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Effective service life prediction of RC bridges subjected to coupled corrosion and fatigue

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ABSTRACT

Corrosion and fatigue jointly decrease the performance of reinforced concrete (RC) bridges, resulting in progressive deterioration over time. To address uncertainties in predicting remaining service life, this study proposes an updated lifetime prediction model that integrates inspection and monitoring data. Bayesian inference and Markov Chain Monte Carlo (MCMC) simulation are employed to update parameters of corrosion-fatigue damage models based on inspection outcomes. Application to an RC bridge shows that updating improves prediction accuracy and reduces uncertainty in lifetime assessment.

1. INTRODUCTION

Reinforced concrete (RC) structures deteriorate over time due to the coupled corrosion and fatigue, which reduces structural reliability and serviceability (Kim et al. 2019; Ge & Kim 2021a). Corrosion leads to material degradation, bond loss, and concrete cracking, while corrosion-induced stress concentrations accelerate fatigue crack initiation and propagation (Arunachalam & Fawaz 2016; Ma et al. 2020). Predicting damage propagation is highly uncertain, necessitating updating based on inspection data. Bayesian inference and MCMC methods have been widely applied to reduce prediction uncertainty, but most studies address either corrosion or fatigue individually, or update limited parameters from single inspection types (Coro et al. 2019). This study proposes a novel approach to update coupled corrosion-fatigue service life predictions by integrating multiple inspection outcomes and identifying optimal parameters to be updated, improving prediction accuracy and reliability.

2. THEORETICAL FRAMEWORK

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The following section outlines the theoretical developments underlying this study, encompassing the formulation of the coupled corrosion-fatigue deterioration model, the Bayesian updating framework, and the strategy for selecting optimal parameters based on comparative analysis.

2.1 Coupled corrosion-fatigue deterioration model

The coupled corrosion-fatigue deterioration process is modeled in three stages: (I) corrosion initiation and pit nucleation, (II) competition between pit growth and fatigue crack propagation, and (III) fatigue crack growth leading to failure.

In Stage I, the corrosion initiation time is predicted by chloride diffusion analysis, while pit nucleation time follows Faraday's law (Jones 1992). These two durations can be defined as the time for the chloride concentration at reinforcement depth to reach a critical threshold and the time required for corrosion pits to reach a nucleation depth, respectively. The corrosion initiation time t_{in} is

$$t_{in} = \frac{c^2}{4D_e}\left[erf^{-1}\left(\frac{C_s - C_{th}}{C_s}\right)\right]^{-2} \tag{1}$$

where C_s = surface chloride concentration (kg/m^3); erf = error function; D_e = chloride diffusion coefficient (m^2/year); C_{th} = critical chloride concentration and c = concrete cover. The time duration for pit nucleation t_{pn} is defined as

$$t_{pn} = \frac{2.281 \cdot c \cdot p_0}{\alpha_d}(1-\alpha_{wc})^{1.64} \tag{2}$$

where p_0 = the threshold of pit nucleation; α_{wc} = water-cement ratio; α_d = the ratio of the maximum corrosion pit depth to the uniform corrosion depth.

Stage II captures the transition from corrosion pit growth to fatigue cracking, using a rate competition criterion where pit growth rate and fatigue crack growth rate are compared, which can be formulated as

$$\frac{dp(t_{as})}{dt} = \frac{da_p}{dt} \tag{3}$$

From Eq. (3), the transition time t_{as} can be estimated. The time interval t_{pf} associated with Stage II can be determined by subtracting the time duration t_{cp} for Stage I (i.e., $t_{cp} = t_{in} + t_{pn}$) from the pitting corrosion to fatigue crack transition time t_{as} ($t_{pf} = t_{as} - t_{cp}$). Stage III models fatigue crack propagation using Paris–Erdogan law (Paris & Erdogan 1963), from initial pit depth to critical failure crack size. The time duration t_{fg} (years) for Stage III is computed as (Bastidas-Arteaga et al. 2009):

$$t_{fg} = \frac{1}{N_{av}} \cdot \left[\int_{a_0}^{a_l} \frac{da}{C_1(\Delta K)^{m_1}} + \int_{a_l}^{a_c} \frac{da}{C_2(\Delta K)^{m_2}}\right] \qquad \text{for } a_0 < a_l \tag{4a}$$

$$t_{fg} = \frac{1}{N_{av}} \cdot \int_{a_0}^{a_c} \frac{da}{C_2 (\Delta K)^{m_2}} \qquad \text{for } a_0 \geq a_I \tag{4b}$$

where a_0 is the initial crack size; a_I is the threshold crack size corresponding to the intermediate fatigue crack propagation beginning and a_c is the critical crack size resulting in structural failure; C_1 and C_2 are material constants associated with early and intermediate fatigue crack propagation, respectively, and m_1 and m_2 are material exponents of fatigue crack propagation in the early and intermediate phases, respectively. The definition of stress intensity factor ∆K can be found in Ge & Kim (2021b). The total coupled corrosion-fatigue life t_{life} is the sum of the time durations for Stages I, II, and III (i.e., $t_{life} = t_{cp} + t_{pf} + t_{fg}$).

2.2 Parameter updating and selection method

This study employs Bayesian inference to update the probabilistic parameters of the coupled corrosion-fatigue deterioration model using inspection outcomes. The posterior distribution is computed using the prior distribution and a likelihood function, while the Markov Chain Monte Carlo (MCMC) method is employed to efficiently generate samples from the posterior distribution, enabling the updating of both single and multiple parameters. Detailed procedures are described in Ge & Kim (2021b). Furthermore, this study adopts a comparison-based analysis to identify the most suitable parameters by minimizing differences between inspection data and updated predictions. Two quantitative metrics are used: the Mean Absolute Error (MAE) and the Bhattacharyya distance. The MAE quantifies the average absolute difference between predicted and observed data, while the Bhattacharyya distance measures the overlap between their probability density functions. The parameter set yielding the minimum assessment value is identified as optimal for updating.

3 APPLICATION EXAMPLES

The proposed approach is applied to an RC bridge girder, focusing on the bottom longitudinal reinforcement at the interface between the concrete cover and stirrup as the critical location for coupled corrosion-fatigue damage. Details of this bridge are provided in Guo et al. (2019).

3.1 Service life assessment considering corrosion-fatigue interaction

The total life is divided into three stages: corrosion initiation and pit nucleation (Stage I), competition between pitting corrosion and fatigue crack growth (Stage II), and fatigue crack propagation (Stage III). Monte Carlo simulations were performed to quantify uncertainties in model parameters. Based on Eqs. (1), (2) and (4), the mean durations for Stages I, II, and III were estimated as 6.80, 5.96, and 7.30 years, respectively, yielding a total mean service life of approximately 20.06 years (SD = 2.39 years), as shown in Fig. 1. A comparison among deterioration mechanisms shows that the service life under coupled corrosion-fatigue is shorter than when considering corrosion or fatigue individually, highlighting the detrimental interaction between these two processes (see Fig. 1). For this case, corrosion inspections and maintenance interventions before fatigue crack propagation are more effective for ensuring structural safety.

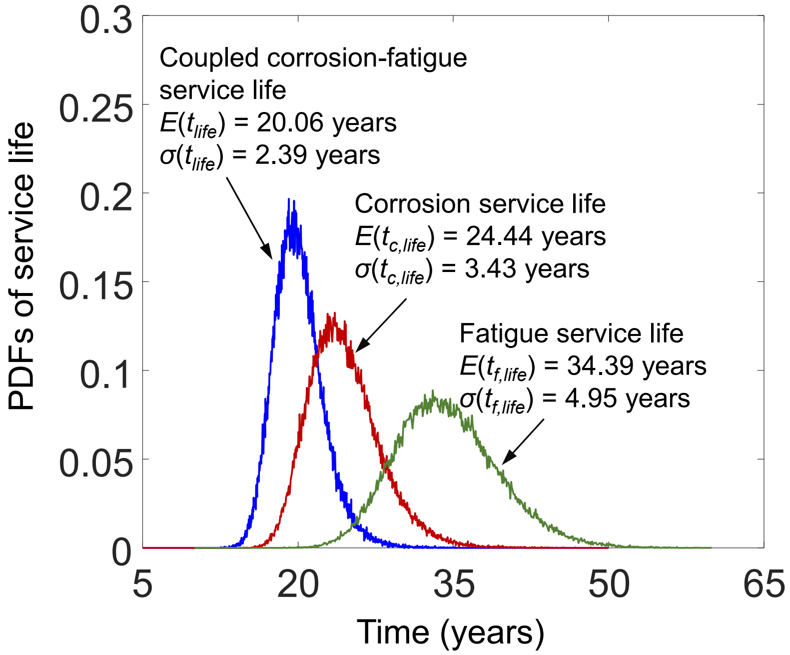


Fig.1 PDFs of corrosion, fatigue, and coupled corrosion-fatigue service lives.

3.2 Parameter updating and selection

Inspection data are used to update probabilistic parameters in the coupled corrosion-fatigue deterioration model. An inspection at year 10 is assumed. Four cases of inspection outcomes are considered:

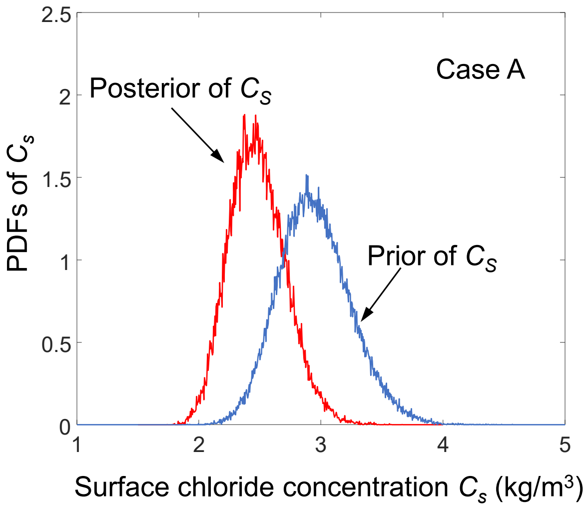
- Case A: Only chloride content detected
- Case B: Only corrosion pit detected
- Case C: Only fatigue crack detected
- Case D: Both corrosion pit and fatigue crack detected

For each case, specific probabilistic parameters are updated. For instance, In Case A, the chloride diffusion parameters C_s, D_e, $\{C_s, D_e\}$ are updated with the detected chloride concentration C_{det} assumed to follow a lognormal distribution with mean 0.6 kg/m³ and standard deviation 0.1 kg/m³. Case B updates the ratio of maximum pit depth to uniform corrosion depth α_d with the detected corrosion pit depth p_{det} assumed as LN (1.0 mm; 0.1 mm). Case C updates intermediate fatigue crack growth parameters (i.e., C_2, N_{av}, S_{re}, and their combinations) considering the detected crack size a_{det} as LN (0.65 mm; 0.05 mm). Case D combines updates for both corrosion and fatigue. A comparison-based analysis using Mean Absolute Error (MAE) and Bhattacharyya distance is conducted to identify the most appropriate updating parameters. The parameters yielding minimum assessment values are selected to achieve the best agreement between predictions and inspection data. Tab.1 lists the assessment values of updated parameters for Cases A and C. For Case A, $\{C_s, D_e\}$ provides the best fit. For Case B, α_d is optimal. For Case C, $\{N_{av}, S_{re}\}$ achieves the smallest discrepancies. In Case D, α_d is selected to update pitting corrosion growth and $\{N_{av}, S_{re}\}$ are determined to update fatigue crack propagation. Fig 2 compares prior and posterior probability density functions (PDFs) of key parameters in Case A, demonstrating reduced uncertainty after updating.

Tab.1 Assessment values of updated parameters for Cases A and C based on MAE and Bhattacharyya distance methods.

Cases	Updated parameters	Assessment methods	
		MAE	Bhattacharyya distance
Case A	C_s	0.62	0.22
	D_e	0.37	0.08
	$\{C_s, D_e\}$	0.32	0.05
Case C	C_2	0.31	0.0055
	N_{av}	0.27	0.0043
	S_{re}	1.42	0.14
	$\{C_2, N_{av}\}$	0.36	0.013
	$\{C_2, S_{re}\}$	0.25	0.0038
	$\{N_{av}, S_{re}\}$	0.21	0.0031
	$\{C_2, N_{av}, S_{re}\}$	0.42	0.016

(a)



(b)

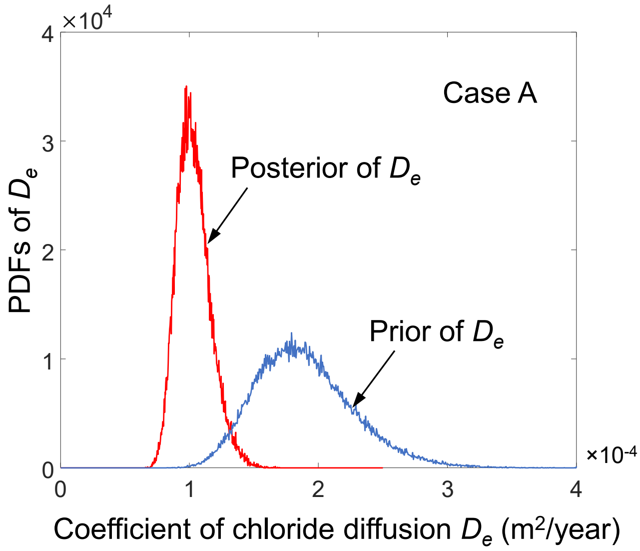
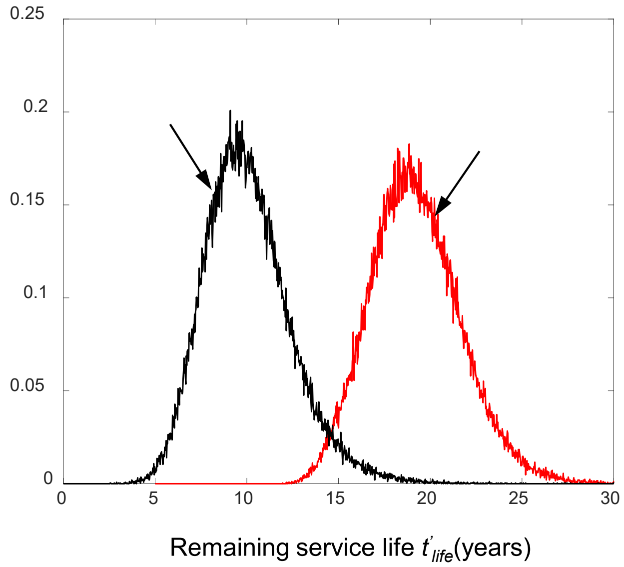


Fig.2 Prior and Posterior PDFs of appropriate updating parameters for Case A (a) surface chloride concentration C_s; (b) coefficient of chloride diffusion D_e.

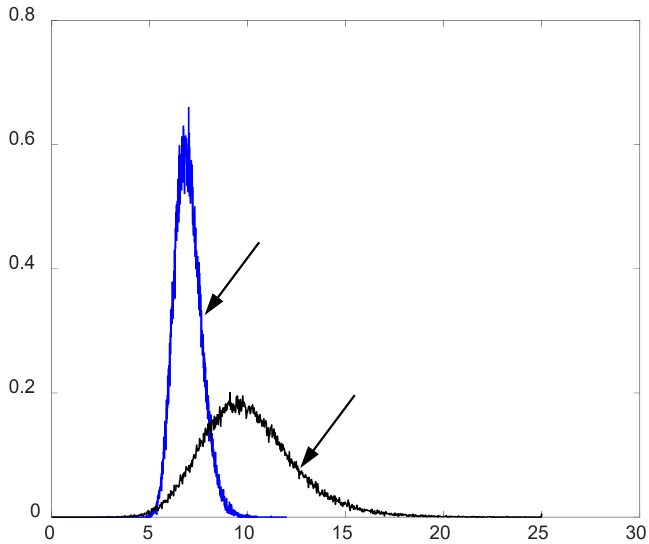
3.3 Remaining service life after updating

The remaining service life t'_{life} after updating is evaluated for Cases A, B and C, defined as the time to reach the critical crack size a_c from the inspection time t_{ins} = 10 years. As shown in Fig 3, Case A yields the largest mean and standard deviation, reflecting no damage detection at inspection and a model still in Stage I deterioration. Case C shows the shortest remaining life due to significant fatigue damage detected. For Case D, analysis of updated propagation rates confirms that corrosion progression had already transitioned to fatigue crack growth by inspection; thus, the remaining service life prediction for Case D matches that of Case C. More details on this study can be found in Ge & Kim (2021b)

(a)



(b)



(c)

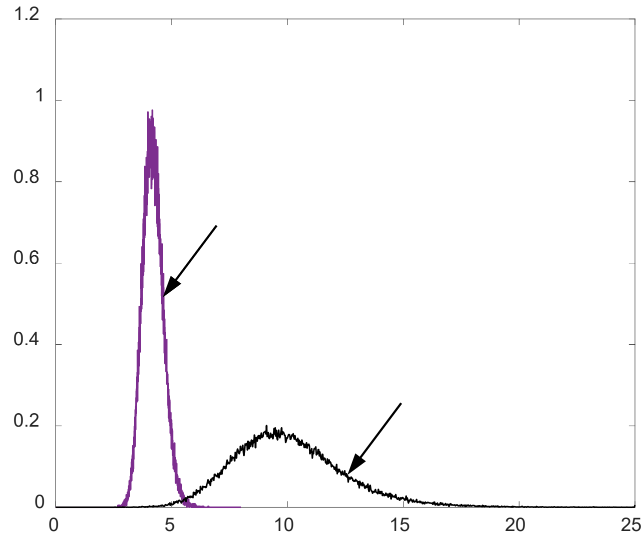


Fig 3 Remaining service life after updating t'_{life}: (a) Case A; (b) Case B; (c) Case C.

4. CONCLUSIONS

This paper presents a probabilistic approach for updating the service life prediction of RC bridges subjected to coupled corrosion-fatigue. The methodology accounts for three deterioration stages and integrates inspection data using Bayesian inference with MCMC. A comparison-based analysis ensures the selection of optimal updating parameters, reducing uncertainty and improving prediction accuracy. The results highlight that coupled corrosion-fatigue damage significantly shortens service life compared to single degradation mechanisms. Appropriate use of multiple inspection outcomes enables timely updates and informed maintenance planning. The proposed framework is broadly applicable to various deteriorating RC structures and can be further enhanced by incorporating factors such as environmental variations and bond degradation effects.

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