Simulation-based Life-Cycle Structural Reliability of Deteriorating RC Bridges using Bayesian Updating

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Abstract. The development of transportation infrastructure systems is an essential part of modern civilization. Any functional deficiency of these systems may cause severe economic losses and social distress. Bridges are among the most vulnerable components of transportation networks. They are exposed to several deterioration processes and traffic loading scenarios during their service life, exacerbating the significant uncertainties on the life-cycle prediction of their structural response. Structural Health Monitoring (SHM) measurements can give significant information and support the damage detection of aging bridges, reducing the uncertainties associated to the structural performance and improving structural reliability of deteriorating systems. This paper presents a life-cycle probabilistic approach to incorporate SHM measurements via Bayesian updating in simulation-based reliability assessment of deteriorating bridges. The proposed methodology is applied to reinforced concrete (RC) bridges exposed to corrosion. The uncertainties of the corrosion model are updated based on SHM data. The Metropolis-Hastings (MH) algorithm is used to update the statistical parameters of the deterioration damage index at the prescribed observation time. The application to time-variant reliability assessment of a RC box-girder continuous bridge under corrosion shows the benefits of SHM to improve the accuracy of life-cycle prediction models.

Keywords: Structural reliability; Deteriorating bridges; Life-cycle assessment; Monte Carlo simulation; Bayesian update; Metropolis-Hastings algorithm.

1 Introduction

The life-cycle assessment of infrastructure systems is of paramount importance in economically developed countries where infrastructure facilities have been serving for more than half a century. In transportation infrastructure networks most bridges either are about to reach or have already reached their expected lifetime [1,2]. Recent bridge damage and failure events highlighted the importance of planning repair interventions during the structural lifetime to guarantee the life-cycle performance from the design stage to the dismantling process. In this context, the direct interventions costs of preventive maintenance and retrofit, essential maintenance and repair, up to demolition and replacement of structurally deficient bridges can severely burden the public economy. Nonetheless, the economic growth and the social well-being of communities heavily relies on transportation systems, which are required to be functional at any time without abrupt interruptions.

Bridges are exposed to environmental aging and different mechanical deterioration phenomena during their service life, including corrosion and fatigue [3]. Aging effects lead to losses over time in strength, ductility and stiffness of structural components that may drastically affect the bridge bearing capacity to service loads and the vulnerability to extreme hazards. An in-depth knowledge of infrastructure assets is crucial for investment, planning, and management policies informing large-scale maintenance, retrofit, and monitoring activities. To ensure the serviceability of transportation systems, it is necessary to assess the aging effects and deterioration processes and to evaluate the time-variant performance of the structural systems throughout their service life. Even though an accurate mathematical description of physical deterioration processes may follow complex patterns, advanced life-cycle models are nowadays established for damage processes such as carbonation and chloride-induced corrosion processes in reinforced concrete (RC) structures [4–6].

Advances in computer technology and new approaches to structural assessment have enabled the use of probabilistic simulation-based frameworks in bridge reliability analysis [7]. Structural model uncertainties associated to geometry, material characteristics, loading conditions and exposure scenario may play a crucial role in the structural reliability assessment of bridges. In these probabilistic approaches, SHM measurements can be integrated into the deterioration models based on Bayesian updating strategies. This allows integrating the empirical evidence with the prior information into the probabilistic distributions of critical mechanical parameters of bridges [8],[9],[10].

This study presents a methodology that incorporates based on Bayesian updating the SHM measurements of damage indices in structural systems within the life-cycle reliability analysis of deteriorating bridges. Probabilistic performance indicators such as the reliability index with respect to prescribed limit states of deteriorating bridges are assessed with and without the information gathered from SHM data. The Metropolis-Hastings (MH) algorithm is adopted to update the distribution of the local damage index of vulnerable bridge components and, in turn, on overall structural reliability. The methodology is applied to a box-girder continuous RC bridge under a prescribed scenario of environmental aggressiveness in terms of corrosion initiation and propagation. The impact of uncertainties of experimental data on the posterior distribution is also investigated.

2 Deterioration in RC Structures

2.1 Corrosion Damage and Propagation Modeling

RC bridges built about 40-50 years ago are showing nowadays aging and deterioration effects, like corrosion of steel reinforcement, which may drastically affect their bearing capacity. The corrosion process is characterized by two phases: initiation and propagation. Aggressive agents such as chlorides penetrate through the concrete cover with a predominantly diffusive physical process. Their concentration $C = C(z,t)$ can be described in time *t* at depth *z* and steel bars corrosion is triggered when a critical concentration threshold C_{cr} is attained at a critical time t_{cr}. The onset of corrosion leads to a progressive degradation of steel and concrete, such as the reduction of steel reinforcement area and ductility and the impairment of concrete cover strength up to spalling. Steel reinforcement mass loss is one of the most critical phenomena, which may severely affect the section capacity under static and dynamic loads. The dimensionless damage index δ s ∈ [0,1] represents the mass loss of the section and it expresses the corroded area of reinforcement A_s as follows:

$$A_s(\delta) = [1-\delta_s(\delta)]A_{s0} \tag{1}$$

where A_{so} is the undamaged reinforcement area and the corrosion penetration index δ ∈ [0,1] represents the corrosion penetration depth normalized by the steel bar diameter. The damage function depends on the type of corrosion mechanism [11]. Uniform corrosion generally occurs in carbonated RC structures. A suitable time-variant deterioration model is required to consider the life-cycle analysis of structure in a proper way. In this case, empirical models can be successfully adopted [3]:

$$\delta(t) = \kappa(t-t_i)^{\eta} \tag{2}$$

where $t_i = t_{cr}$ represents the corrosion initiation time, whilst κ and η are shape parameter that could be determined based on available experimental data via statistical regression [12,13].

3 Life-Cycle SHM of RC Bridges

Structural Health Monitoring (SHM) systems can be used to determine the damage and deterioration of critical bridge components with more objectivity and based on empirical evidence. However, installing and operating SHM systems is inherently expensive. Structural damage of bridge components can develop in a short period of time due to the occurrence of extreme events that mechanically impair the material structural properties. On the other hand, long-term degradation processes are related to progressive impairment of the structural integrity, which reduce in time the structural capacity.

SHM typically allows measuring the time-histories of critical demand parameters such as generalized strains and displacements. The measured dataset can be adopted to suitably calibrate structural models. Long-term measurement also allows determining eventual changes on the traffic density and intensity affecting the loading conditions and subsequently the structural demand on vulnerable aging viaducts [14]. Nonetheless, short-term SHM activities can be planned not only to assess the structural response, but also to directly evaluate the deteriorating mechanical properties of structural members and their constitutive materials. Recurrent visual inspection coupled with periodical destructive and non-destructive testing can be adopted for this purpose.
There are numerous corrosion depth detection technique in the literature and some of them are Ultrasonic Detection Technique [15], Acoustic Emission Testing Technique [16], Eddy Current Technique.[17], and Magnetic Flux Leakage (MFL) Method [18]. With the help of the mentioned advanced techniques corrosion depth can be easily determined and the obtained data can be used to update the performance of the bridge and it enables to improve the probabilistic approaches that used to estimate structural deterioration during lifetime.

4 BAYESIAN UPDATING

4.1 Basics of Bayesian statistics

Collecting information from the experimental study, theoretical study, and expert judgment is an essential part of decision-making processes of public and private managing road networks. However, the underlying phenomena associated with the time-variant structural demand and capacity of key network components are inherently affected by aleatory and epistemic uncertainties and decision-making should be informed by a probabilistic framework. The Bayesian approach of statistics is a mathematical tool that is typical of problems involving the combination of new information with the current knowledge on the system.
Bayesian updating allows incorporating the information coming from observed data into the analytical models of the constitutive random variables describing the physical phenomena. More specifically, their prior probability distributions of these random variables are updated based on the application of the Bayes' theorem to obtain a posterior distribution that incorporates the information obtained from empirical evidence [19]. Initially, the possible values of a parameter θ with prior relative likelihood $p_i = P(\Theta = \theta_i)$ is existed. With the available additional information, the prior assumption on the parameter θ is modified through the Bayes' theorem [19]:

$$P(\Theta = \theta_i | \varepsilon) = \frac{P(\varepsilon | \Theta = \theta_i) P(\Theta = \theta_i)}{\sum_{i=1}^{k} P(\varepsilon | \Theta = \theta_i) P(\Theta = \theta_i)} \quad i = 1, 2, ..., k \tag{3}$$

where $P(\varepsilon|\Theta=\theta_i)$ is the likelihood function associated with the i-th of the k additional measurements, whilst prior and posterior probabilities are $P(\Theta=\theta_i)=P'(\Theta=\theta_i)$ and $P(\Theta=\theta_i|\varepsilon)=P''(\Theta=\theta_i)$, respectively. Based on probabilistic continuous analytical models for both additional information $(fx(x_i|\theta))$ and prior knowledge $f'(\theta)$, the posterior Probability Density Function (PDF) can be expressed as follows [19]:

$$f''(\theta)=\frac{\left[\prod_{i=1}^{n} fx(x_i|\theta)dx\right]f'(\theta)}{\int_{-\infty}^{\infty}\left[\prod_{i=1}^{n} fx(x_i|\theta)dx\right]f'(\theta)d\theta} \tag{4}$$

The analytical expression of the posterior distribution can be achieved in closed form when prior distribution and likelihood functions are characterized by statistical conjugate distribution. Nevertheless, this assumption is rarely valid in most practical applications and approximate numerical approaches can be adopted to estimate the posterior distribution, such as the MH algorithm [20].

4.2 Metropolis-Hastings Algorithm

The MH algorithm is a Markov chain Monte Carlo (MCMC) method, which generates a set of random samples to obtain the posterior distribution based on prior distribution and expected likelihood. These methods are easily used to generate any model when direct sampling is difficult. Some basic steps of the algorithm are listed [21]:

1. Set counter $t = 1$.
2. An initial sample value $x(t)$ from prior distribution is determined to start the number generation.
3. A candidate sample $y(t)$ is generated.
4. The candidate points accepted or rejected depends on ratios of the proposed $y(t)$ and old $x(t)$ candidate samples likelihood. If the candidate point is accepted, initial values $x(t+1)$ equalize to $y(t)$.
5. Increase the iteration number $t \rightarrow t+1$ and repeat steps 2 and 3 until the target number of samples generated.

For this propose, any symmetric distribution can be used for generating the candidate point. Different approaches are adopted to minimize the number of iterations and guarantee a reasonable degree of accuracy. For example, the removal of the initial trivial iteration terms is an effective strategy since the selection of the initial sampling conditions tend to be negligible after a large number of samples is generated.

5 Case Study

5.1 Continuous RC box girder bridge

The two-span continuous RC bridge shown in Figure 1, with span length l=30 m, is considered. The box-girder cross-section of the deck is characterized by reinforcement S1 for the outer deck segments with length l_1=25 m and S2 for the inner segments over the mid-support with length l_2=5 m. The bridge deck is subject to a dead load G, live load Q_s in each span s=1,2.

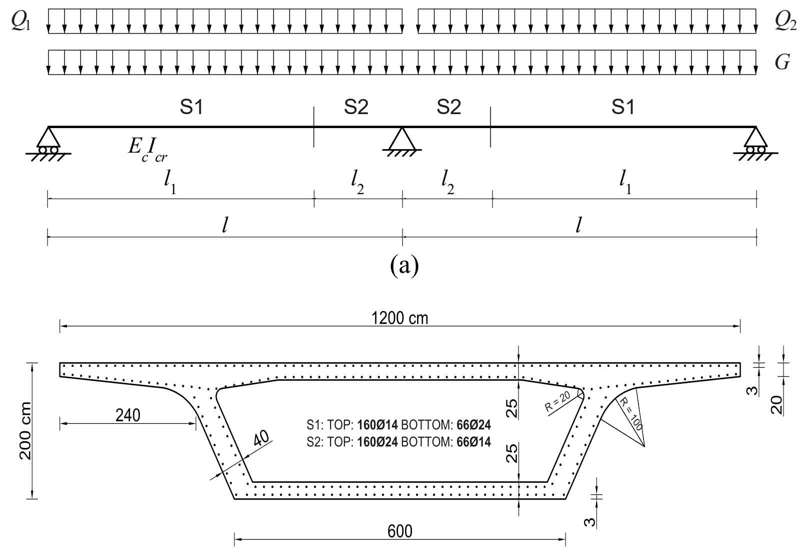
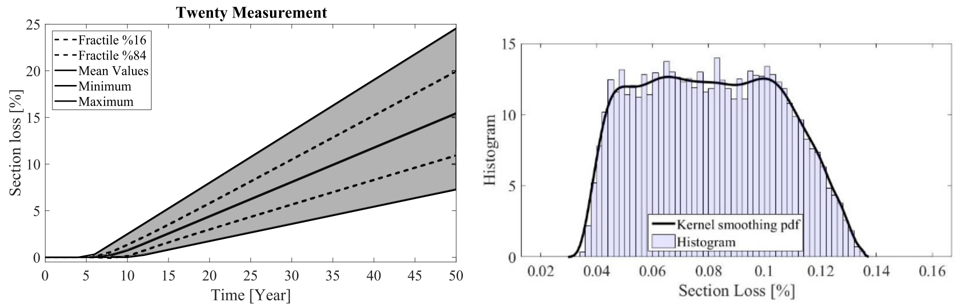


Figure 1. RC box girder bridge: (a) structural scheme and loadings; (b) geometry and reinforcement layout of the deck cross-section (dimensions in cm).

5.2 Simulation of corrosion processes and Bayesian updating

A uniform distribution is assumed for corrosion initiation time t_i bounded between $t_{\min}$ = 5.4 years and $t_{\max}$ = 10.8 years. Shape parameters κ and η of the time variant-deterioration model (Eq. 2) are modeled by symmetric triangular distributions over the intervals $\kappa = 3.7 \cdot 10^{-3} \pm 2.0 \cdot 10^{-3}$ and $\eta = 8.1 \pm 2.7$.
Figure 2a shows the probabilistic time-variant steel reinforcement section loss, with both sample mean and sample standard deviation significantly increasing over the structural lifetime. A SHM system is installed at time t_s = 30 years. A Kernel smoothing function is assumed for the section loss at time t_s. Figure 2b compares the empirical probability mass function (histogram) with theoretical PDF of the assumed distribution.



(a) (b)

Figure 2. (a) Time-variant steel reinforcement section loss; (b) empirical probability mass function and theoretical probability density function of section loss at time t_s.

5.3 Bayesian updating and structural reliability assessment

The steel reinforcement section loss resulting from the SHM system measurement is characterized by a normal distribution characterized by a mean value of 0.08 and covariance of 5%. The corrosion loss index is updated with Bayesian updating. Figure 3 shows the comparison among prior distribution, experimental distribution, and posterior distribution of the section loss in case of twenty and one hundred measurements.

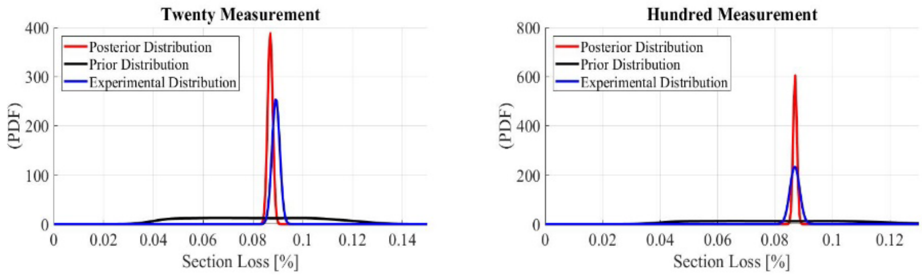


Figure 3. Comparison among prior distribution, experimental distribution and posterior distribution of section loss index for twenty and one hundred samples.

A second set of measurements is simulated with 0.09 mean values and CoV equals to 5%. Updated section loss are assumed as the prior distribution and the second set of measurements is used as a target function. The MH numerical Bayesian updating procedure has been adopted twice to evaluate the posterior distribution (Figure 4).
The life-cycle reliability of the RC bridge is computed by Monte Carlo simulation, including the uncertainties associated to dead and live loads, concrete and steel mechanical characteristics. Figure 5 shows the effect of information updating on the time-variant reliability index associated to the collapse limit state.

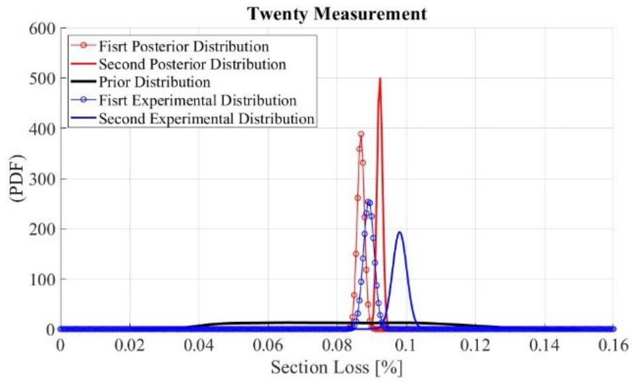


Figure 4. Bayesian updating procedure after two SHM-based damage estimate.

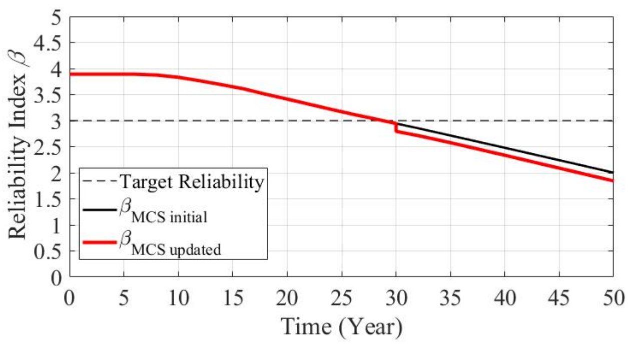


Figure 5. Time-variant reliability index.

6 CONCLUSIONS

The condition state assessment of critical bridges within transportation networks is fundamental to define robust strategies and inform decision-making processes for effective infrastructure management policies. In this context, Bayesian updating can be adopted to properly incorporate instrumental measurements into structural reliability assessment. In this study, life-cycle analysis of bridges has been presented and the information obtained from the probabilistic model and SHM measurements are combined based on a Bayesian approach. The posterior probabilistic deterioration model is generated adopting the ME algorithm. The proposed approach has been applied to life-cycle reliability assessment of a RC box-girder bridge under corrosion. The life-cycle performance of the bridge is simulated using both initial and updated probabilistic models and it is shown how SHM measurements are effective in assessing the lifetime bridge performance. This approach can be used to exploit information from bridge inspection and SHM to plan bridge maintenance and repair activities and support infrastructure management procedures.

References

1. ASCE: Report Card for America's infrastructure. Reston. VA (2021).
2. Chen H.P.: Monitoring-based reliability analysis of aging concrete structures by Bayesian updating. Journal of Aerospace Engineering 30(2) , 1–10 (2015).
3. Ellingwood B.R.: Risk-informed condition assessment of civil infrastructure : state of practice and research issues. Structure and Infrastructure Engineering 1(1), 7–18 (2005).
4. Biondini F., Frangopol D.M.: Life-cycle performance of deteriorating structural systems under uncertainty: Review. Journal of Structural Engineering 142(9), 1–17 (2016).
5. Biondini F., Bontempi F., Frangopol D.M., Malerba P.G.: Probabilistic service life assessment and maintenance planning of concrete structures. Journal of Structural Engineering 132(5), 810–825 (2006).
6. Apostolopoulos C.A., Papadakis V.G.: Consequences of steel corrosion on the ductility properties of reinforcement bar. Construction and Building Materials 22(12), 2316–2324 (2008).
7. Jacinto L., Neves L.C., Santos L.O.: Bayesian assessment of an existing bridge: a case study. Structure and Infrastructure Engineering 12(1), 61–77 (2016).
8. Strauss A., Frangopol D.M., Kim S.: Use of monitoring extreme data for the performance prediction of structures: Bayesian updating. Engineering Structures 30(12), 3654–3666 (2008).
9. Enright M.P., Frangopol D.M.: Condition prediction of deteriorating concrete bridges using Bayesian updating. Journal of Structural Engineering 125(10), 1118–1125 (1999).
10. Kim C.W., Zhang Y., Wang Z., Oshima Y., Morita T.: Long-term bridge health monitoring and performance assessment based on a Bayesian approach. Structure and Infrastructure Engineering 14(7), 883–894 (2018).
11. Biondini F., Vergani M.: Deteriorating beam finite element for nonlinear analysis of concrete structures under corrosion. Structure and Infrastructure Engineering 11(4), 519–532 (2015).
12. Granata R.D., Wilson J.C., Fisher J.W.: Assessing corrosion on steel structures using corrosion coulometer. Journal of Infrastructure Systems 2(3), 139–144 (1996).
13. Naus D.J., Oland C.B., Ellingwood B.R., Hookham C.J., Graves Iii H.L.: Summary and conclusions of a program addressing aging of nuclear power plant concrete structures. Nuclear Engineering and Design 194(1), 73–96 (1999).
14. Sousa H., Rozsas A., Slobbe A., Courage W.: A novel pro-active approach towards SHM-based bridge management supported by FE analysis and Bayesian methods. Structure and Infrastructure Engineering 16(2), 233–246 (2020).
15. Grosser P.: Ultrasonic Detection and Measurement of Isolated or Pitting Corrosion (IPC). In: Asia-Pacific Conf. NDT. Auckland, New Zealand, pp 1–7 (2006).
16. Andruschak N., Saletes I., Filleter T., Sinclair A.: An NDT guided wave technique for the identification of corrosion defects at support locations. NDT & E International 75, 72–79 (2015).
17. Atlam A, Omar AA, Waheed A.F. Shafy M., Habashy, M.: Non destructive testing measurement for monitoring pitting corrosion using DCPD techniques. In: 4th Environ. Phys. Conf. Hunghada, Egypt, pp 10–14 (2010).
18. Park S., Kim J., Lee C., Lee J.: Magnetic flux leakage sensing-based steel cable NDE technique. Shock and Vibration 1–8 (2014).
19. Ang A.H.-S., Tang W.H.: Probability concepts in engineering planning and design: Emphasis on application to civil and environmental engineering. 2nd ed.. Wiley (2007).
20. Okasha N.M., Frangopol D.M.: Integration of structural health monitoring in a system performance based life-cycle bridge management framework. Structure and Infrastructure Engineering, 8(11), 999–1016 (2012) .
21. MathWorks. Toolbox, Statistic 7 user's guide Natick, MA: The MathWorks, Inc. 2112. (2009).