Chapter 3
Supporting Life Cycle Management of Bridges Through Multi-Hazard Reliability and Risk Assessment

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Abstract Bridge infrastructure is susceptible to damage from a large host of threats including natural hazards, aging and deterioration, and demands that increase with population growth and urbanization. Life cycle management of bridge infrastructure requires an understanding of the relative contribution of these threats to the risk of damage or impending consequences, such as life cycle costs. Traditionally, limited attention has been given to understanding the hazard risk profile to bridge infrastructure, defined as the relative risks posed by multiple hazards and the synergies or trade-offs in protecting for different hazards. Furthermore, effective strategies are needed to jointly consider cumulative damage (e.g., from aging) and punctuated damage (e.g., from natural hazards) when assessing the influence of design or upgrade decisions that may mitigate risks from multiple potentially competing hazards. This chapter utilizes metamodels as an efficient strategy for developing parameterized time-dependent bridge fragilities for multiple hazards, thereby facilitating multi-hazard risk assessment and life cycle management. Threats considered in the case studies include earthquakes, hurricanes, aging and deterioration, and live loads. The applications illustrate the relative contribution of earthquake and hurricane hazards to the risk of losses given variation in bridge parameters, the influence of considering aging when assessing the hazard risk profile, and the impact of concurrent threats (e.g., truck and earthquake) on the life cycle risk.

3.1 Introduction

Bridge infrastructure in the United States is susceptible to multiple hazards such as earthquakes, hurricanes, floods, and collisions. Even individual bridges within a regional portfolio of bridges may be subjected to multiple hazards during their

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life span. For example, bridges in Charleston, South Carolina may be susceptible to earthquakes and hurricanes; while bridges in the Houston, Texas ship channel region may be susceptible to hurricane surge and vessel collision. The issue of multiple hazards has been acknowledged by bridge design engineers in several states and they also consider multiple hazards in the design process (Lee et al. 2011). However, in order to optimally design bridges subjected to multiple hazards, the risk profile of hazards in consideration, i.e., trade-offs and synergies in risk, should be understood well. Several studies have comprehensively studied the risk to bridges due to individual hazards; for example, seismic reliability and risk has been extensively studied in the literature (Gardoni et al. 2002, 2003; Mackie et al. 2008; Nielson 2005; Ghosh and Padgett 2011). However, only recently studies have started focusing on multi-hazard risk assessment. In contrast, several studies exist on multi-hazard risk assessment for building structures. For example, risk assessment of residential wood buildings considering earthquake, hurricane wind, snow, and similar extreme loads has been the focus of many studies (Li and Ellingwood 2009; Ellingwood et al. 2004; Li and van de Lindt 2012; Yin and Li 2011). McCullough and Kareem (2011) have proposed a general performance-based design framework for designing coastal structures susceptible to multiple hazards. Even though these studies significantly improve the existing multi-hazard risk assessment procedures, they cannot be directly applied to bridges due the unique complexities of bridge behavior under hazard loading as well as the advances required to efficiently apply these concepts for comparative analysis across a range of design parameters. However, a few studies have recently focused on multi-hazard risk assessment of bridge structures. Decò and Frangopol (2011) assess risk due to several hazards including earthquakes, pier scour, and live loads. Effects of aging were also included in seismic and live load performance. In seismic performance assessment, fragility parameters were modified with time as per Ghosh and Padgett (2010), and for live load reliability, the load carrying capacity of girders was decreased with age. Kameshwar and Padgett (2014) have proposed a parameterized multi-hazard risk assessment framework for a portfolio of bridges and showed its application for earthquake and hurricane hazards. Liang and Lee (2013a, b) assess load effects and estimate bridge failure probabilities for concurrent occurrence of scour, earthquake, and truck collision. Wang et al. (2014) consider combined effects of scour and earthquake to evaluate load factors for concrete bridges. Furthermore, several studies have also studied the effect of aging on seismic performance of bridges (Choe et al. 2009; Ghosh and Padgett 2010).

Most of the abovementioned studies solely focus on risk assessment due to several nonconcurrent hazards or concurrent hazards. However, decision making under multiple hazards should acknowledge and consider the effect of multi-hazard combinations on the performance of bridges. For example, seismic risk may be exacerbated by the presence of additional loads due to a concurrent hazard, or two nonconcurrent hazards may have competing influence on selection of a specific design parameter. Moreover, joint consideration of hazards with aging of structures and its implications on the life cycle risks should also be considered.

Kameshwar and Padgett (2014) consider the effect of nonconcurrent hazards, earthquakes and hurricanes, on the selection of optimal column height. However, current literature lacks studies that explore and categorize different types of multi-hazard combinations and their effects on bridge reliability, risk, and design parameter selection while considering the effects of aging. Therefore, to address these gaps, this chapter will define categories of multi-hazard combinations based on occurrence, influence on fragility and risk, and influence on design parameter selection. Furthermore, several examples of multi-hazard combinations will be categorized into the abovementioned groups based on risk assessment of a case study bridge situated in Charleston, South Carolina. Since the bridge is located in coastal Charleston, the bridge is subjected to hurricane wave and surge loads in addition to earthquake and truck loads while considering the effects of aging.

The following section will define the categories of multi-hazard combinations described above. Section 3.3 will characterize the hazards considered in this study, i.e., the probabilities of hazard occurrence and load patterns for each hazard are established. In Sect. 3.4, the demands imposed by the hazards for different combinations of design parameters are evaluated using metamodels. The demands are used along with component capacities to evaluate bridge fragility in Sect. 3.5 which is further used to evaluate risk, quantified herein as the annual failure probability of the bridge. The results from the risk assessment procedure are discussed in Sect. 3.6 where the multi-hazard combinations are categories into different groups. Finally, the conclusions of this study are presented in Sect. 3.7.

3.2 Categorization of Multi-Hazard Combinations

Categorization of multi-hazard combinations based on criteria such as occurrence, effect on reliability, and bridge design is an important first step in understanding the effect of different hazards for multi-hazard decision making. Occurrence-based classification would help in determining the load combinations that the bridge would have to resist during extreme events. This classification of hazards based on occurrence is relatively straightforward and is discussed in the following subsection. Understanding of the demands imposed by multiple hazards and their subsequent classification is crucial for multi-hazard design and decision making, since in a multi-hazard scenario, a remedial action may be potentially detrimental to the performance of the bridge during another hazard. Even though classification of multiple hazards based on their effects on bridge reliability and design parameter selection is important for multi-hazard decision making, current literature lacks guidance or efficient methods to support classifying multiple hazards based on this criteria. Therefore, this study aims to classify the hazards based on occurrence, on effect on bridge reliability and risk, and on influence on design parameter selection, which are discussed in Sects. 3.2.1, 3.2.2, and 3.2.3, respectively.

3.2.1 Based on Hazard Occurrence

The first approach for classifying multi-hazard combinations requires assessment of the hazard occurrence potential. Based on occurrence of the hazard events, multiple hazards can be broadly classified in to the following categories:

3.2.1.1 Nonconcurrent Hazards

This category includes hazard combinations whose probability of occurring simultaneously is very low. For example, earthquakes and hurricanes have very low joint probability of occurrence. Similarly, hurricane loads and truck loads have low chance of simultaneous occurrence since people either evacuate before the hurricane or take shelter during a hurricane. Disjoint occurrence of hazards allows independent modeling of load effects on the bridge. However, independence of load effects does not necessarily imply uncorrelated influence on design parameter selection.

3.2.1.2 Concurrent Hazards

As the name suggests, this category of hazards includes combination of hazards which either always act simultaneously or have appreciable probability of joint occurrence. For such hazards, modeling of load effects must consider the joint load effects due to the multiple hazards. For example, during hurricanes coastal bridges may be subjected to combined wave and surge forces; similarly, earthquakes may happen while trucks are passing over the bridges, as observed in past events. Furthermore, the probability of joint occurrence of hazards must be obtained to evaluate risk.

3.2.1.3 Cascading Hazards

Occurrence of a hazard may trigger other hazards; for example, earthquakes or vessel collisions may cause fire. The main hazard and the subsequent hazards can be considered collectively as cascading hazards. Cascading hazards may also be considered as a special case of nonconcurrent hazards where the main hazard and the subsequent hazards occur within very short duration of time. This category of multiple hazards is one of the most challenging and least studied categories of multiple hazards. Evaluation of reliability and risk under such multiple hazards involves accumulation of damage due to the main extreme event and the following cascading events. To add to the complexity of the problem, probabilities of occurrence of the cascading events also have to be evaluated which may depend on the damage caused due to the main event. This study will focus on nonconcurrent and concurrent hazards for reliability and risk assessment; cascading hazards will be addressed in future research.

3.2.2 Based on Influence on Fragility and Risk

The second category for classifying combinations of hazards entails evaluating the fragility and risk to the structure under multi-hazard exposure. In multi-hazard design and decision-making situations, a better understanding of the risk portfolio of the bridge may help in choosing optimal retrofit options or design parameters. Categorization of hazard combinations based on their effect on reliability and risk can improve the understanding of the risk portfolio. Therefore, in this category, this chapter classifies hazard combinations as amplifying or diminishing.

3.2.2.1 Amplifying Hazards

Hazard combinations where the presence of one hazard increases the vulnerability (decreases the reliability) of the bridge during the occurrence of other hazards can be classified as amplifying hazards. For example, in some cases pier scour has been shown to be detrimental to seismic performance of bridges, so scour and earthquakes can be considered as amplifying hazards. Identification of amplifying hazards is important because the overall risk to the bridge increases due to such hazard combinations.

3.2.2.2 Diminishing Hazards

Bridge performance may improve during a hazard, i.e., increase in reliability may be observed, due to the presence of other hazards or additional loads due to other hazards. Such combinations of hazards can be included into the category of diminishing hazards. For example, in some cases the presence of trucks on the bridge deck may actually improve the seismic reliability of bridges, due to vehicle bridge interaction or in some cases due to a favorable shift in the natural period of the system.

3.2.3 Based on Influence on Design Parameter Selection

The final category for classifying hazard combinations includes exploration of the design parameter space and its influence on reliability and risk. Understanding this influence of design parameter variation is important in multi-hazard decision making since improving the performance of the bridge to one hazard may inadvertently worsen its performance during the other hazard. Further, identification of design parameters which can improve the bridge performance for several hazards or optimize the ultimate design parameter selection is also important for economical design. However, literature lacks classification of hazards into such categories that may shed light on practical design consideration. Therefore, this study will classify the combination of hazards into groups based on their influence on selection of design parameters as competing or complementary hazards.

3.2.3.1 Competing Hazards

Hazard combinations that have opposing or competing influence on bridge design parameter selection may be categorized as competing hazards. For example, earthquakes and hurricanes may have competing influence on column height selection. Increase in column height has been shown to improve the reliability of bridges subjected to wave and surge loads; however, increase in column height alone may increase the seismic risk (Kameshwar and Padgett 2014).

3.2.3.2 Complementary Hazards

The group of hazards where mitigation of one of the hazards serves as a remedial action for the bridge during other hazards, or a combination of hazards for which change in a design parameter improves the performance of the bridge for all the hazards in the combination, may be categorized as complementary hazards. For example, improving the ductility of bridge columns may improve bridge performance during seismic events and collision events involving trucks or vessels with bridge columns. Identification of this type of hazard combination is also important since cognizance of these hazards and their associated preferable design parameters may reduce the overall cost of reaching a target system reliability or risk level.

3.3 Characterization of Hazards

In order to accomplish the goals of this study, i.e., to classify the hazards into various categories, the risk must be evaluated for the case study bridge due to earthquakes, hurricane, and combined seismic and truck loads. The first step in the risk assessment is to categorize the multiple hazards based on occurrence and the second step involves estimating probabilities of occurrence and the related load effects. Among the hazards, earthquakes and hurricanes are treated as nonconcurrent hazards since the probability of their joint occurrence is extremely low. Therefore, their probabilities of occurrence and load effects can be evaluated independently. On the other hand, earthquake and truck loads are considered to be concurrent hazards. This implies that that their joint probability of occurrence and joint load effects must be determined. In addition to these hazards, threats due to deterioration of the case study bridge due to aging are also taken into consideration.

Table 3.1 Bridge parameter values

Variable	Range
Column height (H_c)	3.60–9.40 m
Column diameter (D_c)	0.76–1.52 m
Longitudinal reinforcement ratio (ρ_l)	0.02–0.04
Transverse reinforcement ratio (ρ_t)	5.00×10^{-3} –1.10×10^{-3}

The case study bridge, situated in coastal Charleston, South Carolina, is assumed to be a simply supported concrete girder bridge. The bridge has three 22.3 m-long equal spans, each 7.6 m wide, while other bridge parameters such as column height, diameter, and reinforcement ratios in transverse and longitudinal direction are varied; the range of the variables is shown in Table 3.1. The bridge is modeled in OpenSees (Mazzoni et al. 2006) following the general modeling recommendations outlined by Nielson (2005). For this case study bridge, the following section elaborates the procedure used to evaluate the probability of hazard occurrence at the bridge site and their load effects on the case study bridge.

3.3.1 *Earthquakes and Truck Loads*

Seismic response of the case study bridge is studied by simulating the response of the bridge for a suite of ground motions. Since recorded ground motions are not available for the Charleston region, suites of synthetic ground motions developed for the Central and Southeastern United States are used. The suite of ground motions developed by Fernandez and Rix (2008), consisting of 288 ground motions, is used along with a second suite consisting of 60 ground motions which was developed by Wen and Wu (2001). Next, seismic hazard occurrence data for the Charleston region is obtained from the US Geological Survey (USGS) (Petersen et al. 2008). The seismic hazard data is fit to a hyperbolic expression proposed by Bradley et al. (2007) to evaluate the risk in Sect. 3.5.

Joint occurrence of earthquakes and truck loads is modeled by placing a truck on the bridge and simultaneously exciting the bridge with ground motions. The truck loads are applied to the truck by placing a WB-20 truck at the centerline of the bridge at various locations along the length of the bridge. The truck weight is assumed to follow the bimodal distribution obtained by Ghosh et al. (2014). The probability of a truck being present on the bridge as per Ghosh et al. (2014) is

$$P\,(\text{one truck}) \approx (L-18)\,Q \times 10^{-5} \tag{3.1}$$

where Q is the flow rate in trucks per hour and L is the length of the bridge (66.9 m). The effect of joint occurrence of trucks and earthquakes on the risk estimates is discussed with the risk assessment procedure in Sect. 3.5.

3.3.2 Hurricanes

Maximum wave and surge load estimates on the bridge are obtained from the coastal guideline specification by the American Association of State Highway and Transportation Officials (AASHTO) (2008). The maximum forces obtained from the AASHTO guidelines are distributed in a phenomenological model of the wave load time series following Ataei et al. (2010). The maximum wave and surge forces are functions of hazard intensity parameters, wave height and surge height, and random variables such as wave period and wave length. In order to assess the risk to the bridge, the probability of occurrence of hurricane and the joint probability distribution of the hazard intensity parameters must be assessed. Hurricane occurrence in the Charleston region is assumed to follow a Poisson process with a mean annual rate of 0.23 (Scheffner and Carson 2001). The joint probability distribution of the hazard intensity parameters for an assumed water depth of 3.0 m and fetch length of 5.0 km is obtained using the procedure outlined in Kameshwar and Padgett (2014).

3.3.3 Aging

Deterioration due to aging may not be considered as a hazard; however, it poses significant threat to extreme event performance of bridges, such as seismic performance. Therefore, this study considers the effects of aging by modeling the reduction in the diameter of the steel reinforcement bars, which decreases the reinforcement ratio and confinement of core concrete, and oxidation of elastomeric bearing pads, which increases the stiffness of the elastomeric bearing pads. For tidal exposure conditions with 40 mm cover, rebar corrosion initiation time is modeled using DuraCrete (2000) and corrosion propagation follows the model proposed by Choe et al. (2008); while for modeling oxidation of the elastomeric bearing pads, formulation proposed by Itoh and Gu (2009) is used. The deck is assumed to be simply placed on the bearings over the substructure without any vertical connection such as dowels. Therefore, aging is assumed to have no effect on the hurricane response of the bridge.

3.4 Demand Assessment

Loads from the concurrent and nonconcurrent hazard combinations, described above, are applied to the case study bridge to estimate the demands on bridge components. However, several parameters of the bridge, listed in Table 3.1, are varied to study the effect of these parameters on bridge reliability and risk. Furthermore, parameters such as concrete strength, steel strength, friction coefficients at bearings, and gap between abutments and deck are considered to be random variables. Each combination of the parameters leads to a new bridge sample and a large number of such combinations may exist. However, simulating all the possible combinations is practically infeasible; therefore, metamodels are used in this study to estimate demands on the bridge with limited number of simulations. Metamodels are efficient mathematical tools which detect underlying relation between input parameters, i.e., hazards and bridge parameters in this study, and the output, i.e., component response. In order to model the component response, a set of design parameters, listed in Table 3.1, and random variables is generated that represents the entire space of variables. For this purpose, Latin hypercube sampling (LHS) (McKay et al. 1979) is used. For each hazard, the set of parameters generated by LHS is randomly paired intensity measures and an age value, where deterioration is considered. Therefore, age of the bridge also becomes a variable which is used to predict the response of the bridge. In case of earthquake and truck loads, the parameters are randomly paired with a ground motion and a truck weighing between 0.0 and 60.0 tons. While for hurricanes, the parameters are randomly paired with a set of wave height and surge height values, which are generated on an evenly spaced grid with surge height ranging between 0.0 and 6.0 m and wave height varying from 0.0 to 3.5 m.

Under seismic excitation and joint truck and seismic excitation, the response of bridge components such as columns, abutments, and bearings is modeled using different metamodels. In this study, the component responses are modeled using response surfaces with higher-order polynomials, Adaptive Basis Function Construction (ABFC) (Jekabsons 2010) which is also a polynomial-based metamodel, multivariate adaptive regression splines (MARS) (Friedman 1991), and radial basis functions (RBF) (Hardy 1971). Each of the aforementioned metamodels has certain advantages and disadvantages. Polynomial-based methods are transparent, but they are not suitable for extrapolation; MARS is a very quick method, but it may overfit the data; and RBF achieve very good accuracy, but the method requires scaling of the input data. Since the metamodels may have different performances in predicting the response of a component, performance measures are used to assess the fit of the selected metamodels. The performance of the metamodels was compared based on goodness of fit measures such as R^2 value, root mean square error (RMSE), and mean R^2 value in 5-fold cross validations. Based on these performance metrics, the fourth-order polynomial response surface generated using the sequential forward selection (SFS) method is found to perform best in predicting bearing deformation. While third-order polynomial, obtained using SFS, is observed to perform best in predicting column drift and abutment displacement. Using SFS for generating polynomial response surface ensures that only most significant polynomial terms are introduced in the polynomial equation. A normally distributed model error term with zero mean and standard deviation equal to the RMSE of the model is also added to each of the metamodels. For brevity, the response surface models are not included herein.

In this study, the bridge is assumed to be safe after the hurricane if the bridge deck is not displaced; however, failure is assumed if the deck is displaced due to the hurricane wave and surge forces. Categorization of the response of the bridge into the two categories leads to a classification problem. Therefore, response prediction of bridges subjected to hurricanes is performed using a different type of metamodels called binary classifiers. This category of metamodels can easily predict failure or survival of the bridge as a binary variable. Random forest (Pavlov 2000) and Support Vector Machines (SVM) (Cristianini and Shawe-Taylor 2000) are used for hurricane response prediction of bridges. Since the response of the classifiers is a binary variable, the performance metrics used for component response prediction under seismic and truck loads cannot be used for these metamodels. So, the performance of these metamodels is assessed using a confusion matrix (Kohavi and Provost 1998) which counts the number of true positives, true negatives, false positives, and false negatives, which can be further used to measure the accuracy of prediction. Among random forest and SVM, random forest was observed to perform better, and therefore random forest is selected for hurricane response prediction in this study.

3.5 Reliability and Risk Assessment

The demands imposed by the hazards on the bridge components are compared with their capacities to assess component reliability. For seismic response such as column drifts, bearing deformation, and abutment displacements, Table 3.2 shows the component capacities for the complete damage limit state and their corresponding distribution. In the expression for mean drift capacity of columns in Table 3.2, ALR is the axial load ratio, L is half the column height, and $\alpha = (1 - s/d)^2$, where s is the spacing between transverse reinforcement and d is the effective depth of the column cross section. As seen from Table 3.2, the limit states for bearings and abutments are invariant to the presence of trucks. However, the presence of trucks is indirectly accounted for in the column drift capacity limit states by including the axial load ratio in the capacity limit state. Moreover, the effect of aging on the capacity of the columns is also included by reducing the reinforcement ratio corresponding to decrease in rebar diameter. Using these demand and capacity estimates, the reliability of the bridge components can be estimated when subjected to seismic loads or to joint seismic and truck loads. In order to assess the reliability, first, a

Table 3.2 Component capacity for complete damage limit state

Component	Median/mean	Coefficient of variation (%)	Distribution
Bearing (Ramanathan et al. 2012)	255.0 mm (median)	47.0	Lognormal
Abutment (Ramanathan et al. 2012)	55.0 mm (median)	47.0	Lognormal
Column (Panagiotakos and Fardis 2001)	$0.9\left(0.2^{\mathrm{ALR}}\right)(6.89f_c)^{0.275}\left(\frac{L}{D}\right)^{0.45}\left(1.1\frac{100\alpha\rho_t f_y}{f_c}\right)$ (mean)	47.0	Lognormal

set of 30×10^{-3} design parameters, described in Table 3.1, and random variables such as concrete and steel strength is generated using LHS. Next, the demands on the bridge components are assessed using the metamodels, described above, and the capacities of the components are obtained from Table 3.2. Demands and capacities are compared with each other, and the outcome is represented by a binary variable; 1 represents failure and 0 represents a survival. For the complete damage limit state considered in this study, the bridge is considered to be a series system where failure of a component leads to system failure. The component binary output is used to evaluate the binary system output which is further used in logistic regression to evaluate fragility of the system. In case of hurricanes, the response from the classifiers is already in binary form; therefore, it is directly used in logistic regression. Failure probability is obtained using logistic regression as

$$P\left(\text{Fail}\,|X,\text{IM},t\right)=\frac{e^{g(X,\text{IM},t)}}{1+e^{g(X,\text{IM},t)}} \tag{3.2}$$

In the above equation, $P(\text{Fail} \mid X, \text{IM}, t)$ is the failure probability conditioned on parameters X, described in Table 3.1, intensity measures IM, and age t. The function $g(X)$ is the logit function which predicts the logarithm of odds in favor of failure. In this study, the logit function is a polynomial in X, IM, and t.

Risk, i.e., the annual failure probability, is assessed for each of the multi-hazard combinations by convolving the corresponding fragility with hazard occurrence. Since the annual failure probabilities (p_f) are small, seismic risk to the bridge can be written as (Der Kiureghian 2005)

$$p_f=\int\limits_{\text{pga}}P\left[\text{Fail}\,|X,\text{pga},t\right]\left|\frac{\mathrm{d}\widehat{\nu}}{\mathrm{d}\left(\text{pga}\right)}\right|\mathrm{d}\left(\text{pga}\right) \tag{3.3}$$

In the above equation, $P[\text{Fail}\,|X,\text{pga},t]$ is the seismic fragility where X represents bridge parameters; pga refers to peak ground acceleration, the intensity measure; t is age of the bridge; and $\widehat{\nu}$ is the seismic hazard curve obtained from the USGS. Similar to Eq. (3.3), in the case of joint earthquake and truck presence, the annual probability of failure can be estimated as

$$p_f=\int\limits_{\text{pga}}P_{LL+EQ}\left[\text{Fail}\,|X,\text{pga},t\right]\left|\frac{\mathrm{d}\widehat{\nu}}{\mathrm{d}\left(\text{pga}\right)}\right|\mathrm{d}\left(\text{pga}\right) \tag{3.4}$$

The term $P_{LL+EQ}\left[\text{Fail}\,|X,\text{pga},t\right]$ is the joint seismic and truck load fragility which is estimated using the total probability theorem as

$$\begin{aligned}P_{LL+EQ}\left[\text{Fail}\,|X,\text{pga},t\right]&=\left[1-P\left(\text{truck}\right)\right]*P\left[\text{Fail}\,|X,\text{pga},t\right]\\&\quad+P\left(\text{truck}\right)*P\left[\text{Fail}\,|X,\text{pga},t,\text{truck}\right]\end{aligned} \tag{3.5}$$

where $P[\text{Fail}\,|X,\text{pga},t]$ is the seismic fragility without the effect of trucks, as in Eq. (3.3), $P(\text{truck})$ represents the probability of truck presence, and $P[\text{Fail}\,|X,\text{pga},t,\text{truck}]$ is the bridge fragility function which is also conditional on truck presence and is given as

$$P\left[\text{Fail}\,|X,\text{pga},t,\text{truck}\right]=\int\limits_{W}P\left[\text{Fail}\,|X,\text{pga},t,\text{truck},w\right]f_W(w)\,\mathrm{d}\,w \tag{3.6}$$

In Eq. (3.6), w is the truck weight, $f_W(w)$ is the probability distribution of truck weights obtained from Ghosh et al. (2014), and $P[\text{Fail}\,|X,\text{pga},t,\text{truck},w]$ is the seismic fragility conditioned on the truck loads, in addition to other parameters. Different truck locations were also considered; however, the truck location was found to have insignificant effect on the response of bridge components. Therefore only truck weight is considered in the joint fragility function in Eq. (3.6). In the joint live load and seismic risk assessment, it is assumed that probability of multiple truck presence is negligible. So, probability of truck absence is calculated as the complement of presence of one truck. However, depending upon the route on which the bridge falls and size of the bridge, presence of multiple trucks may have significant probability and its influence on reliability and risk to the bridge may be studied in future work.

Hurricane risk is also evaluated using a procedure similar to the seismic risk assessment procedure described above. In case of hurricanes, the deck uplift fragility does not depend on age due to lack of any physical tie-down between the deck and the bent; therefore, the risk is independent of age. The annual probability of failure due to hurricanes can be obtained using

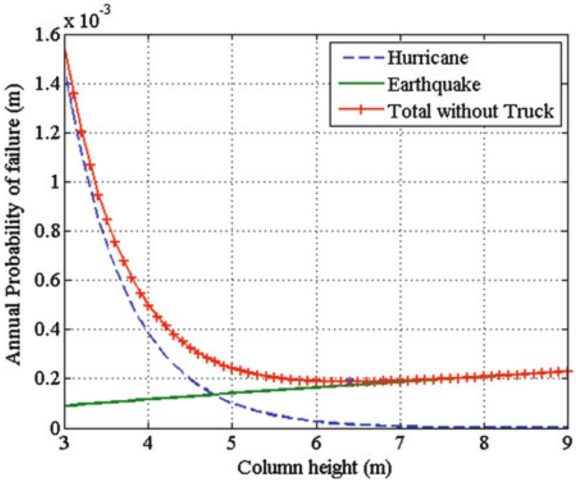
$$p_f=\lambda\int\limits_{S}\int\limits_{H}P\left[\text{Fail}\,|X,s,h\right]f_{s,h}\left(h,s\right)\mathrm{d}\,h\,\mathrm{d}\,s \tag{3.7}$$

$P[\text{Fail}\,|X,s,h]$ is the uplift fragility of bridge deck which is conditioned on the bridge parameters (X) and the intensity measures, wave height (H) and surge height (S), $f_{S,H}(h,s)$ is the joint probability distribution of wave height and surge height, and λ is the annual rate of hurricane occurrence. Using the above equations, risk to the bridge is evaluated as various bridge parameters are varied. The trends in risk for variation in parameters are discussed in the following section.

3.6 Results and Discussions

One of the primary aims of this study is to understand the nature of multiple hazard combinations and categorize them based on their effect on reliability and design parameter selection. First, the effect of two nonconcurrent hazards, i.e., earthquakes and hurricanes, is studied. Figure 3.1 shows the effect of varying column height

Fig. 3.1 Variation of hurricane, seismic, and total annual failure probability with column height



while keeping other parameters constant ($D = 1.0$ m, $\rho_l = 3.0\,\%$ and $\rho_t = 0.5\,\%$), on the hurricane risk and seismic risk, without aging or truck loads. It can be observed that as the column height increases, the hurricane risk decreases rapidly; however, increase in the column height also leads to a slow increase in earthquake risk. Since the two hazards are independent, the total risk shown as "Total without Truck" in Fig. 3.1 can be obtained as the sum of seismic and hurricane risk. With initial increase in column height, the total risk decreases sharply due to the rapid decrease in hurricane risk, which dominates at lower column heights. However, as the column height increases further, the total risk starts to increase since seismic risk dominates at larger column heights. These observations show that earthquakes and hurricanes have competing requirements for the column height. Therefore, these two hazards can be categorized as competing hazards with respect to their influence on column height.

Bridges are often exposed to harsh environments leading to deterioration due to aging, which significantly affects the risk over the lifetime of the bridge. In order to assess the effects of aging on the bridge during its life cycle, the bridge is assumed to be exposed to tidal exposure conditions. Figure 3.2 shows the total annual probability of failure along the life span of the bridge as the column height varies. The hurricane risk is assumed to remain constant along the life cycle of the bridge and variation in the total risk is due to seismic hazard only. Qualitatively, at each value of age, the variation in risk with changing column height is similar to that in Fig. 3.1. However, with increase in age, the hazard risk changes and increases up to 10 % in comparison to a pristine bridge. Thus, deterioration due to aging has an amplifying effect on the seismic risk. This result suggests although aging considerations are currently are not included in the modern design and retrofit codes, future research should support the development of design guidelines where time-evolving hazard risks, which may be significant as the bridge ages, are accounted for when designing for extreme events.

Fig. 3.2 Variation in total risk with age and change in column height

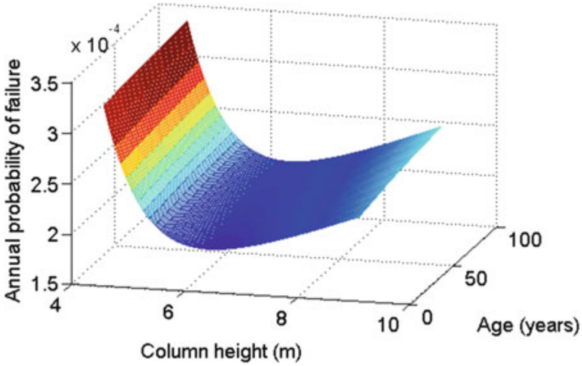
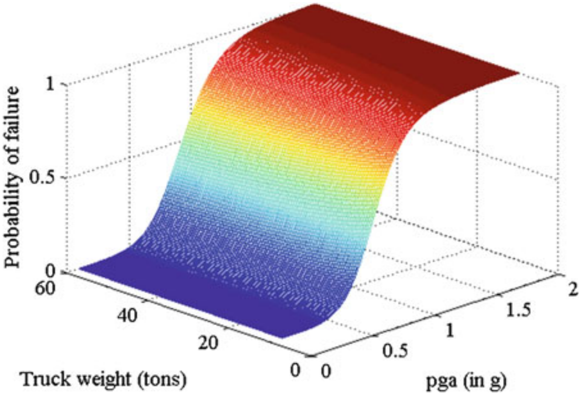


Fig. 3.3 Joint seismic and truck load fragility



Performance of the bridge ($H = 7.0$ m, $D = 1.0$ m, $\rho_l = 3.0\,\%$ and $\rho_t = 0.5\,\%$) under the two concurrent hazards, earthquakes and truck loads, is shown in Fig. 3.3, which shows the joint fragility of the bridge due to truck and seismic loads. From the figure, the effect of pga can be clearly seen on the failure probability. As expected, with increase in pga, the probability of failure increases. However, the effect of truck weight is not apparent from the figure. So, Fig. 3.4 shows the change in the median pga for failure as the truck weight increases. It can be seen that the median pga increases as the truck weight increases, implying that the fragility decreases due to the presence of the truck. The decrease in fragility can be attributed to two reasons: firstly, due to increase in the drift capacity of the column because of higher axial load ratio with increased truck loads and, secondly, due to the ground motions used in this study. The mean response spectra of all the ground motions used in this study show that the spectral acceleration decreases after natural period of 0.25 s, and all the bridges used in this study have periods larger than 0.25 s. Therefore presence of a truck, which increases the period of the bridge, decreases the spectral acceleration demand on the bridge. The effect of truck presence and age on the seismic risk is shown in Fig. 3.5. As the flow rate of trucks, Q, increases, the annual probability of

Fig. 3.4 Variation in median pga with truck weight

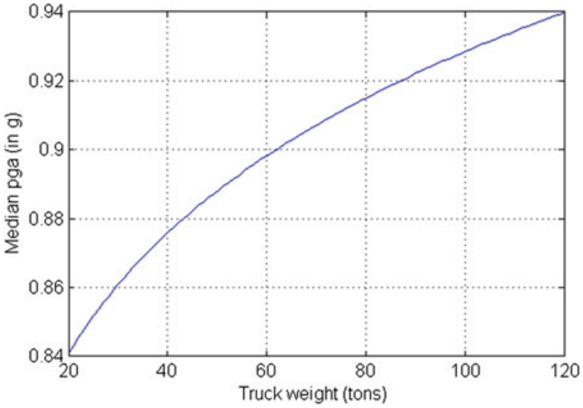
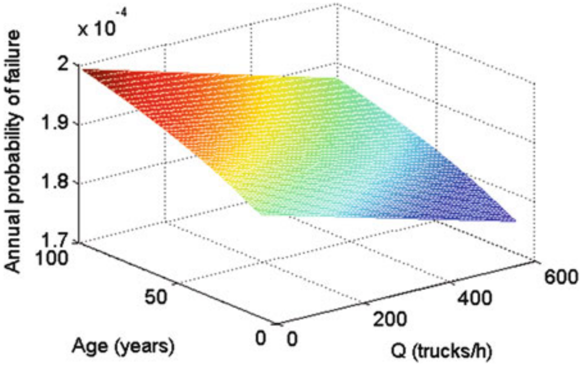


Fig. 3.5 Effect of truck presence on seismic risk



failure decreases. The probability of truck presence described in Eq. (3.1) increases with Q and presence of a truck decreases the fragility; therefore, increased truck flow decreases the risk. With age, the variation is similar to Fig. 3.2, with about 10 % change in risk between a pristine and 100-year-old bridge. Therefore, the multi-hazard combination of truck and seismic loads can be considered as diminishing in nature for this case study since presence of trucks actually helps decrease the seismic risk. However, it is acknowledged that these results are case study specific; variation in design details may lead to different results.

3.7 Conclusions

This study offers potential nomenclature and taxonomy for categorizing multi-hazard cases of interest for life cycle management of bridges. Furthermore, it explores various multi-hazard cases offering categorization of the class of multi-hazards and insights from the multi-hazard risk assessment to a case study bridge.

Such an assessment is achieved through application of a proposed parameterized multi-hazard risk assessment framework which also includes the effects of deterioration due to aging. Multi-hazard combinations are categorized in this chapter into several groups based on their occurrence, i.e., concurrent, nonconcurrent, and cascading, based on their influence on reliability and risk as amplifying or diminishing, and based on their effects on design parameter selection as competing or complementary.

The categorization of hazards is performed on the basis of applying the parameterized risk assessment framework for the case study bridge in Charleston, South Carolina. While considering the effects of aging, the bridge is subjected to earthquakes, hurricanes, and joint seismic and truck loads. For each of these hazards or hazard combinations, this study employs metamodel-based demand assessment to assist in exploration of the parameter space without additional simulations. The results from the application of the multi-hazard risk assessment procedure on the case study bridge provide important insight to the risk portfolio. The results highlight the competing influence of the two nonconcurrent hazards, earthquakes and hurricanes, on column height. This competing nature of the two hazards shows the importance of risk assessment considering nonconcurrent multiple hazards and categorization of multiple hazards according to their influence on selection of bridge design parameters. Reliability assessment of the bridge for concurrent occurrence of seismic and truck loads show that truck presence decreases the seismic fragility of the case study bridge. Consequently, for this particular case study, the risk, i.e., the annual probability of failure, decreases due to presence of a truck whose magnitude depends on the flow rate of the trucks. Thus, the results uncover the diminishing nature of the seismic and truck load combination. Future work will focus on classifying additional multi-hazard combinations and extending the proposed framework to a portfolio of bridges. In addition to this, effects of cascading hazards on reliability and selection of design parameters should also be explored.

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