Preliminary Extension of First Order Reliability Methods for Combined Seismic and Wind Hazard Loss Estimation for a Portfolio of Buildings

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ABSTRACT: In this paper, an initial analysis is performed to assess the potential loss to a building portfolio subjected to multiple, independent hazards. The procedure extends prior research that uses the First Order Reliability Method (FORM) to analyze the vulnerability of a portfolio of buildings to a seismic hazard. The paper includes discussion of issues to consider for community-wide damage measures and dependencies. The results are applied to Charleston, South Carolina, a community that has both seismic and hurricane hazards.

1. INTRODUCTION

It is important to be able to address the potential loss due to natural hazards for a community composed of a portfolio of buildings. Assessing potential losses for a portfolio of buildings is more complex than for a single site because of the correlations that exist between building performances (i.e., characterized by building damage or loss) due to shared building characteristics, common spatial properties, and collective hazard demands. Recent papers by the authors address these issues for community subject to a seismic hazard (e.g., Bonstrom and Corotis 2014; 2015). This paper extends the concept to a multi-hazard framework by considering both hurricane and seismic hazard.

This paper proposes the use of the First-Order Reliability Method (FORM) to quantify the loss to a portfolio of buildings from potential seismic and wind excitation. The basic theory behind FORM is to approximate the limit state failure surface around the design point (the point on the failure surface in resistance and demand space with the highest probability of occurring) by a linearized surface to compute the failure probability. Sensitivity measures are easily computed within the FORM evaluation, and are used in this study to prioritize the most cost-effective retrofit scheme with respect to reducing portfolio loss due to both earthquake and wind.

2. MULTI-HAZARD LOSS ASSESSMENT

Risk-assessment frameworks for structures subjected to different natural hazards share many similarities including the quantification of the hazard intensity and the associated probable loss and damage. This study desires to extend the FORM-based approach for seismic loss assessment to other types of hazards. Specifically, this extension focuses on estimating the probability distribution of loss for a portfolio under mutually exclusive multi-hazard conditions. Regions subjected to both earthquake and hurricane wind hazards are the primary emphasis in this study. Techniques applied in extending the proposed approach to multi-hazard conditions, however, are applicable to other types of hazards as well.

Many areas of the world are subjected to multiple hazards such as earthquakes, tsunamis, hurricanes, snow storms, etc. While a specific hazard may dominate the design of structures for a region, there are many regions where more than one hazard may pose a significant threat to buildings. In the United States, many coastal areas are exposed to both hurricane and earthquake hazards, such as Boston, MA and Charleston, SC. The nature of the hazards varies greatly in terms of frequency, return period in design, warning time, and mitigation strategies. The physical, economic and social impacts of these hazards may, however, be quite similar (Scawthorn et al. 2006).

For example, Charleston, South Carolina has experienced a large amount of losses from both earthquake and hurricane occurrences. The Charleston Earthquake of 1886 is considered the most damaging earthquake in the southeastern United States. The M7.3 earthquake damaged over 2,000 buildings, resulting in $6 million worth of damage (approximately 25% of the whole city worth at the time) and killing at least 60 people (USGS 2013). This level of devastation was reiterated in 1989 when Hurricane Hugo made landfall just north of Charleston resulting in over $7 billion in damage, 27 fatalities and leaving 100,000 homeless (National Research Council 2003). This demonstrates that despite the unique characteristics of earthquake and wind hazards, their impacts on society can be quite similar.

In such multi-hazard regions, the risk of exceeding a performance-based limit state may be larger than for those regions subjected to only one hazard. In fact, the level of risk that a structure is exposed to in a multi-hazard situation may be twice as high as anticipated for a single hazard (Crosti et al. 2011). In current practice, however, the final design of structures exposed to multiple hazards is governed by the more demanding of the existing hazard loading conditions. Structures are first analyzed as if they are subjected to one hazard, and then as if they are subjected to others. The controlling design corresponds to the highest demand for each member. Such an approach ignores the increased risk of exceeding a performance limit state for the additional less demanding hazard(s).

In order to account for the additional risk of the less dominant hazard(s) and achieve a desired building performance over time, design and construction practices should address the risk due to multiple hazards in an integrated manner (Crosti et al. 2011; Duthinh and Simiu 2010; Li and Ellingwood 2009; Li and van de Lindt 2012). Assuming negligible probability that two hazards will occur simultaneously, the probability of exceeding a performance limit state criterion for at least one can be expressed as

$$P(s_1 \cup s_2) = P(s_1) + P(s_2) \tag{1}$$

where $P(s_1)$ is the probability of exceeding a performance limit state criterion s_1 associated with one hazard event and $P(s_2)$ is the probability of exceeding a performance limit state criterion s_2 associated with a different hazard. $P(s_1 \cup s_2)$ is the probability of exceeding either s_1 or s_2. For example, $P(s_1 \cup s_2)$ may represent the probability of exceeding an economic loss threshold associated with earthquake and hurricane wind hazards over the lifetime of a structure. Equation (1) shows that $P(s_1 \cup s_2) > P(s_1)$ and and $P(s_1 \cup s_2) > P(s_2)$. Therefore, the risk associated with multiple hazards is greater than that associated with one dominant hazard. It is emphasized that while there is a small probability of s_1 and s_2 occurring simultaneously, this is considered negligible in this study. Each event, however, has a unique probability of occurring over a specified period of time.

Many researchers have examined the performance of individual structures under such an integrated multi-hazard approach. For example, Wen (2001) showed that the optimal design of structures subjected to more than one hazard is not governed exclusively by the dominant hazard but is also influenced by a less dominant hazard. Similarly, Li et al. (2012) introduced a conceptual performance-based design approach for optimal structural design and risk mitigation for buildings subjected to multiple hazards. The level of significance that an integrated multi-hazard approach holds for potential risk varies for different hazards and regions. The contribution of less dominant hazards to hazard-induced risk over time, however, is recognized.

A comparative assessment of the impact individual hazards have on a structural system also provides valuable information for public policy, insurance underwriting and disaster planning purposes (Li and van de Lindt 2012). Performance-based engineering requires structural performance objectives for various hazard levels. These are characterized by the return periods associated with design-level hurricanes and earthquakes, and on the level of disparity and impact resulting from each hazard. For example, lack of advanced warnings for earthquakes makes life safety more of a threat in seismic design, compared with advanced warning systems associated with hurricanes. While the different nature of hazards lends to a non-uniform assumed risk in the design for various hazards, competing hazards must be addressed consistently to achieve overall building performance goals (Li and van de Lindt 2012; Wen 2001).

This comparative assessment of hurricane and earthquake risks may also provide a tool for rank-ordering strategies for managing risks due to multiple hazards. Mitigating one risk may reduce building vulnerability for another, or in some cases, may increase potential risk. For instance, a lighter structure may reduce seismic forces, while simultaneously increasing the potential for wind damage. To address this tradeoff, Li and Ellingwood (2009) performed a comparative assessment of potential risk for wood-frame residential construction given earthquake and hurricane wind hazards. The effectiveness of multi-hazard mitigation strategies is evaluated through comparison of the reduction in risk for each competing hazard.

In this study, the proposed FORM method is used to perform an integrated and comparative risk assessment for earthquake and hurricane wind hazards. For each assessment, consequences are modeled as the probability of exceeding a specified level of monetary loss, expressed in terms of the building repair cost as a percentage of the portfolio of buildings value. Since the intensity of each is expressed in incompatible units (spectral acceleration and wind speed), the return period for each hazard is used as a common variable.

3. PORTFOLIO OF BUILDINGS AS A SYSTEM

3.1. Summation of Losses

Loss estimates are often characterized by two quantities: the expected value and the variance of losses. Many commercial loss assessment tools, such as HAZUS-MH, use the expected value of economic losses, casualties, etc. as the measure of risk (HAZUS 2009). Although in a risk neutral context, minimizing expected losses is consistent with maximizing utility for a region (von Neumann and Morgenstern 1944), the uncertainty around this loss is not quantified. According to Schubert and Faber (2012), decision makers often prefer decisions that yield a low probability of experiencing large losses. This is captured only by including the uncertainty in loss, and can be represented by a probabilistic distribution. This distribution, which is typically presented in the form of a loss exceedance curve, includes the effects of uncertainties as well as the correlations that exist between the components of a system.

Similarly, the performance of a building portfolio is determined by the performance of the individual buildings and the spatial correlations that exist between the building performances. These correlations, paired with uncertainties in the loss assessment process, characterize the variance in the collective loss probability distribution for a suite of buildings. Such correlations may be a result of effects from an earthquake or wind storm affecting more than one building in a portfolio simultaneously. This is a function of the spatial distribution of the group of buildings, where each building site may share common hazard sources or site effects.

The distribution of potential portfolio loss is based on the summation of losses for each building. In this case, the expected total loss $E(TL)$ is equal to the summation of expected losses at each building site, i. When the building losses at each site are not perfectly dependent, some buildings will experience higher losses in a given event, while others will experience lower. The expected total loss is the summation of losses at each site (l_i) for a given event:

$$E(TL) = \sum_i E(l_i) \approx \sum_i l_i \tag{2}$$

If the performances of individual buildings are strongly positively correlated, the portfolio may experience losses that are skewed primarily either higher or lower than average for a given event. Therefore, the variance of the predicted losses is much greater than if there was no correlation considered between buildings. The variance of the total loss can be expressed as:

$$V(TL) = \sum_i V(l_i) + 2\sum_{i<j}\sum_j COV(l_i, l_j) \tag{3}$$

where $COV(l_i, l_j)$ is the covariance matrix, and is a function of the correlation between sites i and j.

3.2. Community-Related Dependencies

In addition to immediate portfolio losses, there are secondary impacts that greatly influence the total loss and resilience of a portfolio (Bonstrom and Corotis 2014a). These may be quantified as economic or social losses accrued over time based on the time period of building downtime and recovery. Such losses are influenced significantly by the interdependence between the physical, economic and social infrastructure units within a system.

The interdependence between infrastructure components is related to the reliance one infrastructure unit has on a service provided by another. Failure in a system can significantly affect the function of many other dependent systems. One of the most notable infrastructure interdependencies is prevalent in utility and transportation lifelines. In post-disaster situations, relief operations require well-functioning systems for transport, electricity, water supply, communications, etc. If any of these systems fails, the performance of other systems, as well as regional response and recovery actions, may be affected greatly.

Infrastructure interdependence plays a large role in the assessment of time dependent losses and resilience specific to a suite of buildings. Residents of a community depend on regional businesses based on employee pay, and the supply of goods and services. By comparison, businesses depend on residents based on their employment and demand for goods and services (Lindell and Prater 2003). If there is an excessive amount of loss to residential, commercial or industrial buildings within a portfolio, those dependent on the functioning of these buildings will also be affected. In addition to business-related losses, the loss of certain building types may also jeopardize dependent industries such as tourism, healthcare, education and recreation.

The level of interdependence between building assets is specific to the spatial, economic and social configurations of a region (Cimellaro et al. 2010; Rinaldi et al. 2001). For example, critical facilities (e.g., hospitals) located in different communities may have different interdependence relations, which influence the magnitude of post-disaster losses and recovery periods. A review of studies that examine these community-related dependencies and their influence on regional loss and resilience is provided in Oh et al. (2010).

4. FIRST-ORDER RELIABILITY METHOD

The First-Order Reliability Method (FORM) is one of many structural reliability methods used to probabilistically evaluate the performance of structures. Performance expectations are specified in the form of limit states. In basic structural design, performance criteria include structural safety and serviceability limit state requirements. FORM depends on the definition of the limit states in terms of the basic variables.

Defining $\underline{R}$ as the vector of resistance variables, and $\underline{S}$ as the vector of load effect variables, the probability of failure is given by the following integral,

$$P(F) = \int_D \int f_{RS}(r,s)\, dr\, ds \tag{4}$$

where D represents the failure domain, delineated by the limit state $G(\underline{R} - \underline{S}) = 0$, and the underscores for R and S have been omitted for simplicity. In FORM, the random variables are converted to standardized, normal forms, with an additional transformation to decouple any correlation (Rosenblatt 1952). The reliability index, β, represents the shortest distance from the origin in this transformed space to the limit state surface, $g(y) = 0$. This index can be computed by minimizing the following equation:

$$\beta = \min \sqrt{\sum_{i=1}^{n} y_i^2} \tag{5}$$

Where y_i represents the coordinates of any point on the limit state surface in n-dimensional
where y_i represents the coordinates of any point on the limit state surface in n-dimensional reliability space and n refers to the number of random variables in the reliability problem. The point on the limit state surface with the shortest distance to the origin is the 'design' or 'checking' point. The probability of failure is given by

$$P(\underline{F}) = \Phi(-\beta) \tag{6}$$

where Φ is the standard normal cumulative distribution function.

The random variables that represent both the excitations and the building responses have to be selected as the quantities characterizing building performance appropriate to the hazard.
Bonstrom and Corotis 2014; 2015) introduced two random variables used to compute the probability distribution of seismic induced loss for a portfolio of buildings. The same principles are extended in this study for wind hazards. In the prior studies for earthquakes, those variables were chosen as the natural logarithm of the spectral acceleration and the maximum interstory drift (Bonstrom 2013, Bonstrom and Corotis 2014). The approach for the wind hazard will be described in the next section.

4.1. Extension of Proposed FORM Method: Wind

A multivariate distribution for modeling spatially distributed hurricane winds is characterized similar to that used to model correlated seismic intensities. Structural response specific to wind-induced building damage is often modeled quite differently from the seismic building response. This is a result of the distinct failure mechanisms unique to wind loading, as opposed to a representative structural response parameter indicative of most structural damage. The following example uses several component-specific fragility models to assess probabilistic wind-related building damage levels. These damage probabilities are then used to compute structural and nonstructural losses.

4.1.1 Wind Intensity

In this study, the wind intensity at each site is characterized by the 3-s peak wind gust at 10m elevation. This intensity measuring is used in wind contour maps of ASCE Standard 7-10 (2010) for computing design loading conditions. Spatially distributed hurricane wind speeds are computed based on the following model proposed by Jayaram and Baker (2010):

$$\ln(V_i) = \ln(\bar{V}_i) + \varepsilon_i \tag{7}$$

where V_i is the peak wind speed at site i, $\bar{V}_i$ is the median peak wind speed at site i computed using wind field prediction models and ε_i denotes the residual or error term at site i. Significant correlation exists between the wind intensity at two closely spaced sites, due to similarities in the wind source, site effects and site location (Jayaram and Baker 2010; Legg et al. 2010; Pang et al. 2012). In general, this correlation is partially accounted for in the wind speed models used to predict median peak wind speeds. There is additional correlation, however, between residual terms used to model the uncertainty in wind speed at each site.

Proposed wind speed models such as Batts et al. (1980), Vickery et al. (2000) and Vickery et al. (2009) are used to predict wind speeds by propagating key parameters characterizing potential hurricane occurrences. These are a function of the expected value and uncertainties surrounding the central pressure, translational speed, radius to maximum winds, occurrence rates and wind speed decay. Residual terms are modeled by a multivariate distribution, characterized by the associated uncertainty at each site and by a correlation matrix computed based on empirical distributed wind field correlation models (Jayaram and Baker 2010; Legg et al. 2010; Pang et al. 2012).

When the predicted wind speed at each site is considered random, median wind speeds as well as spatially correlated residuals at each site are sampled randomly following a simulation approach. The predicted wind speeds and simulated residuals are then combined using Equation (7) to obtain realizations of the wind speeds at all sites of interest. A multivariate distribution is fit to the simulated wind speeds at each site and linear regression is used to compute the total spatial correlation in wind intensity between sites. If median wind speeds are considered deterministic (assuming an expected central pressure, translation speed, occurrence rate, etc.), the multivariate distribution can then be characterized directly from the predicted wind speeds, associated uncertainty, and computed correlation matrix, without using simulation.

This study assumes deterministic median wind speeds at each site, modified based on distance inland, as a representation of wind decay after landfall. Predicted wind speeds are taken from Li and Ellingwood (2009). The reduction in wind speed is computed based on wind field decay models proposed by Kaplan and DeMaria (1995) with translational hurricane speeds predicted based on historical hurricane occurrences (Purvis and McNab 1985).

The wind field distribution used in this example is considered to be Gaussian, based on findings in Jayaram and Baker (2010). Following an empirical study of wind fields from Hurricane Jeanne the residual terms in Equation (3) are assumed to follow a multivariate normal distribution with a mean of zero and standard deviation of 0.15. The residual distribution is characterized by a correlation matrix computed using the empirical model fit to Hurricane Jeanne wind field data (Jayaram and Baker 2010).

It is noted that many studies suggest that wind fields are best modeled by a Weibull distribution rather than a Gaussian distribution (Batts et al. 1980; Li and Ellingwood 2009). Additional information on the uncertainty and spatial correlation of distributed wind fields may be used to refine the wind field distribution used in this study for future applications.

4.1.2 Structural Response: Wind

Unlike seismic induced damage, which can be largely related to excessive lateral drift for most building systems, wind-related damage is characterized by a variety of building parameters. The most vulnerable part of a building to hurricane winds is its envelope (i.e., building enclosure). This can be breached as a result of roof-to-wall connection failure due to wind uplift, roof panel uplift, breakage of windows and doors due to excessive wind-induced pressure or projectile impact (Li and Ellingwood 2006). The engineering demand parameter used to model wind-related structural response is dependent on the building type and damage mode of interest (Petrini et al. 2009).

Many quantitative wind damage prediction models rely heavily on expert opinion and insurance claims as there is a lack of test data on building behavior in extreme wind loading. Extrapolating building wind vulnerability relationships on insurance losses, however, is still filled with uncertainty as there lacks an abundance of insurance losses to develop and calibrate the damage prediction models (Khanduri and Morrow 2003). When insurance losses are available, they are generally amassed over a suite of buildings, making it difficult to disaggregate damage data specific to building type classes.

In this study, wind-related damage is modeled based on damage bound probability density functions proposed in Unanwa et al. (2000). These are specific to representative building types and are primarily developed and calibrated based on expert opinion. The model considers each building type to consist of the following components: roof covering, roof structure, exterior doors and windows, exterior walls, interior (including contents), structural system and foundation. Upper and lower bound damage thresholds are determined with respect to each building component, and are associated with the highest and lowest probabilities of failure in a wind hazard.

Each building component may experience damage through direct wind impact or due to propagational effects resulting in damage to other components. For each building component i, the probability of full component failure resulting from direct wind impacts (P_{fi}^D) is computed based on probability density functions provided in Unanwa et al. (2000). Conditional probability data due to damage propagation (P_{fi}^P) are also provided. The final probability of failure for each component (P_{fi}) is computed as:

$$P_{fi} = P_{fi}^D + P_{fi}^P - P_{fi}^D P_{fi}^P \qquad (8)$$

where $P_{fi}^D P_{fi}^P$ is the joint probability of damage due to both direct and propagational damage. The total degree of damage (DD) for building and occupancy category j at wind hazard level *l* is then computed as:

$$DD(l)_j = \sum_{i=1}^{n} P_{fi} * CCF_{ij} * \alpha_i \qquad (9)$$

where CCF_{ij} is the component cost factor for component i and building and occupancy category j relative to the total building cost, and α_i is a component location factor.

For total portfolio loss (*TL*) Unanwa (2000) replaces individual building summation (see Eqs. (2) and (3)) with the following algorithm as a function of upper and lower damage bands:

$$TL(l) = \sum_{j=1}^{4} RRI_j^{av} * 1/2\left(DD(l)_j^U + DD(l)_j^L\right) * BRCj \qquad (10)$$

where RRI_j^{av} is the average relative resistivity index for building/occupancy category j, $DD(l)_j^U$ and $DD(l)_j^L$ are upper and lower bound damage degrees in Eq. (9) given hazard level *l*, and BRC_j is the total building replacement cost for building/occupancy category *j*. This method assumes building/occupancy types can be classified into four primary categories: 1-3 story residential, 1-3 story commercial/industrial, 1-3 story government/institutional and 4-10 story buildings and further disaggregated based on occupancy for the Eq. (9) component cost factor.

Using the wind hazard model, FORM is used to evaluate the probability of exceeding various loss thresholds. For an integrated multi-hazard assessment, earthquake and hurricane wind losses are combined using Eq. (1). These are then used to compute the probability of exceeding a specified level of portfolio loss given either earthquake or hurricane wind hazards with a common return period.

4.2 Case Study: Multi-Hazard Loss Assessment

The building portfolio in Charleston County, South Carolina is chosen for this case study since the region is at risk to both earthquake and hurricane-wind hazards. For comparison purposes, a 500-year return period is used as the control variable to perform an integrated and comparative assessment of losses for each hazard.

Charleston County's building inventory is disaggregated into 78 census tracts with over 2,000 building combination types, yielding a reliability space of over 4,000 random variables.

Figure 1 shows the case study region relative to the Charleston seismic zone consisting of three fault segments: North Woodstock Fault, South Woodstock Fault and the Sawmill Branch Fault. Charleston is most strongly influenced by potential earthquakes within this fault zone (Student 1997). Therefore, it is assumed that the seismic activity from these faults best represent the potential earthquake hazard for this study. From paleoseismicity studies, a magnitude 7.0 earthquake is considered the characteristic magnitude with a 500-year recurrence interval from this zone (Talwani and Schaeffer 2001). According to Student (1997), it is assumed that there is equal probability of such a characteristic earthquake occurring at any point along the fault.

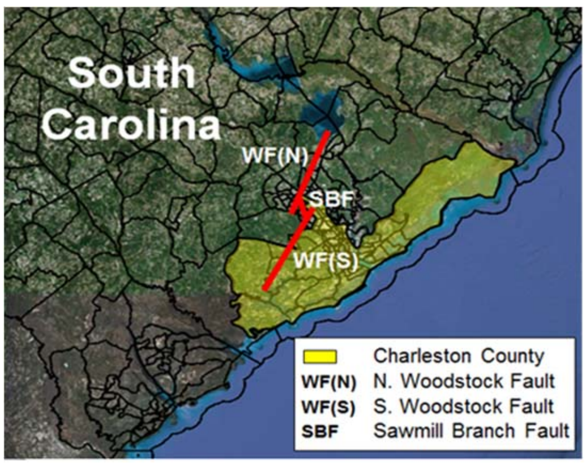

Figure 1: Charleston County case study portfolio region and potential earthquake fault zone.

Given these assumptions, seismic intensity is computed at the center of the 78 Charlestown County census tracts. The hurricane intensity distribution characterized by a 500-year return period is computed based on a median wind speed taken from Li and Ellingwood (2009), spatially correlated residuals computed from the method proposed in Jayaram and Baker (2010) and using the wind decay model by Kaplan and DeMaria (1995).

The exceedance probabilities computed for the portfolio using FORM and MCS are shown in Figure 2 for earthquake and hurricane wind hazards characterized by a 500-year return period. The exceedance probabilities obtained by ignoring the spatial correlation between the hazard intensity at each site are also shown.

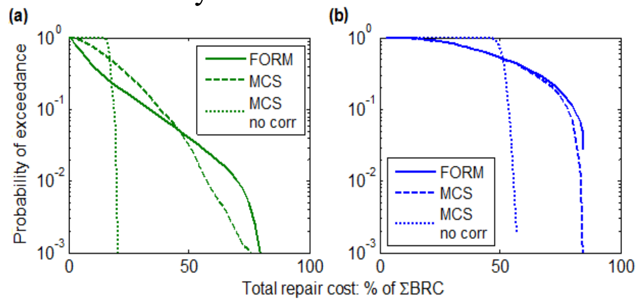

Figure 2: Loss exceedance curves using FORM and MCS for (a) earthquake and (b) hurricane wind hazards for 500-year return period.

Figure 2 shows that ignoring the spatial correlation between hazard intensities results in an overestimation of the probability of exceeding small losses and an underestimation of the probability of exceeding large, rare losses. It is also observed that FORM results follow closely with exceedance probabilities computed using MCS for hurricane wind hazards. There are, however, notable deviations in results for earthquake loss, as has been found in other case studies. The deviations in FORM results are a function of the dissimilarity between variables at each site. Since the seismic intensities at each site are less correlated than hurricane wind speeds, the errors are less for wind.

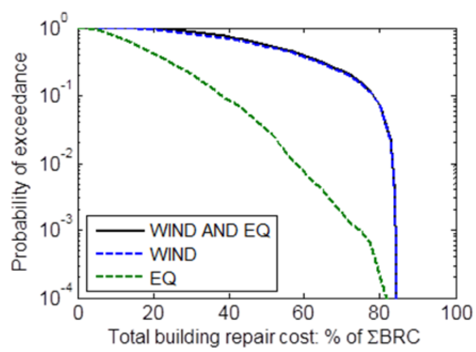

Figure 3: Loss exceedance curves using MCS for combined earthquake and hurricane wind hazards for a 500-year return period.

The exceedance probabilities for each hazard are combined using Equation (1) to compute the integrated multi-hazard exceedance curves shown in Figure 3 for MCS results. In this case study, the majority of regional loss is attributed to hurricane winds as opposed to earthquakes for most loss thresholds. For high loss thresholds associated with low probabilities, however, exceedance probabilities associated with earthquake losses become more comparable to wind loss exceedance. If the trend continues, earthquake loss exceedance probabilities would likely exceed those for wind losses. Generally speaking, the influence of each hazard on regional risk varies based on the region and hazard return period in question.

The results of each assessment, paired with the fundamental characteristics of each hazard and its effects on society, can be used for hazard management in regions exposed to multiple hazards. This may be particularly useful for decision makers in public policy, emergency response planning and insurance underwriting. The information can also be used to assess the effectiveness of hazard mitigation options in reducing regional risk. A sensitivity analysis can be used to prioritize retrofit options specific to either earthquake or wind hazards, or a combination of both, over time. While the less dominant hazard(s) may be less influential in terms of regional loss exceedance over time, retrofit options specific to such hazard type(s) may be cost-effective in reducing regional loss. Marginal retrofit costs would need to be assigned to changes in each structural response variable for each building retrofit scheme. Sensitivity measures would then be computed relative to changes in loss per each dollar of retrofit specific to each hazard of interest

5. CONCLUSION

The FORM approach developed previously for seismic hazards is used in a preliminary study to assess the potential risk for regions subjected to multiple, mutually exclusive hazards; specifically earthquake and hurricane wind. A multivariate random variable is used to model the spatially correlated wind intensity for a region and a set of probability density functions are used to model wind-related structural response for a suite of buildings. FORM is implemented to compute the distribution of loss specific to each hazard for the building portfolio Charleston County, South Carolina. It is also used to perform an integrated assessment for potential risk over time due to both hazards. This case study demonstrates that FORM provides an accurate method to consider losses due to multiple hazards. It is noted that the significance of evaluating multi-hazard risk as opposed to the risk related to a single dominant hazard is specific to the region and time period of interest.

6. ACKNOWLEDGMENTS

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