AN APPLICATION OF THE RESPONSE SURFACE METAMODEL IN BUILDING SEISMIC FRAGILITY ESTIMATION

P. Towashiraporn[1], L. Dueñas-Osorio[2], J. I. Craig[3], and B. J. Goodno[4]

[1] *Senior Research Engineer, AIR Worldwide Corporation, Boston, MA, USA*
[2] *Assistant Professor, Dept. of Civil & Environmental Engineering, Rice University, Houston, TX, USA*
[3] *Professor, School of Aerospace Engineering, Georgia Institute of Technology, Atlanta, GA, USA*
[4] *Professor, School of Civil & Environmental Engineering, Georgia Institute of Technology, Atlanta, GA, USA*

Email: ptowashiraporn@air-worldwide.com

ABSTRACT :

Seismic fragility plays an essential role in the estimation of potential earthquake losses to a building. Its probabilistic framework allows the damage assessment to take into account uncertainties in earthquake hazard as well as in building properties. However, the relationship between building damage, earthquake loads, and structural characteristics is complex and can hardly be represented by a closed-form expression. Therefore, propagation of the uncertainties to formulate damage probability distributions has to rely upon numerical techniques such as Monte Carlo simulation. This approach requires a large number of trials in order to obtain a reliable probabilistic distribution of the damage. Computational demand becomes impractical when thousands of dynamic nonlinear time-history analyses of building models must be performed for that purpose. This work explores an alternative approach for carrying out the intensive structural simulations. Response Surface Methodology in conjunction with Monte Carlo simulation achieves an efficient compromise in building fragility computation. In particular, a response surface is systematically developed to predict the structural response based upon a few nonlinear finite element dynamic analyses. Computational costs imposed by the Monte Carlo simulation are significantly reduced because the propagation of uncertainties can now be performed on a polynomial response surface function, rather than on a complex dynamic finite element model. An example application of the methodology is presented for the seismic fragility assessment of a 5-story steel moment resisting frame (SMRF) building. The building is assumed to be located in Memphis, Tennessee, USA, and is designed in accordance with the seismic provisions commonly used in the region. The computed fragility curves of the building reveal potential damage to the building from future earthquakes, and provide the basis for prioritizing mitigation actions.

KEYWORDS: response surface, metamodel, fragility, earthquake, damage

1. INTRODUCTION

A building's performance under future earthquakes is largely unknown and cannot be predicted with certainty. This is primarily due to the fact that an earthquake is a complex phenomenon in nature and that no two earthquakes are alike. Another source of uncertainty comes from the building itself as construction material properties can exhibit deviation from their designed or expected values. Performance assessment based only on a deterministic response analysis may be misleading and a probabilistic assessment is deemed more appropriate in some cases. The concept of seismic fragility curves is utilized as a measure of damage likelihood of a building subjected to seismic events with various intensities.

Conventional methods for developing analytical fragility curves use simulation of seismic responses. However, the simulation normally requires a large number of samples in order to obtain a consistent probability density of the outcomes. Tens of thousands of samples may be needed in this regard. It quickly becomes impractical when each sample in the simulation involves a nonlinear dynamic analysis of a complex structural model. This work proposes an alternative approach for deriving the simulation-based fragility curves by using a statistical technique called a response surface metamodel.

2. THE RESPONSE SURFACE METAMODELS

In most physical systems, the mechanism of a computed response is governed by an implicit relationship between the response and a set of input variables that influence the response. An exact relationship is typically unknown and the response has to be computed by conducting an experiment or running complex computer codes. In many circumstances, resources are too limited so that a sufficient number of numerical experiments cannot be performed. In the case of computer analysis codes, the computational expense of running computer analysis codes may become prohibitive when a large number of models need to be examined.

A metamodel is a statistical approximation of the complex and implicit physical phenomena. A response is estimated from a closed-form function of input variables which is computationally simpler to run. Construction of metamodels generally involves 3 main steps: (1) choosing an experimental design for selecting a set of inputs for observing or running an analysis for outputs, (2) choosing a functional form for the metamodel, and (3) fitting the model to the observed data. Several options in each step result in various approximation techniques that can be used for a metamodel. Typical metamodels include polynomial regression models of complex computer analyses based on experimental designs (e.g., the response surface methodology), artificial neural networks, kriging or inductive learning metamodels [Simpson et al., 2001].

One of the most widely-used metamodels is the Response Surface Methodology (RSM). The origin of the RSM can be traced back to the work of several researchers in the early 1930's. However, it was Box and Wilson [1951] who formally developed the methodology to determine an optimal condition in a chemical investigation. Since then, the RSM has been successfully applied in many different fields of study such as chemical engineering, industrial engineering, manufacturing, aerospace engineering, structural reliability, and computer simulation.

Response Surface Methodology refers not only to the use of a response surface as a multivariate function but also to the processes for predefining a parameter space (or a design space) and determining the polynomial coefficients themselves. A response surface equation is simply a polynomial regression to a data set. The process is straightforward if a sufficiently large data set is available, that is if the number of members in the data set is at least as large as the number of coefficients in the polynomial. On the other hand, if the data set must be determined and if the process is time-consuming and computationally expensive, then the overall usefulness of the method will depend on the use of an efficient method for selecting the fewest possible data points. Design of Experiments (DOE) techniques provide the needed basis for this critical step in the methodology.

There have been a number of applications of the response surface methodology in the field of structural reliability. Bucher and Bourgund [1990] were among the first researchers to pioneer the application. In their study, the method was used to approximate limit state conditions of a nonlinear single-degree-of-freedom oscillator and a frame structure. Good quality of the response surface prediction was observed in this study. Rajashekhar and Ellingwood [1993] evaluated an existing response surface approach in structural reliability analysis and proposed a way for selecting experimental points at the distribution extremes instead of the entire range of the distributions. Numerical examples were given to confirm the efficiency of the approach.

The Response surface methodology was found to provide good approximation of complex analysis codes in all published literature. These successful applications have led to an idea that the method could be useful in other fields where complex and implicit analysis codes can be replaced by a simple response surface function. Seismic fragility analysis of a building typically requires repetitive runs of dynamic analysis code in order to obtain reliable damage statistics and it can easily become computationally prohibitive. This work implements the response surface concept for predicting building damage due to earthquake loadings. The approaches are described in the subsequent section.

3. COMPUTING BUILDING FRAGILITY WITH A RESPONSE SURFACE

Building seismic fragility describes the likelihood of damage to a building due to various levels of earthquake intensity. It takes into account randomness in earthquake loadings and uncertainties in the structural characteristics (e.g. material strength and modulus of elasticity) in deriving probabilistic descriptions of the damage. Seismic fragility assessment requires repeated damage simulations of a building with random properties subjected to random earthquake inputs. Each realization of seismic damage is carried out through complex finite-element time-history analysis. It usually becomes impractical because of the large number of time-consuming analyses needed to obtain reliable statistics of the outcomes. A response surface metamodel is sought to approximate an implicit building seismic damage computation using an explicit polynomial function. A Monte Carlo simulation can then be performed on the simpler response surface metamodel instead of the complex dynamic analyses. The process for calculating seismic fragility based on the use of response surface metamodels is described in the following paragraph.

The first step is to define input and output (or response) variables for the response surface. An appropriate building response or damage measure such as a maximum inter-story drift is defined as an output variable. Random building and earthquake parameters characterizing the response calculation are used as input variables, and the applicable range of each input variable is defined. When a large (generally more than 5) number of input variables are identified, a screening process is generally used to determine a subset of variables that have the largest influence on the output. A Design of Experiments (DOE) technique is then utilized for the selection of an efficient set of input variable combinations (experimental sampling). Next, a detailed computational analysis is performed on a building model constructed to represent one combination of input variables defined by the DOE step, and the chosen seismic response is extracted from each analysis run. The process is repeated for all other combinations of the input variables defined in the DOE step. A least-squares regression analysis is then performed on the sampled input data points and corresponding outputs to formulate a polynomial response surface function. This response surface model is very computationally inexpensive for use in a brute-force Monte Carlo technique with a large number of simulations. Consequently, probabilities of the chosen response exceeding certain damage limit states can be computed from the simulation outcomes and in the final step, the fragility curves can be constructed.

4. EXAMPLE APPLICATION: A 5-STORY STEEL BUILDING

To present an application of the response surface methodology with full details, a fictitious building of steel moment-resisting frame construction located in downtown Memphis, Tennessee, is chosen for an example of the application. The building is square in its plan with 5 bays in each direction. The bay width is 7.62 meters (25 feet). The building has 5 stories with each story being 3.96 meters (13 feet) tall. It was designed according to the seismic provision of the 1985 SSBC (Southern Standard Building Code). Moment-resisting frames are located only in the perimeter frames of the building. The building in this study represents a typical stock of older steel buildings that can be found in the area. Memphis is located in close proximity to the New Madrid seismic zone. This seismic zone is known to be capable of generating large magnitude earthquakes in the past, but since recent history shows no sign of a recurrence of those events, many people in this region appear to forget about the threat and the likelihood that a damaging earthquake in this region could severely impair their built-environment. Fragility curves for the building will indicate the likelihood of this building being damaged from future earthquakes of various intensities.

4.1. Damage or Response Measures

The first step in the process is to define a response measure that is suitable for the quantification of seismic damage. A number of researchers have proposed damage measures for buildings as a result of earthquake loadings. Some utilized a displacement-based measure such as a maximum roof drift ratio to quantify the damage. Some used energy-based criteria that relate the amount of hysteretic energy to the levels of damage. Some researchers combined the displacement-based and the energy-based criteria to derive unique measures. However, there has been little consistency on the most appropriate measure to quantify the seismic damage. In light of these available damage measures, FEMA [2000] proposed the use of the maximum drifts for assessing building performance as well as the levels of damage to structural components. The work described in this paper uses the maximum inter-story drift ratios as the response parameter due in part to its simplicity, but largely because the drift is well-correlated with seismic damage.

4.2. Response Surface Input Parameters

The main idea of approximating a complex and implicit dynamic structural analysis model with a more tractable response surface metamodel is that the propagation of uncertainties from random building properties to the response measure can be done with relative ease. For this reason, input parameters for the response surface should be those random building properties that contribute to the extent of damage the building would experience during an earthquake. Strictly speaking, any of the building properties will have an influence on the damage; however, having too many input parameters can spoil the simplicity of the response surface model. A screening test of the input parameters can be performed to screen out less important parameters and leave only those that have the most contribution to the computation of the building response. Towashiraporn [2004] performed a Pareto screening test on a similar steel building and found that the most influential building properties (in no particular order) include a building's damping ratio, and also the yield strength and elastic modulus of the steel.

In addition, the intensity of the earthquake also plays a major role in the computation of the damage. From correlation analyses of various earthquake intensity measures and the building response (maximum drift), it was found that the most appropriate intensity measure is the spectral acceleration at the fundamental period of the building ($S_{a,T1}$). The spectral acceleration is then defined as another input variable of the response surface. Finally the response surface model in this work will describe, in functional form, the building's maximum drift ratio by the 4 input variables (namely, the building's damping ratio, the steel's yield strength, the steel's elastic modulus, and the spectral acceleration at the building's fundamental period).

A parameter range for each of the input variables expanding from its expected value must be defined in order to form an experimental design space. Choosing meaningful regions of interest for the input variables must be done with caution. On the one hand, the regions should be large enough to include all possible parameter spaces. On the other hand, the regions cannot be too large or they will reduce the prospect of a good regression fit of the response surfaces to the actual response. Table 1 presents the input parameters defined for the response surface model in this work as well as their expected values (center point), and the lower and upper bound values. These bounds form a multi-dimensional design space where the responses are to be calculated.

Table 1: Input Parameters for the Response Surface Function and their Design Spaces

Parameter	Lower Bound	Center Point	Upper Bound
Steel Yield Strength (MPa)	259	324	389
Steel Elastic Modulus (GPa)	190	200	210
Damping Ratio	0.01	0.02	0.03
$S_{a,T1}$ (g)	0.1	0.6	1.1

4.3. Design of Experiments

The design of experiments (DOE) systematically defines an efficient set of experimental sampling points at which the responses must be computed or observed. There are many types of experimental designs that can be used for this purpose. Among them, the most commonly used experimental designs are a Full Factorial design and a Central Composite design. However, these types of experimental designs are more appropriate for physical experiments where random or replication errors (i.e., replicating experiments with an identical set of inputs produces different values of outputs) exist. In this work, an experiment is actually a computer analysis in which the random or replicating error term is absent. This lack of the random error term leaves the least-square fit of a model without obvious statistical meaning [Sacks, 1989], so instead of the commonly used 'classical' designs, an experimental design for computer analyses should have its design points filling the design space and treat all regions of the design space equally [Simpson, 2001]. This work implements a Uniform Design, which is one of the 'space filling' designs appropriate for deterministic computer experiments.

Table 2 shows parts of a Uniform Design table for 4 input parameters with each parameter having 3 levels (lower, center, and upper). This Uniform Design table consists of 39 different combinations of the input parameters. The values -1, 0, and +1 in the table represent the lower bound, center point, and upper bound values, respectively. For example, the DOE case 2 takes the lower bound values of the yield strength and the elastic modulus, the expected (or center point) value of the damping ratio, and the upper bound value of the spectral acceleration. Each of the 39 DOE cases represents one realization of the steel building in our study.

Table 2: Uniform Design Table of 4 Parameters and 3 Levels

DOE #	Input Parameter				Response	
	Yield Strength	Elastic Modulus	Damping Ratio	$S_{a,T1}$	Mean Drift (%)	Std Dev Drift (%)
1	-1	-1	-1	0	4.477	0.826
2	-1	-1	0	+1	7.185	2.238
⋮	⋮	⋮	⋮	⋮	⋮	⋮
39	+1	+1	+1	+1	6.471	1.959

The earthquake intensity parameter ($S_{a,T1}$) indicates loadings to be applied to each of the building realizations. Due to the complexity of how an earthquake interacts with a building, the building responses from different earthquakes of similar intensity can vary. This record-to-record dispersion of the responses must be accounted for in a fragility analysis. This research addresses this dispersion issue with the use of an ensemble of earthquake records for computing the responses. However, actual earthquake records in the central and southern regions of the United States are largely unavailable. As a result, a suite of 500 artificial ground motion records generated for Memphis [Wen and Wu, 2001 and Rix and Fernandez, 2006] is utilized for the fragility analysis in this research. In order to preserve the underlying physical properties of the simulated earthquakes, there is no scaling of the records in this work. Instead this large pool of earthquake records are grouped together according to their spectral acceleration values. For a specific DOE case, dynamic analyses are performed on the building realization subjected to a group of the earthquake records pertaining to the intensity defined for the case. For example, a group of earthquake records that have their spectral acceleration around 1.1g is applied to the building realization in the DOE case 2. The use of a group of various earthquakes records results in a distribution of the responses for a given DOE case. The responses sought in this work are really an expectation of the maximum drift as well as a measure of its record-to-record dispersion. In this work, the maximum inter-story drift ratios computed for a given spectral acceleration are assumed to be lognormally distributed [Cornell et al., 2002]. As a result, the lognormal mean and standard deviation of the drift ratios are computed as response parameters for all DOE cases (Table 2).

4.4. Response Surface Model Fitting

The most widely used response surface function is a mathematical polynomial function. A typical response surface model limits the order of the polynomial to one or two since low-degree models contain fewer terms than higher-degree models and thus require fewer experiments to be performed. A second-order polynomial function is considered as a response surface model in this research since the seismic responses usually exhibit nonlinear behaviors that a first-order model cannot capture appropriately. A typical response function considering the second-order polynomial model is presented in Eqn. 4.1.

$$\hat{y} = b_0 + \sum_{i=1}^{k} b_i x_i + \sum_{i=1}^{k} b_{ii} x_i^2 + \sum_{i=1}^{k-1} \sum_{j>i}^{k} b_{ij} x_i x_j \tag{4.1}$$

where

$\hat{y}$	=	the predicted response
x_i , x_j	=	the input variables
b_0 , b_i , b_{ii} , b_{ij}	=	unknown coefficients to be estimated
k	=	number of input variables

In order to capture the expectation as well as the record-to-record variability due to earthquakes, the responses sought in this work are the natural logarithmic (or lognormal) mean and standard deviation of the maximum inter-story drift ratios. Many linear statistical models can be used for deriving the polynomial response surface functions of the mean and standard deviation. In this work coefficients of the polynomial functions are determined by a least-square regression analysis of the responses and the experimental data points (Table 2).

Figure 1 shows the response surface functions derived in this work. Each response surface function is really a multi-dimensional predictive model. However, for illustration purposes, the plot is presented in a 2 dimensional space in which the relationship between the predicted mean of the maximum drifts and the $S_{a,T1}$ is shown (solid blue line). The values for the yield strength, the modulus, and the damping ratio are fixed at their respective central point values. The predicted standard deviation is displayed as a departure from the predicted mean values (or mean ± std dev, shown as dotted blue lines). It is apparent from this figure that the record-to-record variability increases as the ground motion intensity increases. Actual maximum drifts calculated from the time-history computer analyses are shown in the same figure as a reference. It is seen from the figure that the predictive response surface models agree with the actual data points with reasonable accuracy.

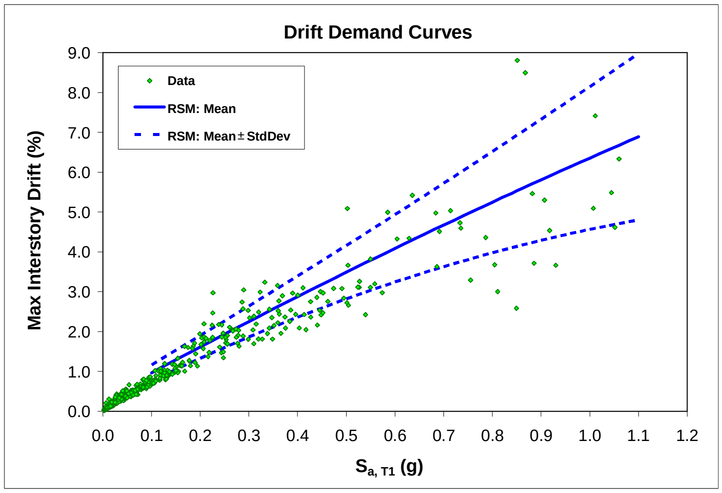

Figure 1: Plots of Maximum Inter-story Drifts versus Ground Motion Intensity $S_{a,T1}$

4.5. Statistical Validation of the Response Surface Models

A least-square regression analysis gives parameter or coefficient estimates for the response surface functions. The next step is to evaluate an adequacy of fit of the predictive models. There are a number of statistical measures that can be used to verify linear regression models. However, statistical testing is inappropriate in this case where outputs are computed by deterministic computer analyses rather than physical experiment trials because the random error term does not exist [Simpson et al., 2001]. The simplest measure for verifying the model adequacy in the deterministic computer experiments is a coefficient of determination (R^2). The value of R^2 characterizes the fraction of total variation of the data points that is explained by the fitted model. However, the R^2 can be misleading since it always increases as more input variables are added. Alternatively, an adjusted-R^2 (R^2_A), which takes into account the number of parameters in the model, can be used for evaluating the goodness-of-fit of the model.

Even though the R^2_A value explains how well the model fits to the predefined experimental points, the value does not, however, reflect the prediction potential of the model to other points not used to generate the model. In order to verify the overall accuracy of the response surface models, statistical tests at additional random data points in the design space must be performed. Those tests include the Average Absolute Error (*%AvgErr*), the Maximum Absolute Error (*%MaxErr*), and the Root Mean Square Error (*%RMSE*) [Venter et al., 1997]. For the purpose of these statistical tests, 100 additional combinations of input variables (N=100) are generated at random. Actual (y_i) and predicted ($\hat{y}_i$) maximum inter-story drifts are calculated for each combination and those statistical measures are computed as follows:

$$\%\mathrm{AvgErr} = 100 \cdot \frac{\frac{1}{N} \cdot \sum_{i=1}^{N} |y_i - \hat{y}_i|}{\frac{1}{N} \cdot \sum_{i=1}^{N} y_i} = 5.22\% \tag{4.2}$$

$$\%\mathrm{MaxErr} = \operatorname*{Max}_{i}\left[100 \cdot \frac{|y_i - \hat{y}_i|}{\frac{1}{N} \cdot \sum_{j=1}^{N} y_j}\right] = 12.87\% \tag{4.3}$$

$$\%RMSE \;=\; 100\cdot\frac{\sqrt{\frac{1}{N}\cdot\sum_{i=1}^{N}(y_i-\hat{y}_i)^2}}{\frac{1}{N}\cdot\sum_{i=1}^{N}y_i} \;=\; 6.22\% \qquad (4.4)$$

The above measures quantify errors, as percentages, that the predicted maximum drifts from the response surface model depart from the actual values. It can be seen that the errors in the model are quite low indicating good prediction accuracy of the response surface model in this study.

Finally, in addition to the use of these statistical measures, visual assessment of the residual and the correlation plots are performed to determine the model accuracy. This correlation plot confirms that the response surface metamodel can provide a good approximation to the much more complex nonlinear dynamic analysis.

4.6. Fragility Curves

The seismic fragility is mathematically defined as a probability of a response (or damage) exceeding some damage state threshold conditional on a specific ground motion intensity. Since the damage measure in this work is based on the maximum inter-story drift ratios, the damage states must be defined with the same measure. The 3 damage states (i.e., Immediate Occupancy, Structural Damage, and Incipient Collapse) suggested by Ellingwood and Wen [2005] for a steel moment frame building in Mid-America are used in this study. The drift ratios corresponding to those damage states are 1% (IO), 2% (SD), and 8% (IC). If the $S_{a,T1}$ is considered as a ground motion intensity for the fragility computation, the fragility can be formulated in terms of a conditional probability as shown in Eqn. 4.5.

$$PF_{DS} = \text{Prob}\,[\, d \geq d_{t|DS} \mid S_{a,T1} \,] \qquad (4.5)$$

where PF_{DS} is the fragility for a damage state DS, $d_{t|DS}$ is a drift threshold for the damage state DS, and d is the drift ratio the building would experience under an earthquake. The drift ratio (d) is assumed to be lognormally distributed with the mean, μ_d, and the natural logarithmic standard deviation, β_d. The mean and the standard deviation of the drifts are described by the response surface as functions of the steel yield strength, the elastic modulus, the damping ratio, and the earthquake intensity $S_{a,T1}$. Randomness in those building properties is introduced into the predictive functions for the mean and the standard deviation. The steel yield strength is described by a Lognormal distribution with a mean value of 324 MPa and a coefficient of variation (COV) of 0.12. The elastic modulus for steel is uniformly distributed with a mean value of 200 GPa and a COV of 0.06 [Song and Ellingwood, 1999]. Finally, the building's damping ratio is assumed to be uniformly distributed with its values ranging between 0.01 and 0.03.

At any given level of the $S_{a,T1}$, a Monte Carlo simulation evaluates the response surface functions for the maximum drift ratios taking into account both the randomness in the building material properties and the record-to-record dispersion due to earthquakes. After a large number of simulated samples (10,000 samples in this work), a probability distribution of the drift ratios can be obtained and probabilities of exceeding the drift thresholds corresponding to the 3 damage states are calculated. Repeating the simulation for all levels of $S_{a,T1}$ results in the fragility curves for the 5-story steel building (Figure 2). It must be noted that the large difference between the structural damage and the incipient collapse fragility curves could be a result of the difference in the drift ratio threshold of the 2 damage states (2% versus 8% respectively)

In order to evaluate the fragilities of this steel building, seismic hazard information at the site of the building is required. The U.S. Geological Survey (USGS) provides spectral acceleration values at short and long structural periods at locations throughout the United States. The values at the assumed location of the building (downtown Memphis) are extracted from the 2002 USGS hazard maps. FEMA [2000] guidelines are used to construct acceleration spectra for both BSE-1 (10% in 50 years) and BSE-2 (2% in 50 years). For this steel building, with a fundamental period of approximately 1.6 seconds, the corresponding spectral acceleration values from the spectra are approximately 0.15g and 0.4g for the BSE-1 and the BSE-2 hazard levels, respectively. From the fragility curves, it is estimated that there is about a 90% chance that the building will not satisfy the Immediate Occupancy criteria under the BSE-1 hazard level and there is more than a 95% chance that the building will sustain structural damage under the BSE-2 hazard level. An appropriate mitigation option may be needed for this building to reduce the damage probabilities to a more desirable level.

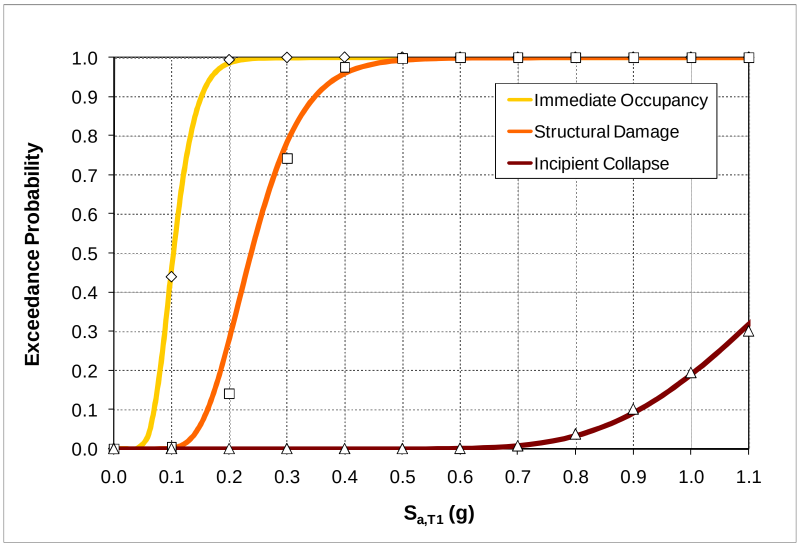

Figure 2: Fragility Curves of the 5-Story Steel MRF Building in Memphis

5. CONCLUSION

This work presents the use of a response surface metamodel in the fragility assessment of a building. A building's seismic fragility curves demonstrate the likelihood of damage while taking into account uncertainties in both the building properties as well as the input earthquake ground motions. The uncertainties are usually propagated to the damage computation by means of a brute-force Monte Carlo simulation. However, complexity in the damage computation (e.g., time-history analyses) complicates the overall simulation process and reduces its efficiency. The response surface functions in this work replace the more complex time-history analyses and relate the maximum inter-story drifts to the building properties and the ground motion intensity through simple polynomial functions. A Monte Carlo simulation is then performed on the more tractable response surface models to simulate the probability density of the damage.

An example of the application is presented using a hypothetical 5-story steel moment-resisting frame building in downtown Memphis. The maximum drift ratio of the building is used as a response measure. Input parameters are defined in terms of the steel yield strength, elastic modulus, the building's damping ratio, and the earthquake intensity $S_{a,T1}$. A Uniform Design DOE table is selected for describing combinations of the input parameter levels at which the responses are calculated. The responses for the model are the expectation and the record-to-record dispersion of the maximum drifts. The resulting response surface function seems to agree reasonably well with the results obtained from the time-history analyses. Statistical tests confirm the accuracy of the response surface function quantitatively. A Monte Carlo simulation evaluates the responses while taking into account uncertainties in the building properties as well as the earthquakes. Finally, fragility curves are derived from the conditional exceedance probabilities of the simulated responses. Engineers or building officials can use this information to develop proper mitigation plans in preparation for potential earthquakes in the future.

It is shown in this work that the application of the response surface metamodel in the field of seismic fragility assessment can reduce the computational demands of the overall approach. The main advantage of the response surface metamodel is that while it provides an admittedly simple functional relation between the most significant input variables and the output (response), the model is computationally very efficient.

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