Seismic Fragility Updating of Highway Bridges using Field Instrumentation Data

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ABSTRACT: Seismic fragility assessment of deteriorating highway bridges using analytical methods often rely on empirical, semi-empirical or numerical models to predict the rate and nature of degradation. Consequently, the predicted structural vulnerabilities of bridge components or overall bridge system during seismic shaking are only as good as the adopted deterioration models. For the sake of simplicity and ease of computational modeling, these deterioration models are often far removed from observed manifestations of time-dependent aging. One such example is the nature of corrosion in reinforced concrete bridge components under chloride attacks. While this deterioration mechanism leads to the formation of pits along the length of the rebar, past literature often adopts the simplified uniform area loss model. This study proposes a probabilistic framework that assists in improved deterioration modeling of highway bridges by explicitly modeling pit formation and also provides the opportunity of updating the analytical models with field measurement data using Bayesian techniques. The framework and case-study results presented in this study are believed to render realistic seismic fragilities for highway bridges when located in moderate to high seismic zones.

Keywords: Seismic fragility, Highway bridges, Pitting, Chloride-induced deterioration, Bayesian updating, Spatial variability

1. INTRODUCTION

Pit formations due to chloride ingress is a well-known, yet commonly ignored phenomena during deterioration modeling and seismic fragility assessment of highway bridges when located near marine sources. Until now a majority of literature on aging bridge fragility assessment tends to model corrosion deterioration of embedded steel using the uniform corrosion model (Choe et al. 2008, Ghosh and Padgett 2010). While such modeling strategies may be acceptable for carbonation induced corrosion, neglecting pitting effects in severe chloride exposure zones such as marine splash or deicing condition may substantially under-predict the seismic vulnerability (Kashani et al. 2015). Primary challenges for modeling pitting corrosion is twofold. Firstly, it may be increasingly difficult to model pits within the finite element cross section of the pier. The second challenge stems from lack of sufficient experimental data to model pit formation probabilistically along the length of the reinforcing bar. Some limited literatures on experimental tests that report statistics on pit formation due to chloride induced corrosion includes Stewart and Al-Harthy (2008).

Addressing the existing drawbacks, the purpose of this research is to provide a framework that rationally combines the information historical tests and data available from possible field instrumentation for realistic estimation of seismic fragility. The proposed methodology can benefit bridge engineers, infrastructure stakeholders, and decision makers to assess the seismic risk of degrading highway bridge infrastructure when located in chloride exposure zones. The paper is arranged as follows. The immediate section provides discussions on chloride induced pit formation modeling. Next, a methodology is proposed that helps infer information from limited field-instrumentation data to arrive at posterior estimation of pit distributions along the length of the rebar using Bayesian updating. The proposed methodology is applied on a three-span continuous steel girder bridge located in Central and Southeastern US. The paper ends with conclusions and recommendations for future work.

2. CHLORIDE INDUCED PITTING CORROSION MODELLING

Corrosion of bridges is mainly found to occur at locations that are close to sea coast and in the regions where deicing salt is used to remove the snow. Hence, the study herein focusses on chloride induced corrosion for one of the two environments, i.e. marine splash. Corrosion typically starts after sometime called the corrosion initiation time. This is the time taken by chloride ions to reach the reinforcement after passing through the concrete cover. Once the corrosion has initiated, corrosion propagation takes place and it depends on the deterioration parameter corrosion rate. Corrosion rates can be time dependent or time independent. In the case of marine splash environment, the corrosion rates are considered to be time dependent. In addition to the uniform corrosion in marine splash due to chloride ions, formation of localized pits also takes place along the length of the reinforcement steel (Darmawan 2010; Ghosh and Sood 2016; Shekhar et al. 2018; Stewart 2004; Stewart and Al-Harthy 2008). Typically, small independent pits or cracks are formed in the initial stages of corrosion which as the time passes blend together leading to uniform corrosion along the length of the reinforcement steel. But in addition to the uniform corrosion loss of area, severe localized corrosion across multiple locations along the length of the reinforcement steel leads to deep pit or cavity formation. The section losses in this pits may be four to eight times higher than the generalized uniform corrosion which reduces the structural strength significantly (González et al. 1995). Hence it is important to consider the effect of pitting corrosion in addition to uniform corrosion while assessing the lateral load carrying capacity of the bridge components such as piers.

The time dependent residual cross-sectional area of steel following a deep pit formation at each pit location can be expresses as (Stewart 2004):

$$A_r^{DP}(t) = A_0 - (A_1 - A_2) \quad for\, p(t) \le \frac{D_0}{\sqrt{2}} \tag{1}$$

$$A_r^{DP}(t) = A_1 - A_2 \quad for\, D_0 > p(t) \ge \frac{D_0}{\sqrt{2}} \tag{2}$$

where the details of areas A_0, A_1, A_2 can be found in Stewart, 2004 and the pit depth $p(t)$ is given by:

$$p(t) = R\int_{T_i}^{t} r_{corr}\, dt_p \tag{3}$$

where R is called the pitting factor and it is defined as the ratio of maximum pit depth to the average pit depth, T_i is the corrosion initiation time, t is the time when we are looking for corrosion and r_{corr} is the corrosion rate.

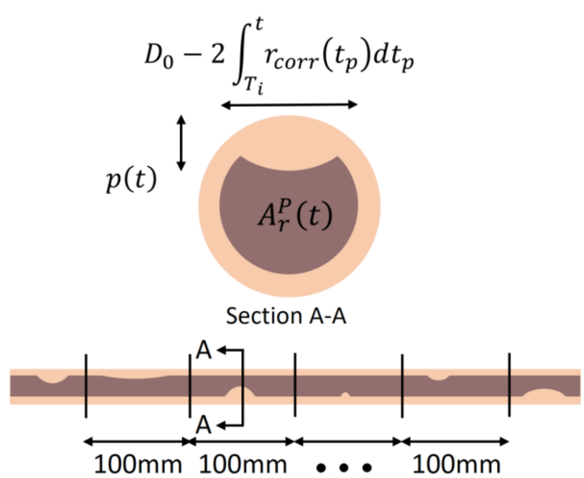

Figure 1: Reinforcement steel with pitting corrosion

Extreme value statistics have been used in the past researches to characterize the distribution of pitting factor R (Darmawan 2010; Stewart 2004). For a series of accelerated corrosion tests carried out on different rebar sizes by Stewart and Al-Harthy 2008, it was found that a Gumbel distribution of Type I extreme value distribution best represents the distribution of R. In another study carried out by González et al. 1995 where concrete specimens were exposed to natural environments, the pitting factor came out to be varying from 4 to 8. At any particular deep pit location, the residual area $A_r^P(t)$ of rebar for pitting corrosion is a function of pristine rebar area A_0, uniform rebar area $A_r^U(t)$ and $A_r^{DP}(t)$ as shown in Eq. (4). The equation for this residual area is given by:

$$A_r^P(t) = (A_r^U - A_0)\left(1 - \frac{a}{2D_0}\right) + A_r^{DP}(t) \qquad (4)$$

3. SPATIAL INTERPOLATION

For accurate estimation of aging highway bridges fragilities, up to date information on deterioration parameters at all locations within a bridge is required. Since it is difficult to monitor each and every bridge component, spatial interpolation techniques are employed to estimate the values of deterioration parameters at unknown locations from the values measured at known locations. In calculation of pitting corrosion, pitting factor R is needed. To find pitting factor R, maximum pit depths are required. These pit depths in the reinforcement need to be obtained along the whole length of the column. They can be obtained by performing non-destructive testing along the length of the column at different locations. But it is not feasible to do testing along the whole length of the column due to reasons like inaccessibility to some locations, expensive and labour intensive tasks, etc. Thus, the pit depths at other locations can be achieved using spatial interpolation techniques like kriging.

3.1. Kriging

Kriging is essentially a method of estimation by local weighted averaging:

$$\hat{Z}(s_0) = \sum_{i=1}^{N} \lambda_i Z(s_i) \qquad (5)$$

where $Z(s_i)$ = the measured value at i^{th} location, λ_i = an unknown weight for the measured value at the i^{th} location, s_0 = the prediction location and N = the number of measured values. The weight λ_i depends not only on the distance the measured points and prediction location but also on the overall spatial arrangement of the measured points. Uncover the dependency rule and make the prediction surface map are the two tasks necessary to make prediction with kriging interpolation technique. Kriging goes through two step process to perform the above mentioned tasks. First, it creates the variograms and covariance functions to estimate the statistical dependence called spatial auto-correlation values that depend on the model of auto-correlation, i.e. fitting a model and second, it predicts the unknown values.

3.2. Application of kriging to aging bridge pier

Kriging is a very useful interpolation technique, employed in this study to predict the pit depth throughout the rebar length using the experimental data at few locations. The process outlined in this section minimizes the error due to kriging and also obtains a big set of pitting factor R values which properly represents the corrosion situation at that location.

The bridge pier is modelled by discretizing it into fragments of length 100mm and the experimental pit depth values are known for only few of these intermittent sections. This study considers that experimental data is extracted of every fourth section leaving a gap of three sections (each of length 100mm) in between them. Therefore, with the data available at every 400mm is used to interpolate the corrosion data of the intermediate three fragments. Furthermore, it is assumed that the experimental data is available for 20 points located throughout the circumference for each of the section at the gap of 400mm (as depicted by red dots in Figure 2). The pit depth values at these 20 points are simulated using the experimental data given by González et al. 1995. A structure in marine region is divided into different zones namely, submerged zone, splash zone and atmospheric zone. The impact of corrosion is maximum in the splash zone because of cyclic wetting and drying which causes accumulation of chloride and hence pit depth is highest compared to other zones (Bertolini et al. 2004). Therefore, higher pit depths are simulated

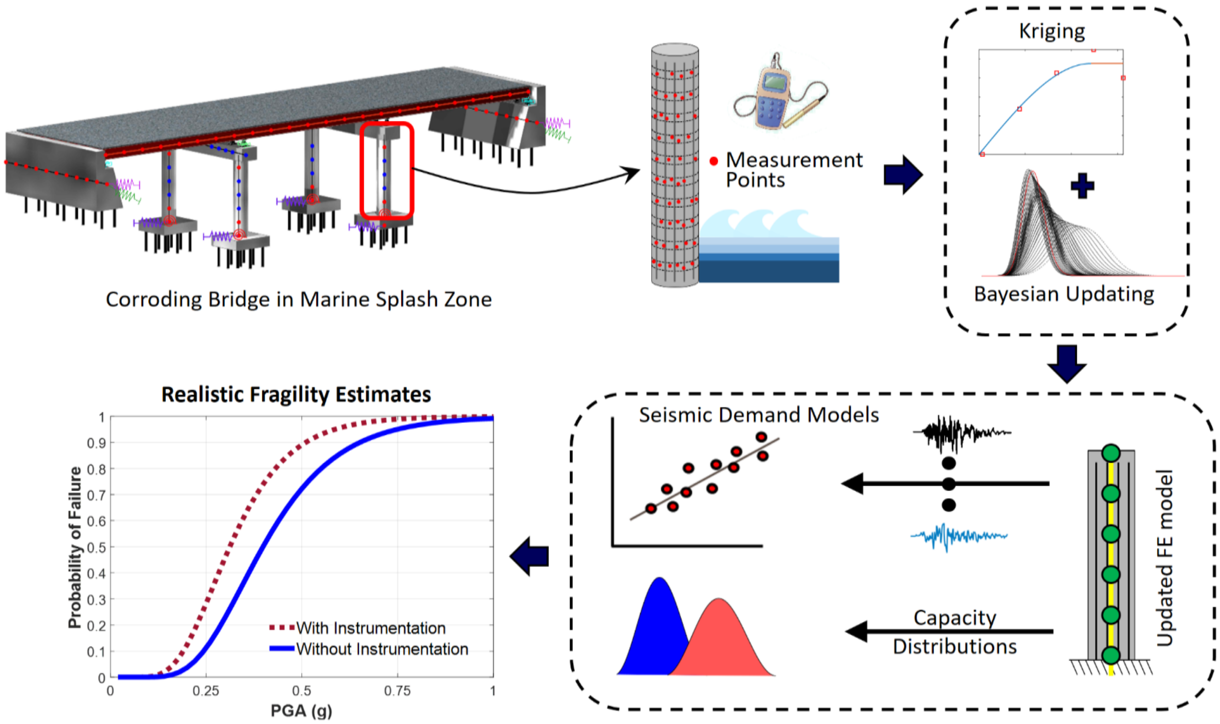

Figure 2: Flowchart for the seismic fragility updating with field instrumentation data

for splash zone. Subsequently, from these 20 values of pit depth, a random value is picked from every section at which the experimental data are available. All these random values are then interpolated using kriging technique to obtain the pit depth values throughout the pier length. This process is repeated 50 times so that sufficient number of combinations of possible pit depth along the length of reinforcement gets considered. The maximum value of pit depth is chosen from amongst 50 interpolated values to obtain a single value of the pitting factor R at each sections. Lastly, this process is repeated 1000 times to get 1000 such values of pitting factor R values at each sections of 100mm length throughout the pier length. The next section outlines the process to update the interpolated data using Bayesian inference as and when new experimental data are made available.

4. BAYESIAN INFERENCE

The prediction of bridge fragilities from the prior knowledge of the deterioration parameters leads to under estimation or over estimation of the strength of the bridges. With the new technologies available the bridges can be monitored and present-day information of the deterioration parameters of the bridges can be obtained. To know the future situation of the bridges some method is required for combining the old and new information on the deterioration parameters. This can be achieved using Bayesian updating.

The prior and the likelihood are the pillars of any Bayesian inference (Faroz 2016). Priors constitute historical data of deterioration parameters while likelihood is the data obtained through non-destructive field testing or instrumentation. The corrosion deterioration parameter, i.e. pitting factor R used for the study is the informative prior taken from Stewart, 2004 with an extreme value distribution (Gumbel) having location parameter (μ) as 6.36 and scale parameter (σ) as 1.13. 1000 pitting factor R values are obtained by performing kriging at each 100mm section which is the likelihood and it is assumed to range from 8 to 20. Posterior obtained after updating is the improved knowledge of prior and likelihood. Hence it can be seen that the main aim of Bayesian Updating is to compute the posterior distribution.

4.1. Markov Chain Monte Carlo simulation

There are several computational challenges involved in computing the posterior distribution from Bayes' Theorem (Faroz 2016). In such cases a Markov Chain Monte Carlo (MCMC) method is usually employed for sampling from posterior distribution. The basic idea of Markov chain is performing "random walk" through the probability distribution and repeat the iteration enough number of times to get frequency proportional to probability. Markov chain is a sequence of random variable whose next state value is dependent only on the previous state. Hence, this process is a memory-less process which depends only on the current state and not on the sequence of events that precedes it. This makes the calculation of conditional probability easy and enables the algorithm to be applied to a number of scenarios. Markov chain has the important property as far as MCMC is concerned, it is ergodic. Meaning that it visits every point in the domain and it visits them in a proportionate amount of probability. There are many algorithms available for MCMC like Metropolis algorithm, Gibbs Sampler, Independence Sampling, Metropolis Hasting algorithm, Cascaded Metropolis Hasting algorithm, etc. For this study, Cascaded Metropolis Hasting algorithm is used. It is a very efficient process where the parameters are not correlated and individual updating of each parameter is to be done which is the case in this study.

4.1.1. Cascaded Metropolis Hastings algorithm

This is an iterative sampling method which generates a Markov chain where the transition between x_i and x_{i+1} is achieved using the acceptance – rejection sampling (Rastogi et al. 2017):

$$x_{i+1} = \begin{cases} x^* \sim q(x|x_i) & with\, probability\; \alpha(x_i, x^*) \\ x_i & else \end{cases} \tag{6}$$

where x^* is a random sample generated using proposal density, $q(x|x_i)$ is the transition density or the proposal density and $\alpha(x_i, x^*)$ is the acceptance probability.

$$\alpha(x_i, x^*) = \min\left\{1, \frac{f_X(x^*)}{f_X(x_i)} \frac{q(x_i|x^*)}{q(x^*|x_i)}\right\} \tag{7}$$

Zero mean Gaussian or uniform density function is the commonly used transition or proposal density. In such a case, the transition density is $q(x^*|x_i) = q(x^* - x_i)$ and a result of symmetry $q(x^* - x_i) = q(x_i - x^*)$ .The acceptance probability then is given by Eq. (8).

$$\alpha(x_i, x^*) = \min\left\{1, \frac{f_X(x^*)}{f_X(x_i)}\right\} \tag{8}$$

The steps for Cascaded Metropolis Hasting algorithm are as follows:

1. Initiate the chain $i = 0$, x_0.
2. Generate a random sample x^* using the proposal density $q(x|x_i)$.
3. Evaluate the 'prior' acceptance probability $\alpha_P(x_i, x^*) = \min\left\{1, \frac{P_X(x^*)}{P_X(x_i)}\right\}$.
4. Compute $u_P \sim$ Uniform [0,1].
   a) If $u_P < \alpha_P(x_i, x^*)$, accept and go to step 5.
   b) Else go to step 2.
5. Evaluate the 'likelihood' acceptance probability $\alpha_L(x_i, x^*) = \min\left\{1, \frac{L_X(x^*)}{L_X(x_i)}\right\}$.
6. Compute $u_L \sim$ Uniform [0,1].
   a) If $u_L < \alpha_L(x_i, x^*)$, accept and set $x_{i+1} = x^*$, $i = i + 1$ and go to step 2.
   b) Else go to step 2.

4.2. Formulation

Each of the 100 mm sections of reinforcement where experimental pitting factor R values are not there, Bayesian updating is done using Cascaded Metropolis Hastings algorithm to obtain the posterior distribution of pitting factor R.

The cumulative density function (CDF) with the empirical CDF of posterior along with the likelihood and prior of pitting factor R for a particular pit in splash zone is shown in Figure 3. The prior, likelihood and the posterior distributions of the pitting factor R for a particular pit in each zone is shown in Table 1.

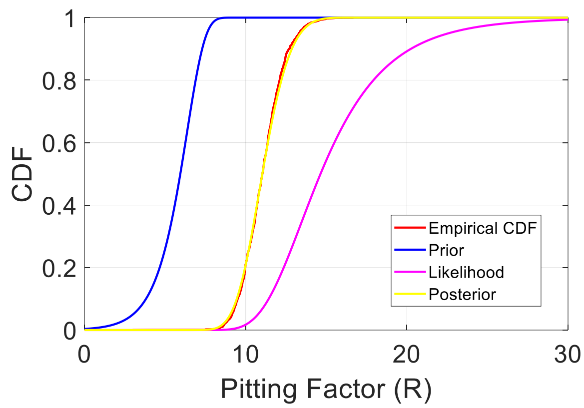

Figure 3: CDF of a pit in splash zone

Table 1: Prior, likelihood and posterior for R

Pit	Distribution		P-1	P-2	P-3
Above splash zone	Prior	Gumbel	6.36	1.13	
	Likelihood	GEV	0.04	1.14	5.55
	Posterior	GEV	-0.05	0.96	5.30
Below splash zone	Prior	Gumbel	6.36	1.13	
	Likelihood	GEV	0.10	0.92	4.71
	Posterior	GEV	0.03	0.77	4.55
In splash zone	Prior	Gumbel	6.36	1.13	
	Likelihood	GEV	0.06	2.72	13.63
	Posterior	GEV	-0.20	1.23	1.06

Distribution(Parameter 1, Parameter 2, Parameter 3); GEV-Generalized Extreme Value; Gumbel (location parameter, scale parameter); GEV (location parameter, scale parameter, shape parameter)

5. SEISIMIC FRAGILITY ANALYSIS OF HIGHWAY BRIDGE PIER

In this study seismic fragility curves for aging bridge columns are developed while considering corrosion due to marine splash exposure with the updated deterioration parameters using Bayesian updating with the help of Cascaded Metropolis Hastings algorithm. Spatial interpolation technique like Kriging are used to predict the deterioration parameters of corrosion at unknown location from the values at known locations in the column. The modelling and analysis of the pier is done in the OpenSees software and post processing of fragility curves development is done using MATLAB.

5.1. Analytical modelling of the bridge pier

The bridge pier is a 914.4 mm diameter circular column with 12nos. of 29 mm diameter rebars. The height of the bridge pier is 4300 mm. For the analytical modelling of the bridge pier in OpenSees, fiber section is used to generate the section and element is modelled using the displacement beam-column element which considers the spread of plasticity along the element length and is based on displacement formulation. *Concrete04* material is used to construct a uniaxial concrete material with degraded linear unloading/reloading stiffness and tensile strength with exponential decay. The confined core is modelled by *Concrete04* material as it takes into account the confinement provided by the stirrups. It is beneficial to use this material as it allows modelling loss of confinement due to corrosion of stirrups. The cover concrete is also modelled with this material. *uniaxialMaterial Hysteretic* material is used to model the longitudinal reinforcement that is capable of capturing pinching of force and deformation, damage due to ductility and energy and degraded unloading stiffness based on ductility.

Uniform corrosion of the reinforcing bars is implemented in the model by evenly reducing the cross sectional area of steel along the rebar length. Pitting corrosion results in the formation of deep-pits along with uniform area reduction along the length of the reinforcement (Ghosh and Sood 2016). The spatial variability of the pit is modelled in the study after dividing the rebar into 100mm sections. In this 100mm sections, the pit is assign at a random location. This type modelling was given by Stewart and Al-Harthy 2008 which they obtained from the experimental test done by them. The depth of the pit is dependent on the pitting factor R. In addition to this, the secondary effects of deterioration such as potential reduction in steel yield strength, likelihood of cracking or spalling of concrete cover and loss of confinement due to corrosion of stirrups is also considered. Also the cross sectional area loss of stirrups is considered along with the subsequent reduction in the confinement of the core concrete. The maximum compressive strength of the confined concrete and the corresponding strain are calculated using theoretical stress-strain model proposed by Mander et al. 1989.

5.2. Formulation of time dependent seismic fragility assessment

Fragility curves represent conditional probability to determine the likelihood of meeting or exceeding a particular damage state given the intensity of seismic shaking. It can be represented as:

$$Fragility(t) = P[D(t) > C(t)|IM] \tag{9}$$

where $D(t)$ denotes the time dependent seismic demand imposed on the bridge pier due to an earthquake intensity IM and $C(t)$ denotes the time varying structural capacity or resistance of the bridge pier (Nielson 2005). Time evolving fragility curves are developed using logistic regression method for bridge pier at 40 years of service life after accounting for uncertainties in deterioration parameters, bridge pier modelling parameters and ground motion characteristics. Effect of pitting corrosion is accounted in the seismic fragility assessment. Flowchart in Table 2 elaborates more on the fragility assessment framework.

5.3. Fragility curves

The corrosion initiation time obtained was 10 years. Here, Bayesian updating is done for deterioration parameter pitting factor R in calculations of the pitting corrosion in the corrosion propagation phase. Each reinforcement of 4300mm is divided into 100mm sections while modelling of column, i.e. 43 sections in total. At measured location (10 locations) of 100mm, pitting factor R is taken from field instrumentation done while for unmeasured location (33 locations) of 100 mm, pitting factor R is taken from the distribution obtained after doing the Bayesian updating. The limit states for the column obtained after doing pushover analysis following a Monte Carlo approach. Nonlinear time history analysis of the bridge is done to record the responses of the different bridge components. Then, the probabilistic seismic demand model (PSDM) for the bridge pier are developed which after comparing with the limit state capacities help derive fragility curves as shown in Figure 4.

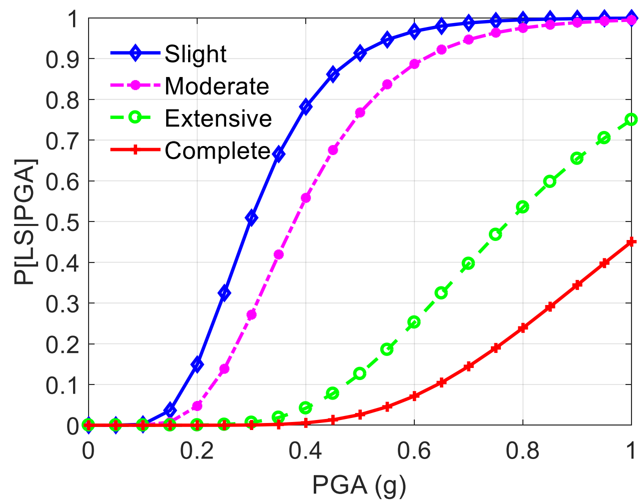

Figure 4: Bridge pier fragility curve

6. CONCLUSION

This study proposes a framework that enables rational combination of field instrumentation data and historical evidence for realistic seismic vulnerability assessment of aging bridge piers. Additionally, for chloride induced corrosion deterioration, this study considers the formation of pits along the length of the reinforcing bars. The proposed methodology is demonstrated on a multispan continuous steel girder bridge located in Central and Southeastern US located in marine splash zone is chosen. While the corrosion deterioration data for uniform loss and pit formation is assumed to be known at certain locations, the estimates at non-monitored locations are interpreted using Kriging. The interpolated distributions of the corrosion mass loss at different locations are then statistically combined with historical data to arrive at updated posterior distributions. This procedure is implemented using Bayesian updating via the Cascaded Metropolis Hastings Algorithm.

With the present day information of deteriorated bridge condition, seismic fragility curves are developed next. Development of such curves requires probabilistic consideration of material parameters, deterioration parameters, and ground motion record-to-record variability. Subsequent to consideration of these sources of uncertainties in statistically similar but nominally different bridge samples, nonlinear time-history analysis of finite element bridge models are conducted to establish relationship between the ground motion intensity and peak deteriorated bridge performance. Consequently, a comparison between the demand and capacity estimates helps establish seismic fragility curves that are most representative of bridge vulnerability given the in-situ bridge condition. Future work will look into spatial correlation of deterioration across different components as well deterioration of other bridge components such as bearings and bridge decks.

7. ACKNOWLEDGEMENT

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