended to account for micro-parameter variation (i.e., mechanical and material properties), and qualitative indicators such as construction age, implemented code, maintenance, etc. Results show that rapid assessment of seismic response of hundreds of thousands of buildings can be achieved by developing predictive metamodels where independent variables are considered to be random. With random variables within the polynomial metamodels, probabilistic analysis of the response is obtained without the computational burden that would occur if randomness were to be included directly in the dynamic analysis of each possible structure. Instead, carefully chosen cases that statistically capture the characteristics of the chosen building stock are fully analyzed to construct building metamodels. The feasibility of carrying out many-simulations is enabled by metamodels when combined with reliability theory which relies upon optimization techniques. This approach indicates that not even Monte Carlo simulation would be needed to determine fragility curves, because FORM reasonably encapsulates the essence of failure hyperplanes, Dueñas-Osorio [16]. Optimization also helps understanding the impact of each predictor variable on overall drift resistance. Aggregation of losses is envisioned to be enhanced by rapid assessment of the response, because predictive models for different building classes will readily provide more realistic probabilities of exceeding predefined performance levels, whose remedial measures or impacts can be translated into monetary terms. On going research is expected to be calibrated and compared with damage and loss estimates for a specific region. Memphis, TN, will be used as a test-bed for implementing developments of this and other critical Mid-America Earthquake Center projects related to localized earthquake hazard, decision support tools, acceptable consequences, and advanced visualization techniques. Comparisons with estimates from HAZUS-MH are also going to be performed.

Regarding the statistical analysis, it is noticed that earthquake incidence direction has a dominant role in predicting the response of most of these three dimensional irregular structures. This expected result suggests that the variable should be discretized further in the experimental design, so that its influence on the curvature of the failure plane is better approximated, and their effect on nearly symmetric L-shaped plans is better assessed. Additional treatments or building configuration ranges are also needed to capture all footprints that pattern recognition techniques are able to provide with current technologies (i.e., L-, T-, H-, and U-shaped). It is expected with further analysis of the problem to describe the geometry of the building plan by simple parameters that directly correlate with torsionally induced drift.

Regarding structural dynamic analyses, it is observed that ground motion loading for the buildings requires a more systematic application so that most of the vibration modes are exited by the earthquake signal. This study scaled ground motions to produce specific spectral acceleration at the fundamental period of the structure in each orthogonal direction. However, torsional modes and combined torsional-translational modes become important and earthquake loading needs to be weighted by the participation of each of the modes in the dynamic response. This means that a weighted sum of excitations is needed for incremental dynamic analysis in three-dimensions for fragility characterization. Damage indices for 3D structures also need to be investigated, so that they account for bidirectional and torsional response effects. On going research at the Mid-America Earthquake Center, MAE [17], is focusing on decomposing 3D irregular structures into planar frames where demand-to-capacity rations provide the basis for damage estimation.

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