PROBABILISTIC LIFE-CYCLE COST: ASSESSMENT AND SENSITIVITY ANALYSIS THROUGH STOCHASTIC GROUND MOTION MODELING FOR SEISMIC HAZARD

A Thesis

Submitted to the Graduate School of the University of Notre Dame in Partial Fulfillment of the Requirements for the Degree of

Master of Science

in

Civil Engineering

by

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Notre Dame, Indiana

July 2011
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ACKNOWLEDGMENTS

I would like to gratefully and sincerely thank my advisor, Dr. Alexandros Taflanidis, for his guidance, support, patience and most importantly friendship during my graduate studies at University of Notre Dame.

I would like to thank all of the members of the HIPAD group, especially Gaofeng Jia for sharing his knowledge regarding computer programming with me and all of my colleagues who made my stay and adaption to United States a lot easier.

I would also like to thank the Department of Civil Engineering and Geological Sciences at University of Notre Dame, especially the members of my doctoral committee, Dr. Ahsan Kareem and Dr. Tracy L. Kijewski-Correa, for their input, valuable discussions and accessibility.

Special gratitude goes to my former professor and advisor for my Bachelor’s Thesis, Demos Angelides, for his mentoring during those years and his support in my decision to pursue a Master in United States.

Last, but not least, I would like to thank my family for their unconditional love and support through the years.
CHAPTER 1:
INTRODUCTION

1.1 Motivation

Life-cycle loss estimation in earthquake engineering requires proper integration of (i) methodologies for evaluating the structural performance using socioeconomic criteria, (ii) probabilistic approaches for treating the uncertainties related to the seismic hazard and to the structural behavior over the entire life-cycle of the building, as well as (iii) algorithms for efficient evaluation of the resultant multidimensional integrals ultimately quantifying seismic cost. The modeling of earthquake losses for a specific seismic event and the characterization of the earthquake hazard, describing the likelihood of occurrence of each event as well as the seismic forces in the specific format required for structural analysis [ground motion time history or some simplified intensity measure], constitute undoubtedly the most important components of this process.

Earlier methodologies for seismic loss estimation expressed these losses in terms of the global reliability of the structural system. Recent advances in Performance-Based Earthquake Engineering (PBEE) quantify, more accurately, repair cost, casualties, and downtime in relation to the structural response, using fragility curves to develop such a relationship. In this context, approaches have been proposed that approximately describe the nonlinear structural behavior by the static pushover response (Fragiadakis et al. 2006; Kircher et al. 2006) and/or estimate earthquake losses in terms of global response
characteristics (Ang and Lee 2001). Other researchers (Porter et al. 2001; Goulet et al. 2007; Ramirez and Miranda 2009) have developed more thorough analytical tools to evaluate seismic vulnerability on a more-detailed level. According to this methodology, the nonlinear time-history response of the structure under a given seismic excitation is used to calculate damages in a component level, by grouping the structural members into assemblies with same vulnerability with regard to that response and same repair cost characteristics.

This approach requires, thus, description of the entire ground motion time history for seismic events. Two are the main methodologies for this characterization (Jalayer and Beck 2007). The first one is based on adopting a parameter (or vector of parameters (Baker and Cornell 2005)) known as an intensity measure (IM) that represents the dominant features of the ground motion. A probabilistic seismic hazard analysis is then performed to characterize IMs for different hazard levels; this analysis takes into account all important sources of modeling uncertainty for the ground motions. Typically only a small number of hazard levels are considered. Then, for each of these levels, ground motion records consistent with the corresponding IMs are selected from some strong-motion database by performing a seismic hazard disaggregation (Bazzurro and Cornell 1999). These recorded ground motions are taken to represent samples of possible future ground motions for each hazard level (each value of IM) and are used in structural analyses to give samples of the structural response. A probability model, usually log normal, is then fit to these samples. The probabilistic structural performance is assessed by combining these probability distributions conditional on IM with a site-specific estimation of the probability that ground shaking with a given value of the IM occurs.
The advantage of this approach is that this probabilistic structural performance is established using a fairly small number of recorded earthquake time histories. This approach suffers, though, from concerns regarding the validity for ground motion scaling (Grigoriu 2011), from scarcity of ground motions for specified earthquake characteristics (magnitude, type of faulting), and from the fact that the variability of the ground motions is somewhat arbitrarily addressed by the exact selection of the ground motions (Jalayer and Beck 2007).

The alternative approach, is to use stochastic ground motion models (Boore 2003; Rezaeian and Der Kiureghian 2008) which are based on modulating a high-dimensional stochastic white-noise sequence through functions that address spectral and temporal characteristics of the excitation. The parameters of these functions, for example duration of strong motion, can be related to earthquake (type of fault, moment magnitude and epicentral distance) and site characteristics (shear wave velocity, local site conditions) by appropriate predictive relationships (Atkinson and Silva 2000; Rezaeian and Der Kiureghian 2010). Description of the uncertainty for the earthquake characteristics (moment, epicentral distance and so forth) and for these predictive relationships, through appropriate probability models, leads then to a complete and detailed probabilistic description of potential future ground-motion time-histories. In general, two types of stochastic ground motion models can be distinguished, ‘source-based’ models (Papageorgiou and Aki 1983; Atkinson and Silva 2000; Boore 2003; Motazedian and Atkinson 2005; Atkinson and Boore 2006; Atkinson 2008) that describe the fault rupture at the source and propagation of seismic waves through the ground medium, and ‘site-based’ (or ‘record-based’) models that are developed by fitting a preselected
mathematical model to a suite of recorded ground motions (Amin and Ang 1968; Shinozuka and Deodatis 1988; Papadimitriou 1990; Conte et al. 1992; Sabetta and Pugliese 1996; Conte and Peng 1997; Somerville 1998; Mavroeidis and Papageorgiou 2003; He and Agrawal 2008; Rezaeian and Der Kiureghian 2008). The first class of models have the advantage that can describe ground motions in areas where records are scarce (Atkinson 2008), since they are based on physical modeling of the rupture and wave propagation mechanisms, but their popularity within the structural engineering community is limited, primarily because they are developed by seismologists and validated only with regard to ground motion characteristics, not structural response quantities.

The focus of all aforementioned studies related to stochastic ground motion models have been, though, primarily on development of the stochastic ground motion models. Limited attention has been given to the impact of such a seismic hazard characterization within the context of PBEE and of life-cycle cost estimation.

1.2 Scope of work

This thesis develops a simulation-based, comprehensive computational approach for further bridging the aforementioned gap. It focuses on seismic loss estimation through adoption of stochastic ground motion models for the seismic hazard description and investigates the potential benefits in terms of detailed, versatile description of seismic risk and the challenges in terms of computational efficiency. Two different stochastic ground motion models will be adopted, a source-based one (Atkinson and Silva 2000; Boore 2003) and a record-based one (Rezaeian and Der Kiureghian 2008; Rezaeian and Der Kiureghian 2010) and comparisons will be drawn between them. A probabilistic
framework for assessment of life-cycle repair cost will be established based on the concepts discussed above for loss estimation and probabilistic earthquake hazard description. In this context, life-cycle repair cost is quantified by its expected value over the established probability models and stochastic simulation (Monte Carlo analysis) is suggested for its evaluation. An innovative probabilistic sensitivity analysis is also presented, based on advanced stochastic sampling concepts. This analysis, demonstrated first in Taflanidis and Jia (2011) for seismic risk applications, aims to identify the importance of each of the various uncertain parameters within the seismic hazard description (i.e., risk factors) in the overall performance of the structural system. This analysis is extended here to further identify potential correlations between the risk factors in impacting the overall risk.

The general methodology is illustrated through application to a four-storey concrete building (Haselton et al. 2008). The numerical model is developed in Open Source for Earthquake Engineering Simulation (Mazzoni et al. 2005) software (OpenSees) and all stochastic simulations are performed in distributed mode using the multi-core capabilities of the high-performance Persephone cluster of the High Performance system Analysis and Design (HIPAD) laboratory (www.nd.edu/~hipad). As part of the research effort of this project, OpenSees is set up in the cluster and tuned to work in both parallel and distributed modes, providing with enhanced computational capabilities for efficiently performing Monte Carlo simulations.

Emphasis is placed in this thesis on the results from the sensitivity analysis for investigating the importance of the ground motion model characteristics on the estimated
repair cost. The influence of a retrofitting system consisting of viscous dampers on the life cycle repair cost is also discussed.

1.3 Previous work in seismic repair-cost assessment

Before proceeding further a brief review of the main approaches that have been proposed so far for earthquake loss assessment is presented. Initially, researchers overlooked the probabilistic nature of the problem because it was extremely computationally ‘expensive’ for the current state of the art and performed a deterministic analysis (Powell and Allahabadi 1988); however, they did establish the necessity of identifying the modeling and analysis assumptions that control the uncertainties. Esteva and Rosenblueth (1964) included in their analysis large uncertainties that affect the intensity and time of occurrence of the seismic events but again due to lack of computational power implied by the use of complex non-linear models, they developed simplified criteria to estimate the peak values of the relevant response variables by referring them to those of a single degree of freedom ‘equivalent’ system. The limits states for performance assessment in this case were related to strength and deformation. Singhal and Kiremidjian (1996) applied stochastic simulation concepts to form relationships between the earthquake ground motion severity and structural damage in the form of conditional probability distributions. For describing the earthquake excitation they used synthetic ground motions based on a stationary Gaussian autoregressive moving average model with an additional time-domain modulating function. Ang and Lee (2001) analyzed reinforced concrete buildings and for each level of intensity for the ground motion they described repair costs using a median global (over the whole structure) index. Der Kiureghian and Fujimura (2009) developed a new approach for
computing seismic fragility curves for nonlinear structures for use in PBEE. This approach makes use of recently developed method for nonlinear stochastic dynamic analysis by tail-equivalent linearization. The approach avoids repeated time-history analysis with a suite of scaled, recorded ground motions. Instead the ground motion is modeled as a stochastic process and, after determining the tail equivalent linear system for each response threshold, simple linear random vibration analyses are performed to compute the fragility curve. Although the accuracy in the corresponding estimated thresholds is generally acceptable, simulation methods, such as the Subset Simulation algorithm by Au and Beck (2003), may be used to produce more accurate results.

Extending the work of Singhal and Kiremidjian (1996), Porter et al. (2001) started developing thorough analytical tools to evaluate seismic vulnerability on very detailed level. According to this approach, the nonlinear time-history response of the structure under a given seismic excitation is used to calculate damages in a component level. This has been the basis of the Pacific Earthquake Engineering Research (PEER) center’s framework which is divided into four main steps; i) hazard analysis, ii) structural analysis, iii) damage analysis and iv) loss analysis. The basis for the loss analysis is the development of fragility functions, which relate structural damage to the time-history response of the structure for each component of the structure. The development of these functions is primarily based on extensive experimental data and/or engineering judgment. To the continuation of PEER center’s effort, Mitrani-Reiser (2007) and her coworkers (Goulet et al. 2007) calculated the future losses of a building addressing uncertainties for the ground motion, the properties of the building, and the damageability and unit repair costs of the facility. For the calculation of the losses a Matlab Damage and Loss Analysis
(MDLA) toolbox was developed. Indirect economic losses, produces by human fatalities and building downtime, were also included in their analysis. The ground motion modeling was based, though, on scaling of ground motions since the computationally complexity of the required nonlinear dynamic structural analysis was deemed extensive for use of stochastic ground motion modeling approaches (which require Monte Carlo analysis for propagation of uncertainty).

Following the PEER approach Aslani and Miranda (2005) presented a methodology to calculate the monetary losses due to repair and replacements of structural and nonstructural components both when the building does not collapse or under the probability of collapse at increasing levels of ground motion intensity. Recently Ramirez and Miranda (2009) presented a simplified version of the PEER methodology to quantify structural seismic performance. In this method engineers do not need to conduct the damage analysis because it has already been computed based on the assumptions on the building cost distribution by defining relationships between the structural response and monetary loss in the form of Engineering Demand Parameters (EDP) functions. Also a methodology was presented to calculate the uncertainties of predicted losses that incorporate correlations in construction cost at the building level rather than the component level. Finally they included losses due to demolition because of excessive permanent deformations. This research showed the need for development of fragility functions for common types of components for further improvement of loss estimation and analysis.

Taflanidis and Beck (2009c) considered the design of viscous dampers for optimal life-cycle evaluation through a similar framework as discussed in this thesis,
implementing a detailed loss estimation methodology based on stochastic ground motion models for description of earthquake hazard. But they restricted their attention to only uncertainties in the moment magnitude and the epicentral distance for describing the seismic hazard, without considering the impact of the uncertainties in the predictive relationships within the stochastic ground motion model itself. Furthermore, they used a parsimonious SIMULINK model for describing the nonlinear structural behavior.

Acknowledging the importance of seismic loss estimation, The Applied Technology Council (ATC) has also launched the ATC-58 project for establishing the Next Generation Performance-based Seismic Design Guidelines. The purpose of the project is to develop a series of resource documents that define procedures that can be used to reliably and economically design new buildings or upgrade existing buildings to attain desired performance goals, and to assist stakeholders in selecting appropriate design performance goals for individual buildings. The project includes the establishment of a methodology for predicting the earthquake performance of buildings characterized in terms of probable life loss, repair costs and time out of service resulting from earthquake effects, expressed in a variety of formats useful to different stakeholders and decision makers. This project is ongoing (just published the 75% draft of their methodology) and is anticipated, once completed, to set the standard for earthquake loss estimation and performance based earthquake engineering. In general the proposed framework by ATC-58 follows very closely the PEER PBEE methodology and it is expected to offer a wide range of standardized fragility functions, to be used in loss estimation.
1.4 Overview of the thesis

In the next Chapter the probabilistic risk quantification framework is presented and comparison is established to the PEER methodology for PBEE. In Chapter 3 the structural model used in this study is presented. Then in Chapter 4 the two stochastic ground motion models of interest are reviewed and the assumptions for their predictive relationships are presented. In Chapter 5 the loss estimation methodology is reviewed and the details of the fragility curves used in the current study are summarized. Chapter 6 presents the computational details for loss estimation and for the probabilistic sensitivity analysis aiming to identify the importance of the various risk factors. Chapter 7 presents the results and the discussion of the case studies considered in this thesis and finally Chapter 8 discusses the conclusions of this research effort.
In this Chapter a generalized probabilistic framework for quantifying seismic risk in terms of economic losses will be discussed. Since PEER’s methodology has been established as the current standard in this field, an overview of this methodology is initially presented so that a clear connection to the proposed framework can be drawn.

2.1 PEER methodology

Performance Based Earthquake Design (PBEE) has emerged as an alternative standard for structural engineering practice (FEMA-445 2006). With PBEE the performance of a building is evaluated given the potential hazard and considering uncertainties in the building design as well as the quantification of the potential hazard and is a combination of structural and nonstructural components performance. For the quantification of losses, and in order to convert them to less technical terms so the stakeholders, owners and investors can base their decisions, measures like economic losses, casualties and downtime are used. In this direction the Pacific Earthquake Engineering Research (PEER) center has established a framework that uses the results from seismic hazard analysis and response simulation to estimate damage and monetary losses incurred during an earthquake.
The PEER’s PBEE methodology involves 4 stages as presented by Porter (2003): hazard analysis, structural analysis, damage analysis and loss analysis as illustrated in Figure 2.1.

Objective of this methodology is to estimate how often a particular performance metric will exceed various levels for a given design at a given location. By this, probability distributions of the performance measures during any planning period of interest can be created and then can be used as decision parameters for the stakeholders. The four analysis steps are presented next.
**Hazard Analysis:** In the hazard analysis the probabilistic seismic hazard is developed, expressed as the frequency of exceeding a ground motion intensity measure \( (IM) \), considering parameters related to the seismic environment (location, soil condition, epicentral distance).

**Structural Analysis:** In this step an analytical model of the structure is created to estimate the structural response in terms of an Engineering Demand Parameter \( (EDP) \) subjected to a given \( IM \), \( (p[EDP|IM]) \). \( EDPs \) can be local parameters like member forces, deformations or global parameters such as interstory drift and floor acceleration. Because of the random nature of \( IM \), \( EDP \) is also a random variable.

**Damage Analysis:** In the damage analysis phase, various damage \( (DM) \) levels are developed using fragility functions which are cumulative distribution functions relating \( EDPs \) to the probability of being at or exceeding particular levels of damage. The damage of a component is defined as the cost for restoring it to the undamaged state. The fragility curves are different for each structural and nonstructural component.

**Loss Analysis:** In this last phase of the analysis, the decision variables \( (DV) \), conditioned on \( DM \) \( (p[DV|DM]) \), are established, which measure the seismic performance in terms of casualties, downtime or in this case economic losses based on repair and replacement costs of damaged building components.

The analysis product is the quantification of the frequency with which various levels of \( DVs \) are exceeded. Based on these frequencies, the stakeholders execute risk management decisions for the design and the location of the structure. The mathematical expression of this procedure is given by the following relationship:

\[
p[DV \mid D] = \iint p[DV \mid DM]p[DM \mid EDP]p[EDP \mid IM]p(IM \mid D)DIDEDPDIM 2.1
\]
As it can been seen from the equation above uncertainty exists in any phase of the analysis procedure and propagates to the next phase. For the hazard analysis the uncertainty comes from the location, the soil properties, magnitude etc. which define the seismic hazard intensity. Even if the model of the structure is deterministic and no uncertainties are taken into concern in this phase of analysis, EDPs are uncertain because of the propagation from the first phase. In the damage analysis the uncertainty comes from the laboratory experiments or the computational models which used to define the fragility curves.

2.2 Proposed framework for probabilistic quantification of life cycle cost

For evaluation of seismic cost, adoption of appropriate models is needed for the structural system itself, the earthquake excitation, and for loss evaluation (Figure 2-2). The combination of the first two models provides the structural response and in the approach adopted here this is established in terms of nonlinear time-history analysis. The loss evaluation model quantifies, then, earthquake performance in economic terms based on that response. This approach is consistent with the Pacific Earthquake Engineering Research (PEER) center’s framework. The approach adopted here simply presents the framework within a formal system theoretic context (distinction between excitation, system and performance evaluation models) and integrates the last two steps of the PEER approach into a common loss evaluation model.
The characteristics of the models in Figure 2.2 are not known with absolute certainty. Uncertainties may pertain to (i) the properties of the structural system, for example, related to stiffness or damping characteristics; to (ii) the variability of future seismic events, i.e., the moment magnitude or the epicentral distance; to (iii) the predictive relationships about the characteristics of the excitation given a specific seismic event, for example duration of strong ground motion or peak acceleration; or to (iv) parameters related to the performance of the system, for example, thresholds defining fragility of system components. A probability logic approach provides a rational and consistent framework for quantifying all these uncertainties though the entire life-cycle of the structure (Taflanidis and Beck 2009c). To formalize this idea let \( \theta \in \Theta \subset \mathbb{R}^{n_\theta} \), denote the augmented vector of model parameters where \( \Theta \) represents the space of possible model parameter values. Vector \( \theta \) is composed of all the model parameters for the individual structural system, \( \theta_s \), excitation, \( \theta_g \), and loss evaluation, \( \theta_p \), models as illustrated in Figure 2-2 and it further includes the stochastic sequence \( Z \). The uncertainty
in these model parameters is then quantified by assigning a probability model \( p(\theta) \) to them, which incorporates our available prior knowledge about the system and its environment into the model and it addresses future variability for both the seismic hazard, as well as for the structural system and its performance. For the seismic hazard these models are based on the regional seismicity characteristics (Kramer 2003; Bray and Rodriguez-Marek 2004), whereas for the structural model and performance evaluation on engineering judgment and available data (Porter et al. 2002; Porter et al. 2004; Goulet et al. 2007). Note that though the focus on this thesis will be on seismic hazard the same framework can be used to additionally address the uncertainties in the structural model description.

Let also the overall cost, for a specific structural configuration and seismic excitation, described by model parameter vector \( \theta \), be expressed by the performance function \( h(\theta) \). In this setting the repair cost is uncertain, with uncertainty ultimately stemming from the uncertainty in \( \theta \). It can be characterized by its expected value given by

\[
C = \int_{\Theta} h(\theta) p(\theta) d\theta
\]  

Another important characteristic for the repair cost is its variability around its mean (expected) value (since it is itself an uncertain variable). This can be quantified by its coefficient of variation \( \delta_c \) (ratio of standard deviation over mean value) which is given by

\[
\delta_c = \sqrt{\frac{\int_{\Theta} h(\theta)^2 p(\theta) d\theta - C^2}{C^2}} = \sqrt{\frac{\int_{\Theta} h(\theta)^2 p(\theta) d\theta}{C^2}} - 1
\]

In this setting the model parameter vector \( \theta \) can be considered as the risk-factors, since ultimately seismic risk (expressed here in terms of the life-cycle cost \( C \)) is
generated by the uncertainty in their description. For estimating different aspects of this
cost, for example for different components of the structure or different floors, the
definition 2.2 needs to be simply extended to the performance function with respect to
each of these components \( \{ h_k(\Theta); k = 1, \ldots, N_a \} \).

For evaluation of Equation 2.2 (and 2.3 when required) a stochastic-simulation
approach will be discussed in this work (Chapter 6). Along with the risk quantification
illustrated in Figure 2.2 this establishes a versatile, end-to-end simulation based
framework for detailed characterization of life-cycle seismic repair cost. This framework
puts no restrictions on the complexity of the models used, allowing for incorporation of
all important sources of nonlinearities and adoption of advanced models for
characterization of the ground motion. The individual structural, excitation and loss
estimation models will be discussed in detail in the following three Chapters, before
focusing on the computational framework for estimation of the life-cycle cost and for the
proposed probabilistic sensitivity analysis.
CHAPTER 3:
STRUCTURAL MODELLING AND SIMULATION

The choice for a structural model for seismic loss evaluation applications ultimately depends on the available computational tools for structural analysis. For example, one can use a fiber model, a plastic hinge model (Goulet et al. 2007) and so forth. The model selected needs to give information about all response variables relevant to the loss estimation methodology, which may include peak values, such as peak transient drifts, peak acceleration and maximum plastic hinge rotation, or cumulative values, such as the energy dissipated by a specific element. Thus, one criterion for selecting the structural model should be the type of response quantities needed for performing the loss estimation. Additionally, it is important that the structural model describes adequately the nonlinear structural behavior under high intensity ground motions, since this behavior is expected to have an important contribution to the expected life-cycle cost. In this study the Open Source for Earthquake Engineering Simulation (Mazzoni et al. 2005) software (OpenSees) is used for the structural analysis. The building considered in the one introduced in (Haselton C. B. 2008); it consists of a four-story office building designed to comply with the 2003 International Building Code (IBC 2003) and ASCE7-02. The building is designed at a site located in the Los Angeles basin, which was selected to represent a typical urban site in a high seismic region of California but without unusually strong, localized near fault effects dominating the hazard.
3.1 Building layout

The structural layout of the building shown in Figure 3.1 represents a four-bay by six-bay plan with 30 ft. span lengths. Figure 3.2 shows the elevation of the frame with a 14 ft. first story and 13 ft. for the three stories above. As shown in Figure 3.1 and Figure 3.2, the lateral system of the perimeter consists of two exterior frames in each direction. TABLE 3.1 shows the beam and column design values for all the beams and columns.

Figure 3.1 Plan view of perimeter-frame benchmark building [taken from (Haselton et al. 2008)].
TABLE 3.1
BEAM AND COLUMN DESIGN VALUES

<table>
<thead>
<tr>
<th>Section Tag</th>
<th>Section Property</th>
<th>Design Value</th>
<th>Section Tag</th>
<th>Section Property</th>
<th>Design Value</th>
</tr>
</thead>
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<td>30</td>
<td>BS1</td>
<td>h(inch)</td>
<td>42</td>
</tr>
<tr>
<td></td>
<td>b(inch)</td>
<td>30</td>
<td></td>
<td>b(inch)</td>
<td>24</td>
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<tr>
<td></td>
<td>Long. Bar #</td>
<td>9</td>
<td></td>
<td>Long. Bar #</td>
<td>9</td>
</tr>
<tr>
<td></td>
<td>$\rho_g$</td>
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<td>$P_{tensile, top}$</td>
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<td>$\rho_g$</td>
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<td></td>
<td>Long. Bar #</td>
<td>9</td>
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<tr>
<td>CS3</td>
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<td></td>
<td>$P_{tensile, top}$</td>
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</tr>
<tr>
<td></td>
<td>b(inch)</td>
<td>30</td>
<td>BS3</td>
<td>$P_{tensile, bottom}$</td>
<td>0.008</td>
</tr>
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<td></td>
<td>Long. Bar #</td>
<td>9</td>
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<td>$\rho_g$</td>
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<td></td>
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<td>24</td>
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<td>CS4</td>
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<td>Long. Bar #</td>
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</tr>
<tr>
<td></td>
<td>b(inch)</td>
<td>30</td>
<td></td>
<td>$P_{tensile, top}$</td>
<td>0.009</td>
</tr>
<tr>
<td></td>
<td>Long. Bar #</td>
<td>8</td>
<td></td>
<td>$P_{tensile, bottom}$</td>
<td>0.006</td>
</tr>
<tr>
<td></td>
<td>$\rho_g$</td>
<td>0.012</td>
<td>BS4</td>
<td>h(inch)</td>
<td>32</td>
</tr>
<tr>
<td>CS5</td>
<td>h(inch)</td>
<td>30</td>
<td></td>
<td>b(inch)</td>
<td>24</td>
</tr>
<tr>
<td></td>
<td>b(inch)</td>
<td>30</td>
<td></td>
<td>Long. Bar #</td>
<td>9</td>
</tr>
<tr>
<td></td>
<td>Long. Bar #</td>
<td>9</td>
<td></td>
<td>$P_{tensile, top}$</td>
<td>0.008</td>
</tr>
<tr>
<td></td>
<td>$\rho_g$</td>
<td>0.018</td>
<td></td>
<td>$P_{tensile, bottom}$</td>
<td>0.005</td>
</tr>
<tr>
<td>CS6</td>
<td>h(inch)</td>
<td>28</td>
<td></td>
<td>b(inch)</td>
<td>24</td>
</tr>
<tr>
<td></td>
<td>Long. Bar #</td>
<td>8</td>
<td></td>
<td>$\rho_g$</td>
<td>0.016</td>
</tr>
<tr>
<td></td>
<td>$P_{tensile, top}$</td>
<td>0.010</td>
<td></td>
<td>$P_{tensile, bottom}$</td>
<td>0.008</td>
</tr>
</tbody>
</table>
Figure 3.2 Elevation view of frame along column line 1 [taken from (Haselton et al. 2008)].

The column confinement consists of closed #4 column ties with each longitudinal bar laterally supported by a #4 tie. The number of top and bottom bars varies and the resulting reinforcing ratios are given in TABLE 3.1. Intermediate bars and related cross-ties are required to be less than 14” apart, by ACI 318-02 so the number of intermediate ties varies dependent on the column depth. Each column is oriented such that the bending axis is perpendicular to the direction of the frame. The slab consists of 8” of concrete with #4 rebar on both the top and bottom of the slab, spaced at 12” on center. The space-frame beams are the same as those of the perimeter, with the exception that the interior frames have a slab on both sides on the beam.

The gravity system which provides incidental lateral resistance consists of 18 in. square concrete columns spaced at 30 ft. centers and an 8 in. post tensioned two way slab. The slab was not explicitly designed, so the reinforcement was taken to consist of #4 reinforcing bars at the top and bottom spaced at 12 in. centers.
3.2 Structural Model

The static and dynamic analysis is performed with the Open Source for Earthquake Engineering Simulation (Mazzoni et al. 2005) software (OpenSees) developed by the PEER Center. “OpenSees is an object oriented framework for finite element analysis. A key feature of OpenSees is the interchangeability of components and the ability to integrate existing libraries and new components into the framework without the need to change the existing code.” OpenSees has been developed as the computational platform for research in performance based earthquake engineering and for simulation of the seismic response of structural and geotechnical systems. The reason for choosing OpenSees, except the advanced capabilities for modeling and analyzing the nonlinear response of a system, which are necessary for capturing the structural response and associated damage, is the distributed computing capabilities which will allow to seemingly perform parallel Monte Carlo implementation.

The building is represented by a model for the perimeter frame connected with a leaning column to account for P-Δ effects and the analysis is performed in two dimensions. The gravity frame it is not included as a separate model but is incorporated in the perimeter (2-1/2 gravity frames) since it does not contribute to the lateral resistance of the structure. The yield strengths of all the nonlinear component models are based on the expected material strength. As stated in (Haselton C. B. 2008), there is currently no single model that can accurately capture the structural response for all ranges of ground motion intensity and since in this research we are trying to measure the structural damage due to cracking and tension–stiffening behavior and not the structural collapse, we only use a fiber model.
A fiber model is used to simulate the beams and columns in the RC frames. Each structural element is divided into a two or more end frame elements and each boundary is linked to a discrete cross-section with a grid of fibers, (Figure 3.3). The material stress strain response in each fiber is integrated to get stress resultant forces and rigidity terms. The nonlinear hysteretic behavior of the element depends to the constitutive relations of concrete and reinforcing steel fibers into which each section is divided (Spacone et al. 1996).

Figure 3.3 Fibers frame end elements
In each element, five integration points are assigned along the length and the nonlinear axial behavior of the cross section is monitored. A large number of core and cover fibers is used to improve numerical convergence of the model. For each of the fibers representing the core (confined) concrete, the cover (unconfined) concrete and the
reinforcement bars, appropriate materials properties are assigned (Figure 3-4). The connection between columns and beams is considered to be rigid.

The masses for the perimeter and two and a half gravity frames are distributed to the joints connecting columns and beams. Each joint takes the mass of half the perimeter elements are framing to it plus the mass from the gravity frames that are connected to it. The self-weight for the concrete is set to 150 pounds per cubic foot. For the static gravity analysis we distribute a uniform load to the beams and columns.

For simulating P-Delta effects a leaning column with gravity loads is linked to the frame by truss elements. The leaning columns are modeled as elastic beam-column elements and have moment of inertia and areas much larger than the frame columns to represent aggregate effect of all the gravity columns. The columns are connected to the beam-column joint by zero length rotational spring elements with very small stiffness values so that the columns do not attract significant moments. These columns are pinned supported at both end ends, thus not resisting any lateral forces. The truss elements used to connect the leaning column with the frame are assumed to be axially rigid.

Rayleigh damping is used with damping ratio of 5%, typical value for RC buildings, assigned to the first two modes of the building.

3.3 Viscous Damper Implementation

Retrofitting of the building by two viscous dampers in each floor will be also considered as part of this thesis investigation. Viscous dampers are hydraulic devices used to mitigate the effects of the seismic action of structures through the dissipation of the kinetic energy transmitted by the earthquake to the structure (Constantinou et al.)
1998; Christopoulos and Filiatrault 2006). The force of a fluid viscous damper is governed by the following equation:

\[ F(t) = C_{nl} \text{sgn}(\dot{x}(t)) |\dot{x}(t)|^{\alpha_{vd}} \]  

where \( C_{nl} \) is the nonlinear viscous damping coefficient, \( \dot{x}(t) \) in is the relative velocity between each end of the device and \( \alpha_{vd} \) is the velocity coefficient characterizing the nonlinearity of the damper. If \( \alpha_{vd} = 1 \) then the device acts as a linear damper. For seismic applications \( \alpha_{vd} \) takes typically values between 0.2 and 0.7.

The design methodology used in this study for the damping coefficients of individual dampers is the one proposed by (Silvestri et al. 2009). It is based on the required reduction of the structural response and it is expressed as a five step procedure. At the \textbf{first step} the target damping ratio \( \bar{\zeta} \) of the structure for a chosen target level \( \bar{\eta} \) of structural performance is identified. This structural performance is measured as the ratio of the expected seismic response of the system characterized by a damping ratio \( \bar{\zeta} \), over the expected seismic response of the system characterized by the assumed damping ratio of \( \zeta = 0.05 \) for concrete structures. Values for these two parameters can be found in (Silvestri et al. 2009). In this study we adopt a target reduction of \( \bar{\eta} = 0.5 \) which gives a damping ratio \( \bar{\zeta} \approx 0.35 \).

For the \textbf{second step} the mechanical characteristics of the linear viscous dampers are identified for preliminary design. After modal analysis of the model without the dampers the first natural frequency of the structure is obtained. The damping coefficient for the dampers can be calculated by the following equation:

\[ c_{total} = \bar{\zeta} \cdot \alpha_{v} \cdot m_{tot} \cdot N(N+1) \]  

\[ 3.2 \]
with \( m_{\text{tot}} \) the total mass of the building and \( N \) the number of the stories of the building. If we assume uniform distribution of \( c_{\text{total}} \) along the height of the building Equation 3.2 leads to:

\[
c_{\text{storey}} = \zeta \cdot \omega_1 \cdot m_{\text{tot}} \cdot (N + 1) \tag{3.3}
\]

In the case that there are \( n \) equal dampers placed at each story, then the damping coefficient of each single device is given by:

\[
c_j = \zeta \cdot \omega_1 \cdot m_{\text{tot}} \cdot \left( \frac{N + 1}{n} \right) \tag{3.4}
\]

At **step three** a preliminary dynamic analysis is performed to verify that the first modal damping ratio of the system is close to the target value and to calibrate the linear damping coefficients of the dampers to be added in the structure. At this point, we also estimate the maximum velocities which are developed by the linear dampers, \( v_{\text{max}} \) under the excitation of 100 synthetic ground motions developed by the procedure presented in chapter 4.1 with a magnitude range \( M=[5 \, 8] \) and epicentral distance \( r=20 \text{ km} \).

In **step four**, the parameters of the nonlinear dampers which can dissipate the same amount of energy as the linear ones under harmonic motion are derived, based on equivalent linearization concepts. This leads to the following equation (Silvestri et al. 2009):

\[
c_{nl} = c_l \left( \chi \cdot v_{\text{max}} \right)^1 \cdot \alpha_{nl} \tag{3.5}
\]

with
\[ \chi = \left( \frac{\sqrt{\pi}}{2} \cdot \frac{\Gamma \left( \frac{a_{vd} + 3}{2} \right)}{\Gamma \left( \frac{a_{vd} + 2}{2} \right)} \right)^{\frac{1}{1-a_{vd}}} \]

and \( \Gamma \) being the Euler Gamma Function.

TABLE 3.2 gives the values of \( \chi \) as a function of \( a_{vd} \).

<table>
<thead>
<tr>
<th>( a_{vd} )</th>
<th>0.2</th>
<th>0.3</th>
<th>0.4</th>
<th>0.5</th>
<th>0.6</th>
<th>0.7</th>
<th>0.8</th>
<th>0.9</th>
<th>1.0</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \chi )</td>
<td>0.7950</td>
<td>0.7994</td>
<td>0.8036</td>
<td>0.8075</td>
<td>0.8112</td>
<td>0.8147</td>
<td>0.8181</td>
<td>0.8213</td>
<td>1.0</td>
</tr>
</tbody>
</table>

For step 5 the time history analyses is repeated with the nonlinear damping coefficient to verify that the nonlinear and linear models have similar behavior.

Following this procedure for \( \alpha=0.5 \) the values for the damping ratio are calculated for the dampers in each floor of the building and shown in Table 3-3. The damper cost reported in this table is calculated based on its force capacity \( F_{ud,i} \) as \( $80(F_{ud,i})^{0.8} \) based on Taflanidis and Beck (2009b). The force capacity is taken here as the force established by the damper for the maximum relevant velocity between the two ends of the damper over the preselected design ground motions. These viscous dampers are incorporated in the OpenSees model as two truss elements in the exterior openings of the building with a nonlinear viscous material assigned to them.
TABLE 3.3
DAMPING RATIO AND COST FOR DAMPERS C_1-C_4 [C_1 CORRESPONDS TO GROUND FLOOR DAMPERS].

<table>
<thead>
<tr>
<th>Damper</th>
<th>Damping ratio (kips*sec/ft)</th>
<th>Damper Cost $</th>
</tr>
</thead>
<tbody>
<tr>
<td>c_1</td>
<td>320</td>
<td>29095</td>
</tr>
<tr>
<td>c_2</td>
<td>305</td>
<td>27280</td>
</tr>
<tr>
<td>c_3</td>
<td>280</td>
<td>23240</td>
</tr>
<tr>
<td>c_4</td>
<td>205</td>
<td>14465</td>
</tr>
</tbody>
</table>
CHAPTER 4:
STOCHASTIC GROUND MOTION MODELLING

The focus of this research is on the impact of stochastic ground motion modeling within the seismic-risk framework discussed in Chapter 2. Two stochastic ground motion models are considered for this purpose. The first one, referenced GM1, is a source-based one (Atkinson and Silva 2000) and the second one, referenced GM2, is the record-based one developed recently by Rezaeian and Der Kiureghian (2010).

4.1 Atkinson’s and Silva’s Ground Motion Model (GM1)

The first ground motion model considered in this study, belongs to the greater family of point-source models, developed by considering the physics of the fault rupture at the source as well as of the propagation of seismic waves through the entire ground medium till the site of interest (Boore 2003). These models are based on a parametric description of the ground motion’s radiation spectrum $A(f;M,r)$, dependent on the earthquake magnitude, $M$, and epicentral distance, $r$, and expressed as a function of the frequency, $f$. The variation of the ground motion in time, $t$, is addressed similarly through an envelope function $e(t;M,r)$, which again depends on $M$ and $r$. These frequency and time domain functions, $A(f;M,r)$ and $e(t;M,r)$, completely describe the model and their characteristics are provided by predictive relationships that relate them to the seismic hazard, i.e., to $M$ and $r$ (Boore 2003). These predictive relationships have been
developed as deterministic functions (Atkinson and Silva 2000), but can be extended to facilitate a probabilistic description (Jalayer and Beck 2007; Taflanidis and Vetter 2011). This is established through adoption of appropriate probability models that use these functions as median predictions but additionally introduce uncertainty in the established relationships, adopting ad-hoc probability models to address the variability around the median predictions.

4.1.1 Amplitude spectrum and time envelope

The total spectrum \( A(f;M,r) \) for the acceleration time history may be expressed as a product of the source \( E(f;M) \), path, \( P(f;r) \) and site, \( G(f) \):

\[
A(f;M,r) = (2\pi f)^2 E(f;M) P(f;r) G(f)
\]

The source spectrum is given by:

\[
E(f;M) = CM_s S(f;M) \quad \text{with} \quad S(f;M) = \left[ \frac{1-e}{1+(f/f_a)^2} + \frac{e}{1+(f/f_b)^2} \right]
\]

where the displacement source spectrum \( S(f;M) \) described above is the two-corner point-source model developed by (Atkinson and Silva 2000) for ground motions in California [see (Boore 2003) for other models for \( S(f;M) \)]. This is why this ground motion model is ultimately referenced here as the Atkinson and Silva model. For the adopted spectrum the lower and upper frequencies and the weighing parameter are given, respectively, by

\[
\log_{10} f_a = 2.181 - 0.496M
\]

\[
\log_{10} f_b = 2.41 - 0.408M
\]

\[
\log_{10} e = 0.605 - 0.255M
\]
In equation 4.2, $M_w$ is the seismic moment (in dyn-cm) which is connected to the moment magnitude by the relationship $\log_{10} M_w = 1.5(M+10.7)$. The constant $C$ is given by $C=10^{-20} R_\phi VF/(4\pi R_\phi \rho_s \beta_s)$, where $R_\phi$ is the radiation pattern, usually averaged over a suitable range of azimuths and take off angles, $V=1/\sqrt{2}$ represents the partition of total shear-wave velocity into horizontal components, $F=2$ is the free surface amplification factor, $\rho_s$ and $\beta_s$ are the density and shear-wave velocity in the vicinity of the source, and $R_o$ is a reference distance, set to 1km.

The path effect, $P(f;r)$, is given by the multiplication of the geometrical spreading and anelastic attenuation:

$$P(f;r) = Z(r) \exp\left[-\pi f \cdot R / (Q(f) \cdot c_Q)\right]$$  \hspace{1cm} (4.4)

where $Q(f)$ is a regional attenuation function, $c_Q$ is the seismic velocity used in the determination of $Q(f)$, $Z(r)$ is the geometrical spreading function and $R=[h^2+r^2]^{1/2}$ is the radial distance from the earthquake source to the site, with $\log_{10} h=0.15M-0.05$ (Atkinson and Silva 2000) representing a moment-dependent, nominal “pseudo-depth”. The site effect, $G(f)$, is given by the multiplication of a high-frequency diminution $D(f)$ and an amplification factor $A_m(f)$, $G(f)=A_m(f)D(f)$. The diminution may be expressed by the $k_o$ filter or the $f_{max}$ filter expressed respectively as:

$$D_1(f) = \exp(-\pi \kappa_o f), \quad D_2(f) = \left[1 + \left(f / f_{max}\right)^8\right]^{-1/2}$$  \hspace{1cm} (4.5)

or a combination of both (Boore 2003). The amplification factor may be described through the empirical curves given in (Boore and Joyner 1997).

The envelope function for the earthquake excitation is represented by
\[ e(t; M, r) = a_t \left( \frac{t}{t_n} \right)^b \exp \left( -c_t \left( \frac{t}{t_n} \right) \right) \tag{4.6} \]

where \( a_t, b_t \) and \( c_t \) are chosen so that \( e(t; M, r) \) has a peak equal to unity when \( t = \lambda t_n \) and \( e(t; M, r) = \eta \) when \( t = t_n \). The equations for these parameters are

\[ b_t = -\lambda_t \ln(\eta_t) / \left[ 1 + \lambda_t (\ln(\lambda_t) - 1) \right], \quad c_t = b_t / \lambda_t, \quad a_t = [\exp \left( 1 / \lambda_t \right)]^b \tag{4.7} \]

The time \( t_n \) is given by \( t_n = 2T_w \) where \( T_w \) is the duration of the ground motion, expressed as a sum of a path dependent (typically chosen a fraction of \( R \)) and a source dependent component (typically chosen as a fraction of \( 1/f_a \)). The following selection, suggested in (Boore 2003), is chosen for the current study:

\[ T_w = \frac{1}{2f_a} + 0.05R \tag{4.8} \]

4.1.2 Stochastic ground motion model

Ultimately the ground motion is generated by modulating a white noise sequence \[ Z = [Z_w(i\Delta t): i=1,2,\ldots, N_f] \] by \( e(t; M, r) \) and subsequently by \( A(f; M, r) \) through the following steps: the sequence \( Z \) is multiplied by the envelope function \( e(t; M, r) \) and transformed to the frequency domain; it is normalized by the square root of the mean square of the amplitude spectrum and then multiplied by the radiation spectrum \( A(f; M, r) \); finally it is transformed back to the time domain to yield the desired acceleration time history. Figure 4.1 presents the important steps of this process. The time envelope and the amplitude spectrum are also illustrated for various values of \( M \) and \( r = 15 \) km. It can be seen that as the moment magnitude increases the duration of the envelope function also increases and the spectral amplitude becomes larger at all frequencies with a shift of dominant frequency content towards the lower-frequency regime.
4.1.3 Details for model parameters and predictive equations

The parameters adopted in the applications considered in the current study for the $A(f;M,r)$ and $e(t;M,r)$ functions are: radiation pattern $R_\phi=0.55$, rock density $\rho_s=2.8$ g/cm$^3$ and shear-wave velocity $\beta_s=c_Q=3.5$ km/sec; an elastic attenuation factor $Q(f)=180f^{0.45}$ (selected for the region of California according to (Atkinson and Silva 2000)) and geometrical spreading function $Z(R)=1/R$ for distances $R<70$km and $Z(R)=1/70$ for distances $R>70$. The diminution is expressed through combination of both $f_{\text{max}}$ and $k_0$. Site amplification is chosen for generic rock sites (Boore and Joyner 1997). The parameters for the envelope function $e(t;M,r)$ are $\lambda_t=0.2$, $\eta_t=0.05$ [as suggested in (Boore 2003)].

The rest of the ground motion parameters are considered as uncertain. This includes the displacement source spectrum characteristics, $f_a, f_b$ and $e$, the parameters
related to the diminution $\kappa_0$ and $f_{\text{max}}$, and the three parameters associated with the
temporal envelope function, $T_w, \lambda_t, \eta_t$. Modeling the uncertainty in source-based
stochastic ground motion models has received very limited attention so far (Atkinson and
Boore 2006). The probability models established in this study are intended to assign a
significant amount of uncertainty over the deterministic predictive equations presented
earlier. $\kappa_0$ is assumed to follow a uniform distribution within the range of its typical
values for California [0.02 0.04] (Atkinson and Silva 2000). Lognormal distribution is
assumed for all other parameters with coefficient of variation 30%. The median values
for $f_{\text{max}}, \lambda_t$ and $\eta_t$ are selected as 20Hz, 0.2 and 0.05 respectively, chosen based on the
suggestion in (Boore 2003). For the displacement spectrum parameters the median values
$\bar{f}_a, \bar{f}_b$ and $\bar{\varepsilon}$ are given by the predictive equations 4.3 whereas for the time duration the
median, $\bar{T}_w$ by equation 4.8. In order to investigate more efficiently the impact of the
uncertainty in the predictive relationships for $f_a, f_b, e$ and $T_w$ the following four auxiliary
variables are defined:

$$
\begin{align*}
    e_a &= \log(f_a) - \log(\bar{f}_a) \\
    e_b &= \log(f_b) - \log(\bar{f}_b) \\
    e_e &= \log(e) - \log(\bar{\varepsilon}) \\
    e_t &= \log(T_w) - \log(\bar{T}_w)
\end{align*}
$$

These variables represent the uncertainty in the displacement spectrum characteristics and
the time duration but they are uncorrelated from the moment magnitude or epicentral
distance ($f_a, f_b$ and $e$ actually do have correlation to $M$ as indicated by the predictive
relationships 4.3 whereas $T_w$ to both $f_a$ and thus $M$ and $r$ as indicated by 4.8). According
to the probability models described earlier all these auxiliary variables are standard
Gaussian variables. Note that either \{ $e_a, e_b, e_e, e_t$ \} or \{ $f_a, f_b, e, T_w$ \} can be used as risk factors
for describing the seismic hazard. The second set has an unambiguous physical meaning but the first is uncorrelated from the moment magnitude and the epicentral distance of the earthquake events, thus it addresses directly the impact on the final risk of the uncertainty in the ground motion predictive relationships. This becomes pertinent in the sensitivity analysis for identification of the importance of the various impact factors. In this thesis the results will be reported with respect to both groups of model parameters.

Finally the uncertain model parameter vector for the GM1 excitation model is
\[ \mathbf{\theta}_q = [M \ e_a \ e_b \ e_e \ e_t \ \lambda \ \eta \ f_{max} \ k_o]. \]

4.2 Rezaeian’s and Der Kiureghian’s Ground Motion Model (GM2)

The second model considered is the record-based one proposed recently by Rezaeian and Der Kiureghian (2010). It is also based on modulation of a white noise sequence through appropriate time and frequency domain functions, but has the additional advantage that addresses spectral nonstationarities (time-evolving intensity and predominant excitation frequency). This model, like all record-based models, is developed by fitting (regression analysis) a preselected mathematical characterization to a suite of recorded ground motions (Rezaeian and Der Kiureghian 2008). This procedure establishes the predictive relationships between the seismic hazard characteristics (represented by the fault mechanism, moment magnitude, source-to-site distance and the site shear velocity) and the model parameters and it can, when appropriately implemented (Rezaeian and Der Kiureghian 2010), directly address the uncertainty in these relationships.

This stochastic ground motion model was first proposed in (Rezaeian and Der Kiureghian 2008). Its model parameters were ultimately calibrated by assigning
probability distributions (Rezaeian and Der Kiureghian 2010; Rezaeian and Der Kiureghian 2011) based on empirical data obtained from fitting the stochastic model to a subset of the Next Generation Attenuation (NGA) strong motion database through the following process. First empirical prediction equations were derived for the transformed to the standard Gaussian space model parameters, in terms of earthquake and site characteristics. A correlation analysis supplemented this procedure for quantifying the correlation between the transformed model parameters. This ultimately provided a fully correlated probabilistic characterization of the model parameters. The empirical prediction equations and correlations can be used to randomly generate sets of realizations of the model parameters, each set providing one realization of a possible ground motion for the specified earthquake and site characteristics.

The main drawback of this model is that it has been developed considering stronger ground motions; it was reported in (Rezaeian and Der Kiureghian 2010) to significantly over predict the response –compared to NGA predictions– for ground motions smaller than 6.5. Since the current study aims to investigate structural performance on a greater range for the seismic hazards (extending to moment magnitudes as low as 5), this drawback is fairly significant. An illustrative comparison, though, will be still facilitated by constraining the magnitude to be over 6.5, thus addressing the range for which the model is recommended.

4.2.1 Stochastic ground motion model

The stochastic ground motion establishes both temporal and spectral non-stationarity. The former is established through a time-domain modulating envelope function (similar to the process of GM1) while the later is achieved by filtering a white
noise process by a filter with characteristics that vary in time. In discrete time the ground
motion can be expressed as (Rezaeian and Der Kiureghian 2008):

\[
x(t) = q(t, \theta) \left\{ \sum_{i=1}^{k} \frac{h[t-t_i, \theta(t_i)]]}{\sqrt{\sum_{j=1}^{k} h[t-t_j, \theta(t_j)]]} Z_i} \right\} \quad t_k < t < t_{k+1}
\]

4.10

In this expression \( Z = [Z_i: i=1,2,\ldots, N_T] \) is a white noise sequence and \( h[t-\tau, \theta(\tau) \] is
impulse response function (IRF) of a filter with time varying parameters \( \theta(\tau) =
(\omega_f(\tau), \zeta_f(\tau)) \) where \( \omega_f(\tau) \) is the frequency of the filter and \( \zeta_f(\tau) \) its damping ratio). The
chosen filter is the pseudo-acceleration response of a single-degree-of-freedom linear
oscillator subjected to a unit impulse, in which \( \tau \) denotes the time of the pulse

\[
h[t-\tau, \theta(\tau)] = \frac{\omega_f(\tau)}{\sqrt{1-\zeta_f^2(\tau)}} \exp\left[ -\omega_f(\tau)\zeta_f(\tau)(t-\tau) \right] \sin\left[ \omega_f(\tau)\sqrt{1-\zeta_f^2(\tau)}(t-\tau) \right]; \quad \tau \leq t
\]

\[
= 0; \quad \text{otherwise}
\]

4.11

A linear function has been proposed for the filter frequency and a constant for the
damping, thus:

\[
\omega_f(\tau) = \omega_{mid} + \omega'(\tau - t_{mid})
\]

4.12

\[
\zeta_f(\tau) = \zeta_f
\]

4.13

with \( \omega_{mid} \) (central frequency), \( \omega' \) (frequency variation) and \( \zeta_f \) ultimately corresponding to
the model parameters for the filter and \( t_{mid} \) corresponding to the mid-time of the strong
motion duration (see discussion next).
Function $q(t, \theta)$ is a deterministic nonnegative, time-modulating function with parameters $\alpha = (\alpha_1, \alpha_2, \alpha_3)$ controlling its intensity, shape and time respectively

$$q(t, \alpha) = \alpha t^{\alpha_2-1} \exp(-\alpha_3 t)$$  \hfill (4.14)

These three parameters can be related to three physical based variables: $T_a$, which represents the expected Arias intensity of the acceleration process, $D_{5.95}$ which is the effective duration of the motion and is defined as the time interval between the instants at which the 5 and 95% of the expected Arias are reached and $t_{\text{mid}}$ which is the time at which 45% level of the expected Arias is reached. This is established by the following process. The Arias intensity is given by

$$\bar{T}_a = E \left[ \pi \int_0^{\frac{\alpha_2}{2g}} \dot{x}^2(t) dt \right] = \frac{\pi}{2g} \int_0^{\frac{\alpha_2}{2g}} q^2(t, \alpha) dt$$  \hfill (4.15)

where $g$ is the gravitational acceleration. For the modulating function chosen, the variance functions $q^2(t, \alpha)$ is proportional to a gamma probability function having parameter values $2\alpha_2$-1 and $2\alpha_3$. If $t_p$ represents the $p$-percentile variate of the gamma cumulative distribution function, then $t_p$ is given in terms of the inverse of the gamma CDF at probability value $p\%$. It follows that $t_p$ is uniquely given in terms of the parameters $\alpha_2$ and $\alpha_3$ and probability $p\%$.

$$D_{5.95} = t_{95} - t_5$$
$$t_{\text{mid}} = t_{45}$$  \hfill (4.16)

Thus $\alpha_2$ and $\alpha_3$ are given by the relationships above and $\alpha_1$ is derived by solving the relationship for the Arias intensity and is ultimately given by (Rezaeian and Der Kiureghian 2010):
\[ a_i = \sqrt[\Gamma(a_1 - 1/2a_2 - 1)]{\frac{(2a_1)^{2a_2 - 1}}{\Gamma(2a_2 - 1)}} \]

where \( \Gamma(.) \) is the gamma function. Note that either \( \{a_1 \ a_2 \ a_3\} \) or \( \{\bar{T}_a \ D_{5.95} \ \tau_{\text{mid}}\} \) can be used as risk factors for describing the seismic hazard. Similarly to GM1 in this thesis the results will be reported with respect to both groups of model parameters.

Ultimately the model parameters for the ground motion model is the vector \( \theta_q = \{\bar{T}_a, D_{5.95}, \tau_{\text{mid}}, \omega_{\text{mid}}/2\pi, \omega'/2\pi, \zeta_f \} \) and for a probabilistic characterization of seismic hazard a relationship between this vector and the regional seismicity characteristics needs to be formulated.

### 4.2.2 Predictive equations

For the model parameter vector \( \theta_q = \{\bar{T}_a, D_{5.95}, \tau_{\text{mid}}, \omega_{\text{mid}}/2\pi, \omega'/2\pi, \zeta_f \} \), predictive relationships were developed (Rezaeian and Der Kiureghian 2010) based on empirical data obtained from fitting the stochastic model to a subset of the Next Generation Attenuation (NGA) strong motion database. Nineteen earthquakes and 206 records were picked, with a magnitude \( 6.06 \leq M \leq 7.68 \), epicentral distance \( 10 \leq R \leq 100 \) and shear wave velocity of the top 30m of the site soil \( V_{s30} \geq 600\text{m/sec} \). The decision to consider only earthquakes with \( M \geq 6 \) was based on the opinion that only this kind of earthquakes are capable for severe damage and nonlinear behavior in structures. As it can be seen later in this work, though, smaller earthquakes can cause significant damage too, especially for the nonstructural components.
The predictive relationships ultimately connect vector $\theta_q = \{ D_{5.95}, t_{mid}, \omega_{mid}/2\pi, \omega'/2\pi, \zeta_f \}$ to earthquake and site characteristics. First a conversion to the standard Gaussian space is established

$$v_i = \Phi^{-1}\left[F_{\theta_q}\left(\theta_{qi}\right)\right]; \quad i = 1, \ldots, 6$$

4.18

where $\Phi$ corresponds to the standard Gaussian CDF and $F_{\theta_q}$ is the fitted probability distribution to the $i^{th}$ component of vector $\theta_q$. These probability distributions for each of the model parameters can be seen in

**TABLE 4.1.**

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Fitted Distribution</th>
<th>Distribution bounds</th>
<th>Mean</th>
<th>Standard deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\bar{T}_a$ (sg)</td>
<td>Lognormal</td>
<td>$(0, \infty)$</td>
<td>0.0468</td>
<td>0.164</td>
</tr>
<tr>
<td>$D_{5.95}$ (s)</td>
<td>Beta</td>
<td>[5, 45]</td>
<td>17.3</td>
<td>9.31</td>
</tr>
<tr>
<td>$t_{mid}$ (s)</td>
<td>Beta</td>
<td>[0.5, 40]</td>
<td>12.4</td>
<td>7.44</td>
</tr>
<tr>
<td>$\omega_{mid}/2\pi$ (Hz)</td>
<td>Gamma</td>
<td>(0, \infty)</td>
<td>5.87</td>
<td>3.11</td>
</tr>
<tr>
<td>$\omega'/2\pi$ (Hz/s)</td>
<td>Eq.4.18</td>
<td>[-2, 0.5]</td>
<td>-0.0892</td>
<td>0.185</td>
</tr>
<tr>
<td>$\zeta_f$</td>
<td>Beta</td>
<td>[0.02, 1]</td>
<td>0.213</td>
<td>0.143</td>
</tr>
</tbody>
</table>

For $\omega'/2\pi$ the fitted distribution is a two-sided exponential with the following PDF:

$$p_{\omega'/2\pi}(\omega'/2\pi) = \begin{cases} 
4.85\exp(6.77\omega'/2\pi) & -2<\omega'/2\pi<0 \\
4.85\exp(-17.10\omega'/2\pi) & 0<\omega'/2\pi<0.5 \\
0 & \text{otherwise}
\end{cases}$$

4.19

Predictive models are then established for $v_i$ that express them as a function of earthquake and site characteristics.
\[ v_i = \beta_{i,0} + \beta_{i,1} F + \beta_{i,2} \left( \frac{M}{7} \right) + \beta_{i,3} \ln \left( \frac{r}{25 \text{ km}} \right) + \beta_{i,4} \ln \left( \frac{V_s}{750 \text{ m/s}} \right) + e_i \]

\[ v_i = \beta_{i,0} + \beta_{i,1} F + \beta_{i,2} \left( \frac{M}{7} \right) + \beta_{i,3} \left( \frac{r}{25 \text{ km}} \right) + \beta_{i,4} \ln \left( \frac{V_s}{750 \text{ m/s}} \right) + e_i; \quad i = 2, \ldots, 6 \]

where \( M \) and \( r \) are the moment magnitude and epicentral distance respectively; \( F \) corresponds to the type of fault \( (=0 \text{ denoting strike slip and } =1 \text{ reverse fault}) \); \( V_s \) is the shear wave velocity of the top 30m of the site soil; \( \beta_{i,j} \) are regression coefficients seen in Table 4.2; and \( e_i \) is the total prediction error in the predictive relationships, corresponding to correlated Gaussian variables with standard deviation \( \sigma_{e_i} \) as shown in Table 4.2 and correlation coefficients

\[
\begin{bmatrix}
1 & -0.36 & 0.01 & -0.15 & 0.13 & -0.01 \\
1 & 0.67 & -0.13 & -0.16 & -0.20 \\
1 & -0.28 & -0.20 & -0.22 \\
1 & -0.20 & 0.28 \\
\text{sym} & & & & \end{bmatrix}
\]

TABLE 4.2

REGRESSION COEFFICIENTS AND STANDARD DEVIATION FOR PREDICTION ERROR FOR GM2

<table>
<thead>
<tr>
<th>( i )</th>
<th>( \beta_{i,0} )</th>
<th>( \beta_{i,1} )</th>
<th>( \beta_{i,2} )</th>
<th>( \beta_{i,3} )</th>
<th>( \beta_{i,4} )</th>
<th>( \sigma_{e_i} )</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>-1.844</td>
<td>-0.071</td>
<td>2.944</td>
<td>-1.356</td>
<td>-0.265</td>
<td>0.654</td>
</tr>
<tr>
<td>2</td>
<td>-6.195</td>
<td>-0.703</td>
<td>6.792</td>
<td>0.219</td>
<td>-0.523</td>
<td>0.730</td>
</tr>
<tr>
<td>3</td>
<td>-5.011</td>
<td>-0.345</td>
<td>4.638</td>
<td>0.348</td>
<td>-0.185</td>
<td>0.658</td>
</tr>
<tr>
<td>4</td>
<td>2.253</td>
<td>-0.081</td>
<td>-1.810</td>
<td>-0.211</td>
<td>0.012</td>
<td>1.001</td>
</tr>
<tr>
<td>5</td>
<td>-2.489</td>
<td>0.044</td>
<td>2.408</td>
<td>0.065</td>
<td>-0.081</td>
<td>0.962</td>
</tr>
<tr>
<td>6</td>
<td>-0.258</td>
<td>-0.477</td>
<td>0.905</td>
<td>-0.289</td>
<td>0.316</td>
<td>1.021</td>
</tr>
</tbody>
</table>
For known site and seismicity characteristics \( \{M, r, F, V_s\} \), a sample of the model parameter vector \( \theta_q \) is obtained by first generating a sample for the prediction error vector \( e = \{e_i\} \) from a correlated Gaussian distribution with zero mean value, standard deviation the one of the last column of Table 4.2 and correlation matrix 4.21, then calculating variables \( v_i \) through 4.20 and finally converting them to \( \theta_q \) through the inverse of Equation 4.18. A sample of the ground motion is then obtained by Equation 4.10. This process completely defines the ground motion model.
CHAPTER 5:
LOSS ESTIMATION

For estimating earthquake losses the comprehensive methodology initially proposed by Porter et al. (2001) is adopted. This methodology is the basis for the main loss estimation approach advocated in ATC-58 and by PEER.

5.1 Assembly-based loss estimation

For the direct losses, the components of the structure are grouped into $n_{as}$ damageable assemblies. Each assembly consists of components of the structural system that have common characteristics with respect to their vulnerability and repair cost. Such assemblies may include, for example, beams, columns, wall partitions, contents of the building, and so forth. For each assembly $j = 1, \ldots, n_{as}$, $n_{dj}$ different damage states are designated and a fragility function is established for each damage state $d_{kj}$, $k = 1, \ldots, n_{dj}$. These functions quantify the probability $P_c[d_{kj}|EDP_j, \theta_p]$ that the component has reached or exceeded its $k^{th}$ damage state, conditional on some engineering demand parameter (EDP$_j$) which is related to the time-history response of the structure (for example, peak transient drift, peak acceleration, maximum plastic hinge rotation, etc.). Vector $\theta_p$ represents the model parameters for this loss evaluation model. Damage state 0 is used to denote an undamaged condition. A repair cost $C_{kj}$ is then assigned to each damage state, which corresponds to the cost needed to repair the component back to the undamaged
condition. The expected losses for assembly \( j \), \( L_j(\theta_p) \), as well as the total losses, \( L(\theta_p) \), in the event of the earthquake are given by:

\[
L_j(\theta_p) = \sum_{k=1}^{n_{d,j}} P[d_{k,j} | \theta_p] C_{k,j} \quad L(\theta_p) = \sum_{j=1}^{n_a} L_j(\theta_p)
\]

where \( P[d_{k,j} | \theta_p] \) is the probability that the assembly \( j \) will be in its \( k \)th damage state and the explicit dependence on EDP\( j \) has been dropped. The probability \( P[d_{k,j} | \theta_p] \) may be readily obtained from the information from the fragility curves:

\[
P[d_{k,j} | \theta_p] = P[d_{k-1,j} | \theta_p] - P[d_{k+1,j} | \theta_p]
\]

This approach can be extended to evaluating the cost of injuries and fatalities, though in this case estimating the “unit replacement” cost is less trivial.

Similar approach may be implemented for the downtime cost, which refers to loss of use/revenue while the building is being repaired. For this purpose the structure is separated into \( n_{as} \) operational units, corresponding to parts of the building that can be considered as independent pieces when evaluating the contributions to its total worth.

The time \( R_m \) needed to bring each of these units to functional condition is then calculated based on the type and extent of the damage to it, using information from the structural response. Note that the time \( R_m \) does not necessarily correspond to the time required to completely repair all the damage to the \( m \)th operational unit since in some cases functionality may be established while the repairs continue. If \( U_m \) is the daily income for operational unit \( m \), the losses due to downtime are finally calculated as:

\[
L_u(\theta_p) = \sum_{m=1}^{n_u} U_m R_m
\]
5.2 Fragility functions

TABLE 5.1 and TABLE 5.2 present a summary for the fragility functions and the expected repair cost for non-structural and structural components, respectively, used in this study. All these pertain to the building presented in Section 3.

TABLE 5.1
FRAGILITY FUNCTION AND EXPECTED REPAIR COST FOR STRUCTURAL COMPONENTS

<table>
<thead>
<tr>
<th>Component</th>
<th>Damage state $d_{kj}$</th>
<th>Repair method</th>
<th>Fragility function parameters</th>
<th>Repair Cost</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td>$x_m$</td>
<td>$b_m$</td>
</tr>
<tr>
<td>Beam-column subassembly</td>
<td>1 (Light cracking)</td>
<td>surface coating</td>
<td>0.007</td>
<td>0.45</td>
</tr>
<tr>
<td></td>
<td>2 (Cracking)</td>
<td>Epoxy</td>
<td>0.017</td>
<td>0.5</td>
</tr>
<tr>
<td></td>
<td>3 (Severe cracking)</td>
<td>Epoxy and patch spalled concrete</td>
<td>0.039</td>
<td>0.3</td>
</tr>
<tr>
<td></td>
<td>4 (Severe spalling)</td>
<td>Remove and replace damaged concrete</td>
<td>0.06</td>
<td>0.22</td>
</tr>
<tr>
<td>Slab-column subassembly</td>
<td>1 (Light cracking)</td>
<td>Surface coating</td>
<td>0.004</td>
<td>0.39</td>
</tr>
<tr>
<td></td>
<td>2 (Severe cracking)</td>
<td>Epoxy</td>
<td>0.01</td>
<td>0.25</td>
</tr>
<tr>
<td></td>
<td>3 (Punching Shear)</td>
<td>Replace concrete</td>
<td>0.09</td>
<td>0.24</td>
</tr>
<tr>
<td>Column</td>
<td>1 (Cracking)</td>
<td>Epoxy</td>
<td>0.011</td>
<td>0.11</td>
</tr>
<tr>
<td></td>
<td>2 (Severe cracking)</td>
<td>Jacketed repair</td>
<td>0.045</td>
<td>0.3</td>
</tr>
<tr>
<td></td>
<td>3 (Severe spalling)</td>
<td>Replacement</td>
<td>0.078</td>
<td>0.35</td>
</tr>
</tbody>
</table>

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### TABLE 5.2
FRAGILITY FUNCTION AND EXPECTED REPAIR COST FOR NON-STRUCTURAL COMPONENTS

<table>
<thead>
<tr>
<th>Component</th>
<th>Damage state $d_{k,j}$</th>
<th>Repair method</th>
<th>Fraility function parameters</th>
<th>Repair Cost</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td>$x_{m}$</td>
<td>$b_{m}$</td>
</tr>
<tr>
<td><strong>Partitions (IDR)</strong></td>
<td>1 (Small cracks)</td>
<td>Patching</td>
<td>0.0025</td>
<td>0.7</td>
</tr>
<tr>
<td></td>
<td>2 (Extensive cracks)</td>
<td>Patching and door replacement</td>
<td>0.006</td>
<td>0.5</td>
</tr>
<tr>
<td></td>
<td>3 (Severe damage)</td>
<td>Replacement of partition</td>
<td>0.014</td>
<td>0.4</td>
</tr>
<tr>
<td><strong>Ceilings (PFA)</strong></td>
<td>1 (Some tiles fallen)</td>
<td>Replacement</td>
<td>0.55 (g)</td>
<td>0.4</td>
</tr>
<tr>
<td></td>
<td>2 (Extensive tile fallout)</td>
<td>Replacement</td>
<td>1 (g)</td>
<td>0.4</td>
</tr>
<tr>
<td><strong>Paint (IDR)</strong></td>
<td>1 (damaged)</td>
<td>Repaint</td>
<td>0.0033</td>
<td>0.2</td>
</tr>
<tr>
<td><strong>DS3-partition (IDR)</strong></td>
<td>1 (damaged)</td>
<td>Replacement</td>
<td>0.014</td>
<td>0.4</td>
</tr>
<tr>
<td><strong>Windows (IDR)</strong></td>
<td>1 (Light)</td>
<td>Replacement</td>
<td>0.016</td>
<td>0.29</td>
</tr>
<tr>
<td></td>
<td>2 (Moderate)</td>
<td>Replacement</td>
<td>0.032</td>
<td>0.29</td>
</tr>
<tr>
<td></td>
<td>3 (Extensive)</td>
<td>Replacement</td>
<td>0.036</td>
<td>0.27</td>
</tr>
<tr>
<td><strong>Generic drift (IDR)</strong></td>
<td>1 (Light)</td>
<td>Replacement</td>
<td>0.0055</td>
<td>0.6</td>
</tr>
<tr>
<td></td>
<td>2 (Moderate)</td>
<td>Replacement</td>
<td>0.01</td>
<td>0.5</td>
</tr>
<tr>
<td></td>
<td>3 (Significant)</td>
<td>Replacement</td>
<td>0.022</td>
<td>0.4</td>
</tr>
<tr>
<td></td>
<td>4 (Extensive)</td>
<td>Replacement</td>
<td>0.035</td>
<td>0.35</td>
</tr>
<tr>
<td><strong>Generic acceleration (PFA)</strong></td>
<td>1 (Light)</td>
<td>Replacement</td>
<td>0.7 (g)</td>
<td>0.5</td>
</tr>
<tr>
<td></td>
<td>2 (Moderate)</td>
<td>Replacement</td>
<td>1 (g)</td>
<td>0.5</td>
</tr>
<tr>
<td></td>
<td>3 (Significant)</td>
<td>Replacement</td>
<td>2.2 (g)</td>
<td>0.4</td>
</tr>
<tr>
<td></td>
<td>4 (Extensive)</td>
<td>Replacement</td>
<td>3.5 (g)</td>
<td>0.35</td>
</tr>
</tbody>
</table>
The first column lists the type of the component with the EDP for each of the component is sensitive to; IDR stands for maximum inter-storey drift and PFA for peak floor acceleration. Is should be pointed out that only two EDPs were selected in this study. Some previous studies have also used plastic hinge rotation for EDP for structural components, but more recent suggestions (including the ATC-58 drafts) are proposing reduction of the EDPs to only two categories, drifts and absolute accelerations. The second column in the previous Tables lists the different damage states for each of these components. The third column states the repair method for each of the damage states, the fourth and fifth lists the medians and lognormal standard deviation of the fragility function used. All adopted fragility functions follow a lognormal distribution. Column six gives the expected value for each damage state related to the quantity at column seven. Next the fragility functions adopted for each assembly are presented in more detail.

5.2.1 Beam-Column subassembly (Figure 5.1)

The fragility functions for beam-column subassemblies were based on Brown and Lowes (2007) with modifications made by Ramirez and Miranda (2009). The fragility functions relate the IDR to the probability of reaching and exceeding the following four damage states: i) a light cracking damage state that is repaired by using surface coating in the damage area, ii) a cracking damage state of at least 10% of the joint surface concrete repaired by injecting epoxy into cracks, iii) a severe cracking of at least 30% of the joint surface concrete repaired by patching spalled concrete, inject cracks with epoxy and replace finishes and iv) spalling of more of 80% of the joint surface concrete repaired by removing and replacing the damaged concrete. The cost for each damage state was calculated as a proportion of the value for replacing the damaged member. The cost of
replacing all structural and nonstructural members was calculated by the 2008 RS Means Square Foot Costs (Balboni 2008).

![Figure 5.1 Fragility function for Beam-Column Subassembly](image)

5.2.2 Slab-Column subassembly (Figure 5.2)

The fragility functions for slab-column subassemblies were based on the work in Aslani and Miranda (2005) and Robertson et al. (2002). The lognormal standard deviations range from 0.25 to 0.40 and the EDP used in this case is the IDR. For this subassembly three damage states are taken: i) a ‘light cracking’ damage state that is repaired using surface coating of the affected area, ii) a ‘severe cracking’ damage state that corresponds to epoxy injection repair of the affected area, iii) a ‘punching shear’ (without collapse) damage state that corresponds to replacing the concrete in the slab surface. The repair cost is based on the suggestions in Goulet et al. (2007).
Figure 5.2 Fragility function for Column-Slab subassembly

5.2.3 Columns subassembly (Figure 5.3)

The fragility functions for column subassemblies are taken from the work by Lu et al. (2005) who presented drift limits and performed performance evaluation for reinforced concrete columns considering three performance levels: i) functional performance level, representing a state whereby the normal function of the building is not interrupted, ii) damage control level which concerns a controllable structural damage and the life safety of building occupants and iii) the ultimate level which is defined to correspond to the confined concrete reaching the ultimate compressive strain or the longitudinal reinforcement reaching the ultimate tension strain. The repair cost is based on the suggestions in Goulet et al. (2007).
Figure 5.3 Fragility function for Reinforced Concrete Columns

5.2.4 Partitions (Figure 5.4)

The interior partition of the building consists of full height 5/8 inch gypsum wallboard screwed on metal studs. The EDP used for the partitions is the peak interstory drift (IDR) according to ATC-58 (2009). The description for the three damage states are i) visible damage and small cracks in gypsum wallboard that can be repaired with taping, patching and painting. No window or door damage. ii) Extensive cracking or crushing in gypsum wallboard and minimal or no damage to metal studs. The repair for this damage state includes re-hanging of doors. iii) Severe damage to gypsum wallboard and enough damage to metal studs and runners to require replacement. The repair measures include some door and minor mechanical repairs. Repair costs are adopted based on ATC-58 (2009) recommendations.
5.2.5 Paint (Figure 5.5)

According to previous studies (Beck et al. 1999; Goulet et al. 2007), paint has a relatively significant contribution to the total repair cost of a damaged structure especially for lower levels of excitation. For estimating the total wall area requiring a fresh coat of paint a simplified formula was developed by Mitrani (2007). According to this formula a percentage of the undamaged wall area is also repainted, considering the desire of the owner to achieve a uniform appearance. This percentage depends on the extent of the damaged area and is chosen here based on a lognormal distribution with median 0.33% and logarithmic standard deviation 0.2 according to Taflanidis and Beck (2009c).

\[
ATP = DA + UA \times P(\text{paint UA/DA})
\]
where ATP: mean area to paint, DA: damaged area, UA: undamaged area and $P(\text{paint \ UA/DA})$: probability of needing to paint an entire floor as a function of the damaged area of wallboard partitions on the same floor.

Figure 5.5 Fragility function for Paint

5.2.6 Ceiling (Figure 5.6)

The ceiling for the building consists of a suspended ceiling system with T bars and acoustical ceiling tiles installed in accordance with ICBO standard. The $EDP$ for ceiling is peak floor acceleration ($PFA$) and the fragility function parameters are taken by ATC-58 (2009) for two damage states: i) Some tiles displaced and fallen, usually in the perimeter of the room, ii) extensive tile fallout and T bar grid failure. Mechanical systems are damaged.
5.2.7 Drift sensitive nonstructural components (Figure 5.7, Figure 5.8)

Three additional subassemblies are considered for the non-structural components based on the recommendations by Ramirez and Miranda (2009). The first one is ‘DS3 partition-like’ which are components like electrical wiring, plumbing, light switches, etc. that have physical and spatial interaction with the partitions (because are often contained within the partitions) so their losses are dependent. If a partition needs to be replaced, these components must be also replaced regardless if they are damaged or not. Consequently these components have the same fragility characteristics as the partition third damage state. The next two are windows and generic drift components such as vertical piping, bath-tubs, ducts and elevators. In the result presentation these three sub-assemblies will be combined and referenced as generic drift.

Figure 5.6 Fragility function for Ceiling
Figure 5.7 Fragility function for DS3-partition like

Figure 5.8 Fragility Function for Generic Drift components
5.2.8 Acceleration sensitive nonstructural components (Figure 5.9)

The acceleration sensitive nonstructural components include the fire protection system, HVAC, heating, cooling, pumps, plumbing and toilets and are taken as calculated and documented by Ramirez and Miranda (2009).

![Figure 5.9 Fragility function for Generic Acceleration components](image)

5.2.9 Summary comparison of repair cost contributions

Figure 5.10 and Figure 5.11 present the expected repair cost as a function of the EDP for the drift sensitive and acceleration sensitive components, respectively. Figure 5.10 illustrates that for IDR values between 0.02 and 0.04 the losses are higher for non-structural components than for structural components. After the IDR value of 0.06 the losses calculated by the fragility functions for structural components estimated to be higher than for the nonstructural. Taking into consideration that the probability of occurrence for inter-storey drift ratios higher than 0.04 is quite small, it is evident that the largest potential to contribute to the total loss comes from the nonstructural drift sensitive
assemblies. For an IDR value of 0.025, which is the value modern reinforced concrete frame buildings are designed not to exceed using equivalent static analyses when subjected to a ground motion intensity equal to the design earthquake (as prescribed by US building codes), the losses from the nonstructural components are higher than those of the structural. This agrees with previous studies that have also suggested that nonstructural components should be expected to make up the majority of seismic induced losses (Taghavi and Miranda 2003; Aslani and Miranda 2005; Ramirez and Miranda 2009) for code conforming concrete structures.

![Graph showing expected repair cost for structural and nonstructural components.](image)

**Figure 5.10 Structural and nonstructural drift sensitive components**

For the acceleration sensitive components now, it is evident that the ceiling contribution is dominant for the smaller acceleration regime (1-3 g), within which the response of the structure is primarily anticipated.
Figure 5.11 Nonstructural Acceleration sensitive components
CHAPTER 6:

ESTIMATION OF LIFE-CYCLE COST AND IDENTIFICATION OF IMPORTANCE OF RISK FACTORS

6.1 Estimation of life-cycle cost

Since the models adopted for characterization of the seismic losses are complex, i.e. involve a large number of model parameters and various sources of nonlinearities, the expected value equation 2.2 cannot be calculated, or even accurately approximated, analytically. Instead it is estimated through *stochastic simulation* (Robert and Casella 2004); using a finite number, $N$, of samples of $\theta$ simulated from some proposal density $q(\theta)$, an estimate for equation 2.2 is given by the *stochastic analysis*:

$$
\hat{C} = \frac{1}{N} \sum_{j=1}^{N} h(\theta^j) \frac{p(\theta^j)}{q(\theta^j)}
$$

6.1

where vector $\theta^j$ denotes the sample of the uncertain parameters used in the $j^{th}$ simulation and $\{\theta^j\}$ corresponds to the entire sample set. As $N \to \infty$, then $\hat{C} \to C$ but even for finite, large enough $N$, equation 6.1 gives a good approximation for equation 2.2. The quality of this approximation is assessed through its coefficient of variation, $\delta$. This is the coefficient of variation for the estimator in equation 6.1, not for the estimate (i.e for the life-cycle cost). An estimate for $\delta$ may be obtained by Robert and Casella (2004):
Thus the stochastic analysis provides not only an estimate for the expected cost integral, but simultaneously a measure for the accuracy of that estimate. The importance sampling density \( q(\theta) \) may be used to improve this accuracy and, ultimately, the efficiency of estimation in equation 6.1. This is established by focusing the computational effort on regions of the \( \Theta \) space that contribute more to the integrand of the probabilistic integral in equation 2.2 (Taflanidis and Beck 2008). The simplest selection is to use \( q(\theta) = p(\theta) \), then the evaluation in 6.1 corresponds to direct Monte Carlo analysis. For problems with a large number of model parameters, as the application discussed here, choosing efficient importance sampling densities for all components of \( \theta \) is challenging and can lead to convergence problems for the estimator in equation 6.1; thus it is preferable to formulate importance sampling densities only for the important components of \( \theta \), i.e. the ones that have biggest influence on the system performance, and use \( q(.) = p(.) \) for the rest (Taflanidis and Beck 2008). For seismic risk applications the characteristics of the hazard, especially the moment magnitude or epicentral distance are generally expected to have the strongest impact on the calculated risk (Taflanidis and Beck 2009c), so selection of importance sampling densities may preliminary target only them.

The coefficient of variation for the life-cycle cost, given by Equation 2.3, can be estimated, in this stochastic-simulation based setting, as

\[
\delta_c \approx \frac{1}{\sqrt{N}} \sqrt{ \frac{1}{N} \sum_{j=1}^{N} \left( \frac{h(\theta^j) P(\theta^j)}{q(\theta^j)} \right)^2 - 1 }
\]  

6.2

\[
\delta \approx \frac{1}{\sqrt{N}} \sqrt{ \frac{1}{N} \sum_{j=1}^{N} \left( \frac{h(\theta^j) P(\theta^j)}{q(\theta^j)} \right)^2 - 1 }
\]  

6.3
For the stochastic analysis described by equation 6.1 the most computationally demanding task is the evaluation of the structural model response through time-domain nonlinear analysis, required for estimation of \( h(\theta) \). The computational burden for generating the required samples \( \{\theta^j\} \), for estimating losses based on that structural response, and for calculation the sample average in Equation 6.1 is small. The efficiency of the stochastic analysis may be, thus, improved by exploiting recent advances in computer and computational science, in particular the widespread use of parallel/distributed computing, to perform the \( N \) required evaluations of the system response in parallel mode. More importantly, this simulation-based evaluation of the life-cycle repair cost facilitates an efficient calculation of this cost for different components [this merely corresponds to evaluation of different performance functions \( h_k(\theta) \) as discussed in Section 2, based on the same response] as well as an estimation for different probabilistic descriptions [different selections for \( p(\theta) \)]. The latter can be established efficiently by selecting the same proposal densities \( q(\theta) \) for all different probabilistic characterizations \( \{p(\theta) = p_s(\theta); s = 1, \ldots, N_s\} \) considered. This means that the same sample set \( \{\theta^j\} \) is used for all cases and thus the structural response simulations, representing the most computationally demanding task in the analysis, are common and do not have to be repeated. The only component changing in the analysis is \( p(\theta) \). This is another advantage that is ultimately established through the proposed simulation-based approach.
6.2 Distributed implementation of stochastic simulation

All computations in this research effort are performed on the “Persephone” cluster at the HHigh Performance system Analysis and Design (HIPAD) laboratory at the University of Notre Dame (www.nd.edu/~hipad). The cluster is composed of 42 nodes, each having eight 2.56GHz Nehalem cores with 12 GB of memory. All stochastic simulations are performed in parallel mode taking advantage of the multi-core capabilities of the cluster and the efficiency of OpenSees for distributed simulations. Thus, up to 336 simulations are simultaneously but independently performed on the cluster at each instance, leading to great computational efficient. A significant part of the research effort (mounting to more than couple of months) was placed on setting up OpenSees to work on the cluster, since this is not a straightforward task, but requires cluster-specific updates and debugging problems to be addressed. Structural simulations were finally established to work in distributed mode, using simultaneously all available cluster nodes.

6.3 Identification of importance of risk factors

This framework for life-cycle repair cost assessment may be extended to additionally investigate the importance of each of the risk factors (uncertain model parameters) for impacting the overall expected cost. This can be established through an innovative sensitivity analysis, based on the ideas initially discussed in Taflanidis (2009). Foundation of this methodology is the definition of an auxiliary probability density function that is proportional to the integrand of the expected life cycle cost in equation 2.2
\[ \pi(\theta) = \frac{h(\theta) p(\theta)}{\int_\theta h(\theta) p(\theta) d\theta} \propto h(\theta) p(\theta) \quad (6.4) \]

where \( \propto \) denotes proportionality and the denominator in \( \pi(\theta) \) is simply a normalization constant that will not be explicitly needed. The sensitivity analysis is established by comparing this auxiliary distribution \( \pi(\theta) \) and the prior probability model \( p(\theta) \); bigger discrepancies indicate greater importance. More importantly, though, this idea can be implemented to each specific model parameter or even to subsets of them \( y \in Y \subset \theta \), by looking at the marginal distribution \( \pi(y) \). This distribution is given by

\[ \pi(y) = \int_X \pi(\theta) d\theta = \frac{\int_X h(\theta) p(\theta) d\theta}{C} \propto p(y) \int_X h(y, x) p(x | y) d\theta \quad (6.5) \]

where \( x \) corresponds to the rest of the components of \( \theta \), excluding \( y \). Comparison between this marginal distribution \( \pi(y) \) and the prior distribution \( p(y) \) expresses the probabilistic sensitivity of the seismic risk with respect to \( y \). Uncertainty in all other model parameters is explicitly considered by appropriate integration of the joint probability distribution \( \pi(\theta) \) to calculate the marginal probability distribution \( \pi(y) \).

A quantitative metric to characterize this sensitivity is the relative information entropy, which is a measure of the difference between probability distributions \( \pi(y) \) and \( p(y) \) (Jaynes 2003)

\[ D(\pi(y) \| p(y)) = \int_Y \pi(y) \log \left( \frac{\pi(y)}{p(y)} \right) dy \quad (6.6) \]

The importance of subset \( y \) is directly investigated by comparison of the relative information entropy value for each of the subsets of interest; larger values for \( D(\pi(y) \| p(y)) \) indicate ultimately bigger importance.
For this comparison the relative information entropy needs to be calculated for all groups of parameters of interest \( \{y_i, i=1,\ldots,n_g\} \). For efficiently establishing this task, and since direct evaluation of in equation 6.5 is challenging, an alternative stochastic-sampling approach is adopted (Jia and Taflanidis 2011). This approach is based on exploiting the information in samples of \( \theta \) from the joint distribution \( \pi(\theta) \). Such samples may be obtained by any appropriate stochastic sampling algorithm. These algorithms start by generating a set of candidate samples for \( \theta \) based on some proposal density and proceed to evaluate the performance function for each of them. Based on this, information samples from \( \pi(\theta) \) may be generated with characteristics for the sampling process dependent on the specific algorithm used. Furthermore this task may be integrated within the stochastic analysis in equation 5.1: each of the samples \( \theta^k \) used for the estimation in equation 5.1 can be selected as a candidate sample \( \theta \) in the context of these stochastic sampling algorithms. This way the required samples from \( \pi(\theta) \) are obtained at a small additional computational effort over the life-cycle cost assessment task, since they require no new simulations for the system-model response. This approach ultimately provides a set \( \{\theta^k\} \) of \( n \) samples from \( \pi(\theta) \).

Projection, now, of these samples from \( \pi(\theta) \) to the space of each subset of interest \( y \) provides samples for the marginal distributions \( \pi(y) \) for each of them separately. Thus using the same sample set \( \{\theta^k\} \) this approach provides simultaneously information for all different groups of model parameters of interest, with no requirement to repeat the process for each of them. Based on the available samples, an approximation for \( \pi(y) \) can be obtained (Scott 1992) through Kernel Density Estimation (KDE). For example, using a
multivariate product Kernel, and \( n \) available samples from \( y \), with \( y_i^k \) denoting the \( i^{th} \) component of the \( k^{th} \) sample of \( y \) the KDE approximation is

\[
\tilde{\pi}(y) = \frac{1}{n} \sum_{k=1}^{n} \prod_{i=1}^{n} \frac{1}{w_i} K \left( \frac{y_i - y_i^k}{w_i} \right)
\]

where \( K(.) \) is the chosen Kernel with bandwidth \( w_i \) for the \( i^{th} \) component of \( y \). In this study the Epanechnikov Kernel is chosen

\[
K(t) = \frac{3}{4} (1 - t^2) \quad \text{if} \quad -1 \leq t \leq 1; =0 \quad \text{else}
\]

with bandwidth selection (Scott 1992)

\[
w_i = \left[ 25 \left( \frac{3}{5} \right)^{2-n_y} (2\sqrt{\pi})^{n_y} \right]^{1/(n_y+4)} \left[ \frac{4}{(n_y + 2)n_y} \right]^{1/(n_y+4)} \sigma_n
\]

An estimate for the relative information entropy may be then obtained by calculating the entropy integral through stochastic simulation (Jia and Taflanidis 2011) as

\[
D(\pi(y) \| p(y)) \approx \frac{1}{n} \sum_{k=1}^{n} \log \left( \frac{\pi(y^k)}{p(y^k)} \right) \approx \frac{1}{n} \sum_{k=1}^{n} \log \left( \frac{\tilde{\pi}(y^k)}{\tilde{p}(y^k)} \right)
\]

where \( y^k \sim \pi(y) \) correspond to samples from \( \pi(y) \) that are readily available. To achieve better accuracy in the relative entropy calculation the density \( p(y) \) in equation 6.10 is also approximated by its corresponding KDE \( \tilde{p}(y) \) based on samples, even when an analytical expression is available for it. This way, any type of error introduced by the KDE is similar for both of the densities compared. For bounded parameters, boundary correction KDE approaches (Karunamuni and Zhang 2008) should be used to circumvent approximation problems close to the boundaries.
This approach ultimately leads to an efficient sampling-based methodology for calculating the relative information entropy for different parameters, which can be performed concurrently with the life-cycle cost assessment, exploiting the readily available system model evaluations for minimizing the computational burden. Comparing the values for this entropy between the various model parameters leads then to a direct identification of the importance of each of them in affecting the overall cost. Parameters with higher value for the relative entropy will have greater importance. Furthermore direct comparison of samples from the distributions $\pi(y)$ and $p(y)$ provides additional insight about what specific values for each parameter contribute more to the risk (Taflanidis and Beck 2009a). This information cannot be directly obtained through the relative information entropy in equation 6.6 that characterizes each parameter over its entire value range.
CHAPTER 7:
CASE STUDIES AND DISCUSSION

In this chapter the life-cycle cost assessment is presented for the considered structure (i) with or (ii) without the dampers and for different cases of interest with respect to the seismic hazard characterization. Also the sensitivity analysis results for the uncertain model parameters are reported and finally the impact of the seismic hazard variability on the risk analysis is investigated through a parametric analysis with different probability models for the seismic hazard description.

7.1 Seismic hazard description

Two different cases are considered for the seismic hazard. In the first case, uncertainty is assumed for both the seismic characteristics (moment magnitude, \( M \), and epicentral distance, \( r \)) as well as for the predictive relationships describing the parameters of the ground motion model. In the second case, uncertainty is assumed only for the latter, and specific values are used for the seismic characteristics \( M=6.5 \) and \( r=20 \) km. This latter investigation focuses on the impact of the uncertainty in the ground motion model itself on the predicted repair cost.

For the case with uncertainty in the moment magnitude, seismic events are assumed to occur following a Poisson distribution and so are independent of previous occurrences. The moment magnitude \( M \) is modeled by the Gutenberg-Richter relationship
truncated on the interval \([M_{\text{min}}, M_{\text{max}}]=[5, 8]\), leading to the PDF and expected number of events per year given, respectively, by (Kramer 2003):

\[
p(M) = \frac{b \exp(-b \cdot M)}{\exp(-b \cdot M_{\text{min}}) - \exp(-b \cdot M_{\text{max}})}; \quad v = \exp(a - bM_{\text{min}}) - \exp(a - bM_{\text{max}})
\]

7.1

Only events with magnitude greater than \(M \geq 5.0\) are considered since earthquakes with smaller magnitude are not expected to lead to significant damages to the structure and thus will not contribute significantly to the expected life-cycle cost. The regional seismicity factors are selected as \(b=0.9 \log_{10}(10)\) and \(a=4.35 \log_{10}(10)\), leading to \(v=0.7\). For the uncertainty in the event location, the epicentral distance, \(r\), for the earthquake events is assumed to follow a log-normal distribution with median 20 km and coefficient of variation 0.35.

Since the GM2 model has been reported to over predict the time history for events smaller than 6.5 moment magnitude another case is considered, with \(M\) following the previous probability distribution but truncated in the interval \([M_{\text{min}}, M_{\text{max}}]=[6.5, 8]\). This case corresponds to estimation of the life-cycle cost for stronger events, that are expected to lead to nonlinear structural behavior. The value for \(v\) in this case is \(v=0.0302\).

Ultimately the following case studies are considered

(a) Seismic hazard defined through GM1 model with \(M\) and \(r\) uncertain, \(M\) truncated in interval \([6.5, 8]\), and structure without dampers.

(b) Seismic hazard defined through GM2 model with \(M\) and \(r\) uncertain, \(M\) truncated in interval \([6.5, 8]\), and structure without dampers.

(c) Seismic hazard defined through GM1 model with \(M\) and \(r\) uncertain, \(M\) truncated in interval \([6.5, 8]\), and structure with dampers.
(d) Seismic hazard defined through GM2 model with $M$ and $r$ uncertain, $M$ truncated in interval [6.5 8], and structure with dampers.

(e) Seismic hazard defined through GM1 model with $M$ and $r$ uncertain, $M$ truncated in interval [5 8], and structure without dampers.

(f) Seismic hazard defined through GM2 model with $M$ and $r$ uncertain, $M$ truncated in interval [5 8], and structure with dampers.

(g) Seismic hazard defined through GM1 model for $M=6.5$, $r=20$, and structure without dampers.

(h) Seismic hazard defined through GM2 model for $M=6.5$, $r=20$, and structure without dampers.

Comparison between cases (a) and (b), (c) and (d), (g) and (h) yields information for the comparison between models GM1 and GM2 in describing the seismic hazard, whereas comparison between cases (a) and (c), (b) and (d), and (e) and (f) yields comparison for the life-cycle cost for the case with or without the dampers.

7.2 Life-cycle performance definition

The total value of the losses from all future earthquake excitations is taken as the quantity representing lifetime repair cost. This leads to selection (based on the Poisson assumption adopted in this study for occurrence of seismic events)

$$h(\theta) = L(\theta)t_{life}$$

where $t_{life}$ is the lifetime of the structure and $L(\theta)$ is the cost given the occurrence of an earthquake event. Earthquake damage and losses are calculated assuming that after each event the building is quickly restored to its undamaged state. For the case for specific $M$
and $r$ the results are reported directly for the expected earthquake losses [i.e. ignore $vt_{life}$ in equation 7.2] per seismic event. The lifetime of the structure is taken as 60 years.

Another risk-quantification used is the present value of future losses, given by

$$h(\theta) = L(\theta) \left[ vt_{life} \frac{1-e^{-r_d t_{life}}}{r_d t_{life}} \right]$$  \quad 7.3

where $r_d$ is the discount rate and the term in brackets is used to calculate the present value of the expected future earthquake losses. This formulation is necessary when the total life cycle cost needs to be calculated by adding any upfront cost (for example, from structural retrofitting). The discount rate is taken as 2.5%.

For the case for specific $M$ and $r$ the results are reported directly for the expected earthquake losses per seismic event [i.e. ignore $vt_{life}$ in equation 7.2].

The cost is reported also for different sub-assemblies: (i) paint; (ii) partitions walls; (iii) ceiling; (iv) structural components, consisting of columns, beam-column subassembly and slab-column subassembly; (v) drift sensitive components, consisting of DS3-partition like components and generic drift components described in section 5.2.7; and (vi) acceleration sensitive non-structural components as described in section 5.2.8.

7.3 Details for stochastic simulation

In this study, the sampling density $q(\theta)$ is chosen equal to $p(\theta)$ for all components of $\theta$ apart from the moment magnitude for which a truncated in [5 8] (or [6.5 8] when moment magnitude is constrained to be larger than 6.5). Gaussian importance sampling density is chosen with mean 6.5 and standard deviation 0.90. This selection is based on prior experience (Taflanidis and Beck 2009c); earthquakes close to 6.5 magnitude are expected to have the biggest impact on the seismic risk. The number of samples is chosen
here as \( N=10000 \) in order to establish a very small coefficient of variation and facilitate a more accurate comparison between the different cases considered. These selections for \( q(\theta) \) and \( N \) lead to an accurate estimate for the expected repair cost, with coefficient of variation (Equation 6.2) ranging from \( \delta=0.6\% \) to \( \delta=4 \% \) for the different aspects of the repair cost considered.

For the entropy evaluation, the accept-reject algorithm (Robert and Casella 2004) is chosen for generating the samples from \( \pi(\theta) \). The efficiency reported ranged from 5-10\% for the different aspects of the repair cost, meaning that around 500-1000 samples were available from \( \pi(\theta) \). 4000 samples were used for \( p(\theta) \), obtained by direct sampling from the proposed distributions for each model parameter. The relative entropy \( D(\pi(y)|p(y)) \) is presented with respect to the total cost, as well as with respect to the repair cost for the different damageable assemblies; the structural components, the drift-sensitive non-structural components and acceleration-sensitive non-structural components. Results are reported for all individual model parameters as well as groups of parameters for which we are interested in potential correlations, for example the parameters \( e_a, e_b, e_e \) describing the uncertainty in the source spectrum for GM1 model or the parameters \( n, \lambda, e_t \) defining the temporal characteristics of the excitation for the same model. If the parameters are uncorrelated then their joint entropy is equal to the sum of their individual entropies. The departure from this sum demonstrates the degree of correlation. The entropy evaluation for GM1 is reported for \( \{e_a, e_b, e_e, e_t\} \) as well as for the resultant model parameters \( \{f_a, f_b, e_T\} \). Since calculation of the entropy is performed using sampling-based concepts this is efficiently performed by simply transforming samples from the former group to samples for the latter group and then using these
samples to estimate the probability distributions of interest through KDE. Similarly for GM2 the entropy is reported for both \( \{ a_1 a_2 a_3 \} \) and \( \{ \bar{T}_a D_{5.95} t_{mid} \} \).

7.4 Life-cycle cost for uncertain \( M, r \) for strong events (\( M=[6.5 \ 8] \))

The expected life time cost of the structure without the dampers and for the GM1, is estimated at $0.335 million. The present value of this cost is $0.1735 million. The distribution to the different assemblies is shown in Figure 7.1. This distribution shows that 35% of this cost is due to damage at the structural components and 11% is attributed to components that are sensitive to the peak floor acceleration (ceiling and acceleration sensitive) and 53% to nonstructural drift sensitive components.

![Figure 7.1 Expected life cycle cost distribution to different assemblies for structure without retrofitting (GM1)](image)

For GM2 the expected life cycle cost is $0.940 million. The present value of this cost is $0.487 million. The distribution to the different assemblies is shown in Figure 7.2. For this case 52% of the cost is due to damage at the structural components and 12% is due to the damage on the acceleration sensitive components.
Figure 7.2 Expected life cycle cost distribution to different assemblies for structure without retrofitting (GM2)

For the structure with the dampers the present value of the expected life cycle cost for GM1 is 0.2026 million. Of this amount $14,600 corresponds to the expected repair cost of damage and $188,000 to the installation of the dampers. The distribution to the different assemblies is shown in Figure 7.3. It can be seen in that figure that the contribution of the damage to the structural components is smaller than the case without dampers and the percentage of cost due to paint is higher. This is anticipated since addition of the dampers leads to reduction of the nonlinear drift response, which then leads to increased contribution to the total repairs by the assemblies that are sensitive to low drift responses (partition walls). For GM2 and the retrofitted structure, the expected life cycle cost for is $0.457 million. Of this amount $0.269 million corresponds to the expected repair cost of damage and 188,000 is the installation cost of the dampers.

As it can be seen the reduction to the repair cost with the use of dissipative devises for each case is 90% and 44% respectively. The additional cost of the dampers though does not justify the retrofitting of the building with the installation of viscous
dampers if strong motions are only considered. For GM1 the present value of the expected life cost is actually increasing (TABLE 7.1) and for GM2 the present value of the expected life cycle cost is decreasing by only 6.12%. This comparison is, though, not reasonable since it focuses only on strong ground motions; the potential benefits from inclusion of viscous dampers need to be judged by considering the entire range of motions that can be damaging to the structure.

Figure 7.3 Present value of expected life cycle and repair cost distribution for structure with dampers (GM1)

Figure 7.4 Present value of expected life cycle (left) and repair cost (right) distribution for structure with dampers (GM2)
The summary results of the analysis for each ground motion model and for structures with and without viscous dampers are given in TABLE 7.1. The coefficient of variation for the cost estimate, as well as the coefficient of variation of the life-cycle cost itself are also shown in the Table 7.1.

**TABLE 7.1**

MEAN REPAIR AND EXPECTED LIFE CYCLE COST

<table>
<thead>
<tr>
<th>Structure type</th>
<th>Ground motion model</th>
<th>Expected repair cost per event ($)</th>
<th>Expected life cycle repair cost ($)</th>
<th>Present value of expected life cycle repair cost ($)</th>
<th>C.O.V. of cost estimate</th>
<th>C.O.V. of cost</th>
</tr>
</thead>
<tbody>
<tr>
<td>Structure without dampers</td>
<td>GM1</td>
<td>1.85e+05</td>
<td>3.35e+05</td>
<td>1.74e+05</td>
<td>1.205</td>
<td>0.010</td>
</tr>
<tr>
<td></td>
<td>GM2</td>
<td>0.52e+06</td>
<td>0.94e+06</td>
<td>0.49e+06</td>
<td>1.931</td>
<td>0.0210</td>
</tr>
<tr>
<td>Structure with dampers</td>
<td>GM1</td>
<td>0.16e+05</td>
<td>0.28e+04</td>
<td>2.03e+05</td>
<td>3.835</td>
<td>0.0336</td>
</tr>
<tr>
<td></td>
<td>GM2</td>
<td>0.29e+06</td>
<td>0.52e+06</td>
<td>0.46e+06</td>
<td>2.665</td>
<td>0.0280</td>
</tr>
</tbody>
</table>

Overall the comparison between the two models demonstrates significant larger cost predictions for GM2. No other insight can be directly, though, gained by simply looking at these costs. Simply estimating seismic risk cannot provide with any information where the differences stem from. Further insight will be provided by the sensitivity analysis discussed later.
7.5 Life-cycle cost for uncertain $M \geq 5.0$, $r$

In this section the results for the analysis of the structure for GM1 with magnitude $M \geq 5$ are presented. Figure 7.5 and Figure 7.6 present the decomposition of the expected life-cycle cost and the lifetime repair cost into its different components for both the initial and the retrofitted structure. The changes into the distribution of the total cost over its different components are minor. The expected life time cost of the structure without the dampers, is estimated at $0.745$ million. The present value of this cost is $0.3858$ million. The present value of the expected lifetime cost for the retrofitted system is $0.269$ million which shows that the addition of the viscous dampers improves significantly the performance of the structural system. Of this amount, $188,000$ corresponds to the cost of the viscous dampers and $81,000$ to the present worth of the expected repair cost for damage for future earthquakes.

Figure 7.5 Lifetime repair cost for structure without retrofitting (left) and for structure with dampers (right) for $M \geq 5$
The summary results of the analysis for structures with and without viscous dampers are given in TABLE 7.2. The coefficient of variation for the cost estimate, as well as the coefficient of variation of the life-cycle cost itself are also shown in the Table. The expected cost for this case is more than two times the cost calculated for the case with $6.5 \leq M \leq 8$. This means that earthquakes with magnitude smaller than 6.5 do lead to significant seismic losses; these losses are of course smaller than the ones corresponding to larger magnitude events, but the higher occurrence probability of the smaller events leads ultimately to an important contribution to the overall life-cycle cost. For example, the expected number of events per year for $[M_{\text{min}}, M_{\text{max}}] = [5,8]$ as calculated by equation 3.9 is $\nu = 0.70$ when for $[M_{\text{min}}, M_{\text{max}}] = [6.5, 8]$ is $\nu = 0.03$. This discussion illustrates the importance of lower intensity earthquakes to the calculation of the expected life cycle cost and it further indicates the need for calibration of the GM2 model to magnitudes lower than 6.
TABLE 7.2

MEAN REPAIR AND LIFE CYCLE COST M ≥ 5

<table>
<thead>
<tr>
<th>Structure type</th>
<th>Synthetic ground motion type</th>
<th>Expected repair cost per event ($)</th>
<th>Expected life cycle repair cost ($)</th>
<th>Present value of expected life cycle repair cost ($)</th>
<th>C.O.V. of cost estimate</th>
<th>C.O.V. of cost</th>
</tr>
</thead>
<tbody>
<tr>
<td>Without dampers</td>
<td>GM1</td>
<td>1.76e+04</td>
<td>7.45e+5</td>
<td>3.86e+05</td>
<td>3.725</td>
<td>0.148</td>
</tr>
<tr>
<td>With dampers</td>
<td>GM1</td>
<td>0.37e+04</td>
<td>1.56e+05</td>
<td>2.69e+05</td>
<td>7.032</td>
<td>0.0236</td>
</tr>
</tbody>
</table>

With the use of the damping system the present value of the expected life cycle cost is reduced by 30%. Comparison with the results reported in previous Section indicates, as expected, the importance of the dampers for reducing the seismic losses for lower intensity ground motions.

![Figure 7.7 Distribution of life cycle cost between different stories](image)

(a) Lifecycle cost for structure without retrofitting
(b) Lifecycle cost for structure with dampers

- $1.067 \times 10^5$
- $1.202 \times 10^5$
- $1.032 \times 10^5$
- $0.532 \times 10^5$
- $0.290 \times 10^5$ [Damper cost]
- $0.187 \times 10^5$ [Repair cost]
- $0.477 \times 10^5$ [Life-cycle cost]
- $0.262 \times 10^5$
- $0.550 \times 10^5$
- $0.248 \times 10^5$
- $0.580 \times 10^5$
- $0.119 \times 10^5$
- $0.699 \times 10^5$
Figure 7.7 shows the decomposition of the repair into the four different stories for both the initial and the retrofitted structure. For the initial structure the earthquake damage is larger for higher floors. This indicates that larger values of interstory drifts occur in the higher floors. Only the top floor has a slight reduction. For the retrofitted structure the cost follows the same distribution along the height with the top floor also having a smaller value comparing to the second and third.

Finally looking at the distribution of the total cost to the different assemblies (Figure 7.6), the biggest contribution to this cost comes from the non-structural components; repairing the partitions and repainting any damaged surfaces. The structural components also have a significant importance and the ceiling a considerable one. The contribution from the generic drift and generic acceleration assemblies is only a small one. Similar patterns hold for each floor separately for the structure without the dampers, as shown in Figure 7.8 as well as for the structure with the dampers, Figure 7.9. The contribution of the acceleration sensitive components (ceiling, generic acceleration) increases for higher floors, an anticipated behavior due to the larger acceleration response of these floors. Also the contribution from the structural components demonstrates a significant drop for the fourth floor.
Figure 7.8 Distribution of cost per floor to assemblies for structure without dampers
7.6 Expected Repair Cost for specific $M$ and $r$

In this section the results for specific moment magnitude, $M = 6.5$ and epicentral distance, $r = 20km$ are presented. The mean repair cost is $81,682 and as demonstrated by the decomposition in Figure 7.10 and its decomposition, paint has the higher contribution with 42% of the total repair cost. Since a stronger average event is considered for the seismic hazard, compared to the previous case with events following the established probability models for $M$ and $r$, a significant increase is reported in the seismic risk (by factor of 4.6). The relative contribution of the partitions and for
repainting the walls increases since the level of interstory drifts in this case is such that creates consistently larger damages to them.

Figure 7.10 Distribution of mean repair (total) cost to assemblies and of total cost to floors

Figure 7.11 Distribution of cost per floor to assemblies
7.7 Identification of importance of risk factors

The sensitivity analysis results for six of the cases considered are reported in TABLE 7.3, TABLE 7.4, and TABLE 7.5.

The entropy is presented for the total cost as well as for three different sub-assemblies; the structural components, the drift sensitive nonstructural components and the acceleration sensitive nonstructural components.

Comparison between the differential entropy for the model parameters illustrates their relative importance. For GM1 and for the case with uncertain $M (M>5)$ and $r$ (TABLE 7.3, left columns) it is clearly evident that the moment magnitude has the highest importance in influencing seismic risk (highest value for the entropy), with the epicentral distance also having a significant, but smaller, impact. The uncertainty in the source spectrum frequency $f_b$, described by the auxiliary parameter $e_b$ is the only other risk factor that has a non-negligible importance. This is an important result, demonstrating that the uncertainty in the rest of the predictive relationships can be neglected with minor only impact on the calculated repair cost. The values for the relative entropy for $f_a, f_b, e$ and $T_w$ are also large but their sensitivity is influenced by the larger reported sensitivity for $M$ with which they are correlated, as pointed out earlier.
### TABLE 7.3

**RELATIVE ENTROPY $D(I|Y)p(Y)$ WITH RESPECT EITHER THE TOTAL REPAIR COST OR THE REPAIR COST FOR DIFFERENT ASSEMBLIES FOR GM1 FOR RETROFITTED AND NON-RETROFITTED STRUCTURE**

<table>
<thead>
<tr>
<th></th>
<th>Uncertain $M(\geq 5), r$</th>
<th>Uncertain $M(\geq 5), r$ retrofitted structure</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Total cost</td>
<td>Cost per assembly</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Struc. Comp.</td>
</tr>
<tr>
<td>$M$</td>
<td>1.182</td>
<td>2.391</td>
</tr>
<tr>
<td>$r$</td>
<td>0.227</td>
<td>0.311</td>
</tr>
<tr>
<td>$f_a$</td>
<td>1.012</td>
<td>2.103</td>
</tr>
<tr>
<td>$f_b$</td>
<td>0.862</td>
<td>1.869</td>
</tr>
<tr>
<td>$e$</td>
<td>0.763</td>
<td>1.651</td>
</tr>
<tr>
<td>$k_s$</td>
<td>0.003</td>
<td>0.003</td>
</tr>
<tr>
<td>$f_{max}$</td>
<td>0.008</td>
<td>0.005</td>
</tr>
<tr>
<td>$\lambda_a$</td>
<td>0.006</td>
<td>0.003</td>
</tr>
<tr>
<td>$\eta_1$</td>
<td>0.007</td>
<td>0.006</td>
</tr>
<tr>
<td>$T_w$</td>
<td>0.569</td>
<td>1.333</td>
</tr>
<tr>
<td>$e_a$</td>
<td>0.030</td>
<td>0.064</td>
</tr>
<tr>
<td>$e_b$</td>
<td>0.124</td>
<td>0.232</td>
</tr>
<tr>
<td>$e_e$</td>
<td>0.052</td>
<td>0.106</td>
</tr>
<tr>
<td>$e_i$</td>
<td>0.015</td>
<td>0.021</td>
</tr>
<tr>
<td>$M\cdot r$</td>
<td>1.436</td>
<td>2.723</td>
</tr>
<tr>
<td>$f_a\cdot e_b$</td>
<td>1.078</td>
<td>2.529</td>
</tr>
<tr>
<td>$e_a\cdot e_b$</td>
<td>0.152</td>
<td>0.304</td>
</tr>
<tr>
<td>$f_{a\cdot f_b\cdot e}$</td>
<td>1.129</td>
<td>2.829</td>
</tr>
<tr>
<td>$e_{a\cdot e_b\cdot e_e}$</td>
<td>0.209</td>
<td>0.401</td>
</tr>
<tr>
<td>$\lambda_a\cdot \eta_1\cdot T_w$</td>
<td>0.017</td>
<td>0.009</td>
</tr>
<tr>
<td>$\lambda_a\cdot \eta_1\cdot T_w$</td>
<td>0.452</td>
<td>1.065</td>
</tr>
<tr>
<td>$k_s\cdot f_{max}$</td>
<td>0.044</td>
<td>0.026</td>
</tr>
<tr>
<td>$k_s\cdot f_{max}$</td>
<td>1.237</td>
<td>2.986</td>
</tr>
<tr>
<td>$e_a\cdot e_b\cdot e_e$</td>
<td>0.174</td>
<td>0.353</td>
</tr>
<tr>
<td>$M\cdot f_a$</td>
<td>1.165</td>
<td>2.803</td>
</tr>
<tr>
<td>$M\cdot f_b$</td>
<td>1.087</td>
<td>2.687</td>
</tr>
<tr>
<td>$M\cdot f_{a\cdot f_b}$</td>
<td>1.129</td>
<td>3.181</td>
</tr>
<tr>
<td>$M\cdot T_w$</td>
<td>0.852</td>
<td>1.764</td>
</tr>
<tr>
<td>$M\cdot e_a$</td>
<td>1.163</td>
<td>2.323</td>
</tr>
<tr>
<td>$M\cdot e_b$</td>
<td>1.281</td>
<td>2.564</td>
</tr>
<tr>
<td>$M\cdot e_a\cdot e_b$</td>
<td>1.253</td>
<td>2.491</td>
</tr>
<tr>
<td>$M\cdot e_i$</td>
<td>1.162</td>
<td>2.327</td>
</tr>
</tbody>
</table>

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### TABLE 7.4

Relative Entropy $D(I(Y)|P(Y))$ with respect either the total repair cost or the repair cost for different assemblies for the structure without dampers for GM1 with uncertain $M$, $R$ ($M \geq 6.5$) or specific $M$, $R$

<table>
<thead>
<tr>
<th></th>
<th>Uncertain $M(\geq 6.5)$, $r$</th>
<th>Specific $M(=6.5)$, $r(=20)$</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Total cost</td>
<td>Total cost</td>
</tr>
<tr>
<td></td>
<td>Cost per assembly</td>
<td>Cost per assembly</td>
</tr>
<tr>
<td></td>
<td>Drift-sensitive</td>
<td>Drift-sensitive</td>
</tr>
<tr>
<td></td>
<td>Non-structural components</td>
<td>Non-structural components</td>
</tr>
<tr>
<td></td>
<td>Accel. sensitive</td>
<td>Accel. sensitive</td>
</tr>
<tr>
<td>$M$</td>
<td>0.093</td>
<td>NA</td>
</tr>
<tr>
<td>$r$</td>
<td>0.141</td>
<td>NA</td>
</tr>
<tr>
<td>$f_a$</td>
<td>0.039</td>
<td>0.104</td>
</tr>
<tr>
<td>$f_b$</td>
<td>0.014</td>
<td>0.022</td>
</tr>
<tr>
<td>$e$</td>
<td>0.023</td>
<td>0.077</td>
</tr>
<tr>
<td>$k_o$</td>
<td>0.004</td>
<td>0.088</td>
</tr>
<tr>
<td>$f_{max}$</td>
<td>0.010</td>
<td>0.020</td>
</tr>
<tr>
<td>$\lambda_a$</td>
<td>0.000</td>
<td>0.002</td>
</tr>
<tr>
<td>$\eta_t$</td>
<td>0.003</td>
<td>0.004</td>
</tr>
<tr>
<td>$T_w$</td>
<td>0.003</td>
<td>0.014</td>
</tr>
<tr>
<td>$e_a$</td>
<td>0.037</td>
<td>0.054</td>
</tr>
<tr>
<td>$e_b$</td>
<td>0.112</td>
<td>0.105</td>
</tr>
<tr>
<td>$\lambda_e$</td>
<td>0.036</td>
<td>0.154</td>
</tr>
<tr>
<td>$e_t$</td>
<td>0.016</td>
<td>0.012</td>
</tr>
<tr>
<td>$M-r$</td>
<td>0.227</td>
<td>NA</td>
</tr>
<tr>
<td>$f_a-f_b$</td>
<td>0.041</td>
<td>NA</td>
</tr>
<tr>
<td>$e_a-e_b$</td>
<td>0.163</td>
<td>NA</td>
</tr>
<tr>
<td>$f_{max}-f_a$</td>
<td>0.043</td>
<td>NA</td>
</tr>
<tr>
<td>$e_{max}-e_a$</td>
<td>0.207</td>
<td>NA</td>
</tr>
<tr>
<td>$\lambda_e-\eta_r$</td>
<td>0.013</td>
<td>NA</td>
</tr>
<tr>
<td>$\lambda_e-T_w$</td>
<td>0.092</td>
<td>NA</td>
</tr>
<tr>
<td>$M-e_a$</td>
<td>0.027</td>
<td>NA</td>
</tr>
<tr>
<td>$M-e_b$</td>
<td>0.054</td>
<td>NA</td>
</tr>
<tr>
<td>$M-e_{max}$</td>
<td>0.015</td>
<td>NA</td>
</tr>
<tr>
<td>$M-e_a-e_b$</td>
<td>0.088</td>
<td>NA</td>
</tr>
<tr>
<td>$M-T_w$</td>
<td>0.036</td>
<td>NA</td>
</tr>
<tr>
<td>$M-e_a$</td>
<td>0.069</td>
<td>NA</td>
</tr>
<tr>
<td>$M-e_b$</td>
<td>0.027</td>
<td>NA</td>
</tr>
<tr>
<td>$M-e_{max}$</td>
<td>0.011</td>
<td>NA</td>
</tr>
<tr>
<td>$M-e_a-e_b$</td>
<td>0.099</td>
<td>NA</td>
</tr>
</tbody>
</table>

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### Table 7.5

**Relative Entropy** \( D(\Pi(Y) \| P(Y)) \) with respect either the total repair cost or the repair cost for different assemblies for the structure without dampers for GM2 with uncertain \( M, R \) \((M \geq 6.5)\) or specific \( M, R \)

<table>
<thead>
<tr>
<th></th>
<th>Uncertain ( M(\geq 6.5), r )</th>
<th>GM2, ( M(=6.5), r(=20) )</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Total cost</td>
<td>Cost per assembly</td>
</tr>
<tr>
<td></td>
<td>Struct. Comp.</td>
<td>Non-structural components</td>
</tr>
<tr>
<td></td>
<td>structure components</td>
<td></td>
</tr>
<tr>
<td>( M )</td>
<td>0.016</td>
<td>0.014</td>
</tr>
<tr>
<td>( r )</td>
<td>0.221</td>
<td>0.273</td>
</tr>
<tr>
<td>( \alpha )</td>
<td>0.640</td>
<td>0.806</td>
</tr>
<tr>
<td>( D_{5.95} )</td>
<td>0.016</td>
<td>0.014</td>
</tr>
<tr>
<td>( t_{\text{mid}} )</td>
<td>0.068</td>
<td>0.044</td>
</tr>
<tr>
<td>( \omega_{\mid \text{mid}} )</td>
<td>0.067</td>
<td>0.107</td>
</tr>
<tr>
<td>( \omega )</td>
<td>0.021</td>
<td>0.040</td>
</tr>
<tr>
<td>( \zeta_f )</td>
<td>0.050</td>
<td>0.079</td>
</tr>
<tr>
<td>( \alpha_1 )</td>
<td>1.422</td>
<td>1.342</td>
</tr>
<tr>
<td>( \alpha_2 )</td>
<td>0.628</td>
<td>0.606</td>
</tr>
<tr>
<td>( \alpha_3 )</td>
<td>0.723</td>
<td>0.769</td>
</tr>
<tr>
<td>( M \cdot r )</td>
<td>0.248</td>
<td>0.289</td>
</tr>
<tr>
<td>( M - \bar{T}_a )</td>
<td>0.582</td>
<td>0.688</td>
</tr>
<tr>
<td>( D_{5.95} - t_{\text{mid}} )</td>
<td>0.108</td>
<td>0.075</td>
</tr>
<tr>
<td>( \omega_{\mid \text{mid}} \cdot \omega )</td>
<td>0.089</td>
<td>0.143</td>
</tr>
<tr>
<td>( \omega_{\mid \text{mid}} \cdot \omega - \zeta_f )</td>
<td>0.171</td>
<td>0.265</td>
</tr>
<tr>
<td>( \bar{T}<em>a \cdot D</em>{5.95} - t_{\text{mid}} )</td>
<td>0.618</td>
<td>0.717</td>
</tr>
<tr>
<td>( \alpha_1 - \alpha_2 - \alpha_3 )</td>
<td>1.296</td>
<td>1.150</td>
</tr>
<tr>
<td>( M - r \cdot \bar{T}_a )</td>
<td>0.618</td>
<td>0.755</td>
</tr>
<tr>
<td>( M - \omega_{\mid \text{mid}} )</td>
<td>0.089</td>
<td>0.119</td>
</tr>
<tr>
<td>( M - \omega )</td>
<td>0.018</td>
<td>0.042</td>
</tr>
<tr>
<td>( M - \omega_{\mid \text{mid}} \cdot \omega )</td>
<td>0.091</td>
<td>0.155</td>
</tr>
<tr>
<td>( r \cdot \bar{T}_a )</td>
<td>0.688</td>
<td>0.848</td>
</tr>
</tbody>
</table>
For the retrofitted structure (TABLE 7.3, right columns) similar trends hold in general, i.e. $M$ and $r$ have the highest importance, but there is an increase in the relative entropy for all the parameters. This is anticipated since introduction of the dampers leads to decrease in the vibration response and thus to reduction of seismic risk, and ultimately to an increase of the sensitivity with respect to all risk factors contributing to this risk. The epicentral distance for acceleration sensitive non-structural components is the only parameter with a decreasing importance. For the important parameters stated above, the moment magnitude for non-structural drift sensitive components and the epicentral distance for structural components have an increase of 46\% and 41\% respectively. The increase for $e_b$ is even higher; since the damping of the structure increased by the introduction of the dampers, the importance of the high-frequency content of the excitation (influenced by $e_b$) increases.

Investigating the potential correlations between the various groups of model parameters examined does not demonstrate any significant correlation. Comparison, now, between the different damageable assemblies (columns of TABLE 7.3) shows a significant dependence of the sensitivity results to the specific repair cost aspects. For the structural components significantly larger sensitivities are reported with respect to the moment magnitude. This should be attributed to the fact that based on the fragility characteristics adopted in this study damages in the structural components occur for larger response thresholds, leading to larger contribution to the overall cost from larger magnitude events. Also for the acceleration sensitive components, the importance of $e_b$ increases. This is also anticipated since $e_b$ impacts the high-frequency content of the excitation, which influences the acceleration response. For the same reasons higher
importance of $\kappa_o$ (impacting high-frequency diminution) exists. An interesting pattern in this case is that additionally greater importance is reported in this case for the uncertainty in the duration of the excitation (expressed through $e_a$).

Moving to the case with $M \geq 6.5$ (TABLE 7.4, left column), $M$, $r$ and $e_b$ still have the highest impact but an overall decrease of the sensitivity is reported; since the seismic hazard considered in this case is higher, the sensitivity to the risk factors decreases. This is especially true for the moment magnitude which is the parameter whose probability model directly changed for the hazard description. Based on the results of TABLE 7.4, the epicentral distance is the most influential risk factor in this case.

For the case with specific $M$ and $r$ (TABLE 7.4, right column) the same trends hold. In this case the results with respect to the $[e_a, e_b, e_e]$ or $[f_a, f_b, e]$ should be the same since there is no uncertainty in $M$. Only small differences are reported in TABLE 7.4, which should be attributed to approximation errors due to the KDE in the different spaces (Gaussian for $[e_a, e_b, e_e]$ and log-normal for $[f_a, f_b, e_T, e_w]$). This further testifies to the robustness of the proposed KDE and sampling-based methodology for efficient estimation of the relative entropy.

For GM2 (TABLE 7.5) the most important risk factors are the characteristics of the temporal envelope function $\alpha_1, \alpha_2, \alpha_3$, with $\alpha_1$ having the biggest importance.

Limiting the focus on the physical parameters, it is evident that the Arias intensity $\bar{T}_a$ is the dominant risk-factor with the epicentral distance also having a significant importance.

The Arias intensity directly affects the strength of the ground motion, thus it was
expected to have a big contribution to the seismic risk. Its strong dominance indicates that based on the probability models proposed in Rezaeian and Der Kiureghian (2010) it has ultimately a very big impact on the seismic risk. Note that GM1 model does not include a similar model parameter impacting directly the strength of the ground motion (apart from the dependence on $M$). This is ultimately where the difference of the two models stems from, and the fact that when GM2 is used to describe the seismic hazard seismic risk is significantly higher. Comparing the sensitivity to the seismic hazard, characteristics, $M$ and $r$ between the two different models GM1 (TABLE 7.4) and GM2 (TABLE 7.5), it is evident that the importance of the moment magnitude $M$ decreases significantly whereas the importance of $r$ slightly increases. The former demonstrates also an important feature of GM2 that it leads to stronger responses for smaller magnitude earthquakes, which is what ultimately creates the smaller sensitivity.

This framework for the identification of the importance of the risk factors is finally used to identify the sensitivity with respect to specific values of these risk factors. As discussed earlier, this can be established by plotting samples of the model parameters. It is illustrated here for samples for pairs of important model parameters in Figure 7.12 for GM1 for the case with uncertain $M$ ($M>5$) and $r$. Samples from the initial distribution $\rho(\theta)$ as well as from $\pi(\theta)$ are illustrated. Comparison between these distributions qualitatively characterizes the sensitivity for each parameter. These plots do provide insight, though, about what specific model parameter values contribute more to the risk. Samples from $\pi(\theta)$ for $M$ and $r$ concentrate in regions with smaller epicentral distance and larger magnitude. These values for the model parameters correspond to excitations with stronger characteristics that have important bearing on the structural response, even
though such excitations are less likely to occur. It is interesting to note that earthquakes with magnitudes smaller than 5.2 have minor impact on the repair cost, but events with larger magnitudes do; this stresses the importance of a ground motion model that can adequately describe seismic events for smaller magnitude ranges. Seismic excitations close to magnitude 6.3-6.7 have in this case the biggest contribution, indicated by the higher density of samples from $\pi(\theta)$. This also verifies the efficiency of the proposed importance sampling densities used in the study for the moment magnitude.

In Figure 7.12 the histograms from $\pi(\cdot)$ for the moment magnitude are further presented for ground motions GM1 with magnitude range [5 8] and [6.5 8] as well as for GM2 with $M=[6.5 8]$. It is obvious that for GM1 and $M=[5 8]$ the most important earthquakes are those with moment magnitude values around $M=6.3$-$6.8$ which is in agreement with previous studies showing that these earthquakes are expected to have the biggest impact on the seismic risk. Comparing GM1 and GM2 for $M=[6.5 8]$, one can see GM2 events with moment magnitude close to 6.5 significantly dominate the seismic risk. This further validates our previous discussion. It is also interesting that comparing (a) for $M=[6.5 8]$ with (b) the distributions are almost identical, which was anticipated since
they correspond to samples from same probability distributions simple truncated in different intervals. Any differences occur due to the randomness of the sampling process.

(a) $\pi(M)$ for GM1 $M=5$–8

(b) $\pi(M)$ for GM1 $M=6.5$–8

(c) $\pi(M)$ for GM2 $M=6.5$–8

Figure 7.13 Moment magnitude histograms

7.8 Influence of Seismic Hazard Variability

For exploring the impact of the seismic hazard variability on the risk analysis and for illustrating the efficiency of the stochastic-simulation based approach for risk estimation, a final investigation is performed considering a range of values for the regional seismicity factor $b_M \in \log_{10}(10) \cdot [0.7, 1.3]$ and for the median epicentral distance $r_m \in [14, 30] \text{km}$. This ultimately corresponds to a parametric analysis with different
probability models for the seismic hazard description. This analysis is performed here computationally efficiently, through the scheme discussed at the end of Section 6.1. The analysis is restricted to the GM1 model for $M (M>5)$ and $r$ uncertain for the structure without the dampers.

Figure 7.14 presents the estimated total cost per earthquake as well as its decomposition to different components (the same as the ones considered in TABLE 7.3). As the regional seismicity decreases, i.e. as the epicentral distance or the seismicity factor $b_M$ increase, the total cost reduces significantly, with the epicentral distance having a stronger influence. The distribution of this cost to the different assemblies also changes. Acceleration sensitive non-structural components exhibit smaller sensitivity to changes in the moment magnitude, whereas structural components exhibit significantly higher sensitivity. This agrees with the patterns identified earlier in the context of the importance analysis (see discussion in previous section) and demonstrates the efficiency of the proposed importance analysis scheme; same patterns were identified as in the parametric analysis reported here.

Finally, Figure 7.15 presents the relative information entropy for some important model parameters. As the regional seismicity decreases, the sensitivity with respect primarily to $r$ and secondarily to $M$ increases. This is easily explained. For decreased seismicity, stronger earthquake events occur less frequently. But the repair cost is more sensitive to such events (since they are associated with significantly larger responses) which leads to an increased importance of these risk factors. The pattern is more evident for $r$ whereas it also holds for the parameters influencing the uncertainty in the source
spectrum \([e_a e_b e_c]\). Note that minor importance is always identified for the parameters of the temporal characteristics \([\lambda_t \eta_t e]\).

Figure 7.14 (a) Expected total cost per seismic event and (b) distribution of that cost to different components for different probability models for the seismic hazard.
Figure 7.15 Relative information entropy $D = D(\pi(y) \| p(y))$ with respect to the total cost for some interesting cases for different probability models for the seismic hazard
CHAPTER 8:
CONCLUDING REMARKS

8.1 Summary

This thesis investigated the application of stochastic ground motion models for characterization of seismic hazard within the context of life-cycle cost assessment for earthquake engineering applications. A versatile, simulation-based, framework was adopted for assessment of the life-cycle repair cost and for the identifications of the importance of the risk factors related to the seismic hazard description. Two different stochastic ground motion models were considered a source-based one [GM1] (Atkinson and Silva 2000) and a record-based one [GM2] (Rezaeian and Der Kiureghian 2010). These models are formulated by modulating a high-dimensional stochastic sequence through functions that address spectral and temporal characteristics of the excitation. The parameters of these models are connected to the regional seismicity characteristics through predictive relationships. Description of the uncertainty for these characteristics and for the predictive relationships, by appropriate probability models, leads then to a complete description of seismic hazard, expressed in terms of ground-motion time-history. An assembly-based vulnerability approach was adopted in this setting to quantify earthquake losses based on the nonlinear time-history structural response. Life-cycle repair cost was quantified by its expected value over the space of the uncertain parameters for (each) excitation model considered and estimation of this expected value
through stochastic simulation was adopted. An efficient probabilistic sensitivity analysis was also discussed, based on advanced stochastic sampling concepts. This analysis aims to identify the importance of the various uncertain parameters within the seismic hazard description (i.e., risk factors) in the overall performance of the structural system as well as potential correlations between them. This methodology is based on the definition of an auxiliary density function, proportional to the integrand of the expected cost integral, and on the comparison of this density to the initial probability models through their relative information entropy.

The framework was illustrated through application to a four-storey concrete building. Results were presented with respect to the total cost as well as with respect to the cost of different damageable assemblies. The influence of the installation of viscous dampers to the structure on the life-cycle repair cost was also considered. Important results stemming from the study are the following:

a) High-performance computing provides significant computational advantages within stochastic-simulation-based risk-assessment since Monte Carlo analysis can be seemingly performed in distributed mode; each simulation is run in a separate computational node. Setting up, though, OpenSees to run in the Perspephone cluster was not straightforward and it required more than couple of months of fine-tuning the problems encountered. This stresses the importance of Open Source software to become more user friendly in the context of high performance computing so that it is easier to fully take advantage the latest developments in computer science.

b) Use of stochastic ground motion models facilitates a powerful approach for detail characterization of seismic hazard in PBEE. This requires no ad-hoc selection and
scaling of recorded ground motions, approach for which there has been increasing concern, but merely adoption of appropriate regional ground motion model and description of the uncertainty in the seismicity characteristics and the predictive relationships within the model. This entails of course the ability to perform a large number of structural simulations to fully address the stochastic variability of the ground motions. But the computational expense for creating the required ground motions is very small; the difficulty ultimately stems from the computational expense for the structural simulation.

c) Simply by looking at the risk assessment results, i.e. the estimate for the life-cycle cost, did not provide direct insight into the origins of this risk and did not allow for a meaningful comparison between the two ground motion models considered in this study. The probabilistic sensitivity analysis, on the other hand, adopted here can provide such information by investigating the importance of the various risk factors as well as the correlation between them. The fact that this is established at a minimal computational cost over the risk assessment task further advocates for the importance of this new tool within natural hazard assessment.

d) The second ground motion model considered (GM2) was shown to overpredict structural response. This was proven to stem from the fact that the Arias intensity was included as a model parameter, and could be attributed to the fact that stronger ground motion models were primarily considered when calibrating this model. Though not reported here, preliminary investigations performed in the range [6 8] for the moment magnitude showed even larger discrepancies, with events with moment magnitude close to 6 significantly dominating the seismic risk (this actually contradicts all previous
studies in this field). This model is adequate for describing nonlinear structural behavior (which was the initial motivation for its development), but fails to adequately describe moderate structural response. Since that response does have ultimately significant contribution in the total life-cycle cost, stemming from damages in the partitions and for repainting walls, one needs to be careful when using it for life-cycle loss evaluation.

e) The main drawback for the first ground motion considered (GM1) is that the uncertainty in its predictive relationships was never properly investigated when the ground motion was developed (contrary to GM2). In this study that uncertainty was quantified through ad-hoc assumptions. A more thorough investigation is required for a more wide-spread acceptance in the probabilistic earthquake engineering community.

f) The main difference between GM1 and GM2 is the fact that the latter included an independent moment parameter, the Arias intensity, that directly affects the level of the seismic hazard.

g) Overall, it was shown in the case studies that repairing partitions and repainting damaged surfaces was shown to have the biggest contributions on the overall cost with repairs to structural systems also having a significant one. For GM1 the moment magnitude was shown to be the most influential parameter for the repair cost for ground motions with $M \geq 5$, especially for the structural components, with the epicentral distance also having a significant impact. The risk factors related to the predictive relationships of the ground motion model had negligible importance apart from the uncertainty in the higher frequency of the source spectrum. This is an important result, demonstrating that the uncertainty in the rest of the predictive relationships can be neglected with minor only impact on the calculated repair cost. For GM2 the parameter that represents the expected
Arias intensity of the acceleration process has the larger contribution to the repair life-cycle cost along with the epicentral distance.

h) The adopted simulation-based approach for seismic risk modeling and for its assessment allowed for a very detailed description for this risk. Though the proposed modeling approach is directly compatible with the state of the art in the field (PEER’s methodology), it is more general, since it stems from system-theoretic concepts and facilitates a simpler characterization of seismic risk. The use of stochastic simulation within this modeling approach provides a powerful and versatile framework for risk assessment and for simultaneous identification of the importance of the various risk factors. Furthermore, the investigation with respect to different performance quantifications or different probability models for the uncertain parameters is very straightforward in this setting. This was demonstrated in this thesis by providing the cost results with respect to different damageable assemblies and also by investigating the impact of the seismic hazard variability (probability models for moment magnitude and epicentral distance) on the entire analysis.

8.2 Future Directions

In this study a detailed fiber-element model was used to describe in detail nonlinear structural behavior. An interesting question is to what degree a simple parsimonious model for that behavior, like the model adopted in Taflanidis and Beck (2009c) representing each floor by a nonlinear spring with strength and stiffness deterioration characteristics, can ultimately provide an accurate description of the life-cycle cost within the proposed probabilistic setting. Such a parsimonious modeling approach can lead to significant computational savings in evaluating nonlinear dynamic
response and could potentially provide an overall adequate description of structural response even in the nonlinear regime, as long as structural collapse is avoided.

This study also proved the versatility of stochastic ground motion modeling for seismic hazard characterization. But for a more widespread adoption of such models, numerical codes need to become available so that users that are interested in implementing them can directly adopt them. This can be easily established by distribution of software accompanied by appropriate Graphical User Interfaces (GUIs); software that incorporates more than one such model can support a wider adoption since it will directly facilitate comparisons between them. Similarly, such GUIs can be developed for a better widespread evaluation of the simulation-based tools adopted here for risk assessment and sensitivity analysis. The basis of this GUI can be pre-computed structural responses, which will facilitate an efficient risk assessment based on the approach discussed at the end of Section 6.1.

Related to the general loss estimation field, one of the major problems encountered in this work was the nonexistence of commonly acceptable fragility functions and repair cost relationships. This is a important drawback, that will be hopefully addressed by the ATC-59 project (ATC-58 2009). Also extension of the loss estimation to downtime as well as to indirect losses from fatalities and injuries is crucial, since these components are generally expected to have a significant contribution towards the total cost. Further research is required in that direction to provide with efficient, general models for the associated loss estimation.


