MOUNTAIN-PLAINS CONSORTIUM

MPC 23-504 | A. Abdallah, R.A. Atadero, and M.E. Ozbek

LIFE-CYCLE COST IMPLICATIONS OF ALTERNATIVE BRIDGE INSPECTION PLANNING

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Technical Report Documentation Page

1. Report No.	2. Government Accession No.	3. Recipient's Catalog No.
MPC-533		

4. Title and Subtitle	5. Report Date
Life-cycle Cost Implications of Alternative Bridge Inspection Planning	September 2023
	6. Performing Organization Code
7. Author(s) Abdelrahman Abdallah Rebecca Atadero Mehmet E. Ozbek	8. Performing Organization Report No. MPC 23-504
9. Performing Organization Name and Address Colorado State University Dept. of Civil and Environmental Engineering Campus Delivery 1372 Fort Collins, CO 80523-1372	10. Work Unit No. (TRAIS) 11. Contract or Grant No.
12. Sponsoring Agency Name and Address Mountain-Plains Consortium North Dakota State University PO Box 6050, Fargo, ND 58108	13. Type of Report and Period Covered Final Report 14. Sponsoring Agency Code

15. Supplementary Notes

Supported by a grant from the US DOT, University Transportation Centers Program

16. Abstract

Routine bridge inspections in the United States are primarily conducted via visual inspection on a fixed two-year cycle. Although this strategy has generally produced a safe bridge network, a variety of research has been conducted to study enhanced inspection planning processes that could more efficiently use inspection resources, consider the importance and risk associated with structures, and incorporate nondestructive evaluation. This report describes one proposed technique for inspection planning based on the principle that bridge inspections should be conducted when the uncertainty about bridge condition is high and the inspection conducted should collect data that can help reduce the uncertainty about condition. The proposed method is applied to a hypothetical bridge scenario considering both corrosion-induced bridge deck damage and fatigue crack growth in a girder to develop an inspection plan for 20 years. The proposed bridge inspection plan uses variable time periods between inspection and nondestructive evaluation methods. The life-cycle costs of the bridge inspection plan are compared with the life cycle costs of the standard visual inspections on a two-year cycle. Although NDE-based inspections usually cost more than visual inspections, when considered on a life cycle basis, the new inspection plan is cost-effective. The uncertainty-based bridge inspection planning framework is a novel planning approach that offers a multitude of advantages. It provides flexibility to adapt inspection schedules, optimizes resource allocation, mitigates risks, and leads to cost savings. Furthermore, it encourages long-term planning, data-driven decision-making, and adaptive management, ultimately improving safety and environmental considerations. This approach enhances public confidence in bridge infrastructure by demonstrating a commitment to proactive maintenance and resilience. This inspection planning framework helps to conduct bridge inspection only when needed, which will save resources and, with the types of inspection tools, provide the most useful information.

17. Key Word	18. Distribution Statement
asset management, bridges, costs, inspection, life cycle costing, nondestructive tests	Public distribution

19. Security Classif. (of this report)	20. Security Classif. (of this page)	21. No. of Pages	22. Price
Unclassified	Unclassified	39	n/a

Form DOT F 1700.7 (8-72) Reproduction of completed page authorized

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Disclaimer

ABSTRACT

Routine bridge inspections in the United States are primarily conducted via visual inspection on a fixed two-year cycle. Although this strategy has generally produced a safe bridge network, a variety of research has been conducted to study enhanced inspection planning processes that could more efficiently use inspection resources, consider the importance and risk associated with structures, and incorporate nondestructive evaluation. This report describes one proposed technique for inspection planning based on the principle that bridge inspections should be conducted when the uncertainty about bridge condition is high and the inspection conducted should collect data that can help reduce the uncertainty about condition. The proposed method is applied to a hypothetical bridge scenario considering both corrosion-induced bridge deck damage and fatigue crack growth in a girder to develop an inspection plan for 20 years. The proposed bridge inspection plan uses variable time periods between inspection and nondestructive evaluation methods. The life-cycle costs of the bridge inspection plan are compared with the life cycle costs of the standard visual inspections on a two-year cycle. Although NDE-based inspections usually cost more than visual inspections, when considered on a life cycle basis, the new inspection plan is cost-effective. The uncertainty-based bridge inspection planning framework is a novel planning approach that offers a multitude of advantages. It provides flexibility to adapt inspection schedules, optimizes resource allocation, mitigates risks, and leads to cost savings. Furthermore, it encourages long-term planning, data-driven decision-making, and adaptive management, ultimately improving safety and environmental considerations. This approach enhances public confidence in bridge infrastructure by demonstrating a commitment to proactive maintenance and resilience. This inspection planning framework helps to conduct bridge inspection only when needed, which will save resources and, with the types of inspection tools, provide the most useful information.

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EXECUTIVE SUMMARY

This report focuses on planning processes for bridge inspections in the United States and presents a new framework for bridge inspection planning and scheduling using uncertainty quantification. This study aims to address limitations in existing bridge inspection practices that are dependent on visual inspection. These limitations include the variation of condition ratings by different inspectors and the fixed inspection timing. Nondestructive evaluation (NDE) has demonstrated the potential to provide quantitative measures of condition and to measure subsurface defects that cannot be detected with visual inspection. NDE use is still constrained by difficulties in interpreting NDE data and the costs associated with adopting NDE for routine inspections. In addition to adopting new methods for inspection, new ways for inspection scheduling could save resources while still providing necessary information for decision making. The objective of this report is to analyze the life-cycle cost implications of a newly proposed methodology for determining the inspection time and technique.

Chapter 2 of this report provides a brief review of bridge inspection planning research and describes the models for predicting bridge deterioration, quantifying the probability of NDE detection, and analyzing life-cycle cost used in this study. Researchers have used optimization techniques to propose inspection frameworks that minimize life-cycle costs as well as risk and reliability-based techniques to recommend inspection intervals. Mechanistic models to predict bridge deterioration can supplement information about bridge condition and may allow for extended inspection intervals. Models for rebar corrosion-induced damage of concrete bridge decks and fatigue cracking in steel bridge elements are introduced. The quality of an NDE inspection can be described using the probability of damage detection and the accuracy of inspection measurements. Probabilistic models for these parameters are described. The life-cycle cost functions used in this study include the direct cost of inspection, the inspection user cost and the inspection failure cost (costs associated with delayed maintenance or bridge element failure due to an inaccurate inspection).

Chapter 3 introduces the inspection planning framework that has been proposed by the authors and is the subject of life cycle cost analysis (LCCA) in this report. The first steps in the planning framework are to gather variables describing the bridge's structural condition and determine deterioration models that can describe the bridge's condition over time. The deterioration models need to include variables that can be updated with the results of NDE testing. The timing of the next inspection is selected using the deterioration model and random variables to project bridge condition into the future, and the next inspection is conducted when the uncertainty in prediction reaches a threshold value. An NDE method is selected for inspection considering the types of data that can be used to update the bridge condition prediction and inspection cost. After the inspection is conducted, Bayesian updating is used to incorporate the data into updated predictions of bridge condition, which allows for the selection of the next inspection time.

The planning procedure described in Chapter 3 is used in an application example in Chapter 4. The example bridge has a reinforced concrete deck and steel girders. Deterioration models for corrosion of rebar in the RC deck and fatigue cracking of the girders are both used to predict bridge condition and the corresponding uncertainty in the prediction. Times determined for the next inspection are compared for corrosion and fatigue cracking, and the inspection timing is set considering which type of deterioration most impacts the bridge's safety. The application example steps through several hypothetical bridge inspection cycles to demonstrate how cost and probability of detection of different NDE methods can be considered in the inspection planning process.

Based on the simulated inspection plan developed in Chapter 4, probabilistic LCCA is conducted in Chapter 5 to compare the costs of biannual routine visual inspections with the costs of an inspection plan developed using the method described in this report. Indirect user costs are a significant part of total costs, which can vary greatly from site to site. The impact of different discount rates, traffic growth, inspection duration, and detour lengths are considered. The potential to have fewer inspections during the service life of the bridge provides the potential for lifetime cost savings, which can be large when indirect costs are included in the analysis, even though a single NDE inspection is more expensive than a single visual inspection.

This report concludes by summarizing findings from the application example and identifying areas for future research that would help improve the inspection planning process described here. Key areas for additional research include further refinement of deterioration models, study of how uncertainty thresholds are set, the role of expert judgment, including the effect of maintenance in inspection planning, and the complexities of inspection budgeting when inspection frequencies and methods become variable.

1. INTRODUCTION

1.1 Problem Statement

Adequate and prompt bridge maintenance can enhance the performance of a bridge and extend its service life while preventing any catastrophic events and optimizing its life-cycle cost (ASCE, 2020). As maintenance decisions mainly depend on inspection results, accurate and timely evaluation of bridges is important in managing bridge maintenance and rehabilitation strategies. This report focuses on bridge inspections in the United States and presents a new framework for bridge inspection planning and scheduling using uncertainty quantification. Also, a probabilistic life cycle cost analysis (LCCA) to study the variables that have the most effect on inspection costs is conducted.

Currently, bridge inspections are conducted based on the National Bridge Inspection Standards (NBIS), which were developed by the Federal Highway Administration (FHWA) after the collapse of the Silver Bridge in 1967 (Dorafshan & Maguire, 2018). The FHWA requires that for almost all bridges a routine inspection should be conducted every two years using visual inspection, and for structurally deficient bridges, annual inspections should be conducted (FHWA, 2012). Inspection findings are used by bridge owners to rate the bridge condition based on the National Bridge Inspection (NBI) coding guide (FHWA, 1995) or the AASHTO Manual for Bridge Element Inspection (MBEI) (AASHTO, 2013).

Although the current inspection programs have helped bridge owners manage their bridge networks, there are still limitations in these programs and room for improvement that the study herein tries to attain. For example, visual inspections are highly subjective and depend mainly on the inspectors' experience (Bu et al., 2014; Lin, Pan, Wang, & Li, 2019). Also, visual inspections are limited to surface defects, and can only locate subsurface deteriorations (i.e., rebar corrosion, delamination, and voids) that have reached a significant level and have emerged to the surface of the bridge element, (Kim, Gucunski, & Dinh, 2019; Morcous, Lounis, & Cho, 2010), which can cause delayed or expensive maintenance actions.

Another major concern about the current bridge inspection system is inspection timing, as was addressed in ASCE/SEI-AASHTO-Ad-hoc (2009). The fixed two-year interval was decided based on engineering judgment 50 years ago (Washer, Connor, Nasrollahi, & Provines, 2016). Many studies do not consider the fixed inspection interval the most efficient scheduling strategy for some bridges and suggest the fixed cycle is sometimes unnecessary and a waste of resources (Atadero, Jia, Abdallah, & Ozbek, 2019; Nasrollahi & Washer, 2015). A variable inspection interval depending on the age and condition of the bridge might be more cost-effective and able to capture the deterioration process more accurately (Soliman & Frangopol, 2014).

A significant body of research has investigated the application of a variety of nondestructive evaluation (NDE) techniques to bridge inspection (particularly bridge decks) (Gucunski et al., 2013). Beyond visual inspection, the potential of NDE methods to enhance our understanding of bridge condition has been demonstrated; but challenges remain in the effective utilization of NDE by DOTs. One significant limitation is the difficulty in interpretation of collected data that limits the accuracy of NDE techniques (Hesse, Atadero, & Ozbek, 2015). Cost is another issue limiting the application of NDE (beyond visual inspection) by state transportation agencies. States currently have well established practices by which they conduct and pay for routine visual inspections. Introducing other NDE methods as routine is challenging because these methods are not yet in a position to replace visual inspection, and thus are viewed as an additional cost. Paying for NDE might reduce the funding available to conduct preventive maintenance or repair structures. On the other hand, NDE might be a cost-saving measure if its findings are accurate enough to prevent mobilizing a large construction crew for a limited amount of repair work, or if the use of NDE ensures that repairs are conducted in a timely fashion while repair costs are still lower (i.e., the structure has not deteriorated to a poorer condition where the cost of repair is significantly higher). In order for transportation agencies to adjust their inspection practices to best use the capabilities of various NDE techniques beyond visual inspection, they must have confidence in the methods to inspect the bridge and an understanding of the life-cycle cost implications of NDE use.

In addition to adopting new methods for inspection, new ways for inspection scheduling could save resources while still providing necessary information for decision making. Deterioration models are commonly used to schedule bridge maintenance activities (Kim, Frangopol, & Soliman, 2013). However, deterioration models can also help in selecting the inspection time and adjusting the inspection techniques depending on the predicted bridge condition (Agrawal & Alampalli, 2010; Morcous et al., 2010). For example, if the deterioration model predicted with acceptable accuracy that the bridge condition will remain the same in the next two years, then an inspection can be conducted after more than two years, reducing total inspection cost (Nasrollahi et al., 2015). Parameters used in the prediction model can be highly variable depending on the uncertainty of bridge properties, therefore probabilistic approaches should be considered during the decision process (Biondini & Frangopol, 2016).

1.2 Objectives

The objective of this report is to analyze the life-cycle cost implications of a newly proposed methodology for determining the inspection time and technique. The new methodology integrates information from bridge condition prediction models and NDE inspection data using Bayesian updating. This inspection framework helps improve knowledge about the bridge condition and decision making for repair actions. The fundamental premise of this study is that inspections should only be conducted when the level of uncertainty regarding bridge condition reaches a defined threshold and, by conducting inspections only when needed, life-cycle costs can be reduced.

This study contributes to the bridge inspection field by analyzing an alternative for planning inspections other than the two-year fixed inspection cycle conducted by DOTs. This study will help bridge owners improve the value of inspection data and the utilization of inspection resources by 1) avoiding delayed or unnecessary inspections, 2) utilizing the capabilities of NDE methods, and 3) considering more than one bridge component during the inspection planning process. A probabilistic LCCA is conducted to study the effect of different variables on the inspection procedure and how the new inspection planning framework and replacing visual routine inspections with other NDE methods can reduce the total inspection cost.

In the presented inspection framework, the inspection time is determined by quantifying the uncertainties associated with the prediction model and remaining bridge service life. Selecting the inspection technique depends on accuracy of the inspection procedure and its probability of detection. For demonstration purposes, in the current work, two deterioration mechanisms will be considered at the same time: fatigue crack propagation of steel girders and corrosion of a reinforced concrete deck. NDE inspection results and prediction models will be considered simultaneously to determine inspection timing and techniques in a Bayesian platform using Monte Carlo simulation. Subsequently the life-cycle costs associated with inspection are analyzed.

2. BACKGROUND

This section will provide an overview of the frameworks provided in the literature to help bridge owners schedule inspections. Then the deterioration models, NDE accuracy quantification methods, and cost functions to be used in this study are presented.

2.1 Inspection planning frameworks

There is a growing recognition that bridge inspection practices need enhancement in order to provide the most effective use of maintenance and repair budgets and maintain a safe and reliable transportation system (ASCE/SEI-AASHTO-Ad-hoc, 2009). Therefore, the last few decades have seen the field of bridge inspection planning as an active area of bridge asset management research. However, in our research we focus on integrating the inspection decision-making process with the bridge life-cycle cost.

Soliman, Frangopol, and Kim (2013) formulated an optimization problem to find the optimum inspection timing and techniques that will have the highest probability of detecting fatigue cracks before reaching a critical crack width. Kim et al. (2013) used life-cycle cost analysis and probabilistic models to find the appropriate inspection procedure while minimizing the inspection cost for fatigue sensitive ship hull structures and RC bridge decks exposed to corrosive environments. Kim et al. (2013) found that using NDE methods with a high probability of damage detection early in the bridge deck service life can help reduce the life-cycle cost of the bridge management process by avoiding delays and expensive maintenance actions.

A risk-based inspection framework has been provided by Washer et al. (2014), the basis of this framework is to schedule inspection intervals based on expert judgment about the likelihood of damage to occur and the consequence of this damage. This framework was approved by the FHWA as alternative for scheduling routine inspections in the recent NBIS updates (FHWA, 2019). Parr, Connor, and Bowman (2010) also used expert judgment to schedule fracture critical inspections for steel bridges. The study found that inspection intervals can be extended from two years to 10 years for certain bridges. Liu and Frangopol (2019) presented a risk-based framework for inspection scheduling and commented on how bridge owners' attitude toward risk and bridge maintenance can have an effect on inspection time. Risk-averse bridge owners will tend to choose shorter inspection intervals.

Reliability-based inspection programs focusing on the time of structure failure have been developed to model the effect of certain deterioration mechanisms on the structure's capacity and to manage inspection intervals and methods. Kwon and Frangopol (2011) proposed an approach that uses mechanistic models to predict fatigue crack growth propagation and to schedule inspections when there is a high probability of damage detection during inspections. Abdallah, Atadero, and Ozbek (2021) and Orcesi and Frangopol (2011) incorporated lifetime reliability functions in the inspection planning process to schedule inspections and choose the appropriate inspection method based on the probability of transition in the bridge condition.

Nasrollahi et al. (2015) presented a study where bridge inspection intervals were decided using statistical analysis of archived NBI rating data to determine the length of time a bridge will stay in a certain condition before deteriorating to a lower condition and performing inspections during this time span. Nasrollahi et al. (2015) indicated that for bridges in good condition, the two-year inspection cycle can be short and result in unnecessary inspections, and for other bridges in worse condition it can be long; therefore, inspection cycles should be based on the bridge condition. Atadero et al. (2019) used uncertainty quantification methods in order to determine bridge inspection and time. Also, inspection results and Bayesian updating were used to update prediction model estimations.

2.2 Mechanistic Deterioration Models

Modeling and forecasting of bridge performance and deterioration is important for bridge asset management. Predicting the deterioration process of a bridge can help in inspection planning and determining the appropriate time for intervention, saving a significant amount of resources while still providing necessary information. Deterioration models are commonly used to predict the condition of a bridge and to plan and optimize the timing of bridge maintenance, repair, and replacement decisions (Kim, Frangopol, & Soliman, 2013; Soliman & Frangopol, 2013). However, they can also be used to provide information that could be useful for planning inspections (Morcous et al., 2010). For example, using deterioration models to consider the likelihood of a significant reduction in bridge condition during a two-year inspection cycle might allow for longer inspection intervals, reducing costs and risks associated with the current uniform inspection program (Nasrollahi & Washer, 2015). Predicting the performance level of a bridge is affected by many uncertainties, including the material properties of the bridge and environmental loads surrounding the bridge; therefore, probabilistic deterioration models should be used (Biondini & Frangopol, 2016; Morcous et al., 2010). The models used in this research are mechanistic models to capture the corrosion behavior and fatigue stresses of concrete and steel members.

2.2.1 Corrosion Deterioration Model

The deterioration of reinforced concrete (RC) structures occurs mainly because of reinforcement corrosion, which can result from carbonation or chloride ion penetration (NCHRP, 2006). This report is concerned with corrosion of RC structures due to chloride ion penetration. This deterioration mechanism consists of two main stages: corrosion initiation and propagation (Enright & Frangopol, 1998; Mori & Ellingwood, 1994). Corrosion of steel reinforcement initiates once the chloride concentration at the rebar level reaches a certain threshold (Tuutti, 1982). The time for corrosion initiation can be predicted using the following deterioration model Equation (2.1) (Crank, 1975; Vu & Stewart, 2005):

$$T_{CI} = \frac{x^2}{4k_{D_c} D_c}\left[erf^{-1}\left(\frac{C_0 - C_{th}}{C_0}\right)\right]^{-2} \tag{2.1}$$

In which T_{CI} is the corrosion initiation time associated with the critical chloride content C_{th}, C_0 is the surface chloride content, D_c is the diffusion coefficient, k_{D_c} is model error factor for the diffusion coefficient, $erf^{-1}(.)$ is the inverse of the error function and x is the depth from the concrete surface.

Corrosion propagation in the RC structure can cause loss of reinforcement cross-sectional area, reduction of bond strength, and cracks in the concrete cover. This deterioration phase can be represented using uniform corrosion or pitting corrosion deterioration models (Val & Melchers, 1997). Based on the studies conducted by (Stewart, 2004), pitting corrosion has a higher effect on the capacity of the RC structure, leading to a larger reduction in area of steel reinforcement. The pitting corrosion depth (PCD) in the steel reinforcement can be estimated as a time dependent deterioration using Equation (2.2) (Val et al., 1997):

$$PCD(t) = r_{corr} V(t - T_{CI}) \text{ for } t > T_{CI} \tag{2.2}$$

Where r_{corr} is the rate of corrosion, and V is the ratio between the maximum pit depth to the mean pit depth.

2.2.2 Fatigue Cracking Deterioration Model

Fatigue is considered one of the main reasons for failure and fracture of steel structures. Crack propagation due to fatigue is a result of cyclic stress such as traffic loads on steel bridges and wave loads on naval ships (Connor & Fisher, 2006). The rate of fatigue crack propagation is affected by the location and geometry of the steel detail, material type, in-service environment, and initial cracks due to welding quality, fabrication, and construction (Fisher, 1984). Using linear elastic fracture mechanics, the time T_a required for a crack to propagate from an initial crack size a_0 to reach a certain crack size a_t under a constant number of annual loading cycles N can be predicted using the following deterioration model Equation (2.3) (Kim & Frangopol, 2011; Paris & Erdogan, 1963):

$$T_a = \frac{1}{N.C.S_r^m} . \int_{a_o}^{a_t} \frac{1}{\left(\xi(a).\sqrt{\pi a}\right)^m} da \tag{2.3}$$

Where S_r is the constant amplitude stress range, C and m represent the material properties as the fatigue growth parameter and the fatigue exponential variable, respectively. $\xi(a)$ is the geometry function, which can be calculated as following Equation (2.4) (Irwin & Paris, 1971):

$$\xi(a) = \xi_e \times \xi_d \times \xi_f \times \xi_s \tag{2.4}$$

In which $\xi_e, \xi_d, \xi_f, \xi_s$ are the correction factors with regard to the elliptical crack shape, contact surface, crack finite width, and non-uniform stress acting on the crack, respectively. For detailed calculations regarding the geometry function refer to Fisher (1984).

Due to the variation in the input parameters of the deterioration models, Monte Carlo simulation can be used to estimate the probability density function (PDF) of T_{CI}, the PCD at a certain time, and T_a while assuming the input parameters as random variables (Kim et al., 2013).

2.3 Quantifying Uncertainty in the NDE Inspection

Two main criteria can be used to describe the quality of an NDE technique, the probability of damage detection and the accuracy of the inspection measurement (Chung, Manuel, & Frank, 2006; Zheng & Ellingwood, 1998). In fact, both aspects represent the main sources of uncertainty associated with NDE inspection (Zheng et al., 1998).

2.3.1 Probability of Damage Detection

The probability of damage detection (PDD) can be described as the probability of detecting a flaw with a certain size (Zheng et al., 1998). The higher the PDD of an NDE method at a predefined level of damage, the higher the quality of the inspection (Kim et al., 2019). PDD can impact inspection and maintenance decision making in several ways. Failing to detect damage can result in delayed maintenance, leading to structure failure or more costly maintenance (Kim et al., 2011). False positives might result in unnecessary maintenance, which could damage the structure and waste resources (Mori et al., 1994). Inspection visits could be wasted if they are scheduled during times in the bridge's service life when flaws will have a low probability of detection.

Among the most widely used in PDD functions are the log-normal distribution function and the log-logistic function (Chung et al., 2006; Kim et al., 2019; Soliman et al., 2013; Zheng et al., 1998). The two functions are respectively demonstrated as following Equations (2.5 and 2.6):

$$PDD_1 = 1 - \Phi\left(\frac{\ln(y(t_{Ins})) - \lambda}{\zeta}\right) \tag{2.5}$$

$$PDD_2 = \frac{\exp\left(\alpha + \beta.\ln(y(t_{Ins}))\right)}{1 + \exp\left(\alpha + \beta.\ln(y(t_{Ins}))\right)} \tag{2.6}$$

$\Phi(.)$ is the standard normal cumulative distribution function, $y(t_{Ins})$ is the predicted defect size at time of inspection, λ is the location parameter and ζ scale parameter for PDD curve, while α and β are the parameters for plotting the log-logistic curve. Note that λ, ζ, α and β are different for each inspection technique and depend on the NDE quality. These parameters can be obtained from experimental studies like the hit-and-miss method and signal response stimuli (Chung et al., 2006; Hovey & Berens, 1988).

2.3.2 Accuracy of Inspection Measurement

The detected structure defect is usually measured in the presence of inaccuracies and noise during inspection. The accuracy of an NDE technique and the relation between the measured defect and its actual size can be expressed using the following linear regression analysis Equation (2.7) (Zheng et al., 1998):

$$Y(t_{Ins}) = \psi_1 + \psi_2 a_M(t_{Ins}) + e \tag{2.7}$$

Where $Y(t_{Ins})$ the actual defect size at inspection time t_{Ins} , $a_M(t_{Ins})$ is the measured defect during inspection, ψ_1 and ψ_2 are regression parameters that need to be calibrated according to the inspection technique (i.e., NDE method) and e is the measurement error described as a normal random variable with a zero mean and a standard deviation σ_e that varies according to the accuracy of the inspection and the geometry of the analyzed element (Atadero et al., 2019; Zheng et al., 1998). Overall, Equation (2.7) can provide a probabilistic representation of the actual defect $Y(t_{Ins})$, which will follow a gaussian distribution with a mean $\psi_1 + \psi_2 a_M(t_{Ins})$ and a standard deviation σ_e (i.e. $Y(t_{Ins}) \sim N(\psi_1 + \psi_2 a_M(t_{Ins}),$ σ_e)). The higher the accuracy of an NDE the lower is σ_e, which will provide measurements closer to the actual deterioration process providing a higher reduction in the uncertainty and improving planning ability (Haladuick & Dann, 2018).

2.4 Bayesian Updating of Prediction Model Parameters

To reduce the uncertainty in the deterioration model prediction, Bayesian updating can be used to update the prediction model parameters θ by combining the new inspection data with the prior or existing information (Atadero et al., 2019). The posterior or updated distributions for the probabilistic model parameters θ can be estimated using Equation (2.8) (Enright & Frangopol, 1999)

$$P(\theta \mid a_M(t_{Ins})) = \frac{L\left(a_M(t_{Ins}) \mid \theta\right) P(\theta)}{\int L\left(a_M(t_{Ins}) \mid \theta\right) P(\theta) d\theta} \tag{2.8}$$

Where $P(\theta \mid a_M(t_{Ins}))$ is the posterior distribution of model parameter θ, $a_M(t_{Ins})$ is the measured defect during inspection, $L(a_M(t_{Ins}) \mid \theta)$ is the likelihood function of measuring $a_M(t_{Ins})$ for given θ and $P(\theta)$ is the prior distribution of θ. Samples from the updated model parameters can be generated using Markov chain Monte Carlo (MCMC) (Soliman et al., 2014). Further, if $a_{DM}(t_{Ins})$ is the prediction of the deterioration model using θ, then based on inspection accuracy represented in Equation (2.7), the likelihood function can be formulated as (Atadero et al., 2019)

$$L(a_M(t_{Ins}) \mid \theta) = \prod_{i=1}^{n_{Ins}} \left\{ \phi \left[\frac{a_{DM}(t_{Ins}) - \psi_1 - \psi_2 . a_M(t_{Ins})}{\sigma_e} \right] \right\} \tag{2.9}$$

Given the number of inspections n_{Ins}, the likelihood function can be updated as the product of the PDF for each inspection measurement conducted by the same inspection technique, while assuming independence between the measurements.

2.5 Inspection Cost Functions

Generally, bridge inspection cost consists of the equipment, personnel, travel, and access costs without the inclusion of any indirect costs such as user costs (Agdas, Rice, Martinez, & Lasa, 2015). Bridge owners in some situations group bridges geographically to reduce travel cost and inspect several bridges in the same day.

In this study, the cost of the i^{th} bridge inspection $C_{Ins,i}$ will be defined as the summation of the inspection direct cost IDC_i, inspection user cost IUC_i and inspection failure cost IFC_i Equation (2.10).

$$C_{Ins,i} = IDC_i + IUC_i + IFC_i \tag{2.10}$$

The IDC_i will include the equipment, personnel, and access costs. The equipment cost depends on the NDE used during inspection, and it includes the operating cost of the equipment and software and maintenance costs. The personnel cost includes the fees for inspectors, inspection data analysis, and reporting. The access cost includes traveling to the site, renting a snooper to reach certain bridge locations, and maintenance of traffic (MOT) cost, which is required for managing traffic during inspection (Taylor, Qiao, Bowman, & Labi, 2016).

The IUC_i considers vehicle operating and traffic delay cost due to lane closure or detouring during inspection, accident costs, and environmental costs, which are caused by air pollution due to traffic delay (i.e. $IUC_i = C_{TL} + C_D + C_c + C_{Env}$). The traffic delay cost at the inspection zone is quantified as (Stein, Young, Trent, & Pearson, 1999):

$$C_{TL} = [c_w O_c (1-s) + (c_c O_t + c_g) s] \times TL \tag{2.11}$$

Where C_{TL} is traffic delay cost, c_w is average wage per hour , c_c is average compensation per hour for truck drivers, c_g is time value of goods transported, O_c is average occupancies for cars, O_T is average occupancies for trucks, s is the ratio of the average daily truck traffic to the average daily traffic, and TL is time lost due to traffic delay, which can be expressed as the following (Shiraki et al., 2007):

$$TL = IH \times ADT \times (\frac{l}{v_z} - \frac{l}{v_f}) \quad (2.12)$$

In which IH is the inspection duration, ADT is average daily traffic, v_f is freeway speed, v_z is inspection zone speed, and l is the length of the inspection zone. The extra running cost due to detouring, if required, is calculated using Equation (2.13) (Stein et al., 1999):

$$C_D = C_{VR} \times l_d \times ADT \times IH \quad (2.13)$$

Where C_{VR} is vehicle running cost; and l_D is the detour length. The crash cost at the inspection zone can be estimated using Equation (2.14) (Mallela & Sadavisam, 2011):

$$C_c = IH \times ADT \times CR \times \frac{l + l_d}{1.609} \times C_a \quad (2.14)$$

Where C_c is the crash cost at the inspection zone, CR is the crash rate, and C_a is the average human crash cost. The environmental cost is estimated based on (Kendall, Keoleian, & Helfand, 2008):

$$C_{Env} = ADT \times (l + l_d) \times IH \times [En_{dc}(1-s) + En_{dt}s] \times \frac{En_{SD} - En_{SO}}{En_{SO}} \times c_{em} \quad (2.15)$$

Where C_{Env} is the environmental cost due to delayed traffic and inspection work; En_{dc} is environmental metric per unit distance for cars, quantified as the carbon dioxide emissions per kilometer; En_{dt} is environmental metric per unit distance for trucks; En_{vz} is carbon dioxide emissions per kilometer at restricted speed; En_{vf} is carbon dioxide emissions per kilometer at free speed; and c_{em} is the cost value of carbon dioxide emissions.

The inspection failure cost (IFC_i) arises from failing to detect damage during inspection and is estimated as the following:

$$IFC_i = (1 - PDD) \times C_{LO} \quad (2.16)$$

In which C_{LO} is the cost of losing an opportunity to perform a timely maintenance action due to misleading or delayed inspections. In this study, C_{LO} will be quantified as the difference between the cost of reactive repair (e.g., replacing bridge deck) and the cost of proactive repair (e.g., adding protective sealant on deck surface) (Kim, Frangopol, & Soliman, 2013; Soliman & Frangopol, 2013).

Finally, over the analyzed bridge service life, the inspection life-cycle cost C_{LCC} can be represented as:

$$C_{LCC} = \sum_{i=1}^{n} \frac{C_{Ins,i}}{(1+r)^{t_{Ins,i}}} \quad (2.17)$$

Where n is the number of inspections, r is the money discount rate, $t_{Ins,i}$ and $C_{Ins,i}$ are the inspection time and cost of the i^{th} inspection, respectively. In this report, cost parameters will be considered as random variables to consider the uncertainty associated with each input parameter or cost.

3. INSPECTION PLANNING FRAMEWORK

The proposed inspection planning process is conducted with the aim of finding the appropriate inspection time and technique. The framework incorporates the information provided by deterioration models (e.g., Equations 2.1-2.3) and NDE inspections and integrates the information through a Bayesian process (Atadero et. al., 2018).

3.1 Analyzing Bridge Properties and Choosing Appropriate Deterioration Models

The framework starts by analyzing the structure properties, in-service environment, inspection and maintenance records, and the deterioration mechanisms that are most likely to affect the bridge performance. Based on the defined deterioration mechanisms, the appropriate prediction models can be adopted. In this framework, which considers both the time of inspection and type of inspection as selections to be made, the deterioration models must be able to describe and predict the uncertainty in the time-dependent deterioration process. Moreover, the proposed framework is an ongoing process and not just a one-time computation, and the frequency and type of inspection are expected to change as the bridge ages. To demonstrate the potential life-cycle cost savings of customized inspection timing and method, it is essential that the uncertainty in the deterioration model prediction can be improved using on-site inspection data. For example, in the corrosion model presented in section 2.2.1, the chloride content or concrete cover can be inspected and updated to reduce the uncertainty regarding their variability, thus improving model predictions about bridge condition. In this research, two bridge deteriorations will be analyzed: the corrosion of the reinforced concrete deck and fatigue crack propagation in the steel girders.

To account for the uncertainty in the deterioration process, the model parameters, θ, should be considered as random variables. Using computational methods (e.g., Monte Carlo simulation), the deterioration models will be utilized to predict the structural condition through time by propagating the uncertainty in the model parameters. The time to reach a certain bridge condition can be probabilistically represented using a PDF or characterized using a mean μ and standard deviation σ.

3.2 Choosing Inspection Time Based on Uncertainty Threshold

Determining the next inspection time (t_{Ins}) relies on the level of uncertainty in the prediction model output (e.g., bridge condition) at different time intervals. The uncertainty associated with model output or the condition of the structure at different time intervals (t) can be quantified using two approaches. The first is by using statistical descriptors such as the standard deviation $\sigma_y(t)$ or coefficient of variation $COV_y(t) = \sigma_y / \mu_y$. Whenever the uncertainty in the bridge condition represented by $\sigma_y(t)$ exceeds a defined threshold σ_{th}, a bridge inspection should be performed. The second method is based on the probability of reaching a certain bridge stage or condition $P_y(t)$, which can be obtained from the cumulative density function (CDF) and used as another representation for uncertainty. Based on a defined probability threshold P_{th}, if $P_y(t) \geq P_{th}$ then inspection should be considered (Atadero et al., 2019).

The framework presented here provides a lot of flexibility for bridge owners, as selection of uncertainty thresholds P_{th} and σ_{th} depends mainly on their attitudes toward uncertainty. This flexibility provides bridge owners with a practical and innovative method for scheduling inspections, which can be adjusted for different types of bridges and agency requirements. The number of inspections conducted through the service life of the bridge relies on the value of the uncertainty threshold. Lower values of P_{th} or σ_{th} can lead to more inspections (Atadero et al., 2019). Attributes such as the quality of bridge construction, age, failure cost, and consequences of deteriorating bridge performance can help decide the acceptable level of uncertainty. Further information on how to choose the uncertainty thresholds can be found in Abdallah et al. (2021).

Bridges may also be subject to several modes of deterioration simultaneously. For example, if two deterioration mechanisms g_1 and g_2 affect the bridge performance, then a bridge inspection is to be considered whenever σ_{g_1} or σ_{g_2} reach σ_{th} at inspection time $t_{Ins}^{g_1}$ and $t_{Ins}^{g_2}$. A conservative decision is that t_{Ins} should be taken as the smaller of $t_{Ins}^{g_1}$ and $t_{Ins}^{g_2}$ (i.e., $t_{Ins} = \min\left\{t_{Ins}^{g1}, t_{Ins}^{g_2}\right\}$). However, several aspects should be considered before choosing the conservative choice, for example, which deterioration mode has the highest effect on the structure capacity and probability of bridge failure. Also, without affecting the bridge integrity, if delaying an inspection (i.e., $t_{Ins} = \max\left\{t_{Ins}^{g1}, t_{Ins}^{g_2}\right\}$) will assure the availability of NDE equipment or even enhance its PDD leading to a better quality of inspection and lowering the probability of inspection failure, then delaying the inspection and delay cost can be considered.

3.3 Select Appropriate NDE Method for Next Inspection

After choosing the inspection time, the next step is to choose the inspection technique (i.e., NDE method) that can best help reduce the uncertainty about bridge condition. First, a bridge inspector should decide on the parameters that can be measured using a well-established NDE. The measured defect can be an input parameter in the prediction model such as the surface chloride concentration C_0 in Equation (2.1) or the model output, e.g., the predicted fatigue crack size a_t using Equation (2.3). If the prediction model has more than one parameter that can be measured, a sensitivity analysis can be used to find the parameters that have the highest effect on the prediction model certainty and prioritize inspection measurements.

Once key inspection parameters and corresponding NDE techniques are selected, the quality of the inspection method represented by the PDD (Equation 2.5 and 2.6) or accuracy (Equation 2.7) can then be used to rank the available NDE methods. For example, if the prediction model predicted a low size crack at t_{Ins}, then an NDE with a high PDD is preferred. However, the cost of the NDE mainly depends on the quality of the inspection, so a high quality NDE might be expensive. According to budget constraints and inspection cost, a bridge inspector should decide which NDE to use during inspection. These cost decisions should not only consider the direct cost of the inspection, but also the life-cycle cost implications of the data collected from the inspection.

3.4 Analyze Inspection Data and Prediction Model

After collecting the new inspection data, Bayesian updating will be used to update the prediction model parameters by incorporating the prior information with the new inspection data represented in the likelihood function Equation (2.9). The updated model parameters will be used in the new prediction to propagate uncertainty and select the next inspection time.

4. APPLICATION EXAMPLE

4.1 Bridge Description

The proposed inspection planning framework is applied to a continuous steel plate girder bridge that spans over local roads and connects between two major cities. The superstructure of the bridge consists of four steel girders carrying a reinforced concrete deck. The spacing between the steel beams is 3 m and the thickness of the reinforced concrete deck is 20 cm, with a concrete cover of 5 cm. The example focuses on the corrosion of the top transverse reinforcement of the concrete deck and the fatigue detail shown in Figure. 4.1. The fatigue sensitive detail is a bottom web gap located at the end of the transverse plate of the exterior girder. Due to induced buckling stresses, this detail is known for substandard fatigue behavior (Connor & Fisher, 2001)

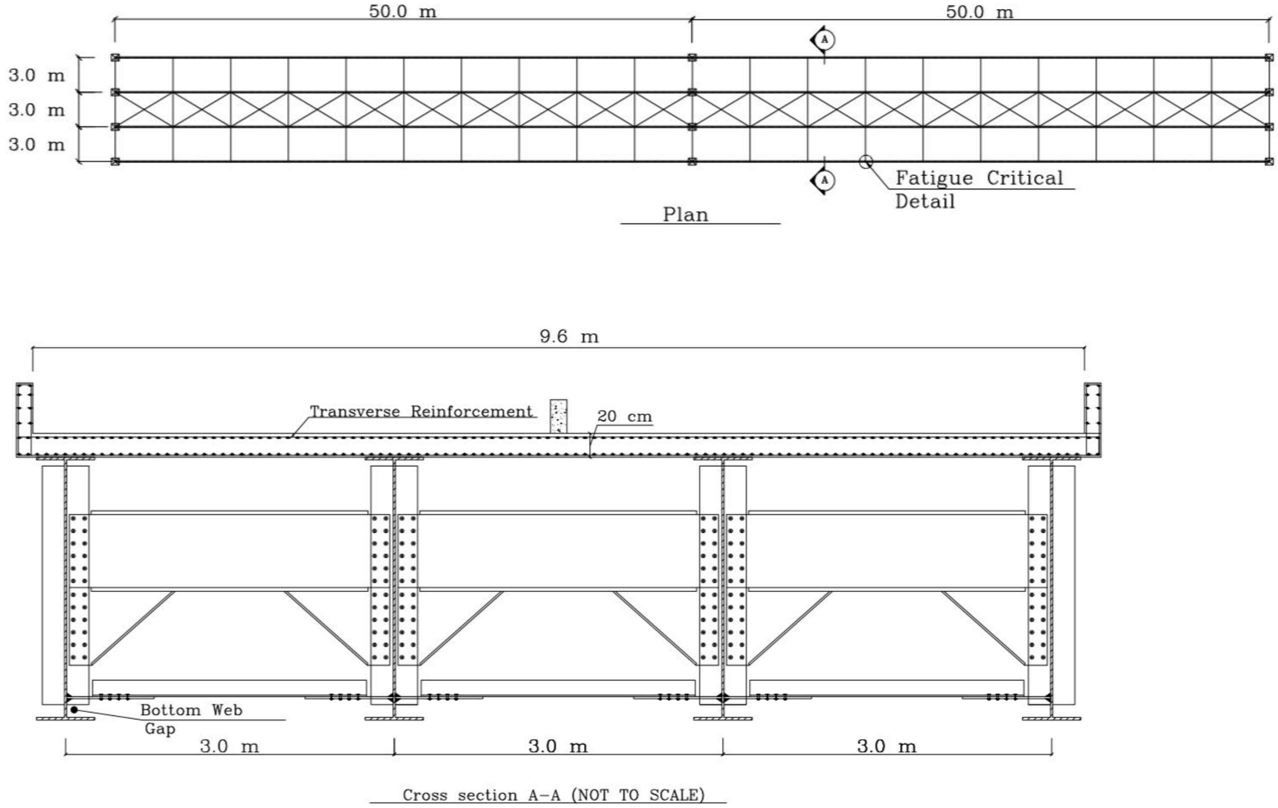

Figure 4.1 Bridge plan view and cross-section

4.2 Predicting Corrosion Initiation Time and Fatigue Crack Propagation with Time

For illustration purposes, it is assumed that the bridge is new, and the chloride content at the rebar level is negligible and the average surface chloride concentration C_0 is 0.13% relative to concrete weight. Regarding fatigue, the size of the initial crack in the girder due to fabrication is estimated to have a lognormal distribution with a mean of 1 mm and COV of 0.2. Corrosion initiation time, pitting corrosion propagation, and the fatigue crack growth will be predicted from the beginning of the bridge service life using Equations. (2.1-2.3), respectively. The random variables used in the equations are provided in Table 4.1.

Table 4.1 Values of random variables in bridge deterioration models based on information in Akgül & Frangopol (2005), Kim et al. (2013), Soliman et al. (2013), and Vu & Stewart (2000)

Variable	Notation (units)	Mean	COV	Type of distribution
Depth from concrete surface	x (mm)	50	0.2	Lognormal
Surface chloride content	C_0 (%)	0.13	0.1	Lognormal
Diffusion coefficient	D_c (mm^2/year)	110	0.1	Lognormal
Critical chloride content	C_{th} (%)	0.043	0.1	Lognormal
Rate of corrosion	r_{corr} (mm/year)	0.065	0.2	Lognormal
Ratio between the maximum pit depth to the mean pit depth	V	6	0.1	Normal
Initial bar diameter	d_{bar} (mm)	20	0.05	
Model error factor for diffusion coefficient	k_{D_C}	1	0.2	Lognormal
Constant amplitude stress range	S_r (MPa)	34.5	0.1	Rayleigh
Fatigue growth parameter	C	2.18×10^{-13}	0.2	Lognormal
Fatigue exponential variable	m	3	0.1	Normal
Annual loading cycles	N (cycles/year)	2.74×10^{13}	0.1	Lognormal
Initial crack size	a_0 (mm)	1	0.2	Lognormal
Critical crack size	a_{cr} (mm)	5	--	--

Corrosion is assumed to initiate when the chloride content at the rebar level reaches 0.043% (Vu et al., 2005) (i.e., 1 kg/m^3 for a 2,320 kg/m^3 concrete). As for fatigue, the critical crack size a_{cr} considered here is 5 mm, after which cracks will be visually detected and maintenance action should be performed (Soares & Garbatov, 1996). As shown in Figure 4.2, using a Monte Carlo simulation with 100,000 samples, the mean and standard deviation of corrosion initiation time T_{CI} are 13.75 years and 7.50 years, respectively, while the mean and standard deviation of the time for critical crack sizes to reach 5 mm are 13.00 years and 6.75 years, respectively.

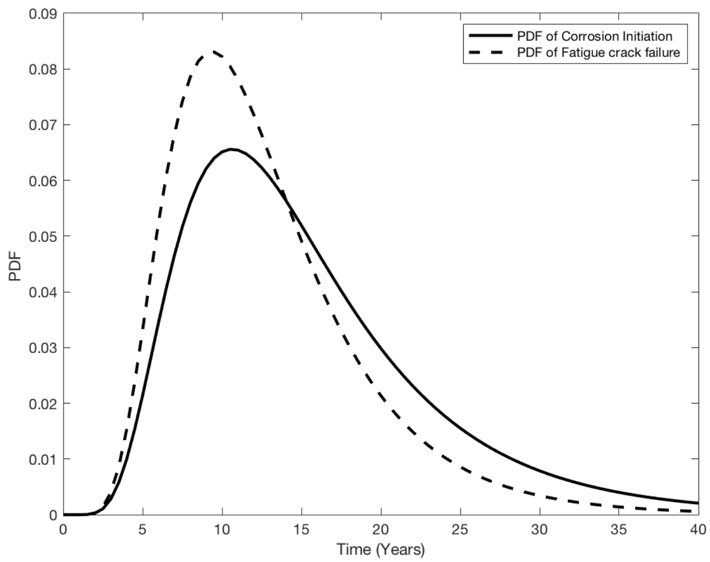

Figure 4.2 PDF of corrosion initiation time and time to reach the fatigue crack size for maintenance

In this example, to quantify uncertainty in the corrosion deterioration process, the standard deviation $\sigma_{T_{Ch}}$ of the time required for a certain chloride concentration to reach the rebar level will be used. Regarding fatigue, the standard deviation σ_{T_a} for the time required to reach a predicted crack size a_t will be utilized for fatigue crack propagation. This means when $\sigma_{T_{Ch}}$ or σ_{T_a} exceed the threshold standard deviation σ_{th} a bridge inspection should be considered. Results of uncertainty propagation for both deterioration mechanisms are summarized in Tables 4.2 and 4.3.

Table 4.2 Predicted chloride concentration at rebar level at different time intervals

Chloride concentration at rebar level (%)	$\mu_{T_{Ch}}$ (years)	$\sigma_{T_{Ch}}$ (years)
0.01	4.00	2.00
0.02	6.25	3.25
0.03	9.00	4.50
0.043	13.75	7.50

Table 4.3 Fatigue crack propagation with time

Crack size a_t	μ_{T_a} (years)	σ_{T_a} (years)
1.5 mm	3.25	2.50
2 mm	5.50	3.50
2.5 mm	7.50	4.25
3.5 mm	10.00	5.00
4 mm	11.25	5.50
4.5 mm	12.00	6.00
5 mm	13.00	6.75

4.3 Scheduling Next Inspection Time

To choose the suitable inspection time, the value of the uncertainty threshold, which is represented in σ_{th}, must be decided. In this example, the value of σ_{th} will be assumed three years; other values can be chosen based on the bridge owner accepted level of uncertainty. For more information on choosing the uncertainty threshold refer to Abdallah et. al. (2021). Based on the uncertainty threshold value and results shown in Tables 4.2 and 4.3, inspection should be done at year 6.25 according to corrosion deterioration, and at year 5.50 based on fatigue cracking. At years 6.25 and 5.50, $\sigma_{T_{Ch}}$ and σ_{T_a} have exceeded three years with values equal to 3.25 and 3.50 years, respectively. Since both inspection timings are close, and at this stage fatigue cracking is considered more critical to bridge safety, the first inspection in the analyzed service period will be conducted at $t_{Ins,1} = 5.50\,years$.

4.4 Choosing Suitable NDE Technique for Next Inspection

For corrosion initiation, the parameter that can be measured without affecting the integrity of the bridge deck in Equation (2.1) is the surface chloride content C_0 using a chloride ion penetration (CIP) test (NCHRP, 2006). For fatigue cracking, several NDE techniques can be utilized to measure the crack size for the studied detail, such as eddy current inspection (ECI), ultrasonic inspection (UI), magnetic particle inspection (MPI), and liquid penetrant test (LPT) (Chung et al., 2006; Ryan, Mann, Chill, & Ott, 2012). With several feasible options, additional analysis can be used to select the most effective option.

4.4.1 Evaluating the Quality of the Inspection Technique

For the CIP, the PDD will be considered 100% based on the information provided in Zambon, Santamaria Ariza, Campos e Matos, & Strauss (2020). For fatigue inspection techniques, depending on the availability of literature (Chung et al., 2006; Soliman et al., 2013), Equations (2.5-2.6) will be used to calculate the PDD for each NDE using the parameters included in Table 4.4, and the predicted crack size a_t, which should be almost 2 mm (i.e., predicted crack size at 5.50 years is 2 mm). This discussion shows the importance of the deterioration models in choosing not only the inspection time, but the NDE technique by providing the bridge manager with a predicted crack size a_t, which can be used in calculating the PDD of each NDE at the next inspection. This will help optimize inspection cost and ensure the money spent to conduct the NDE inspection produces results that meaningfully increase the understanding of bridge conditions.

Table 4.4 Values of the parameters used to calculate PDD for fatigue inspection techniques (Chung et al., 2006; Soliman et al., 2013)

NDE technique	$PDD_1 = 1 - \Phi\left(\frac{\ln(a_t) - \lambda}{\zeta}\right)$			$PDD_2 = \frac{\exp(\alpha + \beta.\ln(a_t))}{1 + \exp(\alpha + \beta.\ln(a_t))}$		
	λ	ζ	PDD_1	α	β	PDD_2
Magnetic particle inspection (MPI)	NA	NA	--	0.466	0.604	70%
Eddy current inspection (ECI)	-0.968	-0.571	99.8%	NA	NA	--
Ultrasonic inspection (UI)	0.122	-0.305	96%	-0.119	2.986	88%
Liquid penetrant test (LPT)	0.829	-0.423	37.5%	-0.561	0.393	43%

As shown in Table 4.4, different PDD functions can yield different results. Thus, upon the availability of more experimental data, the parameters describing a certain NDE or the functions selected to compute PDD can be updated along with the PDD. According to the calculations in Table 4.4, the ECI has the highest PDD with a value of 99.8% for an expected 2 mm crack size at $t_{Ins,1} = 5.50\,years$. Referring to Equation (2.7), it is assumed that the NDE methods are unbiased with equation parameters $\psi_1 = 0$ and $\psi_2 = 1$. Also, the error associated with the inspection measurement will have a standard deviation σ_e equal to 10% of the detected flaw (i.e., surface chloride concentration and fatigue crack). The effect of the NDE equipment accuracy on the Bayesian updating process will be subsequently addressed.

4.4.2 Estimating Inspection Cost at First Inspection Time

The direct inspection costs of using CIP with either LPT, MPI, UI, or ECI for an eight-hour inspection are $8,950, $9,550, $10,450, and $11,450, respectively. These direct costs include the cost of personnel, NDE equipment, MOT, and renting a snooper and traveling to the site. Details regarding these amounts are discussed in the inspection life cycle cost analysis section. Note that the NDE equipment costs rely heavily on its speed, accuracy, precision, and accessibility (Soliman et al., 2013).

Inspection failure in this study is defined as the failure to detect a bridge deterioration or reporting a deterioration that does not exist. The cost of not detecting a crack during inspection can result in two different decisions by the bridge manager. The first is to believe that there is no flaw in the bridge and the deterioration model is conservative in its predictions and, as a result maintenance actions, can be delayed. In this case, if a flaw does exist, the performance of the bridge will continue deteriorating, resulting in failure, or missing the chance to perform proactive maintenance rather than replacing the whole bridge element. The second possible decision is to refuse to take any risks and performing unnecessary bridge maintenance. Thus, the inspection failure cost IFC will be calculated using Equation (2.16), where C_{LO} is assumed herein to equal $225,000, representing the difference between a replacement maintenance action and a preserving maintenance such as welding a fatigue crack (Kim et al., 2013). Table 4.5, summarizes the cost of the different inspection options

Table 4.5 Inspection cost considering only IDC and IFC

NDE inspection	IDC_1	$IFC_1 = (1 - PDD).C_{LO}$	$IDC_1 + IFC_1$
LPT & CPI	$8,950	$128,250	$137,920
MPI & CPI	$9,550	$67,500	$77,050
UI & CPI	$10,450	$9,000	$19,450
ECI & CPI	$11,450	$450	$11,900

As demonstrated in Table 4.5, considering only the inspection direct cost, using ECI and CPI will be the least favorable choice, while if the expected cost of inspection failure is considered it will be the most preferable option. This is a result of the high PDD associated with ECI compared with other NDE methods. Hence, the inspection at $t_{Ins,1} = 5.50\,years$ will be carried out using ECI and CPI.

4.5 Bridge Performance Updating Using Inspection Results

At $t_{Ins,1} = 5.50\,years$, it is assumed for demonstration purposes that the measured surface chloride concentration C_0 and fatigue crack length a_t are larger than their initial estimated values (i.e., $C_0 = 0.13\%$ and $a_t = 2mm$), such that the mean $\mu^L_{C_0}$ of the measured surface chloride is 0.15% and the standard deviation $\sigma^L_{C_0}$ is equal to 0.015%, while the mean $\mu^L_{a_t}$ and standard deviation $\sigma^L_{a_t}$ of the measured fatigue crack a_t are 2.5 mm and 0.25, respectively. Note that the standard deviation of the measurements depends on the accuracy of the NDE according to Equation (2.7). Based on the new inspection measurements and the prior information of the model parameters indicated in Table 4.1, a posterior PDF for the corrosion initiation time and time to reach the fatigue crack size for maintenance were obtained using Bayesian updating.

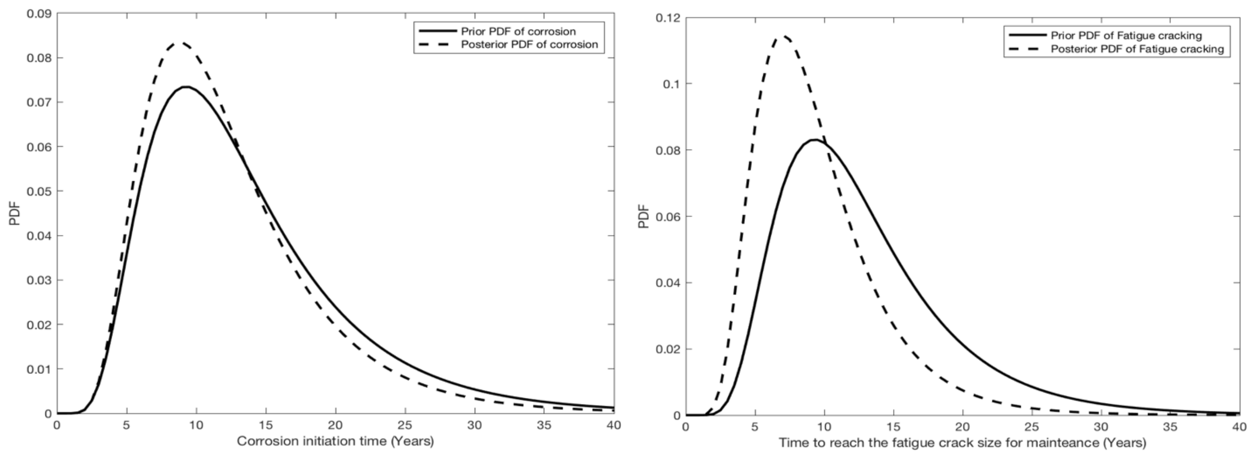

Figure 4.3 (a) Corrosion initiation time after Bayesian updating (b); Time to reach the crack size for maintenance after Bayesian updating

As shown in Figure 4.3, the updated models predicted that corrosion is expected to initiate at year 12.5 with a standard deviation of 6.00 years, and fatigue cracks will reach 5 mm at year 9.5 with a standard deviation of 4.25 years. However, the initial predictions estimated that corrosion will initiate at year 13.75 with a standard deviation of 7.50 years, and cracks will reach 5 mm at year 13.00 with standard deviation of 6.50 years. These updated predictions are based on assumed inspection results but show how new inspection information is important in maintenance management and can change the time or procedure of the repair action. Late maintenance at year 13 could have resulted in increasing the maintenance cost while losing the opportunity to perform a preserving maintenance.

The next inspection time $t_{Ins,2}$ is chosen based on the updated uncertainty propagation results shown in Table 4.6 and Table 4.7. To demonstrate the flexibility of the proposed study, the second inspection will be conducted when $\sigma_{T_{Ch}}$ and σ_{T_a} reach 4 years. Therefore, $t_{Ins,2}$ will be conducted at year 8.75, which is after 3.25 years from the first inspection. In practice, bridge owners could increase the threshold with time when they are more certain of the deterioration model predictions. On the other hand, owners could reduce the threshold because risks of failure increase as the bridge ages and deteriorates with time.

Table 4.6 Predicted chloride concentration at rebar level at different time intervals using updated model parameters

Chloride concertation at rebar level (%)	$\mu_{T_{Ch}}$ (years)	$\sigma_{T_{Ch}}$ (years)
0.02	6.00	2.75
0.025	7.25	3.50
0.03	9.00	4.25
0.035	10.00	5.00
0.043	12.50	6.00

Table 4.7 Fatigue crack propagation with time using updated model parameters

Crack size a_t	μ_{T_a} (years)	σ_{T_a} (years)
3 mm	6.50	3.00
3.5 mm	7.25	3.25
4 mm	8.25	3.50
4.5 mm	8.75	4.00
5 mm	9.50	4.25

At $t_{Ins,2} = 8.75 years$ the expected fatigue crack size is 4.00 mm, hence the UI test will have a high PDD, reaching almost 100%; therefore, based on the PDD and the cost of inspection, the UI test and a CIP test will be used in the second inspection.

4.6 Analyzing the Effect of the NDE Accuracy on Inspection Planning

Subsequent to the inspection at year 8.75, maintenance at year 9.5 is assumed to include adding a sealant to the concrete deck to reduce the corrosion propagation and welding fatigue cracks. The maintenance can be considered as the end of the first phase in the service life of the bridge and the beginning of the second phase, where corrosion of the deck moves from the initiation stage to the propagation stage. In the second phase, pitting corrosion is considered the primary deterioration affecting bridge performance. According to the diameter of the transverse slab reinforcement (i.e., $d_{bar} = 20mm$), the maximum allowable pitting corrosion depth (PCD) considered in this paper will be 4 mm (Gonzalez, Andrade, Alonso, & Feliu, 1995), after which an in-depth maintenance action must be conducted. Based on Equation (2.2) and the values of the parameters indicated in Table 4.1, the predicted time for PCD to reach 4 mm has a mean of 21.50 years and the standard deviation of 3.25 years.

During the maintenance conducted at year 9.5, a linear polarization test (LPR) could be conducted to measure the corrosion rate r_{corr} allowing for an updated and bridge-specific prediction of the time to reach the PCD of 4 mm. To demonstrate the impact of NDE method accuracy, assume that that r_{corr} at $t_{Ins,3}$ was equal to 0.09 mm/year, which is higher than what was initially estimated ($r_{corr} = 0.065mm / year$). To analyze the effect of the accuracy of the NDE technique on the updating process and the inspection planning, four inspection scenarios for the LPR test, as noted in Table 4.8, will be investigated using Equation (2.7), where a_M represents the corrosion rate.

Table 4.8 Parameters of Equation (2.8) with respect to different inspection scenarios

Inspection scenario	$Y(t_{Insp}) = \psi_1 + \psi_2 a_M (t_{Insp}) + e$			
	ψ_1	ψ_2	σ_e	$Y(t_{Insp}) \sim N(\psi_1 + \psi_2 a_M (t_{Insp}), \sigma_e)$
Scenario 1	0	1	$\mathbf{0.1 a_M}$	$Y(t_{Insp}) \sim N(0.09(9.5yrs), 0.009)$.
Scenario 2	0	1	$0.2a_M$	$Y(t_{Insp}) \sim N(0.09(9.5yrs), 0.018)$.
Scenario 3	0	1.2	$0.1a_M$	$Y(t_{Insp}) \sim N(0.108(9.5yrs), 0.009)$.
Scenario 4	0	0.8	$0.1a_M$	$Y(t_{Insp}) \sim N(0.052(9.5yrs), 0.009)$.

In the first and second scenarios, the NDE measurements are assumed to be unbiased with ψ_1 equal to zero and ψ_2 equal to 1, with a low error standard deviation σ_e equal to $0.1a_m$ and high error equal to $0.2a_m$, respectively. In scenario 3, it is assumed that the actual defect Y (in this case the corrosion rate) is larger than what is measured and the NDE technique is biased and underestimates the true bridge condition with a regression line slope ψ_2 equal to 1.2. Conversely, in the fourth scenario it is assumed that ψ_2 equals 0.8, representing a corrosion rate that is smaller than measured by the NDE test.

The probabilistic values of Y will be used as the likelihood functions in the Bayesian updating process. Figure. 4.4a shows the posterior PDF of the r_{corr} associated with each inspection scenario. For example, in the third inspection scenario, the measured r_{corr} will have a mean value $\mu^L_{r_{corr}}$ of 0.108 mm/year and a standard deviation $\sigma^L_{r_{corr}}$ equal 0.009 mm/year. Using these values as the likelihood function will yield a posterior r_{corr} with a mean $\mu^P_{r_{corr}}$ and a standard deviation $\sigma^P_{r_{corr}}$ equal to 0.089 and 0.0074, respectively.

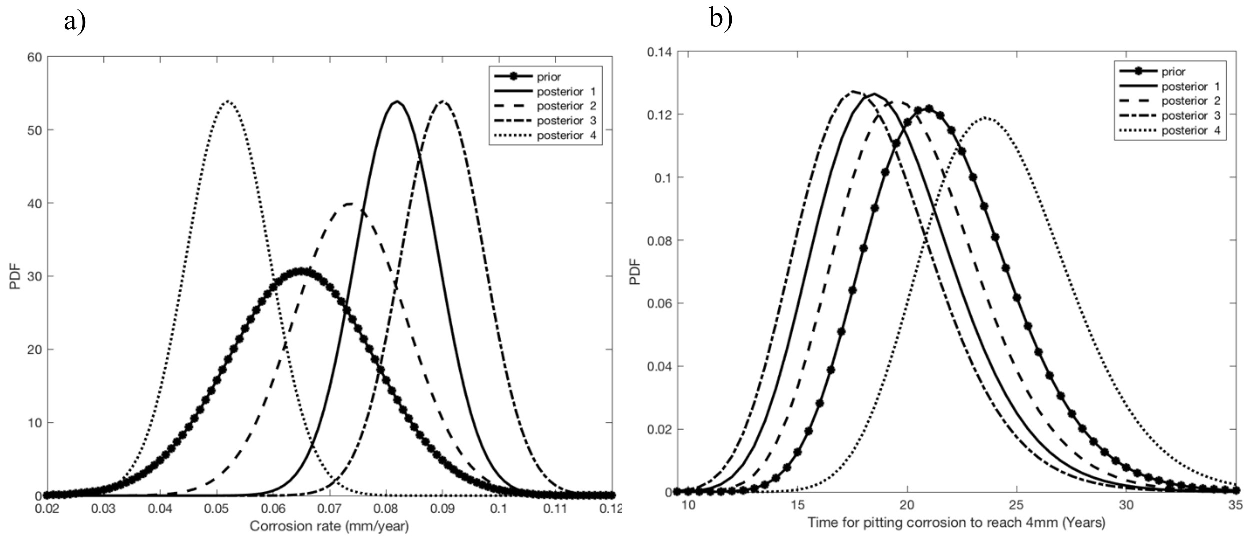

Figure 4.4 (a) Bayesian updating of corrosion rate using different inspection scenarios; (b) PDF of time for pitting corrosion depth to reach 4 mm based on the updated corrosion rate

Figure 4.4b indicates that, based on the updated values of r_{corr}, different PDFs of the time for PCD to reach 4 mm will be obtained, which can affect the bridge management process, including the prediction of future inspection schedules. For demonstration purposes, in this phase of the bridge service life uncertainty will be quantified using the probability of pitting corrosion depth reaching 4 mm P_{th}, which can be obtained from the CDF diagrams shown in Figure 4.5. An inspection is to be considered when there is a 20% chance that corrosion depth will reach 4 mm (i.e., $P_{th} = 20\%$) at $t_{Ins,4}$, followed by a second maintenance action when P_{th} equals 50% at $t_{m,2}$.

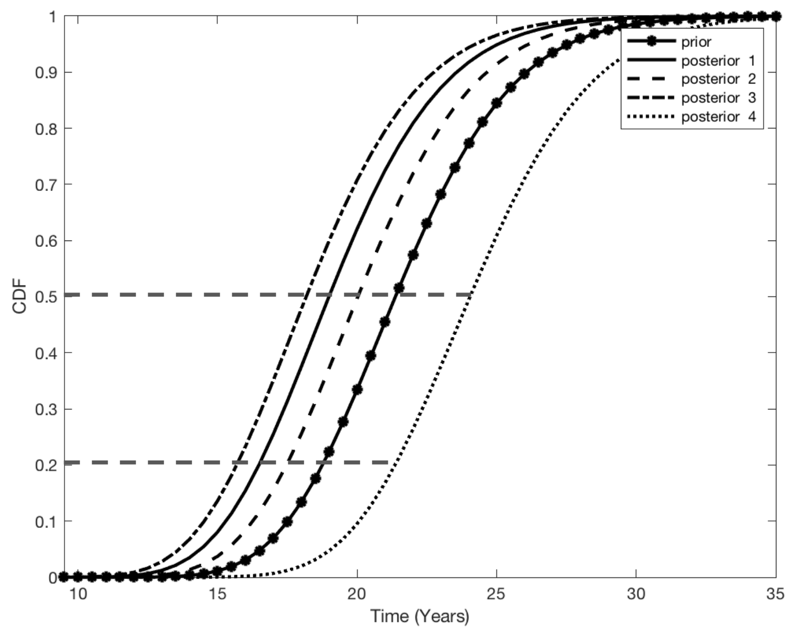

Figure 4.5 The updated CDF of the time for PCD to reach 4 mm, based on each inspection scenario

Different NDE qualities (in terms of accuracy and reliability) can lead to different predicted times when the inspection threshold will be reached. For example, based on the posterior CDF associated with Scenario 1 (the highest quality NDE scenario), the fourth inspection in the service life of the bridge is to be conducted at $t_{Ins,4} = 16.5 years$, which is almost seven years from the inspection conducted at year 9.5. While according to Scenario 4 (which assumes the NDE method overestimates the rate of corrosion), the inspection should be done at year 21.25. Also, Scenario 1 concludes that maintenance should be done at year 20.00, compared with year 24.5 according to Scenario 4. This analysis shows that the inspection quality has a direct effect on the inspection planning and maintenance decisions, which can cause delayed or unnecessary maintenance, resulting in failure of the bridge element or a waste of resources. Data about the accuracy and reliability of NDE methods are an important part of effectively using NDE results to update inspection plans. Table 4.9 summarizes the results obtained from each inspection scenario.

Table 4.9 The expected second maintenance time and fourth inspection time associated with different inspection scenarios

Inspection scenario	Posterior r_{corr}		$t_{Ins,4}$ (years)	$t_{m,2}$ (years)
	$\mu^P_{r_{corr}}$	$\sigma^P_{r_{corr}}$		
Prior prediction	--	--	18.4	21.6
Scenario 1 (unbiased, low error)	0.0819	0.0074	16.5	20.00
Scenario 2 (unbiased, high error)	0.0736	0.010	17.5	20.25
Scenario 3 (under estimating, biased, low error)	0.090	0.0074	15.75	18.5
Scenario 4 (over estimating, biased, low error)	0.052	0.0074	21.25	24.5

The remainder of the example continues using the first inspection scenario. Accordingly, it is assumed that at $t_{Ins,4} = 16.5 years$ an inspection using an LPR and an ECI was conducted and confirmed that maintenance should be done at year 20.00. In the next section, a life-cycle cost analysis (LCCA) will be performed to analyze the cost of the proposed inspection planning process during an almost 20-year period starting from beginning of the bridge service life to $t_{m,2}$.

5. INSPECTION LIFE-CYCLE COST ANALYSIS

During a 20-year period, four inspections were conducted after applying the proposed inspection planning framework. In this section, the direct and indirect cost of the inspection plan will be calculated along with the inspection failure cost. To mitigate the uncertainty and variations in the inspection cost values, a probabilistic LCCA will be conducted based on Equations (2.10) to (2.17) using Monte Carlo simulation with 100,000 samples. The probabilistic characteristics of the cost parameters used are stated in Table 5.1, and all variables are assumed to follow a lognormal distribution if not deterministic. The user costs are considered time dependent, relying to a great extent on the ADT, which is subjected to an annual increase rate. Thus, assuming a constant rate of increase (*k*), the ADT at t_{Ins} can be estimated as (Soliman & Frangopol, 2015):

$$ADT(t_{Ins}) = ADT(1+k)^{t_{Ins}} \tag{5.1}$$

In this example, it is assumed that during inspection, traffic control will be executed by reducing the speed limit of the vehicles crossing the bridge within 40 m before and after the bridge (i.e., $l = 0.12 \text{ km}$). A detour route of 1 km will be organized for the highway traffic underneath the bridge to avoid the fatigue inspection performed using a snooper. Road crashes during inspection are assumed to cause injuries with no fatalities.

Table 5.1 Probabilistic descriptors of cost parameters

Cost Parameter	Notation (units)	Mean	COV	References
Average wage per hour	c_w (\$/hr)	24.07	0.28	(Soliman et al., 2015)
Average wage per hour for truck drivers	c_c (\$/hr)	29.28	0.31	(Soliman et al., 2015)
Time value of goods transported	c_g (\$/hr)	4.12	0.2	(Soliman et al., 2015)
Average occupancies for cars	O_c	1.5	0.15	(Soliman et al., 2015)
Average occupancies for trucks	O_T	1.05	0.15	(Soliman et al., 2015)
Ratio of the average daily truck traffic to the average daily traffic	s	0.12	0.2	(Soliman et al., 2015)
Inspection durations	IH (hrs)	8	0.15	Assumed
Average daily traffic	ADT (vehicles/day)	45000	--	Assumed
Freeway speed	v_f (km/hr)	30	0.1*	(Soliman et al., 2015)
Inspection zone speed	v_z (km/hr)	90	0.1*	(Soliman et al., 2015)
Length of the inspection zone	l (km)	0.12	0.05	Assumed
Length of the detour route	l_d (km)	1	0.05	Assumed
Vehicle running cost	C_{VR} (\$/hr)	0.16	0.25	(Gong & Frangopol, 2020)
Crash rate	CR	2 x 10^{-7}	--	(Mallela et al., 2011)

Average human crash cost	C_a ($/per crash)	152,374	0.46	(Mallela et al., 2011)
Environmental metric per unit distance for cars	En_{dc} (kg/km)	0.22	0.2	(Soliman et al., 2015)
Environmental metric per unit distance for trucks	En_{dt} (kg/km)	0.56	0.2	(Soliman et al., 2015)
Carbon dioxide emissions per kilometer at restricted speed	En_{vz} (kg/km)	0.42	0.05	(Soliman et al., 2015)
Carbon dioxide emissions per kilometer at free speed	En_{vf} (kg/km)	0.3	0.05	(Soliman et al., 2015)
The cost value of carbon dioxide emissions.	c_{em} ($/ton)	45	$\sigma = 76$	(Kendall et al., 2008; Mallela et al., 2011)
Maintenance of traffic cost	MOT ($/hr)	162	0.12*	(Taylor et al., 2016)
Snooper cost	($/inspection)	2500	0.15*	(Agdas et al., 2015)
NDE inspector hourly wage	($/hr)	47	0.15*	(Taylor et al., 2016)
Travel cost	($/mile)	0.575	0.04	(Taylor et al., 2016)
Chloride Ion penetration test cost (CIP)	($/m^2)	0.8	0.1*	(Taylor et al., 2016)
Linear polarization test cost (LPR)	($/m^2)	0.6	0.1	(Olson, 2020)
Eddy current inspection cost (ECI)	($/inspection)	5500	0.15*	(Soliman et al., 2013)
Ultrasonic inspection cost (UI)	($/inspection)	4500	0.15*	(Soliman et al., 2013)
Liquid penetrant test cost (LPT)	($/inspection)	3000	0.15*	(Soliman et al., 2013)
Magnetic particle inspection cost (MPI)	($/inspection)	3600	0.15*	(Chung et al., 2006)

*Estimated based on different ranges in the literature.

The inspection direct cost (IDC) is a summation of the NDE equipment cost, personnel cost, MOT, snooper rental, and travel cost. The indirect costs (IUC) are estimated using Equations (2.11-2.15). The cost of the fatigue inspection techniques is calculated based on the information provided in Soliman et al. (2013) and includes both the equipment cost and personnel cost specified for the inspected detail. As for the concrete slab, the cost of the NDE equipment depends on the total area of the deck, which is 960 m^2 (9.6 m width x 100 m length) in the simulated example. Added to the concrete deck inspection cost is the hourly rate of three NDE experts, who will be responsible for collecting, analyzing, and reporting inspection results associated with each NDE method. The trip to and from the bridge site was assumed to be 140 miles, and two vehicles were used in transporting the NDE equipment and inspectors. It is initially assumed that each inspection will take eight hours (i.e., IH=8hrs), and the value of k is 1%. Regarding the PDD, the expected inspection failure cost (IFC) arises only at $t_{Ins,1} = 5.50\,years$, adding a value of $450 to the inspection cost. Table 5.1 summarizes the expected inspection cost of the four inspections discounted to their present value at T_0 using a discount factor r equal to 2%.

Table 5.2 Inspection cost with 2% discount factor

Cost item	$t_{Ins,1} = 5.50 years$ NDE used: CIP & ECI		$t_{Ins,2} = 8.75 years$ NDE used: CIP & UI		$t_{Ins,3} = 9.5 years$ NDE used: LPR		$t_{Ins,4} = 16.5 years$ NDE used: LPR & ECI	
	μ ($)	σ ($)	μ ($)	σ ($)	μ ($)	σ ($)	μ ($)	σ ($)
DIC_i	11,450	1,026	10,470	907	3,190	443	11,284	1,028
IUC_i	4,826	1,266	5,012	1,312	5,049	1,331	5,417	1,393
$C_{Ins,i} = DIC_i + IUC_i + IFC_i$	16,725	1,795	15,482	1,765	8,239	1,598	16,701	1,903
$C_{LCC} = \dfrac{C_{Ins,i}}{(1+r)^{t_{Ins,i}}}$	14,999	1,610	13,018	1,484	6,826	1,323	12,045	1,373

Based on the results in Table 5.2, the total inspection life-cycle cost C_{LCC} is $46,888, with a standard deviation equal to $2,903, for a 2% discount factor. The results show that the IUC should not be neglected as they represent 50% of the DIC, when both a fatigue and corrosion inspection were performed. In fact, when only an LPR was used at $t_{Ins,3}$ the user costs were almost 58% more than the direct costs. The variability in the IUC can be high, reaching a COV of almost 26%, while the COV in the DIC is much smaller at about 8%. The high uncertainty and location-specific nature of IUC, which includes vehicle operation costs associated with closures and detours, traffic accidents, and environmental costs, make it difficult to assign a dollar figure for the user impacts of inspection; however, user costs can be a significant burden on the agency's road network budget if not recognized early (Soliman et al., 2015).

In this example, the effects of four main variables on the inspection cost were analyzed as shown in Figure 5.1. First, Figure 5.1a depicts the PDF of the C_{LCC} using different discount factors (i.e., r = 0%, 2%, and 4%) while holding k=1% constant. The mean of C_{LCC} at r equal 0% and 4% were almost $56,860 and $38,915, respectively. This cost difference can have major effects on the decision-making process and planning for future investments. A high discount factor when estimating future inspection costs can mislead bridge managers into saving less for the future. A low discount factor can lead to unnecessary savings of resources rather than better allocating them. Figure. 5.1b shows the PDF of the time dependent inspection life-cycle cost for k = 0%, 1%, and 2% using a discount factor of 0%. The results show that increasing k from 0% to 2% corresponds to a 12% increase in the C_{LCC}. This increase in inspection costs due to traffic growth is notable when considered in the context of an agency's full bridge network.

The inspection speed can have major effects on the cost of an inspection, as outlined in Figure 5.1c. The inspection durations (IH) were assumed, 4 hours, 8 hours, and 16 hours, when r and k = 0%. When the IH was 4 hours, the C_{LCC} was $41,072 with a standard deviation of $2,130. When IH was equal to 8 hours and 16 hours, the average inspection life-cycle cost was $53,102 and $83,634, respectively, with standard deviations equal to $3,183 and $6,229, respectively. Increasing the IH from 4 hours to 16 hours increased the inspection life-cycle cost by more than double. Managing the inspection speed can help bridge managers optimize resources. This can be mainly performed by enhancing the NDE equipment speed, increasing the number of inspectors and equipment, or even improving the personnel quality through training; however, these improvements can come with a cost.

The effect of the inspection zone length l and the detouring length l_d on the inspection cost, especially the IUC, were examined as illustrated in Figure 5.1d. Different simulations were conducted by increasing both l and l_d from 0.12 km and 1 km, respectively, to 0.24 km and 2 km, then to 0.36 km and 3 km, for *r* and *k*=0%. Correspondingly, the mean C_{LCC} increased from \$53,102 to \$74,151, and \$92,950, with standard deviations equal to \$3,183, \$5,717, and \$7,993, respectively. The results demonstrate that minimizing the inspection zone and detour length can lower the inspection cost by almost 40%, mainly due to reductions in the traffic delay and detouring costs.

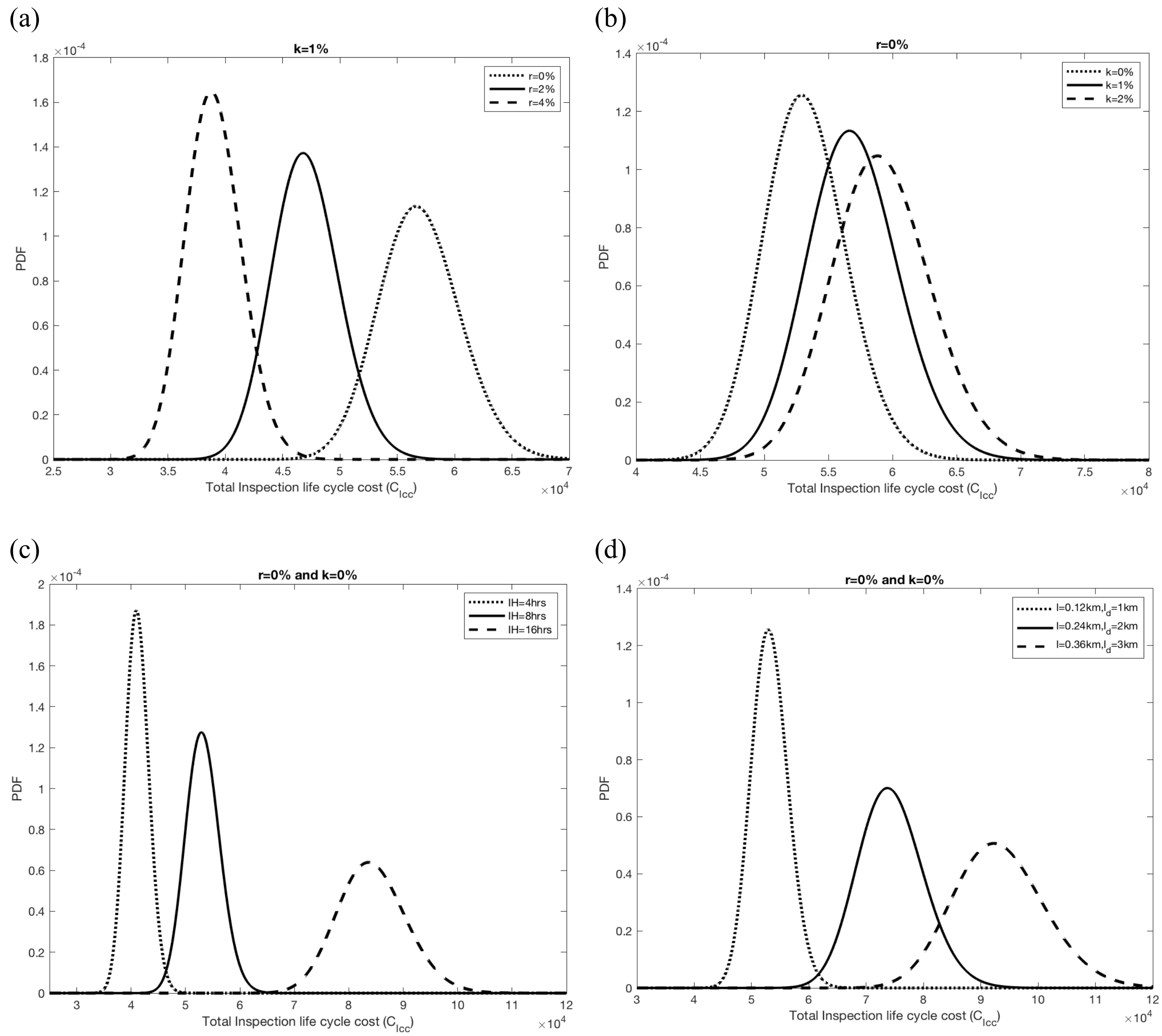

Figure 5.1 (a) PDF of total inspection life-cycle cost for r= 0%, 2%, and 4%; (b) PDF of total inspection life-cycle cost for k= 0%, 1%, and 2%; (c) PDF of total inspection life-cycle cost for different IH; (d) PDF of total inspection life-cycle cost for different l and l_d

The perceived cost of implementing NDE inspections is a barrier to their widespread adoption. To emphasize the cost benefits of the proposed framework, one can consider the routine visual inspection conducted by most bridge agencies every two years, which in a 20-year period would lead to 10 inspections compared with four herein. Based on the information provided in Agdas et al. (2015), a routine visual inspection for the model bridge can cost almost $5,700, considering only the inspection direct costs (i.e., personnel cost, travel cost, snooper, and MOT). Thus, during a 20-year period considering a 0% discount factor, the total inspection costs for 10 routine visual inspections will be $57,000. On the other hand, the total IDC after applying the proposed inspection planning process is $36,105. Although the cost of a single visual inspection is almost half the cost of an NDE inspection due to the reduction in the number of inspections during the life cycle of the bridge, major cost savings can be achieved even when only considering the costs directly associated with inspection. The reduction in user costs associated with fewer inspections and corresponding closures or delays would further enhance the LCC benefit of using more in-depth NDE inspections.

Moreover, the risk associated with the variable quality and subjectivity of visual inspection should be considered. For example, the cost and consequences of inspection failure and how a visual inspection has a high probability of not detecting early fatigue cracks or even subsurface corrosion can have major ramifications, such as causing delayed maintenance that can affect the performance of the bridge or even lead to complete failure (Kim et al., 2013). Although these conclusions are based on the uncertainty threshold assumed in the example (e.g. $\sigma_{th} = 3 years)$, which resulted in only four inspections limiting the C_{LCC} , the ideas presented in this study are worth further exploration and can provide bridge agencies and transportation departments with major cost savings during times of limited budgets, especially if applied to an agency's bridge network and not just a single a bridge.

6. CONCLUSION

This study investigated the life-cycle cost implications of one alternative method of bridge inspection planning. First, an approach to probabilistic inspection planning for two different bridge deterioration modes using prediction models and NDE methods was proposed. After quantifying uncertainty in the model predictions using the standard deviation or non-exceedance probability, a suitable inspection time is chosen based on the threshold level of uncertainty. Based on the accuracy, PDD, and cost of inspection, an NDE method is chosen to provide bridge managers with new information regarding the bridge condition. According to the new inspection measurements and prior information, Bayesian updating is performed and the posterior PDF of the damage propagation with time is obtained. The inspection planning process was demonstrated on an example bridge, and the demonstration example provided the opportunity to investigate life-cycle cost implications of an alternative bridge inspection plan.

After analyzing the proposed framework and applying it to a bridge example, the following conclusions are drawn:

1. In the studied example, three prediction models were used to determine corrosion initiation time, fatigue crack propagation, and pitting corrosion depth at different time intervals. The uncertainty associated with the model prediction depends highly on the variation in the input parameters. Therefore, addressing these uncertainties and reducing the model uncertainties by timely bridge inspection and Bayesian updating will result in more accurate predictions and planning. For example, in the initial prediction process, fatigue cracks were estimated to reach 5 mm, requiring maintenance at year 13.00. But after the continuous inspection planning process, it appeared that maintenance should be done at year 9.5. A late maintenance could have resulted in increasing the maintenance cost or even leading to bridge failure if the appropriate actions were not performed.
2. The PDD associated with an NDE can help bridge managers choose the appropriate inspection method. Although NDE methods with high PDD might require extra financial resources, by considering the cost of inspection failure these extra costs will be justified. In the example, the ECI was estimated to have the highest direct inspection cost compared with other NDE equipment. However, based on the cost of inspection failure, it turned out that the ECI will be the most optimal choice due to its high PDD at limited crack sizes.
3. The accuracy of the NDE used is important in the decision-making process. As shown in the analysis of the bridge example, different inspection qualities can yield different inspection and maintenance schedules. A biased NDE inspection can lead either to an early, unnecessary maintenance action or a delayed maintenance and inspection resulting in a deteriorated bridge performance.
4. The probabilistic life-cycle cost analysis (LCCA) sought to quantify the uncertainties corresponding with the inspection cost. The LCCA showed that although the IUC is associated with high uncertainty, neglecting user costs in the inspection cost estimations can create an inaccurate picture of the costs and benefits of NDE inspection. When high accuracy NDE can be used to reduce the number of inspections, user costs associated with delays and closures are significantly reduced, further justifying the direct costs of the NDE.
5. Deciding on the appropriate discount factor when planning for future investments is very important in bridge management. Choosing a high discount factor when estimating future inspection costs can mislead bridge managers in saving less for the future. A low discount factor can lead to saving more resources than what is required for future investments.
6. The average daily traffic, inspection duration, and inspection zone and detouring length highly control the inspection cost. The example showed that limiting the inspection duration and detouring and inspection zone length can help in reducing the inspection cost by more than 40%.
7. During a 20-year duration of the service life of the bridge, the proposed framework resulted in only four inspections, compared with 10 inspections, corresponding to the routine visual inspection applied every two years. The cost of a visual inspection is almost half the cost of an in-

depth NDE inspection, but the reduction in the number of inspections can lead to major cost savings if applied to a whole bridge network.

Incorporating uncertainty-based bridge inspection planning into bridge inspection offers a multifaceted approach with numerous compelling advantages. First, it provides flexibility in inspection scheduling, enabling resources to be allocated adaptively, minimizing unexpected costs and enhancing efficiency. This flexibility is closely tied to risk mitigation, as identifying and prioritizing bridges with higher uncertainty or deterioration signs reduces the risk of costly surprises and enhances overall safety. Furthermore, cost savings are realized by utilizing resources more effectively and prolonging the life span of bridge infrastructure through long-term planning. Additionally, it fosters data-driven decision-making, informs more effective maintenance strategies, and encourages adaptive management practices, enhancing resilience to evolving conditions. Environmental considerations are also addressed, minimizing ecological impacts. Finally, by highlighting proactive maintenance and safety measures, uncertainty-aware planning can boost public confidence in the reliability and safety of bridges, benefiting both the infrastructure and the communities it serves.

It is essential to emphasize that more in-depth analysis and research are needed to fully understand the utility and potential advantages of the proposed framework. Expanding the application of this framework to encompass real-time investigations on intricate bridges is crucial. Given that the framework is still in its developmental stages and has not been put into practical use, it is advisable to refrain from using it for assessing new bridges until initial or regular inspections have been conducted. The variability in inspection intervals can pose budgetary challenges for bridge owners when planning inspections for their bridge inventory. Therefore, it is essential to develop this methodology to assist bridge owners in estimating the life-cycle cost of bridge inspections. It is worth noting that certain aspects of the framework demand expertise in statistics and software coding, which may not be readily available among personnel in government agencies. Consequently, prior to implementing this program, specific training for some employees may be necessary. Additionally, incorporating considerations of bridge redundancy and load ratings into the framework could further enhance the planning process.

This study raises questions that should be analyzed in future research. For example, can a formal quantitative method be used to choose the uncertainty threshold, or does this threshold necessarily depend on expert judgment. Multi-attribute decision-making might provide a rational basis for this process. Also, the framework was applied on a new bridge, thus further analysis should be conducted on existing bridges and real-time case studies. Implementing the effect of maintenance actions on the planning process can have major effects that should be explored further. Additional study of the cost implications is also needed.

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