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Advancing Bridge Technology, Task 10: Statistical Analysis and Modeling of US Concrete Highway Bridge Deck Performance -- Internal Final Report

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FHWA Collaborative Project

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INTERNAL FINAL REPORT

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ABSTRACT

Concrete highway bridge deck repairs represent the highest expense associated with bridge maintenance cost. In order to optimize such activities and use the available monies effectively, a solid understanding of the parameters that affect the performance of concrete bridge decks is critical. The National Bridge Inventory (NBI), perhaps the single-most comprehensive source of bridge information, gathers data on more than 600,000 bridges in all fifty states, the District of Columbia, and the Commonwealth of Puerto Rico. Focusing on concrete highway bridge deck performance, this research developed a nationwide database based on NBI data and other critical parameters that were computed by the authors, referred to as the Nationwide Concrete Highway Bridge Deck Performance Inventory (NCBDPI) database. Additionally, two performance parameters were computed from the available concrete bridge deck condition ratings (CR): Time-in-condition rating (TICR) and deterioration rate (DR). Following the aggregation of all these parameters in the NCBDPI database, filtering, and processing were performed. In addition to a basic prescriptive analysis, two types of advanced analysis were applied to the new dataset. First, binary logistic regression was applied to a subset of the data consisting of the highest and lowest DR. Second, a Bayesian survival analysis was performed on the TICR considering censored data. Through the analyses it was possible to show which parameters influence deck performance and create tools that can help agencies and bridge owners make better decisions regarding concrete bridge deck preservation.

DISCLAIMER

SI* (MODERN METRIC) CONVERSION FACTORS

APPROXIMATE CONVERSIONS TO SI UNITS

Symbol	When You Know	Multiply By	To Find	Symbol
		LENGTH		
in	inches	25.4	millimeters	mm
ft	feet	0.305	meters	m
yd	yards	0.914	meters	m
mi	miles	1.61	kilometers	km
		AREA		
in^2	square inches	645.2	square millimeters	mm^2
ft^2	square feet	0.093	square meters	m^2
yd^2	square yard	0.836	square meters	m^2
ac	acres	0.405	hectares	ha
mi^2	square miles	2.59	square kilometers	km^2
		VOLUME		
fl oz	fluid ounces	29.57	milliliters	mL
gal	gallons	3.785	liters	L
ft^3	cubic feet	0.028	cubic meters	m^3
yd^3	cubic yards	0.765	cubic meters	m^3
		NOTE: volumes greater than 1000 L shall be shown in m^3		
		MASS		
oz	ounces	28.35	grams	g
lb	pounds	0.454	kilograms	kg
T	short tons (2000 lb)	0.907	megagrams (or "metric ton")	Mg (or "t")
		TEMPERATURE (exact degrees)		
°F	Fahrenheit	5 (F-32)/9 or (F-32)/1.8	Celsius	°C
		ILLUMINATION		
fc	foot-candles	10.76	lux	lx
fl	foot-Lamberts	3.426	candela/m^2	cd/m^2
		FORCE and PRESSURE or STRESS		
lbf	poundforce	4.45	newtons	N
lbf/in^2	poundforce per square inch	6.89	kilopascals	kPa

APPROXIMATE CONVERSIONS FROM SI UNITS

Symbol	When You Know	Multiply By	To Find	Symbol
		LENGTH		
mm	millimeters	0.039	inches	in
m	meters	3.28	feet	ft
m	meters	1.09	yards	yd
km	kilometers	0.621	miles	mi
		AREA		
mm^2	square millimeters	0.0016	square inches	in^2
m^2	square meters	10.764	square feet	ft^2
m^2	square meters	1.195	square yards	yd^2
ha	hectares	2.47	acres	ac
km^2	square kilometers	0.386	square miles	mi^2
		VOLUME		
mL	milliliters	0.034	fluid ounces	fl oz
L	liters	0.264	gallons	gal
m^3	cubic meters	35.314	cubic feet	ft^3
m^3	cubic meters	1.307	cubic yards	yd^3
		MASS		
g	grams	0.035	ounces	oz
kg	kilograms	2.202	pounds	lb
Mg (or "t")	megagrams (or "metric ton")	1.103	short tons (2000 lb)	T
		TEMPERATURE (exact degrees)		
°C	Celsius	1.8C+32	Fahrenheit	°F
		ILLUMINATION		
lx	lux	0.0929	foot-candles	fc
cd/m^2	candela/m^2	0.2919	foot-Lamberts	fl
		FORCE and PRESSURE or STRESS		
N	newtons	0.225	poundforce	lbf
kPa	kilopascals	0.145	poundforce per square inch	lbf/in^2

*SI is the symbol for the International System of Units. Appropriate rounding should be made to comply with Section 4 of ASTM E380. (Revised March 2003)

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CHAPTER 1 – INTRODUCTION

Introduction

Bridges represent the backbone of the US' transportation system, and, are its most visible part. There are over 600,000 bridges across all US states ensuring network continuity. The American Society of Civil Engineers (ASCE) estimates that one in nine of the nation's bridges are structurally deficient (ASCE, 2013). With limited funding available to keep all bridge decks in a state of good repair, reliable tools are needed to estimate the service-life and life-cycle costs so that informed decisions can be made on which decks should be (1) repaired first and (2) what repair techniques should be employed (Frangopol and Estes, 1999). Additionally, these tools can also assist during the design process to estimate the expected service-life limit of new concrete bridge decks. Bridges are designed following two criteria: strength and serviceability, which ensure structural integrity and functionality, respectively. The major effort in preservation is directed to serviceability, which is ensured by a durable design combined with appropriate and effective maintenance work. The main reason for bridge superstructure repair and rehabilitation is deterioration of concrete decks (Li and Zhang, 2000). Under federal law, bridge decks are inspected biannually for both structural and functional adequacy and assigned ratings ranging from "0" to "9" ("0" representing a failed condition and "9" excellent condition). Currently, the States' DOTs have their own criteria on when to repair or rehabilitate a bridge deck (VDOT, 2015). Deck rehabilitation decisions are often based on a bridge's worst span lane, usually the right hand lane which receives the most traffic (Williamson et al., 2007). Some guidance on bridge preservation and its terminology is provided in the FHWA Bridge Preservation Guide (FHWA, 2018).

Although corrosion can be considered the main contributor to deterioration of a concrete deck, there are many other factors affecting bridge deck deterioration will be discussed later in this report. According to the Federal Highway Administration (FHWA) two billion dollars are spent annually for maintenance and capital costs for concrete bridge decks (ASCE, 2013), it is important to understand the durability of these structures and to develop a model that accurately predicts their service life.

Motivation

Although many studies predict probability of condition rating (CR) change over time, not all of these studies are concentrated on concrete bridge decks. Moreover, most studies have been limited to specific states within the United States. A great number of studies use simple statistical models such as simple curve fitting or third degree polynomial to determine deterioration curves. Furthermore, most studies do not consider maintenance actions to be an interferer or interrupter of the deterioration process of a deck. Only one group has considered data censorship, which was found to be critical when dealing with NBI data. Certain other studies take into consideration in their deterioration models only one or two parameters that the authors think are most important (such as ADTT or age), leaving unexamined the reasons behind choosing specific structural or environmental categories in their deterioration models. The here created database, referred to as Nationwide Concrete Highway Bridge Deck Performance Inventory (NCBDPI) database, contains 21 critical structural and environmental parameters. Advanced data analysis approaches were performed and evaluated to study this database, with the aim to create tools that help identify controlling parameters and accurately model the deterioration process of concrete bridge decks.

Objective

The main objective of this research was to provide an in-depth literature review of concrete bridge deck performance, discuss the most important research that serves as a foundation for this work, perform and evaluate different statistical analyses for concrete bridge deck condition data based on our own nationwide database, and determine which parameters influence concrete bridge deck performance. The ultimate goal was to create recommendations and tools to assist agencies and bridge owners in making informed decisions regarding optimal bridge deck preservation actions.

Overview of Report

In this section, summaries are provided for each of the main chapters of this internal final report. This report is based in part on a PhD dissertation (Ghonima, 2017) and Chapters 4 and 5 were submitted as articles to refereed journals and are currently under review.

Chapter 2 – Background

This chapter gives the reader relevant background information about how concrete bridge decks deteriorate, the factors that drive deck performance, and an overview of research attempting to quantify deterioration through analysis and modeling using both NBI and other data.

Chapter 3 - A Nationwide Concrete Highway Bridge Deck Performance Inventory Database

Abstract: Concrete highway bridge deck repairs represent the highest expense associated with bridge maintenance cost. In order to optimize such activities and use the available monies effectively, a solid understanding of the parameters that affect the performance of concrete bridge decks is critical. The National Bridge Inventory (NBI), perhaps the single-most comprehensive source of bridge information, gathers data on more than 600,000 bridges in all fifty states, the District of Columbia, and the Commonwealth of Puerto Rico. Focusing on concrete highway bridge deck performance, this research developed a nationwide database based on NBI data and other critical parameters that were computed by the authors, referred to as the Nationwide Concrete Highway Bridge Deck Performance Inventory (NCBDPI) database. Additionally, two performance parameters were computed from the available concrete bridge deck condition ratings (CR): Time-in-condition rating (TICR) and deterioration rate (DR). Following the aggregation of all these parameters in the NCBDPI database, filtering, and processing were performed. Approaches to deal with inconsistencies and missing data are proposed as well. A preliminary descriptive statistical analysis was performed on the TICR parameter to determine applicable procedures. Finally, three examples demonstrating how the database can be used to answer questions regarding bridge deck performance are presented further research is proposed.

Chapter 4 - Performance of US Concrete Highway Bridge Decks Characterized by Binary Logistic Regression

Note: This chapter was submitted to the *ASCE-ASME Journal of Risk and Uncertainty in Engineering Systems, Part A: Civil Engineering* and is currently under review. Please look for the peer-reviewed journal publication version of this chapter entitled "Performance of US Concrete Highway Bridge Decks Characterized by Random Parameters Binary Logistic Regression" under the following link: https://ascelibrary.org/journal/ajrua6.

Abstract: This study employs binary logistic regression (LR) to characterize the impact of environmental and structural parameters on concrete highway bridge deck deterioration. A total of 3,262 bridge deck deterioration observations derived from the authors' Nationwide Concrete Highway Bridge Deck Performance Inventory (NCBDPI) database were used for this study. Deterioration rate (DR) was computed as the decrease in the concrete bridge deck condition rating (CR) over time. Bridge decks with deterioration rates (DR) below a certain threshold were categorized as the lowest deteriorated bridge decks ("lowest DR") and decks with DR above a certain threshold were considered among the highest deteriorated ("highest DR"). The following six parameters were found to be significant in the final model: average daily truck traffic (ADTT), climatic region, distance from seawater, functional classification of inventory route, type of design and/or construction, and maintenance responsibility. The results show that bridge decks with a high ADTT, located in cold regions, with an urban functional classification, and that are close to seawater are associated with the "highest DR" group of bridge decks. Furthermore, type of design and/or construction and maintenance responsibility play a role in deck being associated with "highest DR". This paper presents the methodology and results of the binary LR, its goodness of fit and validation of predicted values, and furnishes two examples demonstrating its utility.

Chapter 5 - Bayesian Survival Analysis for US Concrete Highway Bridge Decks

Note: This chapter was submitted to the *ASCE Journal of Infrastructure Systems* and is currently under review. Please look for the peer-reviewed journal publication version of this chapter entitled "Bayesian Survival Analysis for US Concrete Highway Bridge Decks" under the following link: https://ascelibrary.org/journal/jitse4.

Abstract: A leading factor in structural decline of highway bridges is the deterioration of concrete decks. Thus, a method to predict bridge deck performance is vital for transportation agencies to allocate future repair and rehabilitation funds. While service-life prediction tools are available, they rely on input parameters that are often difficult to obtain or estimate. This research aimed to discover the relationships between concrete highway bridge deck performance and information readily available from the National Bridge Inventory (NBI), perhaps the single most comprehensive nationwide source of bridge information. The NBI relies upon visual inspection to quantify the condition of bridge decks and subsequently assign a condition rating (CR). This paper presents the application of Bayesian survival analysis to the time-in-condition ratings (TICR), which was defined as the time duration a bridge deck is assigned the same CR before it decreases. Since the dataset is limited to 23 years of observations, the Bayesian approach provides a coherent method for handling censored observations. In our example, censorship occurs for four reasons: (1) data is censored as its CR prior to 1992 is unknown, (2) data is censored as its rating after 2014 is unknown, (3) data is censored due to missing observations, and (4) data is censored due to an increase in CR from one year to the next, which we consider repair or rehabilitation. The results provide insight into what parameters drive bridge deck deterioration and may help agencies with maintenance repair prioritization.

Chapter 6

This chapter discusses some overall conclusions and lessons learned and presents some recommendations for future work.

CHAPTER 2 – BACKGROUND

This chapter explains the concept of concrete bridge deck functionality and adds the definition of deck service life. Factors contributing to bridge deck deterioration are discussed, along with a brief explanation of bridge deck corrosion. Practical methods of deck protection, repair, and rehabilitation are then proposed. Two service life programs, Life 365 and STADIUM, are briefly reviewed. An introduction to the National Bridge Inventory (NBI) and its system of concrete bridge deck condition rating (CR) is then presented. The chapter includes a narrative of a field trip that the research team undertook with an experienced bridge inspector in order to get a better idea of the inspection process. A literature review of concrete bridge deck studies concludes the chapter.

Function of Bridge Decks

Bridge decks serve to 1) distribute the loads from vehicles to the bridge's superstructure main elements (i.e., the diaphragms and girders), 2) increase bending capacity of the supporting girders, and 3) provide a wear-resistant surface (Kyle, 2001). There are two types of deck design types: composite and non-composite. A deck integrally connected to the superstructure components (i.e., able to transfer shear between them) is considered composite, and non-composite when unconnected (Tonias, 1995). Furthermore, most concrete decks are composite cast-in-place as opposed to precast concrete panels (Azizinamini et al., 2013; Koch, 2002)). Composite decks have significant advantages, because they are working with the superstructure members to resist load. Some of the advantages are as follows (Tonias, 1995):

- Reduced steel diameter
- Greater vertical clearance from reduced stringer depth
- Greater load capacity

Bridge Deck Service Life and Deterioration Process

Despite abundant discussion in the literature regarding bridge deck service life, deterioration, and how to measure service life, there seems to be no agreement as to what the criteria are when the actual end of bridge deck service life has been reached. Does it depend on the deck's actual condition? If so, how is condition defined: level of corrosion (e.g., rebar diameter, section loss, crack widths, surface roughness, etc.) How do other non-technical factors influence deck condition such as level of state or federal funding or ownership?

The Service-Life Prediction – State-of-the-Art Report (ACI, 2000) defines end-of-life as:

> *Structural safety is unacceptable due to material degradation or exceeding the design load-carrying capacity; Severe material degradation, such as corrosion of steel reinforcement initiated when diffusing chloride ions attain the threshold corrosion concentration at the reinforcement depth; Maintenance requirements exceed available resource limits; Aesthetics become unacceptable; or Functional capacity of the structure is no longer sufficient for a demand, such as a football stadium with a deficient seating capacity.*

According to the Design Guide for Bridges for Service Life report (Azizinamini et al., 2013), two general design approaches predict service life: finite service-life approach and target service-life approach.

Finite service life approach: This approach uses deterioration modeling (such as mathematical models, empirical or semi-empirical models using previously collected data such as LRFD or based on expert opinions e.g., model used in ASHTOWARE) to estimate service life. The service life should be greater than or equal to the specified bridge-system service life.

Model results can be expressed in the form of a fully-probabilistic approach, requiring probability distribution functions (PDF) for all variables used in the deterioration model, or in the form of a semi-probabilistic approach developed from a fully-probabilistic approach.

Target service life approach: This method is often used if deterioration models are unavailable. An alternative approach, target service life, is achieved by 1) using high-performing materials to control deterioration (usually referred to as an avoidance-of-deterioration approach), or 2) using expert opinion to specify a target service life.

The difference between the two methods is that the finite service life approach can track the condition of the bridge element through deterioration models. On the other hand, target service life method only estimates the total expected service life, and thus condition detection can be performed over the life time of the component.

Service life is the duration in which bridge elements or systems provide the desired level of performance or functionality, in connection with the required level of repair/maintenance.

After a bridge deck is constructed at time, T_i , which is a new condition, it starts to deteriorate, eventually reaching an unacceptable condition state (C_f) at time, T_f. The time between T_i and T_f is considered the service life of the bridge deck. There is no interference with the deck until it reaches failure (Figure 1).

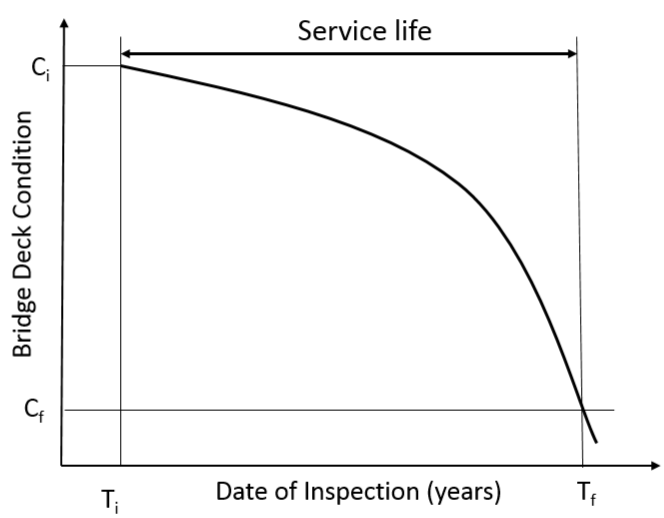

Figure 1. Hypothetical curve for bridge deck condition vs. time.

However, a deck undergoes maintenance, repair, or rehabilitation, which will restore its condition to a higher level (Figure 2). For a concise definition of these terms please consult FHWA (2018). Note that in this report, for simplicity, we use the term “maintenance” to refer to any actions that increase the CR, similar to many published materials in the past. The goal of asset management strategies is to optimize the time of improvement action to get the highest benefit from the investment (FHWA, 2018).

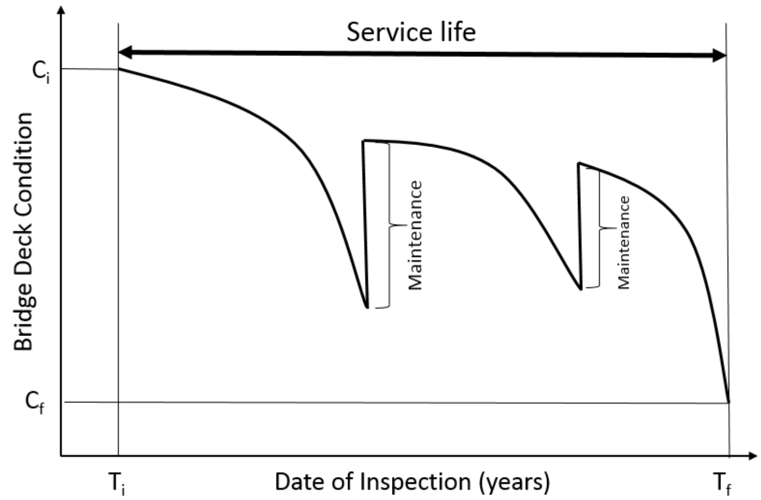

Figure 2. Hypothetical curve for bridge deck condition vs. time including maintenance.

A sample of three bridge deck CR from the NBI for the state of Oregon is shown in Figure 3. As can be seen, the curves for bridge deck CR are not as smooth as shown in Figs. 1 and 2 and only available starting from 1992. The reason for this is two-fold: (1) the curves are theoretical depictions and (2) actual bridge deck condition and condition ratings (CR) are not the same thing. An introduction to the NBI and its CR is Section "National Bridge Inventory (NBI)".

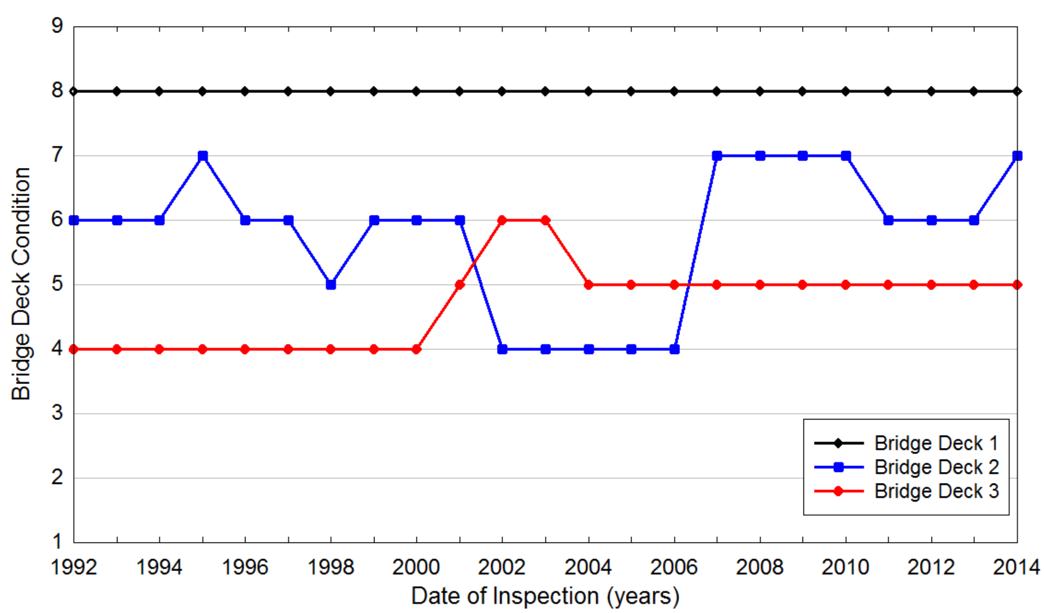

Figure 3. Three samples of deck condition rating (CR) vs. date of inspection from NBI data for the State of Oregon.

It should be noted that since the 2000s, states also collect so-called element-level inspection data, which assigns a condition state (CS) on a scale from 1 to 4, as defined in the AASHTO Guide Manual for Bridge Element Inspection (AASHTO, 2011). This data is more detailed in nature and quantifies types of deterioration and associated areas. Because this data is currently not available publicly, it was not considered in this research.

Factors Affecting Bridge Deck Deterioration

During the design and construction of cast-in-place or precast concrete bridge decks, several factors are taken into consideration that directly affect bridge deck deterioration. In the following sections, the role of individual parameters in affecting deck deterioration is explained in more detail.

Concrete cover

Concrete cover, the layer of concrete on top of the reinforcement, serves mainly to prevent excessive carbonation and consequent steel corrosion. Additionally, the cover plays a major role in the diffusion of chlorides, thereby affecting the time of corrosion initiation. Because cover depth varies across a concrete bridge's deck, the zone with the lowest cover depth or cracking usually initiates the corrosion process. Past research demonstrates a positive correlation between cover depth and the onset of chloride diffusion leading to corrosion, and impelling the conclusions that increasing cover depth (1.5 to 3 inches) will increase the time for chlorides to diffuse (Kirkpatrick et al., 2002; Kassir and Ghosn, 2002). Once corrosion has initiated, the process will cause the concrete cover to crack, in turn resulting in increased chloride penetration, which further accelerates corrosion (Williamson et al., 2007). Cover depth, however, can only be increased up to a certain limit, which once passed, can lead to wider surface flexural cracking, itself a cause of corrosion initiation (Stewart and Rosowsky, 1998). Increasing concrete cover depth invokes a trade-off requiring designers to stay within certain limits to prevent cracking while still providing minimum depth to prevent rapid chloride diffusion.

Permeability of concrete

Concrete permeability relates to the ease with which liquids can flow through a solid, and is mainly influenced by the factors of w/c ratio, maximum aggregate size, type of cement, curing temperature, chemical admixtures, humidity, and temperature (ACI, 2000; Vu and Stewart, 2000). Reducing w/c ratio decreases capillary porosity, resulting in decreased permeability Stewart and Rosowsky, 1998). Research conducted by Bentz el al. was able to develop a relationship between the effects of w/c ratio on diffusion, using 16 different sets of data. A least squares regression curve on the best fit of the predicted diffusion coefficients data produced the following equation:

$$D \sim 10^{-10+4.66 \mathrm{w}/\mathrm{c}} \qquad \text{Equation 1}$$

where D is diffusion (cm^2/s) and *w/c* is water-to-cement ratio (unitless).

Compressive strength

Compressive strength affects chloride concentration, and hence bridge deck deterioration. Stewart and Rosowsky (1998) conducted experiments on concrete elements with compressive strengths of 3,000, 4,000 and 5,000 psi in order to test chloride concentrations at a depth of 50 mm, observing that once compressive strength decreases, chloride concentrations at 50 mm depth increase over time.

Type of reinforcing bar steel

Reinforcing bar (rebar) steel is an important structural element in a bridge deck and the main target of corrosion. Types and sizes of rebar steel can profoundly influence corrosion initiation. Several reinforcements currently used in bridge decks are available in the market to help extend service life, the most common ones being epoxy-coated steel, microcomposite steel (MMFX), galvanized steel, stainless steel, and fiber- reinforced polymer (FRP) bars (Russell, 2004).

The most researched type of preventive reinforcement is epoxy coating, first implemented in 1973 on a bridge near Philadelphia with the main goal of corrosion reduction (Russell, 2004). Up until now there have been mixed results regarding epoxy coating. Research conducted in the state of Virginia showed epoxy coating debonds from the reinforcement as quickly as 4 years but usually around 12-15 years (Kirkpatrick et al., 2002). Moreover, other research results suggests that epoxy coatings lose adhesion of their coating when exposed to moisture (Russell, 2004). Stainless steel was first used in Detroit, Michigan, in 1984. Its main disadvantage was that it costs about 6 times as much as normal black rebars. Nevertheless, the advantage of using stainless steel over epoxy is that it remains passive in a chloride environment and that the material is not easily damaged since epoxy rebars can lose the coating if dropped or scratched.

FRP rebars were first introduced around 1996 in Virginia. Made from continuous fiber (such as aramid or carbon embedded in resin material), FRP does not corrode; however, it is vulnerable to other forms of deterioration and is expensive. Made from high chromium and low carbon content steel, MMFX steel has been of interest in recent years (Russell, 2004). Galvanized steel is another type used to enhance the service life of bridge decks. The steel is galvanized by dipping it into 435-454°C molten zinc, which causes the zinc to react with oxygen and the steel to form a layer of zinc oxide (Williamson, 2007).

Distance from seawater

The distance of a bridge deck from sea (i.e. salt) water is another important component in deck service life. Sea salt can travel by wind and settle on a concrete deck. Winds can carry sea salt up to 3 km (1.9 mi) or more inland (Vu and Stewart, 2000). Over time, chloride content increases as a result of a constant transfer of sea salt (Stewart and Rosowsky, 1998). Based on a study performed by McGee on 1,158 bridges in Australia, the surface chloride concentration on bridge decks relative to the distance from sea water was found out to be as follows (Vu and Stewart, 2000):

$$C_0(d) = 2.95\ {}^{kg}/_{m^3} \qquad d < 0.1\ km \qquad \text{Equation 2}$$

$$C_0(d) = 1.15 - 1.81\log_{10}(d) \qquad 0.1\ km < d < 2.84\ km \qquad \text{Equation 3}$$

$$C_0(d) = 0.03\ {}^{kg}/_{m^3} \qquad d > 2.84\ km \qquad \text{Equation 4}$$

A study by Stewart and Rosowky shows that chloride concentration varies exponentially as bridge decks come closer to seawater, with percentages of accumulated chloride on concrete surfaces reaching to 100% for bridge decks passing on top of seawater, and nearly 0% for bridges 3 km (1.86 miles) or more away (Stewart and Rosowsky, 1998).

Early stage bridge deck cracking

Early cracking in a deck is mainly caused by several factors such as plastic shrinkage, thermal shrinkage, drying shrinkage, bending stresses, and concrete subsidence (Kyle, 2001), the latter caused when concrete is in a plastic stage undergoing differential concrete settlement). Early cracking expedites chloride ingression, leading to early corrosion initiation. Moreover, crack width is significant: according to a National Cooperative Highway Research Program, crack widths of 0.002 inch or wider can cause salt contaminants containing chlorides to pass through a deck cover (Krauss and Rogalla, 1996). Another study suggests that corrosion initiation is affected by surface cracks larger that 0.3 - 0.6 mm (0.012 - 0.024 in) (Stewart and Rosowsky, 1998).

Type of cement

Various cement types affect cracking of concrete decks. Russell suggests that decks constructed from Type II cement crack less than those from Type I cement. Moreover, Type III cement gains strength rapidly making it more susceptible to early cracking (Russell, 2004). According to Krauss and Rogalla (1996), cement used nowadays causes concrete to gain strength more rapidly, resulting in higher moduli of elasticity and compressive strength, in turn causing the concrete to have a higher chance of early cracking. Hadidi and Saadeghraziri recommended the following mix design in order to reduce deck cracking:

- Cement content ranging between 650 to 660 lb/yd^3
- Low early strength concrete (if the deck won't be opened to traffic straightaway).
- Water cement ratio of less than 0.45
- Use of water reducing agents
- Largest maximum aggregate size and the maximum aggregate content
- Avoidance of concrete mixes that have a tendency for cracking

Type of restraint

Bridge decks can be restrained when cast over already hardened concrete or steel girders causing tensile stresses to develop. Moreover, the boundary conditions of a bridge deck can cause additional axial tension forces in deck. Girders, parapets, abutments, etc. all play a role in causing axial forces or tensile stresses in a deck (Azizinamini et al., 2013). According to Krauss and Rogalla (1996), multi-span continuous girder bridges are more susceptible to deck cracks than simply supported girders. Furthermore, cast-in-place, post-tension bridges are the least likely to undergo cracking, mainly because girders and deck shrink together and the post tensioning introduces compressive stresses in the deck (Russell, 2004; Krauss and Rogalla, 1996).

Freeze and thaw

Water particles contained in a concrete bridge deck expand during freeze cycles causing stresses in the concrete and subsequent cracking. Cycles of freeze and thaw can accelerate fatigue of a concrete bridge deck, as well as cracking, scaling, and spalling. In order to avoid the effects of freeze and thaw, concrete needs to have small air voids uniformly distributed and closely spaced, which can be achieved by using the proper admixtures (Azizinamini et al., 2013).

Construction practice

Poor concrete placement and curing practices can affect the service life of bridge decks (Azizinamini et al., 2013). Curing is important in bridge deck construction and should be implemented with care. If done properly, curing reduces the permeability of a concrete deck through the increased hydration of the available cement (ACI, 2000). The transportation of concrete precast panels from a facility and erection to a bridge site, if not done properly, can damage the panels. In addition, during the transportation of epoxy-coated steel, damage to the product can leave it susceptible to corrosion. The type of formwork, if below par, can also affect the surface of concrete, reducing strength and decreasing durability. Casting sequence and schedule should be taken into consideration. A qualified, well-trained total workforce in order to insure quality of concrete and the testing methods is crucial in the service life of bridge decks (Azizinamini et al., 2013).

Design practice

Design decisions made for concrete bridge decks such as the type of LRFD specifications, expansion joints, type of construction joints, and drainage factors play an important role in deck peformance (Azizinamini et al., 2013).

Deicers

Many DOTs apply deicing salts, a safety provision for the public, during winter to melt the snow and enhance tire tractions. The use of deicing salts in the US has increased from less than one million tons per year in the 1950s to around fifteen million tons per year in the 1990s (Stewart and Rosowsky, 1998), making deicing salts one of the main factors of bridge corrosion. If a bridge deck is exposed to these salts early in its life (under three months old), service life is more impacted than if the deck were exposed at an age greater than six months (Williamson, 2007).

Traffic loads

Deck-rehabilitation decisions are often based on a bridge's worst-span lane (usually the right hand lane) the one receiving the most traffic (Williamson et al., 2007). Average daily truck traffic (ADTT), other vehicle traffic, and the loads induced by those two are important factors in deck deterioration. These factors can cause (Azizinamini et al., 2013):

- Fatigue: Structural damage to an element due to cyclic loading from traffic resulting in the initiation of cracks and subsequent chloride ingression.
- Overloads: Loads exceeding individual state weight limit regulations (overloads) are a major factor behind deck deterioration. Overload causes added flexural stress on a bridge deck, which can result in excessive cracking.
- Wear and Abrasion: Abrasion is caused by (1) high ADTT, (or ADT) and (2) types of tires used. Moreover, chains, grooves, and studs used in winter season to help with vehicle control cause deck abrasion. Wear and abrasion reduce the thickness of a deck, in turn speeding up the corrosion process as a result of reduced concrete cover.

NCHRP 333 Report

This report (Russell, 2004) discusses the effects of material and mix design on the durability of deck concrete, different types of steel reinforcements and how they affect deterioration, bridge deck protective systems, design and construction practices, different types of cracking, how these cracks are caused and how they affect bridge performance, and best practices to reduce cracking.

Based on responses to a survey (sent out to all states), on present practice and research, this report concluded that the use of the following materials and practices enhances the performance of concrete bridge decks:

- Appropriate selectin of concrete constituent materials
- Types I, II, and IP cements;
- Fly ash up to 35% , silica fume up to 8%, and ground-granulated blast furnace slag up to 50% of the total cementitious materials content;
- Low modulus of elasticity, low coefficient of thermal expansion, and high thermal conductivity aggregates;
- Largest size aggregate suitable for construction;
- Water-reducing and high-range water-reducing admixtures;
- Air-void system with a spacing factor no greater than 0.008 in., specific surface area greater than 600 in.^{2} /in.^{3} of air-void volume, and number of air voids per inch of traverse significantly greater than the numerical value of the percentage of air;
- Water-cementitious materials ratio in the range of 0.40 to 0.45;
- Concrete compressive strength in the range of 4,000 to 6,000 psi; and
- Concrete permeability per AASHTO T277 in the range of 1,500 to 2,500 coulombs.
- Reinforcement Materials
- Epoxy-coated reinforcement in both layers of deck reinforcement and
- Minimum practical transverse bar size and spacing.
- Design and construction practices
- Maintain a minimum concrete cover of 2.5 in;
- Use moderate concrete temperatures at time of placement;
- Use windbreaks and fogging equipment, when necessary, to minimize surface evaporation from fresh concrete;
- Provide minimum finishing operations;
- Apply wet curing immediately after finishing any portion of the concrete surface and wet cure for at least 7 days;
- Apply a curing compound after the wet curing period to slow down the shrinkage and enhance the concrete properties;
- Use a latex-modified or dense concrete overlay;
- Implement a warranty requirement on bridge deck performance; and
- Gradually develop performance-based specifications.

Bridge Deck Corrosion

Bridge deck corrosion is the result of all the factors stated above. In order to understand corrosion in bridge decks, one needs to understand the entire process, which can be broken down into two main steps (see Figure 4):

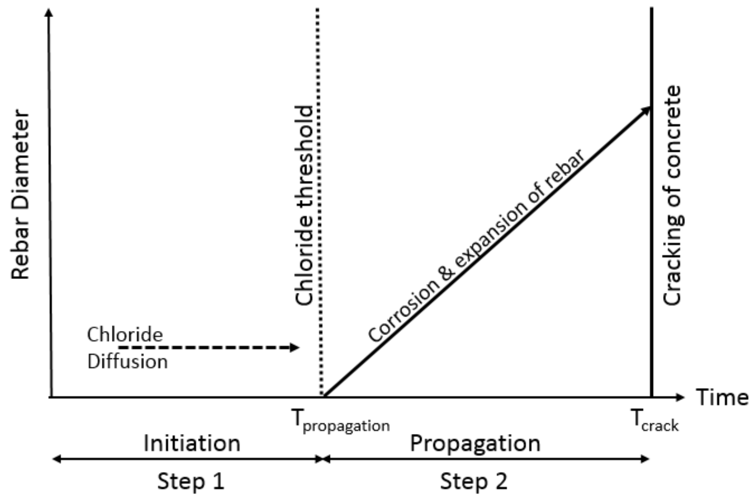

Figure 4. Corrosion process of steel reinforcement.

Step 1 – Chloride initiation

Corrosion cannot begin until the passivity layer protecting the steel is deactivated (Hansen and Saouma, 1999). As long as this passive layer (composed of iron oxide and hydroxide, which relates to the pH of concrete solutions) stays intact, corrosion is inhibited (Williamson, 2007). Chloride ingression affects the passive layer on top of the steel. A certain level of chloride concentration at the depth of the reinforcement (defined as the chloride threshold) is required in order for corrosion to be initiated. Angst et al. (2009) argue that these threshold values for total chloride wt% cementitious material found by a number of researchers vary greatly, i.e., between 0.17 and 2.5, indicating that such values may not be a reliable indicator for the time of corrosion initiation. Various steel reinforcement types have differing chloride thresholds. Several factors can affect corrosion initiation, such as the concentration of hydroxyl ions in the pore solution, the potential of the steel, the presence of voids at the steel or concrete interface, cement composition, moisture content, w/c ratio, and temperature (Williamson, 2007).

Step 2 – Corrosion Propagation

Following the initiation process, corrosion propagation occurs, where the steel rebars start to corrode causing them to rust and increase in area resulting in concrete cracking and, eventually, loss of bond (Figure 5).

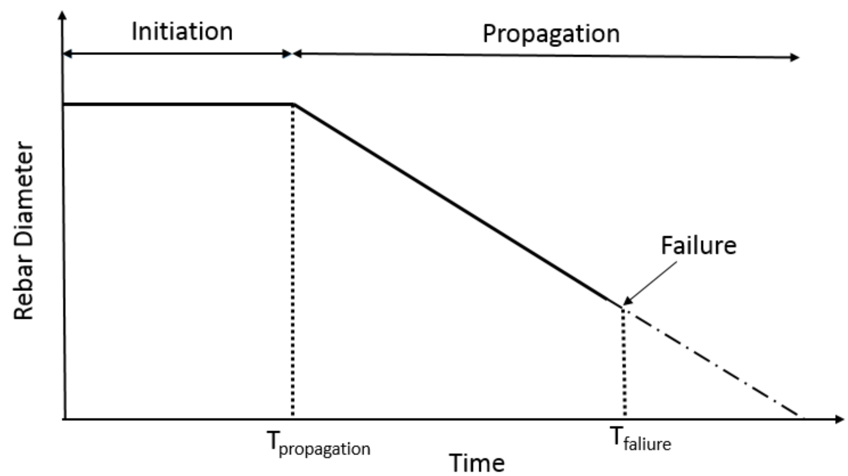

Figure 5. Concrete bridge deck corrosion process.

According to Stewart and Rosowsky (1998), once the propagation period occurs, the rebar loss of area can be modeled as a uniform reduction by the following equation:

$$D(t) = \begin{cases} D_i & t \leq T_i \\ D_i - 2\lambda(t - T_i) & T_i < t \leq T_i + \left({}^{D_i}/_{2\lambda}\right) \\ 0 & t > T_i + +\left({}^{D_i}/_{2\lambda}\right) \end{cases} \qquad \text{Equation 5}$$

Here D_i is the initial bar diameter, T_i is the time to initiation, and λ is the corrosion rate (mm/year), a rate usually measured from experimental studies and influenced by the availability of water, oxygen, and steel surface area (Stewart and Rosowsky, 1998).

Figure 6. Example photo of corrosion of reinforcing steel.

Cracking in concrete is caused by iron oxides (rust) (Figure 6) that form on the steel layer causing it to expand. This results in tension in the concrete which causes it to crack. The corrosion process that transforms metallic ions to rust can in fact produce a 300% increase in volume (Stewart and Rosowsky, 1998). Life 365, a service-life prediction tool discussed in Section "Life-365", assumes a propagation period of six years for bare steel, while ACI suggests a higher value (Bentz, 2003); Williamson (2007) suggests sixteen years, and Weyers (1993) between two and five. Unfortunately, it can be concluded that modeling service life by corrosion is extremely challenging, if not controversial, due to the variability of chloride threshold and propagation period used in the literature. Furthermore, readers need to keep in mind that many studies that measure concrete deck deterioration do not consider other factors (see Section "Factors Affecting Bridge Deck Deterioration") that influence deterioration, the main once being the presence of cracks.

Deck Protection Methods

Deck protection methods are used in the design of bridge decks in order to extend a deck's service life. The type of steel and concrete properties (such as type of cement and permeability of concrete methods) discussed in Section "Factors Affecting Bridge Deck Deterioration" are examples of such protective methods. Other types of protection methods include the following:

Cathodic prevention and protection

This method is applied to prevent corrosion from initiating. Sufficient direct current is applied between titanium anodes placed in the concrete to shift the potential of the steel in the negative direction, causing the reinforcement to become cathodic, thereby halting corrosion. However, there are some disadvantages to it (Williamson, 2007; Russell, 2004; OECD, 1989; Xanthakos, 1996):

- High cost.
- Need for periodic adjustment and constant monitoring.
- Continuous power requirement.
- Possible disbanding of concrete overlay.
- Diminished steel potential (The potential of the steel must be maintained within a specific range. Going outside the range may produce deterioration.)

This process can also be used as a deck rehabilitation method (Section "Deck Repair and Rehabilitation Methods") once a structure is already experiencing corrosion and would then be called cathodic protection.

Membranes

These are usually placed on top of the concrete and protected by another material (usually asphalt) that functions as the riding surface (Azizinamini et al., 2013; Russell, 2004). The main purpose is to protect the deck from freeze-and- thaw cycles, and protect the reinforcement from corrosion. The types of waterproofing membranes used are preformed sheets, liquid membranes, and built-up systems. Experience with membranes have been variable by different states and are therefore not consistently used.

Sealers

Sealers protect the concrete from aggressive environments and prevent the ingress of chlorides. Sealers can be either solvents or water-based liquids blockers. They can either form an extremely thin (up to 2 mm) impermeable layer on the concrete surface or, by slightly penetrating into the concrete and act as hydrophobic agents. Most water-based liquids blockers are not used because they do not provide adequate friction for tires. Sealers prevent chloride infused water from penetrating into a deck. Penetrating sealers (silanes and siloxanes) are usually recommended. The effectiveness of a deck sealer also depends on the permeability of the deck concrete (Azizinamini et al., 2013; Williamson, 2007).

Corrosion inhibitors

Various liquid admixtures are used in bridge decks in order to hinder the corrosion process. The idea behind using corrosion inhibitors (CI) is to raise the chloride threshold of the steel, which will slow the rate of corrosion (Russell, 2004). Calcium nitrate admixtures are the most widely used CI (Azizinamini et al., 2013). Although inhibitors do not form a barrier to slow down chloride ingression like membranes or sealers, they modify the steel surface, either electrochemically or chemically. CI can be applied to the concrete mixture or on the surface directly. However, it is usually applied in the mix design to ensure adequate dosages. The main disadvantages of using CI are using an incorrect dosage (using low dosages can speed up corrosion process), leaching of CI, and penetration of CI to the reinforcement in the deck (Azizinamini et al., 2013; Williamson, 2007; Russell, 2004).

Deck Repair and Rehabilitation Methods

There are many different definitions of bridge deck repair and rehabilitation. Weyers (1993) defines repair as a method to:

"*restore deteriorated concrete element to a service (almost) equal to the as built condition*"

and rehabilitation as a method that

"*corrects the deficiency that resulted in the assessed deteriorated condition*".

Williamson (2007) defines repair as a method to

"*increase the level of functionality, but without addressing causes of deterioration*"

and rehabilitation as a method to

"*restore a bridge deck to an acceptable level of performance, addressing the cause of deterioration*."

Repair and rehabilitation are often used interchangeably. Subsequently, two common methods are discussed. Please also see the latest "Bridge Deck Preservation Guide" for additional terminology (FHWA, 2018).

Deck patching (deck repair method)

Patching is normally used to replace areas of a deck that have suffered some type of deterioration (spalls, corrosion, delamination). Patch repair can be of partial-depth (if the top reinforcing is corroded) or full-depth (if the top and bottom reinforcing are corroded). Portland cement concrete, quick-set hydraulic mortar and concrete, and polymer mortar and concrete are used for deck patching (Weyers, 1993). Unless care is taken, areas surrounding patches may delaminate as they become more anodic to the patch (an example of this is discussed in Section "Second inspected bridge", Figure 15) (Xanthakos, 1996). This might be triggered by the low chloride presence in patches that causes them to become cathodic, resulting in a higher corrosion rate of the surrounding steel (Williamson, 2007). Most studies conclude that patching is a questionable method of repair, is costly, and involves frequent traffic disturbances, and thus only a short term solution (Williamson, 2007; Xanthakos, 1996; OECD, 1989).

Deck overlays (deck repair and rehabilitation method)

Overlays become a repair method when the corrosion process has started but has not caused any damage or cracks. Overlays used as a repair method are often placed on top of the concrete (Williamson, 2007). The purpose of overlay is to create a low-permeability protective layer over the concrete deck that reduces chloride ingression (due to increased cover and low permeability overlay) (Azizinamini et al., 2013). The technique is used as a rehabilitation method if significantly damaged or cracked concrete areas are removed and replaced before a deck is overlaid. In this case, the bridge deck is restored to a certain level of functionality and deterioration is addressed (Williamson, 2007).

Various types of deck overlays (Russell, 2004):

- Latex-Modified Overlays: Conventional Portland cement concrete along with a polymeric latex emulsion.
- Low-Slump Dense Concrete Overlays: Concrete with a cement content as high as 470 kg/m3 and water cement ratio as low as 0.3.
- Silica Fume Concrete Overlays: Consists of low water/cement ratio microsilica-modified Portland cement. Using 7% silica fume and maximum w/c ratio of 0.4 improves permeability.
- Portland Cement Concrete Overlays: Usually 2-inch thick layer that is compatible with the bridge deck.
- Polymer Concrete: Usually thinner than other overlays (0.5 in.) due to high resistance to chloride penetration, it consists of cement concrete with polymer added during mixing.
- Internally Sealed Concrete: Usually a minimum of 2-inch thick layer, consisting of polymer-modified concrete. Small wax spheres are added during mixing which melt after concrete has cured to seal the concrete against the ingress of moisture and chemicals. This method is not common.

Service Life Software Packages

Life-365

Life-365 is a free-of-charge service life and life cycle program that can be used to model marine structures, parking garages, bridge decks, and transportation infrastructure (Life-365, 2008). The model assumes that corrosion of steel is the main source of degradation. Moreover, the definition of service life of reinforced concrete is the sum of the initiation time of corrosion and the propagation time required for corrosion to cause sufficient damage that requires repair. Further, Life-365 does not model the uncertainties in the propagation period; it assumes 6 years and 20 years for uncoated and stainless steel, respectively; however, it can also be defined by the user. The initiation period is calculated using either one or two-dimensional Fickian diffusion (Ehlen et al., 2009). Fick's second law of diffusion is expressed as:

$$\frac{\partial C}{\partial t} = D_c \frac{\partial^2 C}{\partial x^2} \qquad \text{Equation 6}$$

where C is a chloride ion concentration at a distance x from the surface at t years; D_c is the apparent diffusion coefficient.

Life-365 assumes that ionic diffusion is the sole mechanism of chloride transport in order to simplify the approach the initiation period (Violetta, 2002). Inputs required for Life-365 are:

1. Location of structure,
2. Structure type and exposure,
3. Concrete cover depth and dimensions of the deck,
4. Corrosion protection strategies used (e.g., water-cementitious ratio and type steel).

Life-365 does provide built-in default values for other inputs (such as costs of the concrete constituent materials and details and costs of the concrete repair strategy); however it is recommended that users update these inputs based on available project information. The outputs of the Life-365 are (Ehlen et al., 2009):

- Time to reinforcement corrosion initiation,
- Cost of initial construction, optional barriers, and repairs to deteriorated portions over the design service life,
- Life-cycle costs (based on present-worth),
- Sensitivity of the service life and life cycle cost results from variations in underlying assumptions.

It should be noted that Life-365 does not directly account for cracking, which obviously has a significant impact on chloride ingression.

STADIUM

STADIUM is a more advanced commercial service life program developed and distributed by SIMCO Technologies. It is a multi-mechanistic tool; however, its main usage is for chloride diffusion modeling (Marchand, 2001). There are three main applications of STADUIM: (1) optimize the service life, (2) extend the service life, and (3) provide information to guide decision-making. STADIUM has a longer list of inputs compared to Life-365:

1. Material density
2. Paste content
3. Diffusion coefficients
4. Water diffusivity
5. Total porosity
6. Capillary porosity
7. Initial values of ion concentration, volumetric water content in the pores, and electrical potential
8. Initial amount of solid phases
9. Equilibrium constants
10. Boundary conditions for ion concentration, volumetric water content in the pores, and electrical potential
11. Temperature

After inputting these parameters, STADIUM has a specific algorithm divided into 2 main modules: (1) the transport module, which makes the species movements during one time step, to account for electro diffusion of species, moisture transport (liquid and vapor), and heat conduction; (2) the chemistry module, which simulates the reactions between the species in the pores and hydrated paste (Marchand, 2001).

STADIUM takes into consideration all these ionic species: OH^-, Na^+, K^+, SO_4^{-2}, $CA^{2+,}$, Cl^-, K^+, Mg^{2+}, $H_2SiO_4^{-2}$, $Al(OH)_4^-$, $Fe(OH)_4^-$, HCO_3^- and NO_2^-. Moreover, the model accounts for the effect of cement and supplementary cementing materials hydration on the transport properties, (e.g., reduction of diffusion coefficients through time due to presence of fly ash). STADIUM also takes into account the effect of pore volume variations from chemical reactions on transport properties (Marchand, 2001).

STADIUM does not use Fick's second law in its model, but uses a more complex equation that models chemical species transport in cementations material. STADIUM models electrical coupling between ionic species and the chemical equilibrium reactions between solid and liquid phases of a concrete matrix (Williamson, 2007).

According to Nathan Sauer (previous SIMCO technologies engineer) there is difference between Ficks's equation used in Life-365 and STADIUM's equation for a simulation done for a chloride profile after 20 years. The results of Life-365 give an over-conservative estimate of chloride content (Sauer, 2014).

Like Life-365, STADIUM does not directly consider, to date, the effect of cracking.

National Bridge Inventory (NBI)

The collapse of the Silver Bridge in Ohio in 1967 resulted in the congressional mandate to all the USDOTs in the 1970s to establish a unified method of national bridge inspection standards for all public highway bridges across the country that are more than 20 feet in length (Markow, 2009). This database is stored in the National Bridge Inventory (NBI). Each of the fifty states, the District of Columbia, and the Commonwealth of Puerto Rico submit the information, which is then compiled in the NBI and provided to the general public. Moreover, it is used as a source of data by the FHWA in its biannual report of bridge condition and performance to Congress (ASCE, 2013). The NBI database allows DOTs to monitor bridge performance and condition and identify what should be done. Based on the 2016 NBI census, there are 425,671 concrete bridge decks in the United States (FHWA, 2016).

NBI Items

The NBI has 116 parameters, referred to as "items," that can be considered in the database of each state. These items are categorized as follows:

Items 1–27: General description and administrative information
Items 28–42: Functional or operational (capacity) information; design load
Items 43–44: Structure/design/construction type and material of construction
Items 45–56: Span information, geometric information, and clearance dimensions (no Item 57)
Items 58–70: Structural condition and bridge loading information
Items 71–72: Waterway and approach data (no Items 73–74)
Items 75–97: Inspector's work recommendations and projected costs
Items 98–116: Other information of various categories

Condition Ratings

Certified trained inspectors assess structural components and operational characteristics and rate them from 0 to 9 (Table 1). According to the FHWA Recording and Coding Guide (FHWA, 1995), concrete bridge decks should be inspected for cracking, spalling, leaching, chloride contamination, potholing, delamination, and full or partial depth failures. When inspecting a bridge deck, the condition of the wearing surface, joints, expansive devices, curbs, sidewalks, parapets, bridge rails, and scuppers are not taken into consideration, nor may they affect the CR of a deck. The influence of a deck on the superstructure or vice versa (e.g., rigid frame, slab, or box girder) is not taken into consideration, the rating is based on the deck only. The results of all the assessments of bridge decks both state-wide and local are reported by the DOTs and recorded in the NBI database.

Table 1. Bridge deck condition ratings (FHWA, 1995).

Rating	Code Description
9	Excellent condition
8	Very good condition: no problems noted.
7	Good condition: some minor problems.
6	Satisfactory condition: structural elements show some minor deterioration.
5	Fair condition: all primary structural elements are sound but may have minor section loss, cracking or spalling.
4	Poor condition: advanced section loss, deterioration or spalling.
3	Serious condition: loss of section, deterioration, or spalling have seriously affected primary structural components. Local failures are possible. Fatigue cracks in steel or shear cracks in concrete may be present.
2	Critical condition: advanced deterioration of primary structural elements. Fatigue cracks in steel or shear cracks in concrete may be present. Unless closely monitored it may be necessary to close the bridge until corrective action is taken.
1	"IMMINENT" failure condition: major deterioration or section loss present. Bridge is closed to traffic but corrective action may put it back in light service.
0	Failed condition: out of service-beyond corrective action.

The FHWA has broad definitions for bridge deck conditions (Table 1), which may make it challenging to differentiate the CR based on the descriptions. However, most DOTs have similar, more in-depth descriptions of the CR, which make it easier to differentiate. An example of the Minnesota Department of Transportation guidelines is provided in Table 2.

Table 2. Concrete bridge deck condition ratings based on the Minnesota Department of Transportation guidelines (MnDOT, 2016).

Code	This rating should reflect the overall general condition of the deck (or slab) - this includes the underside of the deck and the wearing surface. The condition of railings, sidewalks, curbs, expansion joints, and deck drains are not considered in this rating.
9	Excellent Condition: Deck is in new condition (recently constructed)
8	Very Good Condition: Deck has very minor (and isolated) deterioration. Minor cracking, leaching, scale, or wear (no delamination or spalling).
7	Good Condition: Deck has minor (or isolated) deterioration. Minor cracking, leaching, scale, or wear (isolated spalling/delamination).
6	Satisfactory Condition: Deck has minor (or isolated) deterioration • Concrete: moderate cracking, leaching, scale, or wear (minor spalling and/or delamination).
5	Fair Condition: Deck has moderate deterioration (repairs may be necessary). Extensive cracking, leaching, scale, or wear (moderate delamination or spalling).
4	Poor Condition: Deck has advanced deterioration (replacement or overlay should be planned). Advanced cracking, leaching, scale, or wear (extensive delamination or spalling) - isolated full-depth failures may be imminent.
3	Deck has severe deterioration - immediate repairs may be necessary. Severe cracking, leaching, delamination, spalling or full-depth failures may be present.
2	Critical Condition: Deck has failed - emergency repairs are required.
1	"Imminent" Failure Condition: Bridge is closed - corrective action is required to open to restricted service.
0	Failed Condition: Bridge is closed - deck replacement is necessary.

Since states may interpret and define the different CR slightly differently, it is expected that this will introduce some bias in a nationwide analysis. While it would be interesting to study this effect, this was outside of the scope of this research project.

Understanding the deck rating process (field inspection report)

While performing this research, the co-authors participated in a field trip to select bridges in Delaware with a certified bridge inspector from TY Lin International. Before becoming a bridge inspector in Delaware or Pennsylvania, individuals must pass a bridge inspection exam. In order to pass the test, one needs to score a bridge within a ±1 range against the ratings given. Once certified, inspectors look into previous deck ratings before inspecting a bridge deck. It should be noted that there is the potential for some bias in the ratings.

First inspected bridge
Deck evaluation for 2015: 7 (Good)
Structure Type: 4 spans and 2 girders
Inspected on: 03/23/2015, **Inspection Frequency:** 24 (months)
Next inspection: 03/23/2017
Year Built: 1980
Deck Type: Concrete Cast in Place
Deck Protection: Epoxy Coated Reinforcement
Membrane: None
Wearing Surface: Monolithic Concrete

The NBI CR from 1992 to 2014 for this bridge is shown in Figure 7. Select photos of the bridge surface and some observed damage are provided in Figures 8 to 10.

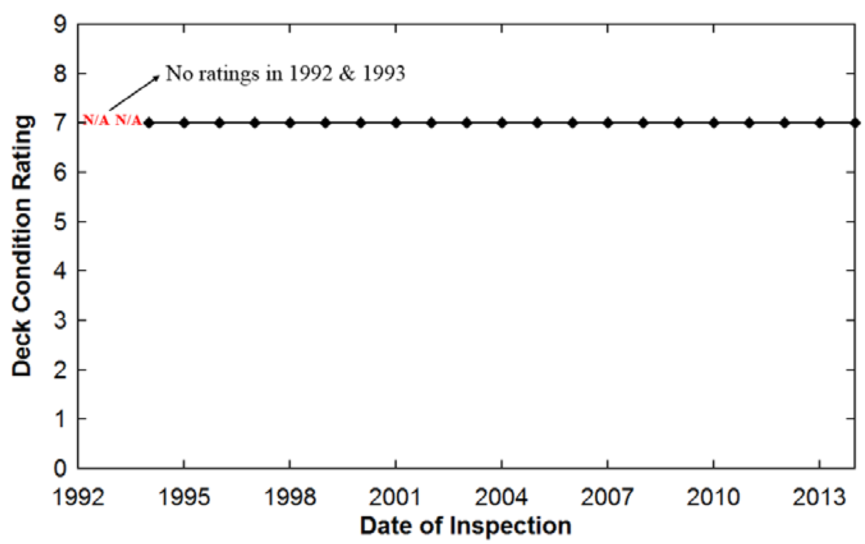

Figure 7. Deck condition ratings for bridge structure Number 1282366.


Figure 8. Bridge deck from both sides of approaching traffic.


Figure 9. Approach slab and joint.


Figure 10. Example of shrinkage and creep cracks.

Upon initial look at the deck, a condition rating of 8 or 9 seemed appropriate since there were no major cracks, corrosion, spalls/ potholes, or anything else unusual. The report indicated that it had been assigned CR = 7. In the inspector's experience, bridge decks having a rating CR = 9 are rare; moreover, in order to assign a 9, the bridge deck has to be brand new without a single crack. If a bridge was a few months old and in perfect condition, it would get an 8. According to this inspector, this bridge was rated 7 due to the observed shrinkage and creep cracks shown in Figure 10.

Second inspected bridge
Deck CR 2015: 5 (Fair condition)
Structure type: 4 span, 2 girder
Inspected on: 5/30/2014 and **Inspection frequency**: 24 (months)
Next inspection: 5/30/2016
Year built: 1955
Deck type: Concrete Cast in Place
Deck protection: None
Membrane: None
Wearing Surface: Latex Concrete

The NBI CR from 1992 to 2014 for this bridge is shown in Figure 11. Select photos of the bridge surface and some observed damage are provided in Figures 12 to 16.

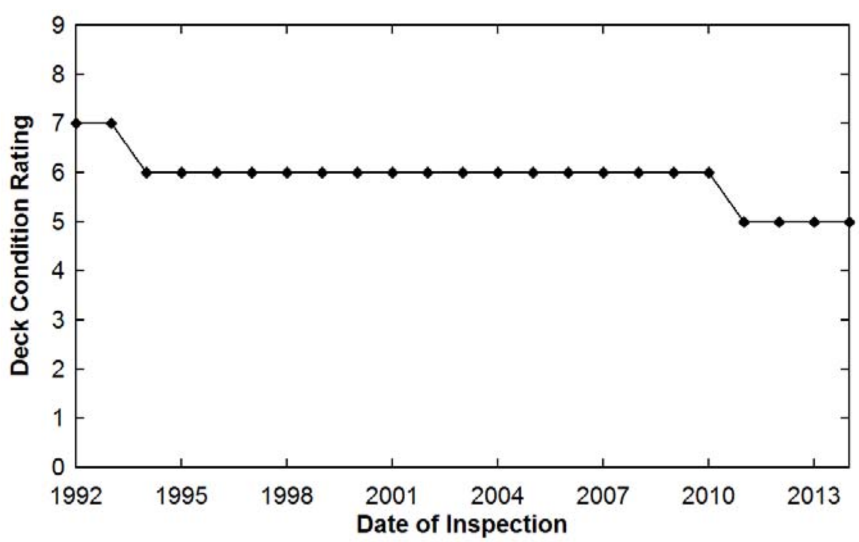

Figure 11. Deck condition ratings for bridge structure number 1680006.

Figure 12. Bridge deck from both sides of approaching traffic.

Figure 13. Examples of corrosion cracks.

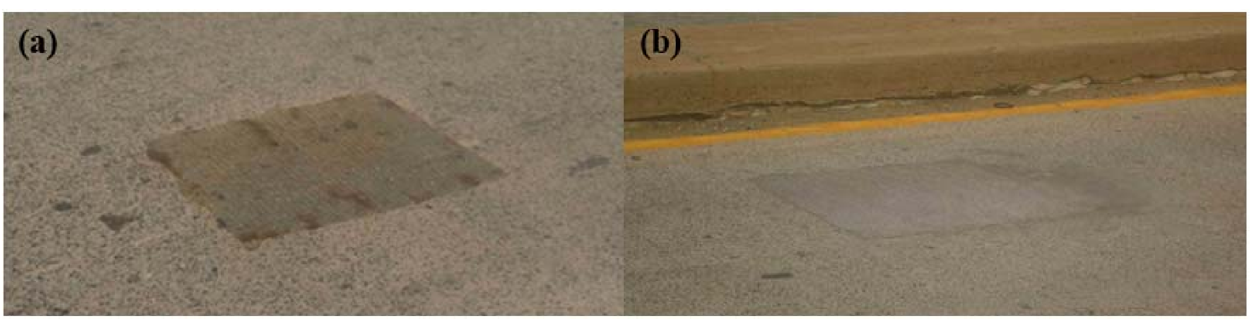

Figure 14. Example of (a) old bituminous patch on the concrete deck and (b) new concrete deck patch.

Figure 15. Two examples of corrosion seepage between deck patch and original deck.

Figure 16. Example of blocked scupper.

This bridge was quite deteriorated and had many (deck) patches, some new and others old. Following an initial look, a CR = 5 or 4 seemed appropriate for this deck. The report had indeed assigned the deck a CR = 5; however, this inspection took place on 5/30/2014. According to the inspector, the DOT report stated that there had been some rehabilitation done on the bridge deck after the inspection. This can be seen from the pictures above. According to the inspector, the bridge deck CR following rehabilitation rating would be a 6. Many of the old patches had evidence of corrosion seen on the surface of the deck and on the edges of the patch (Figure 15). The main source of corrosion was a gap between the concrete/bituminous patch and the original deck, which led water and air inside, the seepage causing the corrosion from the side.

Note: If spalling of a concrete deck is spotted, inspectors strike the deck with a hammer, and any resulting hollow noise verifies that part of the deck is spalled.

CHAPTER 3 - A NATIONWIDE CONCRETE HIGHWAY BRIDGE DECK PERFORMANCE INVENTORY DATABASE

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Introduction

Concrete Highway Bridge Decks

Highway bridge decks serve to (1) distribute the loads from vehicles to the bridge superstructure's main elements (i.e., diaphragms and girders), (2) increase the bending capacity of the supporting girders, and (3) provide a smooth and wear-resistant surface (Kyle, 2001). The main reason and highest cost for bridge superstructure repair and rehabilitation is deterioration of concrete decks (Li & Zhang, 2000). Several factors have been found to affect concrete bridge deck performance: depth of concrete cover (Williamson et al., 2007; Kirkpatrick et al., 2002; Kassir & Ghoshn, 2002; Stewart & Rosowsky, 1998), permeability of concrete (Stewart & Rosowsky, 1998; Vu & Stewart, 2000; ACI 365, 2000), type of reinforcing bar (rebar) steel (Russel, 2004; Violetta, 2002; Kirkpatrick, et al., 2002), compressive strength (Stewart & Rosowsky, 1998), distance from sea water (Vu & Stewart, 2000; Stewart & Rosowsky, 1998), early-age surface cracking (Kyle, 2001; Stewart & Rosowsky, 1998), concrete subsidence (Kyle, 2001), type of cement (Azizinamini et al., 2013; Russel, 2004), type of restraint (Russel, 2004), exposure to freeze-thaw cycles (Azizinamini et al., 2013), construction practices (Azizinamini et al., 2013; ACI 365, 2000), overload, and fatigue loading. Most studies conclude that the driving factor in concrete bridge deck performance in North America is corrosion of the reinforcing steel (Yannis et al., 2011), and all the factors stated above play a role in corrosion.

Background

The NBI database is perhaps the most comprehensive and consistent accessible dataset containing records of bridge parameters and condition data across the US. This in combination with the recent advances in data mining and visualization methodologies is perhaps the reason for the growing interest in NBI studies. This section provides a summary of relevant research. Terms relating to NBI items that appear in this section will be discussed in detail in the "The NBI Database" section.

Of the many published studies predicting future bridge ratings through statistical models, one example is the work done by Morcous that uses two methods, one of which is deterministic, using simple first-degree polynomial curve fit to find the deterioration of various bridge components, and the other stochastic, a Markov chain deterioration model (Hatami & Morcous, 2011). This approach only takes into consideration current CR, which can be adverse, given that the time elapsed from a bridge's initial CR is ignored (Dekelbab et al., 2008). Work by Bolukbasi et al. (2004) plots deterioration curves using a third-degree polynomial curve fit of condition rating versus bridge age, comparing that to another method that uses linear approximation. A more advanced approach has been developed by Nasrollahi and Washer (2015) that utilizes a probabilistic approach to estimate CR-based inspection intervals needed for concrete, steel, and prestressed concrete superstructures using NBI data for the State of Oregon. Their analysis is based on the duration a specific CR remains constant before it changes, referred to as a time-in-condition rating (TICR). A Weibull probability density distribution (PDF) was found to best represent TICR for each CR. Cumulative distribution function (CDF) graphs were developed based on the created PDF for each CR.

These CDF were used to develop probability-based inspection intervals in lieu of the standard 24-month intervals mandated by the FWHA. Maintenance effects, i.e. when the CR increases, were not considered in the analysis. Dekelbab et al. (2008) used NBI data from 1983 to 2006 to come up with a time-series data analysis based on the Kaplan-Meier method. These survival function curves show the percentage of bridge decks maintaining a specific CR versus their time in that condition. Another study by Tae-Hoon et al. (2006) using six different linear regression equations only considers bridge age to produce deterioration graphs for 30 different DOTs. The deterioration equations were chosen out of the six based on highest R squared values and a significance value of more than 95 %. Tabatabai et al. (2011) developed a two-parameter hypertabastic PDF to determine the service life of bridge decks in Wisconsin using 2005 NBI data. Deck CR of 4 and 5 were defined as the end of service life. Work by Abed-Al-Rahim and Johnston (1995) developed an equation based upon the average change from a specific CR in order to plot deck deterioration.

The FHWA Bridge Portal

As part of the long-term bridge performance (LTBP) program, the FHWA is creating a user-friendly internet-based program to access, analyze, and visualize data from the NBI that includes visual inspection data, nondestructive evaluation results, and some material testing results (FHWA, 2017). From this program called Bridge Portal, one can access: 1) simple search with predefined quick filters, 2) advanced search containing a larger list of filters, giving the user greater control over the search. Users can view bridges on Google maps and sort, reorder, add columns, and filter information on a population of bridges or a single bridge. Moreover, summaries of the search can be exported to Excel, PDF or KML.

Motivation and Objective

Several studies have introduced new deterministic and stochastic models to predict condition ratings (CR) based on the NBI database; however, most authors neither take into consideration nor consider the effects of maintenance as an interferer or interrupter of the natural deterioration of bridge decks. While many studies predict probability of CR change over time, not many focus on concrete highway bridge decks. Moreover, all such studies are limited to specific states. The objective of this research was to create a nationwide database for the US, referred to as Nationwide Concrete Highway Bridge Deck Performance Inventory (NCBDPI) database that captures the natural deterioration of concrete highway bridge decks. The NCBDPI contains 21 critical structural and environmental parameters, some of which were derived from the NBI database and others were computed and added by the authors such as state code, deck area, International Energy Conservation Code (IECC) Climatic Regions, distance from seawater, and bridge age. Additionally, two new performance parameters were computed from the available concrete bridge deck CR: Time-in-condition rating (TICR) and deterioration rate (DR). This paper introduces the created database and provides three select examples of how it can be used by agencies to answer questions regarding concrete highway bridge deck performance.

The NBI Database

Background and Overview

The collapse of the Silver Bridge in Ohio in 1967 resulted in a congressional mandate to all the State DOTs in the 1970s to establish a unified method of national bridge inspection standards (NBIS) for all the public highway bridges across the country with a span length of more than 20 ft. The associated data consisting of 116 items are stored in the National Bridge Inventory (NBI) and represent one of the most comprehensive sources of bridge information. Each of the fifty States, the District of Columbia, and the Commonwealth of

Puerto Rico submit their substructure, superstructure, and deck condition ratings every two years, which is then compiled in the NBI and made available to the general public. The data is used by the FHWA in their biannual report of bridge condition and performance to Congress. Based on the 2016 NBI census there are 614,387 bridges in the US (FHWA, 2016). Finally, the NBI database allows the State DOTs to monitor bridge performance and condition and identify if and what maintenance actions should be taken (Wu, 2010; Markow, 2009). The NBI's 116 items can be categorized as follows (Markow, 2009):

- "Items 1–27: General description and administrative information
- Items 28–42: Functional or operational (capacity) information, design load
- Items 43–44: Structure/design/construction type and material of construction
- Items 45–56: Span information, geometric information, and clearance dimensions (no Item 57)
- Items 58–70: Structural condition and bridge loading information
- Items 71–72: Waterway and approach data (no Items 73–74)
- Items 75–97: Inspector's work recommendations and projected costs
- Items 98–116: Other information of various categories."

This dataset was downloaded from the FHWA web site (FHWA, 2015) for all 50 States, Washington, D.C., and Puerto Rico. The parameters, referred to as "items" in the NBI, were imported from the NBI database using MATLAB. This was performed for the entire country.

Inspections and Condition Ratings

Trained and certified bridge inspectors assess structural components and operational characteristics and assign a condition rating (CR) between 0 to 9 separately for the bridge substructure, superstructure, and deck. Table 3 shows an example from Michigan DOT's (MDOT, 2011) evaluation of CR for bridge decks.

Table 3. Bridge deck CR (NBI Item 58) per Michigan NBI rating guide (MDOT, 2011).

CR	Description
9	**Excellent Condition** – No noticeable or noteworthy deficiencies, which affect the condition of the deck. Usually reserved for new decks.
8	**Very Good Condition** – No noticeable or noteworthy deficiencies, i.e., delamination, spalling, scaling or water saturation.
7	**Good Condition** – Scalable deck cracks, light scaling (less than ¼ in depth). No spalling or delamination of deck surface but visible tire wear. Substantial deterioration of curbs, sidewalks, parapets, railing, or deck joints (need repair). Drains or scuppers need cleaning.
6	**Satisfactory Condition** – Medium scaling (¼ to ½ in depth). Excessive number of open cracks (5-ft intervals or less). Extensive deterioration of curbs, sidewalks, parapets, railing, or deck joints (requires replacement of deteriorated elements).
5	**Fair condition** – Heavy scaling (½ to 1 in depth). Excessive cracking and up to 5% of the deck area is spalled; 20-40% is water saturated and/or deteriorated. Disintegrating of edges or around scuppers. Considerable leaching through deck. Some partial depth fractures, i.e., rebar exposed (repairs needed).
4	**Poor condition** – More than 50% of the deck area is water saturated and/or deteriorated. Leaching throughout deck. Substantial partial depth fractures (replace deck soon).
3	**Serious condition** – More than 60% of the deck area is water saturated and/or deteriorated. Use this rating if severe or critical signs of structural distress are visible and the deck is integral with the superstructure. Full depth failure or extensive partial depth failures (repair or load post immediately).
2	**Critical condition** – Some full depth failures in the deck (close the bridge until the deck is repaired or holes are covered).
1	**“Imminent” failure condition** – Substantial full depth failures in the deck (close the bridge until deck is repaired or replaced).
0	**Failed condition** – Extensive full depth failures in the deck (close the deck until the deck is replaced).

According to the FHWA recording and coding guide (FHWA, 1995), concrete bridge decks should be inspected for cracking, spalling, leaching, chloride contamination, potholing, delamination, and full or partial depth failures. When inspecting a bridge deck, the condition of the wearing surface, joints, expansive devices, curbs, sidewalks, parapets, bridge rails, and scuppers are not taken into consideration nor may they affect the CR of the deck. The influence of the deck on the superstructure or vice versa (e.g. rigid frame, slab, or box girder) is not to be taken into consideration and the rating is to be based on the deck only (FHWA, 1995). Concrete highway bridge decks were the focus of this research. Furthermore, CR between 1992 through 2014 were investigated.

Proposed Performance Parameters

Two concrete highway bridge deck performance parameters are proposed and presented in detail subsequently. Both are derived on the NBI Item 58: bridge deck condition rating (CR) and time-in-condition rating (TICR). The pre-processing necessary to compute these parameters are discussed first.

Pre-Processing of Condition Ratings

The condition ratings (CR) for concrete bridge decks (NBI Item 58) had numerous missing data (e.g., Table 4, where "NaN" entries mean "not a number").

Table 4. Sample concrete bridge deck CRs for years 1992 to 2014 for Oregon.

1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014
NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	7	7	7	7	7	7	7	7
NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	7	7	7	7	7	7	7	7
NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	7	7	7	7	7	7	7	7
NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	3	NaN	NaN	NaN	NaN	NaN	NaN	NaN
NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	7	7	7	7	7	7	7	7
NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	7	7	7	7	7	7	NaN	NaN
NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	8	8	8	8	8	8	8	8
NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	7	7	7	7	7	7	NaN	NaN
NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	8	8	8	8	8	8	8	8
6	NaN	NaN	6	6	6	6	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
NaN	7	7	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	7	7	7	7	7	7	7	7	7	7	6
NaN	3	3	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	3	3	3	3	3	3	3	NaN	NaN	NaN	NaN
NaN	4	4	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	4	4	4	4	4	4	4	NaN	NaN	NaN	NaN

The following pre-processing steps were performed to account for the missing data:

1. If there were one or two NaN, and the CR before and after the NaN were the same, the NaN was replaced by the corresponding CR. The assumption is that this CR may have gotten misplaced and it is unlikely to differ from the ones before and after.
2. If there was one NaN between two CR that were not the same, a random number (uniform distribution) was generated between 0 and 1. If that number was more than 0.5, the larger of the two CR was assigned to the NaN and if it was less than 0.5, the smaller one was assigned.
3. If there were two NaNs after each other and the CR before the NAN was a certain number and the CR after the NaN was another number, the first NAN was assigned the CR before it and the second NaN the CR after it.
4. An increase or decrease of the CR by one (CR) over a period of one year was considered as "noise." This was based on discussion with field inspectors and a recommendation by the North Carolina DOT (Abed-Al-Rahim & Johnston, 1995). Whenever that occurred, the CR was replaced with the CR before the spike (Figure 1).

Two performance parameters were proposed and computed from the CR data from 1992 to 2014 for every concrete highway bridge deck: time-in-condition rating (TICR) and deterioration rate (DR). TICR was proposed by Nasrollahi and Washer[16] but was modified for this research, as explained in the following section.

Time-In-Condition-Rating (TICR)

Proposed by Nasrollahi and Washer (2015), this performance parameter represents the number of years for which the CR of a bridge deck is constant, regardless of what the following CR is. Our methodology differs from this definition as we only consider the cases where the CR at the end of the TICR (= CR") is lower than the initial CR (= CR'), as illustrated in Figure 17. CRs that started in 1992 and were not constant (same) for at least five years were discarded. Moreover, CRs that ended in 2014 and did not have the same CR for the 5 years preceding was discarded. The reason why 5 years was chosen as a cutoff point was because given the 23 year interval over which data was analyzed, a range of values tested from 3 to 7 using a sensitivity analysis and it was found that 5 years is a suitable number. It was concluded that little difference is observed in the overall outcome of the data analysis, regardless of which value was chosen (3 to 7 years) (Nasrollahi & Washer, 2015). Different CRs that came after the first CR in 1992 were used, regardless of whether the CR stayed for less than five years since the start date of that CR was observable. Based on this, a procedure to compute a modified TICR, which we will subsequently refer to TICR, was implemented as follows:

1. Determine CR', i.e., CR at the beginning of TICR
2. Compute TICR, i.e., number of years between the year of CR' and the year of CR''. Only cases for which CR'' < CR' were considered to capture the "true" deterioration. Cases for which CR'' > CR' were considered maintenance actions and thus excluded.

It should be noted that by eliminating censored data, which is done here, bias is introduced in the analysis. A convenient way to consider both observed and censored data is by employing a Bayesian survival analysis, which is discussed in Chapter 5.

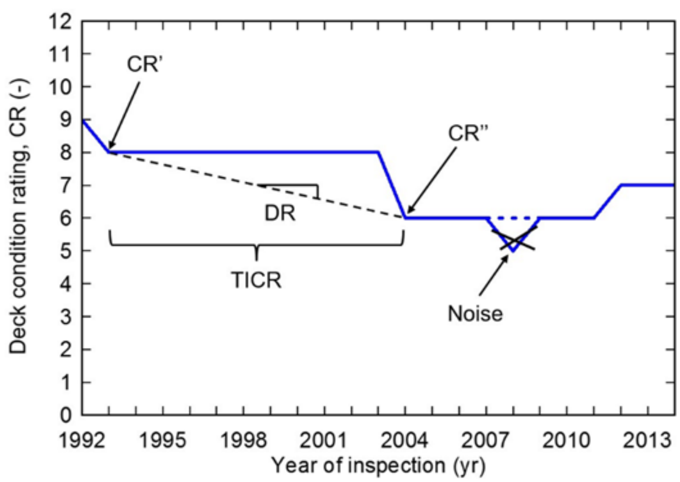

Figure 17. Sample bridge deck CR and computed TICR and DR parameters.

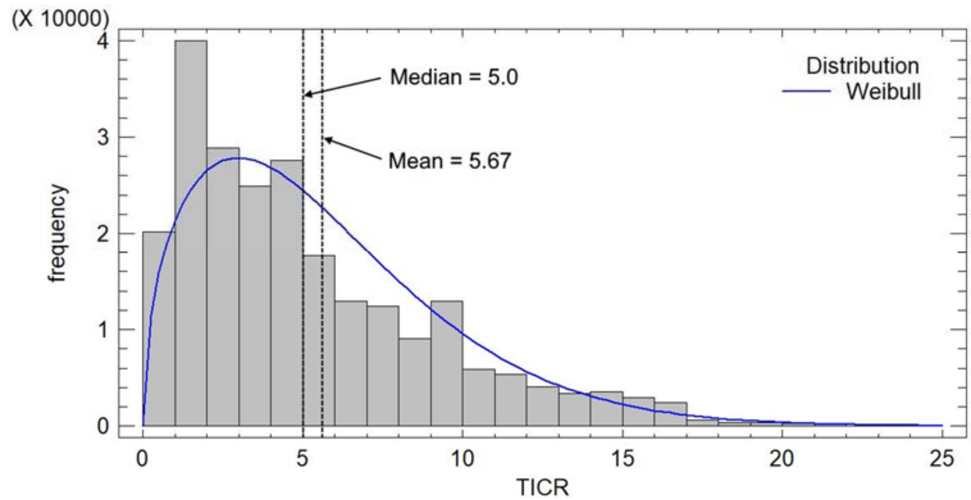

Figure 18. Histogram and inferred Weibull distribution for TICR for the entire US (all CR).

A standard Weibull distribution with shape and scale factors of 1.49 and 6.30, respectively, was found to be one of the best fitting distributions for TICR for the entire country (Figure 18). This distribution has been used in other fields to model in lifetime modeling and survival analysis and is thus appropriate for TICR data. Also given are the mean and median TICR, which correspond to 5.67 and 5.0 years, respectively. This means, on average and across the US, a concrete highway bridge deck is assigned the same CR for 5.67 years before it is assigned a lower one. Tests for normality using a Chi-square test, skewness Z-score, and Kurtosis Z-score test all produced p-values of zero, confirming that the hypothesis that the TICR parameter comes from a normal distribution can be rejected with 95% confidence.

Figure 19 shows the mean TICR for each state for all CR. As can be observed, the results vary notably between states: Arkansas has the highest and Oregon the lowest TICR. Minnesota, Missouri and Massachusetts did not have any data available to compute any TICR, due to the large amount of missing CR data (NANs).

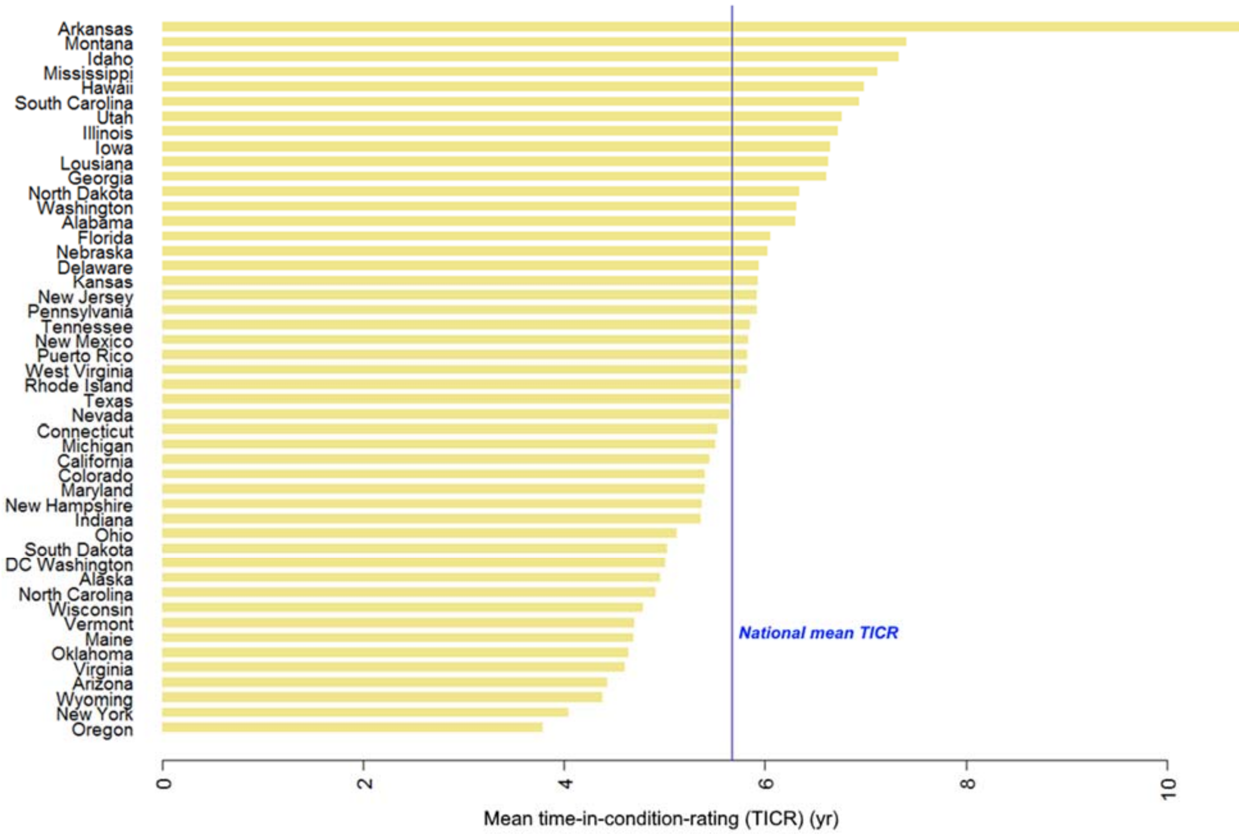

Figure 19. Mean TICR for all states.

Deterioration Rate (DR)

This performance parameter is computed as the change of CR, as illustrated in Figure 17. Although this parameter technically represents the change of CR (Figure 17), it is subsequently referred to as deterioration rate (DR). It should be noted that it is based on the change of the CR and thus based on a number of deterioration mechanisms observed during bridge inspections.

The computation of DR follows the same process as for the TICR. However, the CR following TICR, i.e., CR", was also needed in order to calculate the DR. To compute the DR, a MATLAB code was implemented as follows:

1. Compute (modified) TICR as described in the previous section
2. Determine CR", i.e., after TICR ends, specifically when the CR has decreased
3. Compute DR = (CR' – CR") / TICR

Figure 20 shows the mean DR of each state. States colored in grey (Minnesota, Missouri, and Massachusetts) had insufficient data to compute any DR. New York, Washington DC, and New Jersey have the highest DR; Arkansas, Georgia, and Alabama have the lowest DR.

Final Comments

It should be noted that it is possible to compute more than one TICR or DR per concrete bridge deck. This can happen if a bridge deck CR decreases multiple times throughout its observable service time (1992-

2014) .When it did happen, new rows of data were created in the database, assuming that the computed TICR and DR are essentially statistically independent observations.

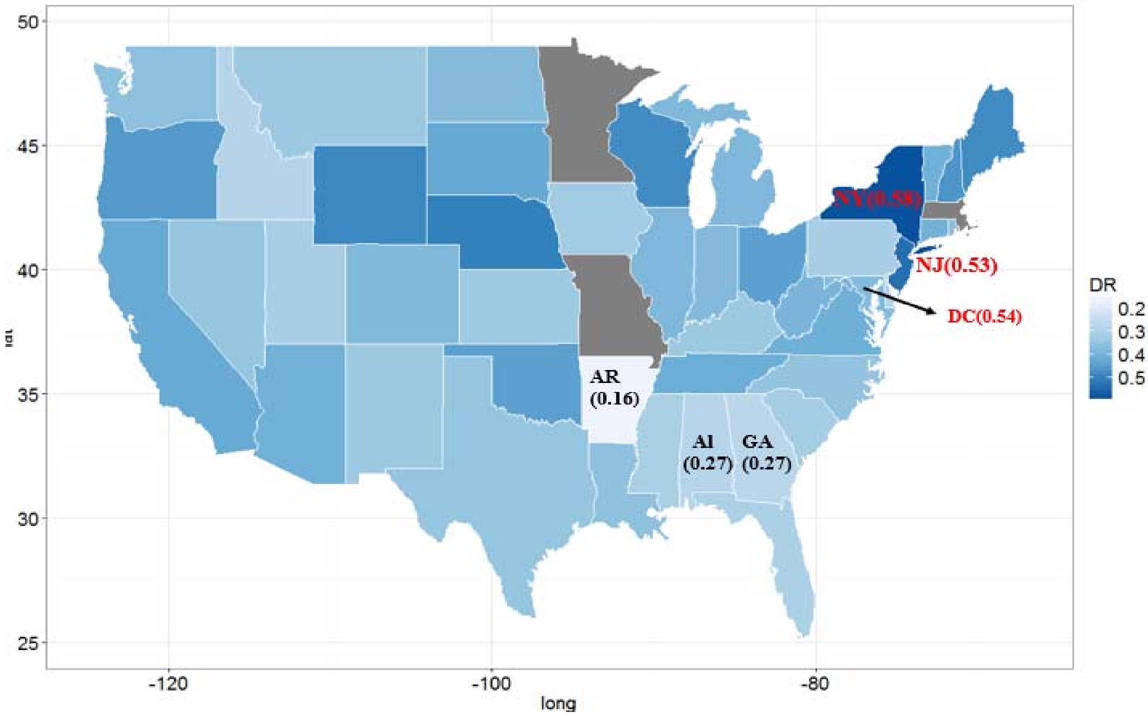

Figure 20. Mean DR for all states.

Creation of the NCBDPI Database

The proposed database with all parameters consisted of 239,794 data rows, corresponding to the total number of TICR and DR calculated from the CR data, as discussed in the previous section. The subsequent sections contain a list of the parameters that were extracted, processed, and thereby made available for statistical analysis.

Initial Filtering

The following filters were applied to the original dataset:

- NBI Item 42a – Type of Service on Bridge: This item was used as a filter to ensure that all bridge decks were associated with highway bridges to exclude pedestrian or railroad bridges.
- NBI Item 107 – Deck Structure Type: Only concrete cast-in-place (Code 1) and concrete precast panels (Code 2) were included in the analysis.

Selected NBI Parameters

Fifteen of the NBI items that were considered influential in affecting concrete highway bridge deck performance were included in the nationwide database, and are:

- NBI Item 3 – Country (Parish) Code
- NBI Item 8 – Structure Number
- NBI Item 21 – Maintenance Responsibility
- NBI Item 26 – Functional Classification of Inventory Route

- NBI Item 27 – Year Built
- NBI Item 28 – Lanes on Structure
- NBI Item 43a – Structural Material/Design
- NBI Item 43b – Type of Design and/or Construction
- NBI Item 58 – Deck Condition Rating (CR)
- NBI Item 91 – Designated Inspection Frequency
- NBI Item 106 – Year Reconstructed
- NBI Item 107 – Deck Structure Type
- NBI Item 108a – Type of Wearing Surface
- NBI Item 108b – Type of Membrane
- NBI Item 108c – Deck Protection
- NBI Item 109 – Average Daily Truck Traffic (ADTT)

Additional Parameters

The following additional important parameters that were not originally in the NBI database were developed by the authors and included in the NCBDPI database:

1. State Code – Although the NBI has a state code (= Item 1), we decided to use a simpler numbering from 1 to 52, which is organized alphabetically. This includes Puerto Rico and Washington DC.
2. Deck Area – This parameter was computed by multiplying two NBI parameters, as follows:

$$\text{Deck Area} = \text{NBI Item 49 x NBI Item 51} \qquad \text{Equation 7}$$

   - NBI Item 49 – Structure Length
     This is defined as the length of roadway that is supported on the bridge structure and should be measured back-to-back of backwalls of abutments or from paving notch to paving notch.
   - NBI Item 51 – Bridge Roadway Width, Curb-to-Curb
     The information to be recorded is the most restrictive minimum distance between curbs or rails on the structure roadway.
3. International Energy Conservation Code (IECC) Climatic Regions

   Climate regions were based on US Department of Energy designations (International Code Council, 2009), comprising eight temperature areas ranging from Zone 1 (hottest) to Zone 8 (coldest), and three moisture regimes, marine, dry, and moist (Figure 5), designations allowing for up to 24 different assessment combinations. Because our research is mainly concerned with the effects of snow on concrete bridge decks, not all 24 combinations were considered. The following are the assumptions used:

   - Zone 1 consisted of three counties in Florida, Hawaii, and Puerto Rico. Because those regions had very few TICR data points, they were combined with Zone 2.
   - Of all moisture regimes, only that of marine was considered, as this moisture regime has little snow for most climatic zones. For example, although the Marine region for Oregon and Washington falls in Zone is 4, it snows much less as compared with Delaware which is also in Zone 4.

- Zones 2 and 1 were considered as “very hot,” 3 as “hot,” 4 as “average,” 5 as “cold,” 6 as “very cold,” 7 as “extremely cold,” and 8 as “subarctic.” Marine areas of Zone 4 were labeled as “average marine,” and those of Zone 3 labeled “hot marine.”

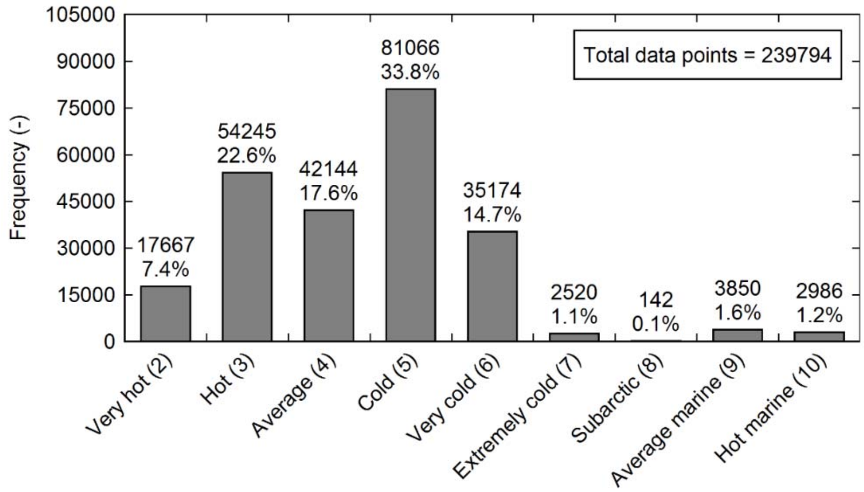

Figure 21. Histogram for IECC Climatic Regions. Numbers in parentheses represent a group code.

The distribution of the nine resulting IECC Climatic regions and regimes is shown in Figure 21.

4. Distance to Seawater
This parameter represents the distance of a bridge deck to the closest seawater body. Elevation of the deck was not considered in the analysis. The distance, *x* was split into three groups guided by a study performed by Stewart & Rosowsky (1998) and its distribution is shown in Figure 22:
    - $x < 1$ km (0.62 miles)
    - 1 km (0.62 miles) $< x <$ 2 km (1.24 miles)
    - $x > 2$ km (1.24 miles)

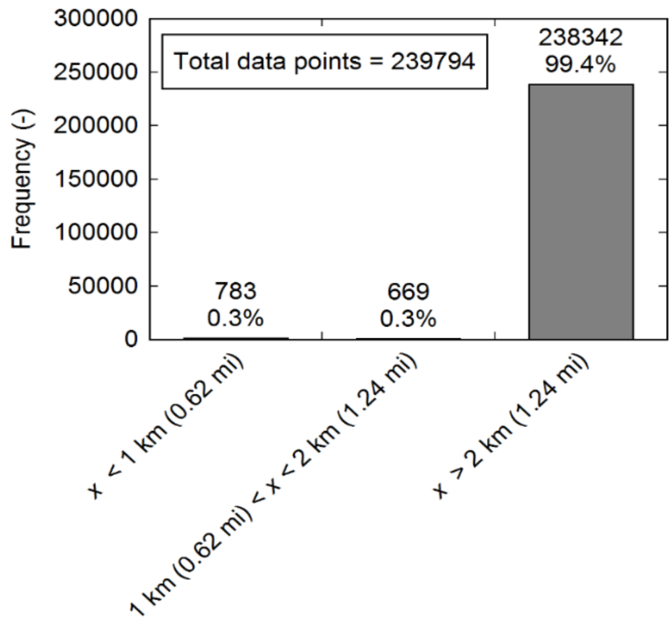

Figure 22. A histogram for Distance to Seawater.

5. Bridge Age

This parameter was calculated for the year 2014, as follows:

$$\text{Bridge age} = 2014 - [\text{larger of (NBI Item 27 or NBI Item 106)}] \quad \text{Equation 8}$$

where NBI Items 27 and 106 correspond to year built and year reconstructed, respectively. The mode and scale for the best-fit distribution, which is a largest-extreme value distribution, are 30.5 and 17.3 years, respectively (Figure 23). The mean and median bridge age correspond to 40.2 and 39.0 years, respectively.

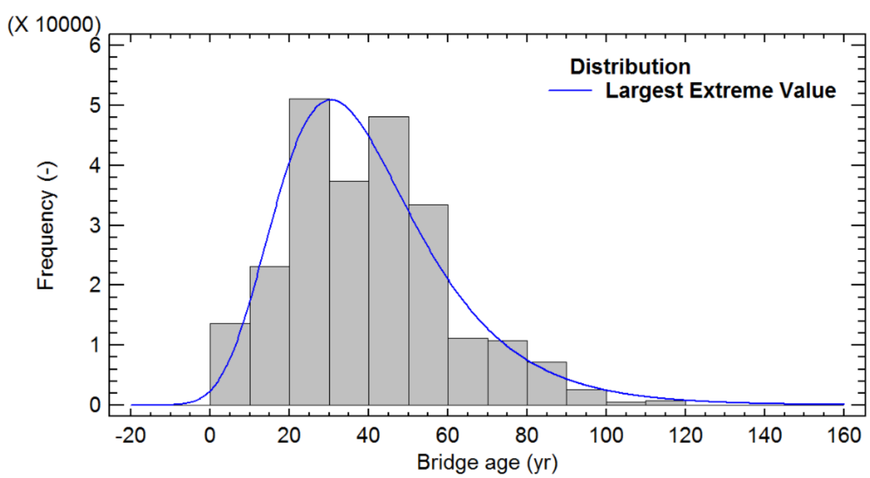

Figure 23. A histogram and best-fit distribution for bridge age.

Parameters not Included in the NCBDPI

Additional parameters such as use of deicing salt or material-related parameters (e.g., concrete mix, strength, and cover, or rebar type and spacings, etc.) could not be incorporated because no relevant detailed historic information was available for them. For example, any changes in state provisions regarding mix designs would have to be connected to the year in which those changed. This information is simply not available, and assigning one value for bridges of all ages is not meaningful. However, it would be straight-forward to expand the new database in the future should such or other information become available.

Final Processing

Before the database could be analyzed, some additional data processing and filtering was deemed necessary. The reason is that histograms of the selected individual parameters revealed that some of the groups have very few entries; such thin data cannot be statistically analyzed as doing so would lead to an uneven distribution of the data in those groups. The solution was to combine certain groups that are similar and omit the ones that are not specific or have very few data points. The number of data rows in the final database after preprocessing was 236,010. The dataset thus lost 3,783 of the data rows, which account for just 1.6% of the data.

Preliminary Descriptive Statistical Analysis

In this section, three examples of how the database can be used to answer questions that agencies might have are presented. Prior to these examples, the TICR parameter is more closely analyzed in order to determine what statistical analysis procedures are applicable. Summary statistics, tests for normality, and Kruskal-Wallis tests were computed with the commercially available program STATGRAPHICS Centurion (2017).

Statistics for TICR Performance Parameter

Table 5 shows some basic statistics of the time-in-condition rating (TICR) parameter, separated by bridge deck condition rating (CR). It can be observed that the values for standard skewness as well as standard kurtosis lie both outside the range of -2 to +2, indicating significant non-normality of the data. Thus, simple analysis of variance (ANOVA) is not applicable. The data for CR < 3 were omitted in the subsequent analysis due to low counts.

Table 5. Summary statistics for TICR parameter.

CR	*Count*	*Mean*	*Median*	*St. Dev.*	*C.o.V.*	*Minimum*	*Maximum*	*Range*	*Stnd. skewness*	*Stnd. kurtosis*
1	1	9.0	9.0	n.a.	n.a.	9.0	9.0	0	n.a.	n.a.
2	35	3.257	2.0	2.894	88.8%	1.0	14.0	13.0	4.828	5.619
3	397	3.131	2.0	2.534	80.9%	1.0	21.0	20.0	19.58	38.72
4	2694	4.212	3.0	3.307	78.5%	1.0	22.0	21.0	32.34	26.44
5	12780	4.749	4.0	3.526	74.3%	1.0	22.0	21.0	61.89	41.38
6	39649	5.310	4.0	3.855	72.6%	1.0	22.0	21.0	99.30	50.40
7	84136	6.193	5.0	4.157	67.1%	1.0	22.0	21.0	-549.2	27.20
8	77914	5.841	5.0	4.057	69.4%	1.0	22.0	21.0	425.6	39.70
9	18404	4.180	3.0	3.374	80.7%	1.0	22.0	21.0	86.87	61.05
Total	236010	5.665	5.0	4.021	71.0%	1.0	22.0	21.0	-92123	80.91

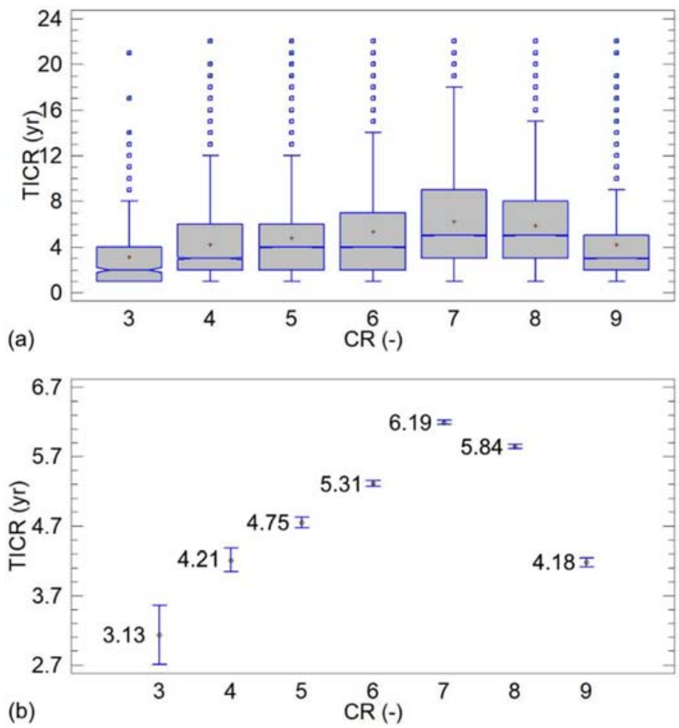

Figure 24. TICR vs. CR for CR > 2: (a) Box-and-Whisker Plot and (b) means with 95% Bonferroni confidence limits. Numerical values for means are given in (b).

Figure 24 compares the TICR graphically. Figure 24 (a) shows the median (notch), upper and lower quartiles (upper and lower limit of box), lowest and highest values (error bars), outliers (dots) and means (red +). It can be observed that the data follows an inverted "bathtub" curve with the highest TICR found at CR = 7. Figure 24 (b) shows the means with 95% Bonferroni confidence intervals. Numerical values for Figure 24 are shown in Table 5.

A Kruskal-Wallis test showed that there was a statistically significant difference between certain CR groups at the 95% confidence level. The Kruskal-Wallis test is a non-parametric (or distribution free) test used to compare data that do not follow a normal distribution. The null hypothesis assumes that the data groups come from identical populations. The P-Value was found as 1.0, which is greater than 0.05, which implies that not all data groups come from the same population with 95% confidence. Table 6 shows a pairwise comparison of the CR categories. Asterisks indicate statistically significant differences at the 95% confidence level.

Table 6. Kruskal-Wallis pairwise comparisons between CR categories.

Contrast	Sig.	Difference	+/- Limits
3 - 4		2835.3	11126.0
3 - 5		5235.1	10547.0
3 - 6		1000.5	10439.0
3 - 7		-6008.7	10411.0
3 - 8		-2163.0	10413.0
3 - 9		1151.0	10498.0
4 - 5		2399.8	4387.4
4 - 6		-1834.8	4120.5
4 - 7	*	-8844.0	4050.6
4 - 8	*	-4998.3	4055.6
4 - 9		-1684.3	4269.1
5 - 6	*	-4234.6	2105.1
5 - 7	*	-11244.	1964.8
5 - 8	*	-7398.1	1975.1
5 - 9	*	-4084.1	2383.0
6 - 7	*	-7009.2	1260.7
6 - 8	*	-3163.5	1276.7
6 - 9		150.53	1845.9
7 - 8	*	3845.7	1029.0
7 - 9	*	7159.7	1684.1
8 - 9	*	3314.0	1696.1

Example 1: Effect of Climatic Region

An agency might be interested in climatic effects on bridge deck performance. The question could thus be: *What are the climatic effects on mean concrete highway bridge deck TICR?* Using the IECC Climatic Regions added by the authors, Figure 25 shows the climatic effects for Regions 2 to 7, which are located in the contiguous US (see Section "Additional Parameters") on the mean TICR. The analysis was performed using CR > 2 and only considered cast-in-place decks (NBI Item 107, Group 1).

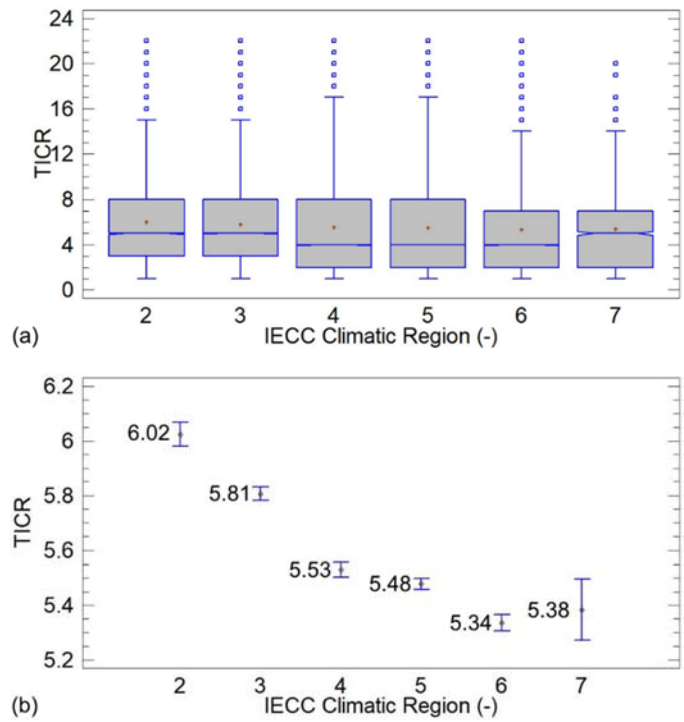

Figure 25. TICR vs. IECC Climatic Region for CR > 2 and NBI Item 107: (a) Box-and-Whisker Plot and (b) means with 95% Bonferroni confidence limits. Numerical values for means are given in (b).

The Kruskal-Wallis P-Value was found to be 1.0, which is larger than 0.05, which indicates that not all of the six groups come from different populations. Also, pairwise comparisons were found significant for all combinations except for Group 4 – Group 5, Group 4 – Group 7, and Group 5 – Group 7 at the 95% confidence level. Figure 25 shows a clear trend for colder climates to be associated with lower mean TICR, which makes intuitive sense.

Example 2: Effect of ADTT

Another question of an agency might be: *How does the number of trucks affect the mean TICR of a concrete highway bridge deck?* To answer this question, all CR > 2 were included and the analysis was performed for Climatic Region 5 (cold). ADDT values were grouped according to the following limits:

- ADTT ≤ 100 – low (Group 1)
- 100 < ADTT ≤ 8500 – medium (Group 2)
- ADTT > 8500 – high (Group 3)

From Figure 26 it can be observed that there is a trend for the mean TICR to decrease with increasing ADTT. The Kruskal-Wallis P-Value was found to be 0.0, which is less than 0.05, which indicates that the three ADTT categories come from different populations. Also, pairwise comparisons were found significant for all combinations at the 95% confidence level. To conclude, a higher number of trucks decreases the mean time duration a bridge deck is assigned a certain CR, which indicates faster deterioration.

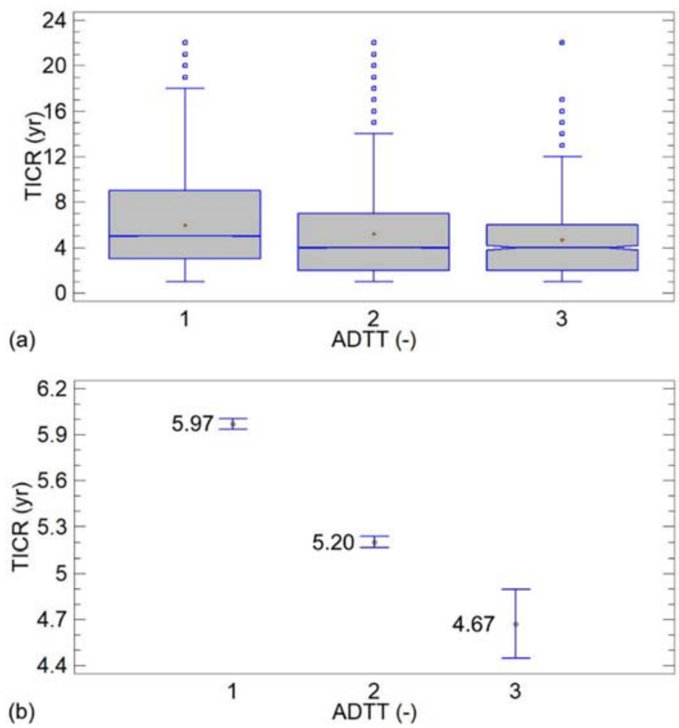

Figure 26. TICR vs. ADTT for CR > 2 and Climatic Region 5: (a) Box-and-Whisker Plot and (b) means with 95% Bonferroni confidence limits. Numerical values for means are given in (b).

Example 3: Effect of Deck Structure Type

Another question that an agency might have could be: *Does the type and material of the supporting structural system influence the decks' mean TICR?* This analysis was performed using CR > 2 and only considered cast-in-place decks (NBI Item 107, Group 1) supported by girders (NBI Item 43b, Groups < 4). The NBI Item considered is 43a (see Figure 27), which consists of the following groups:

- Concrete – simple span (Group 1)
- Concrete – continuous (Group 2)
- Prestressed concrete – simple (Group 3)
- Prestressed concrete – continuous (Group 4)
- Steel – simple span (Group 5)
- Steel – continuous (Group 6)

The Kruskal-Wallis P-Value was found to be 0.0, which is less than 0.05, which indicates that the six groups come from different populations. Also, pairwise comparisons were found significant for all combinations except for Group 1 – Group 5 and Group 3 – Group 6 at the 95% confidence level.

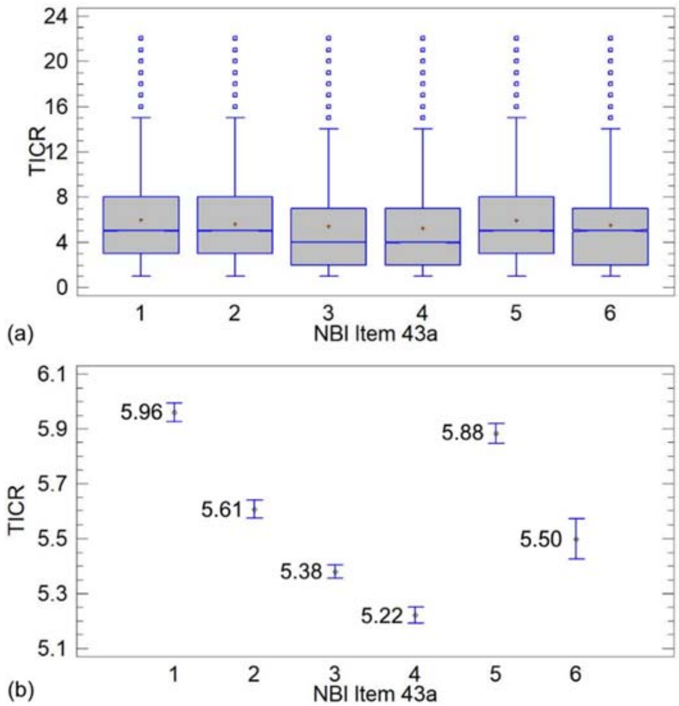

Figure 27. TICR vs. NBI Item 43a for CR > 2, NBI Item 107, Group 1, and NBI Item 43b, Groups < 4: (a) Box-and-Whisker Plot and (b) means with 95% Bonferroni confidence limits. Numerical values for means are given in (b).

Several interesting observations can be made from Figure 27:

- Simply-supported bridge decks have consistently higher mean TICR compared to when they are part of a continuous system.
- Bridge decks supported by a concrete simple span system have the highest mean TICR.
- Bridge decks supported by a prestressed concrete continuous span system have the lowest mean TICR.

Overall, the data suggests that simple span deck systems perform better, which can be explained by the fact that they do not experience negative bending moments that result in tensile stresses in the deck.

Conclusions and Future Work

In this research, a nationwide database for concrete highway bridge decks, referred to as Nationwide Concrete Highway Bridge Deck Performance Inventory (NCBDPI), was created based on NBI data and additional computed parameters: state code, deck area, International Energy Conservation Code (IECC) Climatic Regions, distance to seawater, and bridge age. Furthermore, two performance parameters were developed from the NBI concrete bridge deck condition ratings (CR): Time-in-condition rating (TICR) and deterioration rate (DR). In order to compute these two parameters, filtering and processing was performed on the NBI CR due to noise and the numerous missing data.

A preliminary descriptive statistical analysis was then performed on a number of select parameters using Box-and-Whisker plots and means with 95% Bonferroni confidence intervals, along with the Kruskal-

Wallis test to determine statistical significance. The performance parameter TICR was found to follow an inverted bathtub relationship with CR. The highest mean TICR, which was 6.19, was found to be associated with CR = 7, which was also the most common CR. Three examples were presented to demonstrate how questions regarding concrete highway bridge deck performance can be answered using the NCBDPI database. The following specific conclusions can be made from the three examples:

- Increasing ADTT is associated with decreasing mean TICR.
- Bridge decks supported by simple span systems exhibit higher mean TICR compared to when they are supported by a continuous system.
- Lower mean TICR are associated with colder climates.

The NCBDPI database can be used in the future to develop more advanced statistical models. It should be noted that this database does not contain certain critical parameters such as structural design characteristics (e.g., concrete cover, reinforcement bar sizes, bar spacings), construction practice (e.g., placement procedures, curing practices), actual early-age properties (e.g., water-to-cement ratio, porosity, compressive strength), and other notable factors (e.g., use of deicing agents, freeze-thaw cycles). We would advise future research to attempt incorporation of such parameters into the database in order to get an improved understanding of the parameters affecting bridge deck deterioration in order to more accurately model it. Also, including censored data by using, for example, a Bayesian survival analysis, would decrease bias in the predictions. This type of analysis is discussed in Chapter 5.

CHAPTER 4 - PERFORMANCE OF US CONCRETE HIGHWAY BRIDGE DECKS CHARACTERIZED BY BINARY LOGISTIC REGRESSION

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Note: This chapter was submitted to the *ASCE-ASME Journal of Risk and Uncertainty in Engineering Systems, Part A: Civil Engineering* and is currently under review. Please look for the peer-reviewed journal publication version of this chapter entitled "Performance of US Concrete Highway Bridge Decks Characterized by Random Parameters Binary Logistic Regression" under the following link: https://ascelibrary.org/journal/ajrua6.

Introduction and Background

The over 600,000 bridges across all states represent critical components of the US transportation system, ensuring network continuity. The highest costs in bridge superstructure repair and rehabilitation are incurred through maintenance, repair, and replacement of concrete bridge decks (Li and Zhang, 2001). Understanding the causes of bridge deck performance is therefore central to asset management. Bridge decks, which are exposed to freeze and thaw cycles, deicers, and heavy traffic loads, are a bridge's most susceptible element. Concrete bridge deck deterioration is also a leading cause for structural deficiency (Russell, 2004). According to the Federal Highway Administration (FHWA), two billion dollars are spent annually for maintenance and capital costs for concrete bridge decks (ASCE, 2013). As a direct consequence, Departments of Transportation (DOT) and the FHWA are interested to determine the reasons behind concrete bridge deck deterioration.

Many published studies have investigated the effects of chloride penetration on deck performance (e.g., Williamson, 2007; Wedding et al., 1983). Other research has attempted to predict future bridge ratings by using various deterministic and stochastic models such as multiple regression (e.g., Tae-Hoon et al., 2006; Bolukbasi et al., 2004), curve fitting (e.g., Morcous and Hatami, 2011), Markov models (e.g., Agrawal et al., 2010; Morcous, 2006), and Bayesian models (e.g., Attoh-Okine and Bowers, 2006). Although promising, these studies are not nationwide and most of them do not focus on concrete bridge decks. Also, they do not attempt to quantify the effects of environmental and structural parameters such as average daily truck traffic (ADTT), climatic region, distance to seawater, or bridge age, on concrete bridge deck performance.

Logistic regression has been widely applied across civil engineering disciplines: transportation, for modeling crashes (e.g., Dissanayake and Lu, 2002; Harb et al., 2008; Donnell and Mason, 2004; Al-Ghamdi, 2002), construction management, for modeling contractors bids (e.g., Lowe and Parvar, 2004; Hwang and Kim, 2016), disputes (e.g., Diekmann and Girard, 1995; Cheung et al., 2010) and contractors performance (e.g., Wong, 2004), and risk analysis (e.g., Ozdemir, 2016; Mwesige et al., 2016; Smith and McCarty, 2009). In structural engineering, LR models have been used to study the performance of beam-column connections (Mitra et al., 2011; Kang and Mitra, 2012).

More closely related to this study, Ariaratnam et al. (2001) used LR to study the performance of local sewer systems in Edmonton, Canada. Age, diameter, material, waste type, and average depth of cover were modeled as the independent variable. Pipe condition ratings from closed circuit television (CCTV) inspections were used as the dependent variable. The study concluded that age, diameter and waste type have a significant effect on deterioration of local sewer systems. Moreover, increasing age increased the odds of pipe deficiency and increasing diameter decreased the odds of pipe deficiency. Shan and Lewis (2016) used a binary LR to characterize deficient steel bridges with concrete cast-in-place deck and multibeam/girder designs based on the NBI data. Condition ratings (CR), which vary from 0 (failed) and 9 (excellent), for the year 2013 were used in their study, which was based on 15 independent variables from the NBI. The dependent variable for the binary LR was CR, where CR ≤ 4 was considered structurally deficient and CR ≥ 5 non-deficient. The best model consisted of eight independent variables (average daily traffic (ADT), structure length, length of maximum span, bridge roadway width, state code, owner, and age), two of which, owner and state code, were insignificant (p-value > 0.05). The model had a sensitivity of 83% and false negative of 19%, which is typically regarded as acceptable.

Objective and Motivation

The objective of this study was to characterize the effect of various environmental, structural, construction, climatic, and traffic related parameters on concrete bridge deck performance. Specifically, the focus was on two extreme groups: bridges that have experienced the highest and lowest levels of deterioration. A binary logistic regression (LR) framework was developed to quantify the impact of various parameters on the likelihood of a bridge deck being associated with the group of highest and lowest deterioration rates (DR). DR was one of two new performance metrics that were proposed in Chapter 3.

Experimental Dataset

The authors have created a Nationwide Concrete Bridge Deck Performance Inventory (NCBDPI) database (Chapter 3) with the specific goal of adopting a more statistical and data mining approach to understanding concrete highway bridge deck performance. The primary source of information for the NCBDPI database is the National Bridge Inventory (NBI) database (FHWA, 2016). For this study, a number of NBI items were extracted and complemented with additional parameters such as climatic region, distance to seawater, bridge age, and deterioration rate (DR).

One of the key performance metrics available in the authors' NCBDPI database is the DR, which the authors defined as follows (Chapter 3):

$$\mathrm{DR} = {}^{(\mathrm{CR}' - \mathrm{CR}'')}/_{\mathrm{TICR}} \qquad \text{Equation 9}$$

where CR' and CR" are the bridge deck CR at the beginning and end of a series of consecutive CR and TICR is the duration in years, as illustrated in Figure 28.

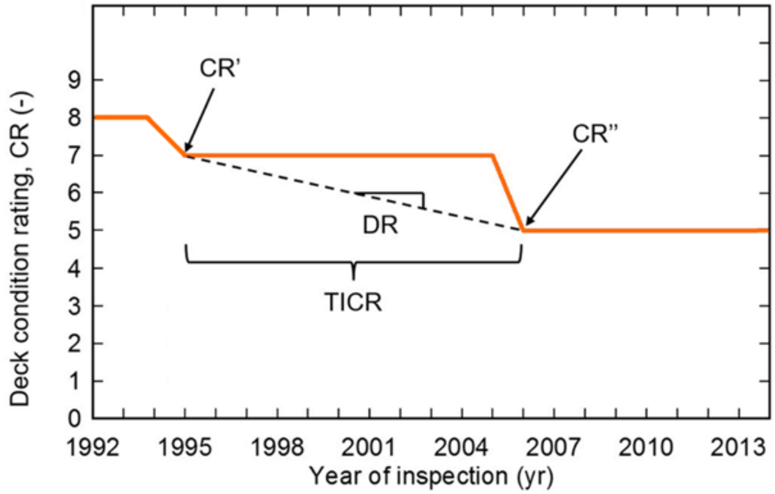

Figure 28. Sample bridge deck CR and computed parameters.

This study regarded concrete bridge decks with DR ≤ 0.056 as the group with the lowest deterioration rate ("lowest DR") with a total of 1,569 observations. DR = 0.056 means that a bridge deck was assigned the same CR for approximately 18 years, i.e. TICR = 18, before experiencing a one-unit CR decrease. Concrete bridge decks assigned a DR ≥ 2 were considered as part of the group associated with the highest deterioration rate ("highest DR") with a total of 1,693 observations. DR = 2 means that the bridge was assigned the same CR for one year, i.e. TICR = 1, before a two-unit CR decrease occurred. The thresholds of 0.056 and 2 were defined by considering both practical aspects as well as the goal to ideally have two groups with a similar number of samples.

The lowest and highest DR groups were coded as binary variables and assigned 0 and 1, respectively. The reason behind taking these values was to make a clear distinction between the best and worst performing concrete bridge decks. Figure 29 shows the histograms for the lowest (a) and highest (b) bridge deck DR as a function of CR.

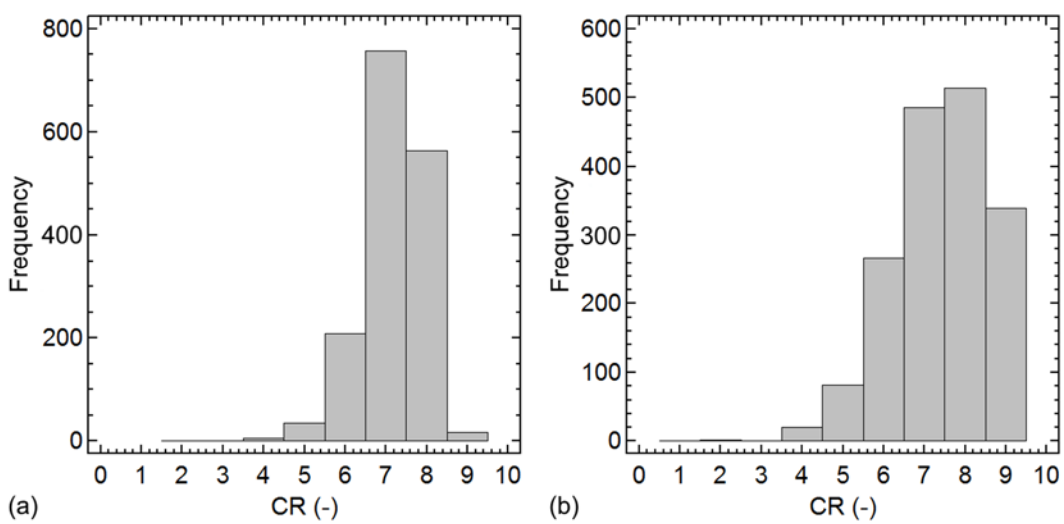

Figure 29. Histogram for (a) lowest and (b) highest bridge deck DR as a function of CR.

Figure 30 shows the histograms and best-fit distributions for the lowest (a) and highest (b) bridge deck DR over all CR.

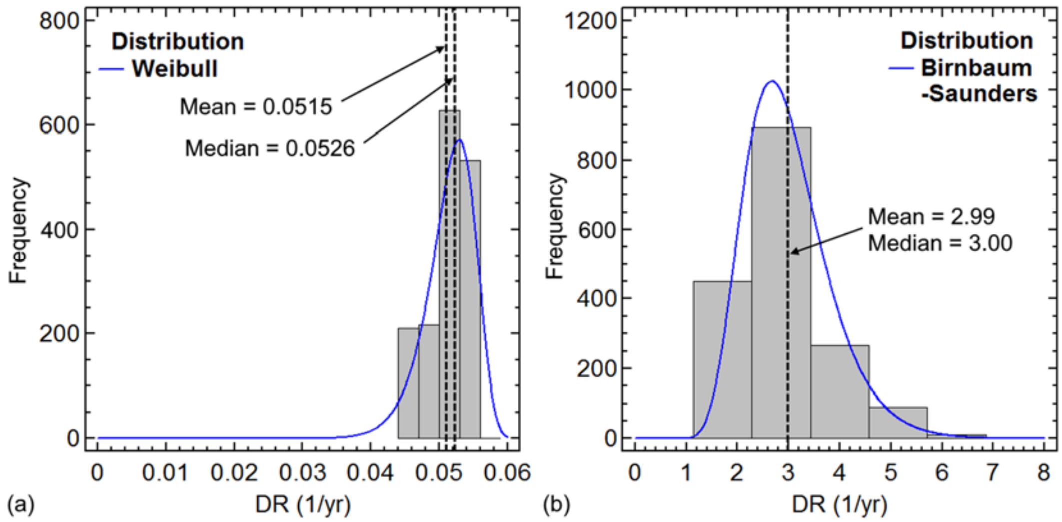

Figure 30. Best-fit distributions of (a) lowest and (b) highest bridge deck DR (all CR).

Table 7 presents a summary of the variables included in the study and/or their frequencies. Refer to Chapter 3 for more details. Following are some observations: The average ADTT on the bridges in the dataset is nearly 1000. A significant majority of the bridges has cast-in-place decks. In terms of structural material and/or design, close to 80% of the bridge decks are part of either a simple or continuous span concrete or prestressed concrete bridge system. Close to 75% of the bridges have no deck protection and more than 75% of the bridges have no membrane. A majority of the bridge decks captured in the sample were in rural areas. Finally, a state highway agency was responsible for the maintenance of nearly two-thirds of the bridges.

Table 7. Summary statistics and counts for the parameters included in this study.

Continuous variable	**Minimum**	**Mean**	**Maximum**
Distance from Seawater (km)	0	5,655	16,619
Deck Area (ft^2) – computed from NBI Items 49 and 51	2370	74,304	4,080,000
Average Daily Truck Traffic (ADTT) – NBI Item 109	0	983	25,432
Bridge Age (yr) – computed from NBI Items 27 or 106	0	39.8	122
Number of Lanes (-) – NBI Item 28	1	1.45	11
Categorical variable	**Categories**	**Frequency**	**Percentage**
Deck Structure Type – NBI Item 107	Cast-in-Place	2,899	88.0
	Concrete Precast Panels	397	12.0
Structural Material/Design – NBI Item 43a	Concrete – simple span	764	23.2
	Concrete – continuous	454	13.8
	Prestressed concrete – simple	872	26.5
	Prestressed concrete – continuous	515	15.6
	Steel – simple span	554	16.8
	Steel – continuous	137	4.2

Climatic Region (IECC)	Very Hot	215	6.5
	Hot	919	27.9
	Average	553	16.8
	Cold	1,045	31.7
	Very Cold (VC)	444	13.5
	Extremely Cold (EC)	33	1.0
	Average Marine (AM)	38	1.2
	Hot Marine (HM)	49	1.5
Deck Protection – NBI Item 108c	None	2,421	73.5
	Epoxy-Coated Reinforcing	487	14.8
	Galvanized Reinforcing	16	0.5
	Other Coated Reinforcing	4	0.1
	Cathodic Protection	2	0.1
	Polymer Impregnated	11	0.3
	Internally Sealed	1	0.0
	Unknown	329	10.0
	Other	25	0.8
Type of Membrane – NBI Item 108b	None	2,566	77.9
	Built-up	106	3.2
	Preformed Fabric	99	3.0
	Epoxy	23	0.7
	Unknown	403	12.2
	Other	99	3.0
Type of Wearing Surface – NBI Item 108a	None	207	6.3
	Monolithic Concrete	1,239	37.6
	Integral Concrete	248	7.5
	Latex Concrete or Similar Additive	131	4.0
	Low-Slump Concrete	59	1.8
	Epoxy Overlay	36	1.1
	Bituminous	1,160	35.2
	Timber	88	2.7
	Other	128	3.9
Functional Classification of Inventory Route – NBI Item 26	Rural	2,339	71.0
	Urban	957	29.0
Type of Design and/or Construction – NBI Item 43b	Slab	664	20.1
	Stringer/multi-beam or girder (SB)	1,628	49.4
	Girder and floor beam system	60	1.8
	Tee beam (TB)	275	8.3
	Box beam or girders – multiple (BBM)	387	11.7
	Box beam or girders – single or spread (BBS)	36	1.1
	Frame	17	0.5
	Truss – through	60	1.8
	Arch-deck	17	0.5
	Channel beam (CB)	152	4.6

Maintenance Responsibility – NBI Item 21	State Highway Agency	2,134	64.7
	County Highway Agency (CHA)	838	25.4
	Town or Township Highway Agency	139	4.2
	City of Municipal Highway Agency (CMHA)	140	4.2
	State Toll Authority (STA)	45	1.4

Analysis

Binary Logistic Regression

Binary logistic regression (LR), a modeling approach that describes the occurrence probability of an event, is a method of fitting a regression curve, $y = f(x)$, where y (= dependent variable) is a categorical binary variable and coded as 0 or 1, for a set of predictors x (= independent variables) (Michy, 2015; Kleinbaum and Klein, 2010). The predictors can be continuous, categorical, or both. In this study, the deck deterioration rate (DR) represents the dependent variable, y, where concrete bridge decks associated with the two groups "lowest DR" and "highest DR" were coded as 0 and 1, respectively. Because some of the independent variables are categorical, dummy variables were introduced to differentiate the different categories. Each categorical variable has a baseline (= the first category) upon which all the remaining categories were compared to. If there were k categories for a categorical independent variable, then k-1 dummy variables were used (Yannis, et al., 2011). For example, the parameter Climatic Region (Table 1) consists of 8 categories and thus 7 dummy variables were modeled, with "Very hot" being the first category representing the baseline. The probability function that describes the dependent variable, $p(X)$ as a function of the number, n of independent variables, X can be represented as an S-shape function (Figure 31) where all the probabilities lie between 0 and 1 (James et al., 2015):

$$p(X) = \frac{e^{\beta_0+\beta_1 X_1+\ldots+\beta_i X_i+\ldots+\beta_n X_n}}{1+ e^{\beta_0+\beta_1 X_1+\ldots+\beta_i X_i+\ldots+\beta_n X_n}} \qquad \text{Equation 10}$$

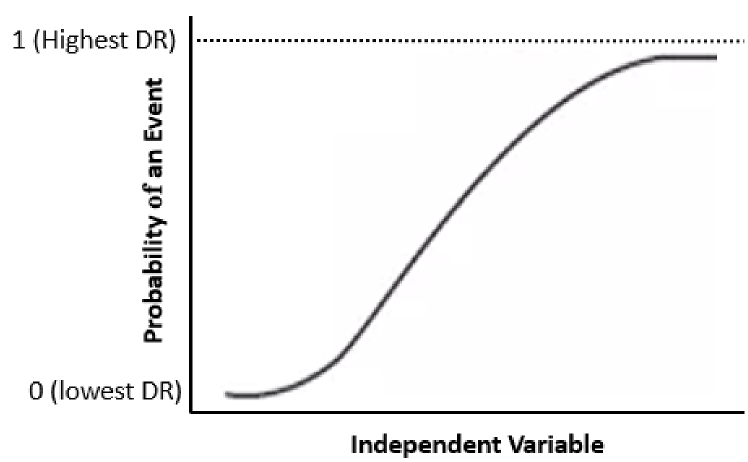

Figure 31. S-shape probability function used in binary logistic regression (LR).

Equation 10 can be written in the following form:

$$\log\left(\frac{p(X)}{1-p(X)}\right) = \beta_0 + \beta_1 X_1 + \ldots + \beta_i X_i + \ldots + \beta_n X_n \,, \qquad \text{Equation 11}$$

$$\text{where } \left(\frac{p(X)}{1-p(X)}\right) = \text{odds} \qquad \text{Equation 12}$$

LR differs from multiple linear regression with respect to the interpretation of the coefficients of the independent variables. The LR coefficients are typically interpreted using the log of the odds. In other words, the logistic coefficients (β) in Equation 11 can be interpreted as the change in the log of the odds associated with a one unit change in the continuous independent variables, or equivalently the change in the odds if one takes the exponent of the independent variables coefficient (e^{β}) (James et al., 2015; Wong, 2004).

Logistic Regression Coefficients

This study began with a model that included all variables, referred to as initial model. Table 8 shows the LR coefficient estimates and their significance at the 95th percentage confidence level (bold numbers mean significance). Although this study sought to consider all parameters that affect bridge deck performance, in the initial model several of the variables were not found to be statistically significant, leading to the consideration of variable combinations based on their relative importance in overall bridge deck performance. As a result, a final model (parameters in Table 8 that are highlighted in yellow), which consisted of both categorical and continuous variables, was derived from the initial model, and included: Maintenance Responsibility, Functional Classification of Inventory Route, Type of Design and/or Construction, ADTT, Climatic Region, and Distance to Seawater. Those parameters were chosen because they 1) were assumed to play a role in bridge deck performance and 2) were all found to be significant except the "Average Marine" category in the Climatic Region parameter and the City or Municipal Highway Agency (CMHA) and State Toll Authority (STA) categories in Maintenance Responsibility. It should be noted that Bridge Age was not found to be significant. This is contrary to what other studies such as the one by Shan et al. (2016) found. The reasons for this difference might be several fold. First, the LR presented in this paper used DR as the independent variable, which is computed using available deck CR from 1992 and 2014. Additionally, the focus of this study was concrete bridge decks. The aforementioned study, on the other hand, was based on the specific CR of 2013 and focused on the superstructure CR. Finally, since this study considered nationwide data, local differences associated with state practice may be suppressed.

Table 8. LR coefficients for initial and final models. The parameters selected for the final model are shown in boxes with thick borders and categories using bold font were found statistically significant.

Parameter	**Parameter Description/ Category**	**Initial Model**		**Final Model**		
		Coefficient	Significance	Coefficient	Significance	odds
Intercept		-8.59E-01	0.006772	-1.8E+00	**6.91E-16**	0.162
Deck Area	continuous variable	-1.21E-07	0.68622			
ADTT	continuous variable	2.22E-04		2.41E-04	**< 2e-16**	1.000

Bridge Age		-8.97E-03	0.000383			
Number of Lanes		-5.41E-03	0.921024			
Deck Structure Type	Cast-in-Place					
	Concrete Precast Panels	3.81E-01	0.036361			
Structural Material Design	Concrete – simple span					
	Concrete – continuous	4.37E-01	0.008925			
	Prestressed concrete – simple	1.09E+00	2.01E-07			
	Prestressed concrete – continuous	3.56E-01	0.110472			
	Steel – simple span	-3.64E-02	0.855252			
	Steel – continuous	9.46E-02	0.733557			
Climatic Region	Very Hot					
	Hot	9.64E-01	1.38E-05	7.50E-01	**0.00022**	2.117
	Average	1.12E+00	7.14E-06	9.29E-01	**1.50E-05**	2.531
	Cold	1.97E+00	1.70E-15	1.74E+00	**< 2e-16**	5.675
	Very Cold (VC)	3.04E+00	< 2e-16	2.80E+00	**< 2e-16**	16.485
	Extremely Cold (EC)	4.42E+00	1.72E-08	4.22E+00	**3.47E-08**	68.240
	Average Marine (AM)	1.37E+00	0.001479	6.46E-01	0.104307	1.908
	Hot Marine (HM)	2.98E+00	4.99E-08	2.86E+00	**4.71E-08**	17.493
Deck Protection	None					
	Epoxy-Coated Reinforcing	7.94E-01	1.44E-07			
	Galvanized Reinforcing	1.40E+00	0.077678			
	Other Coated Reinforcing	1.24E+01	0.962246			
	Cathodic Protection	1.31E+01	0.972178			
	Polymer Impregnated	2.44E+00	0.02259			
	Internally Sealed	1.15E+01	0.982813			
	Unknown	8.50E-02	0.749746			
	Other	1.28E+00	0.012473			
Type of Membrane	None					
	Built-up	3.12E-01	0.208767			
	Preformed Fabric	-1.12E-01	0.655022			
	Epoxy	8.11E-01	0.168913			

	Unknown	9.46E-01	0.000145			
	Other	-4.60E-01	0.062145			
Type of Wearing Surface	None					
	Monolithic Concrete	-1.43E+00	2.38E-11			
	Integral Concrete	-7.51E-01	0.007582			
	Latex Concrete or Similar Additive	-9.98E-01	0.000875			
	Low-Slump Concrete	-7.54E-01	0.047433			
	Epoxy Overlay	-1.27E+00	0.006024			
	Bituminous	-1.42E+00	8.83E-11			
	Timber	-1.38E+00	3.72E-05			
	Other	-1.40E+00	1.54E-06			
Functional Classification of Inventory Route	Rural					
	Urban	1.51E-01	0.191215	2.20E-01	**0.032134**	1.246
Distance from Seawater (DSW)	Continuous variable	-4.05E-05	0.000163	-3.99E-05	**2.36E-05**	1.000
Type of Design and Construction	Slab					
	Stringer/multi-beam or girder (SB)	3.27E-02	0.870043	4.65E-01	**2.09E-05**	1.592
	Girder and floor beam system	7.32E-01	0.065179	9.52E-01	**0.005068**	2.591
	Tee beam (TB)	9.94E-01	5.13E-08	8.07E-01	**1.16E-06**	2.242
	Box beam or girders – multiple (BBM)	6.15E-01	0.003687	6.75E-01	**8.94E-06**	1.963
	Box beam or girders – single or spread (BBS)	1.29E+00	0.01033	1.65E+00	**0.000331**	5.204
	Truss – through	4.81E-01	0.208548	1.02E+00	**0.001431**	2.764
	Channel beam (CB)	-5.42E-01	0.066925	-7.81E-01	**0.002048**	0.458
Maintenance Responsibility	State Highway Agency					
	County Highway Agency (CHA)	4.97E-01	2.15E-05	4.85E-01	**3.31E-06**	1.623
	Town or Township Highway Agency	-1.07E+00	1.32E-05	-9.94E-01	**4.42E-06**	0.370
	City of Municipal Highway Agency (CMHA)	3.41E-01	0.122857	8.66E-02	0.680019	1.090
	State Toll Authority (STA)	-2.10E-01	0.590248	-4.70E-01	0.185469	0.625

The final model coefficients, β and independent variables, X can now be substituted into the right hand side of Equation 11 to give:

$$\log\left(\frac{p(X)}{1-p(X)}\right) = -1.82 + \frac{2.41}{10^4}ADTT + \frac{7.5}{10}Hot + \frac{9.29}{10}Average + 1.74Cold + 2.8\,VC + 4.22EC + 2.86HM + \frac{2.2}{10}Urban + \frac{-3.99}{10^5}DSW \; + \frac{4.65}{10}SB + \frac{9.52}{10}Girder + \frac{8.07}{10}TB + \frac{6.75}{10}BBM + 1.65BBS + +1.02Truss - \frac{7.81}{10}CB + \frac{4.85}{10}CHA - \frac{9.94}{10}Town \qquad \text{Equation 13}$$

Because the combination of independent variables considered (and others modeled by the authors) in each model led to the same sign of the coefficient estimates, β (Table 2, Columns 3 and 5), this LR was considered robust. An example is the continuous variable ADTT, where both models (initial and final) gave a positive coefficient. Moreover, this positive coefficient estimate suggests that if ADDT is increased, then the deck is more likely to be associated with "highest DR" group. The negative estimate for Distance from Seawater (continuous variable) suggests that if distance from seawater is increased then the bridge is less likely to be associated with the "highest DR" group (i.e., more likely to be in the "lowest DR" group). Having a different interpretation than continuous variables, the estimates for categorical variables are compared to the first category in that variable. An example of this can be seen for Climatic Region: since "Very Hot" constitutes the first category, there is no estimate for it, and all interpretations are performed relative to it. What can be concluded is that "Hot", "Average", "Cold", "Very Cold", "Extremely Cold", "Average Marine" and "Hot Marine" are all more likely to be associated with the "highest DR" group than to the "Very Hot" Climatic Region since all their estimates are positive.

Another way to interpret the results is by looking at the odds (Equation 12 and Table 8, last column). In taking ADTT (continuous variable) as an example, and holding all other parameters at a constant value, we can observe a 0.024% increase in the odds of ADTT being associated with the "highest DR" group for a one-unit increase in ADTT , since $e^{(2.41E-04)}$ = 1.000241. Thus a 1,000 unit increase in ADTT results in a 27.2 % increase in the odds, since $e^{(2.41E-04*1000)}$ = 1.272. While the interpretations are the same for categorical variables, they are relative to the first category in the variable. Climatic Region can provide an example, where each coefficient estimate is relative to the category "Very Hot". For example, there is 112 % increase in the odds of being in the "highest DR" group for a bridge deck in the "Hot" region relative the "Very Hot" region, since $e^{(7.50E-01)}$ = 2.12. Another example: there is a 153 % increase in the odds of being in the "highest DR" group for a bridge deck in the "Average" region relative to the "Very Hot" region , because $e^{(9.29E--01)}$ = 2.53. The same approach can be used for the other categorical variables.

Variable Importance

To assess the relative importance of the individual predictors in the model, the absolute value of the t-statistic for each model parameter can be used to get variable importance. All measures of importance were scaled to have a maximum value of 100. As can be seen in Figure 32, Climatic Region and ADTT are the most influential variables.

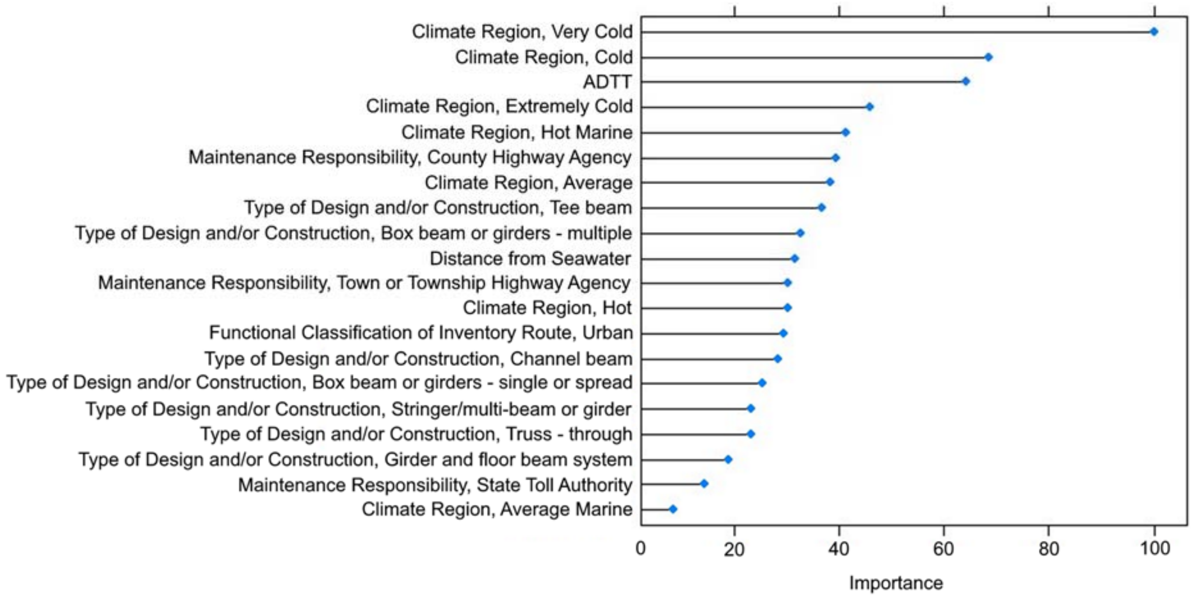

Figure 32. Relative importance based on t-statistic of model parameters (scaled to 100).

Variable Elasticities

In addition to the estimated coefficient interpretation, another way to study the effects of continuous and categorical variables is by interpreting elasticity, a property that is useful because as a unitless measure it captures choice sensitivity to each independent variable (Yannis et al., 2011; Broach, 2012). The calculations for elasticities is different for continuous and categorical variables.

Continuous Variables

Elasticities for continuous variables give an average percentage change in probability when the variable experiences a 1% increase (Ulfarsson and Mannering, 2004). The equation used to calculate elasticity is as follows (Broach, 2012):

$$\text{elasticity} = \beta_{ik} X_{ikq}(1 - P_{iq}) \qquad \text{Equation 14}$$

where i is the alternative (i.e., in this case the binary outcome "1" when a bridge deck is associated with the "highest DR" group), k is the continuous variable under consideration, q is the observation (there are a total of 3,262 observations in this case), β is the coefficient of the variable, X is the variable value, and P is the probability of the variable based on the LR. A naïve pooling method by Hensher was used where elasticity for each observation was calculated and the mean of all cases was taken as the elasticity (Hensher et al., 2015) (Table 9).

Table 9. Elasticities for continuous parameters.

Continuous Variable	**Elasticity** (%)
ADTT	0.0614
Distance from seawater	-0.130

As can be seen in Table 9, the elasticity of ADTT means that a 1% increase in ADTT results in a 0.0614% increase in the probability that a bridge deck is associated with the “highest DR” group. On the other hand, a 1% increase in distance from seawater results in a 0.13% decrease in the probability that a bridge deck is in the “highest DR” group.

Categorical Variables

Elasticities for continuous variables measure the effect of a 1% change of the variable, which is not applicable for categorical variables. Calculating elasticity for categorical variables with two categories such as Functional Classification of Inventory Route (see Table 7) is fairly straight forward. For this case, we can calculate the increase of probability when changing functional classification from “Rural” to “Urban”. The first step of this process is taking each observation and finding the probability of a bridge deck being associated with the “highest DR” group (Equation 10) for both “Rural” and “Urban” while keeping all other variables constant. The next step is to subtract the probability of “Rural” from “Urban” and then divide it by the probability for “Rural” or for each observation. Once we calculate that we can take the mean, which in this case is 11%. What this tells us is that when we change the Functional Classification of Inventory Route parameter from “Rural” to “Urban” results in an 11% increase in the probability of a bridge deck being associated with the “highest DR” group. Calculating the elasticities for categorical variables with multiple indicators is less straightforward and not further discussed in this paper.

Statistical Evaluation of the Final Model

To evaluate the statistical fit of the LR model, a likelihood ratio test was performed on the final model. In a binary LR, a model having more predictors is expected to provide a better fit to the data than a model having fewer predictors. A likelihood ratio test estimates the overall explanatory power of a model to determine if the independent variables chosen for the model improve the overall prediction (Kang and Mitra, 2012). The equation for the likelihood ratio test is computed as follows (UCLA, 2017):

$$\chi^2 = 2(\mathrm{LL}_{\mathrm{restricted}} - \mathrm{LL}_{\mathrm{unrestricted}}) \qquad \text{Equation 15}$$

where $LL_{restricted}$ is the log likelihood of the restricted model, that is, the one with all independent variables equal to zero, and $LL_{unrestricted}$ is the log likelihood of the unrestricted model, which in this case is the final model (Table 8). The χ^2 is the chi-squared distribution with the number of degrees of freedom equal to the difference in the number of parameters in the restricted and unrestricted models (Kang and Mitra, 2012). In the likelihood ratio test, the null hypothesis is that the restricted model is true, thus, if the p-value for the overall model fit statistic is less than 0.05, evidence is provided against the restricted model and, consequently, the null hypothesis can be rejected (Mathew, 2015) (Table 10).

Table 10. Likelihood ratio test results.

Model	#Df	LogLik	Df	Chisq	P-value
restricted	22	-1831.3			
unrestricted	1	-2258.7	-21	854.83	<2.20 E-16

The p-value in this model is less than 0.05, which indicates that the unrestricted model (final model) fits significantly better than the restricted model, and thereby improves the goodness of fit measure.

Validation of the Model

K-fold cross validation, a method focused on a model's predictive ability, can be used to assess how well a model performs when predicting the dependent variable ("lowest DR" or "highest DR" group) from numerous subsets of data split into training sets and testing sets. A binary LR is modeled on the training set and based on the coefficients of the model and is then tested on the testing set (Alice, 2015). This process is repeated several times in order to see how well the LR predicts the accuracy of the dependent variable. For this study, the data was split into 30 different training sets consisting of 95% of the data, and 30 different testing sets, consisting of 5% of the data. Based on the 30 predicted accuracies, the model has an average of 70.2%, which is satisfactory given taht accuracies above 65% are generally considered as acceptable (Yannis, 2011). Figure 33 shows a histogram and a box-and-whisker plot for the computed accuracies, which range from 64 to 76%. The LR model here is performing adequately with the minimum accuracy being 64%.

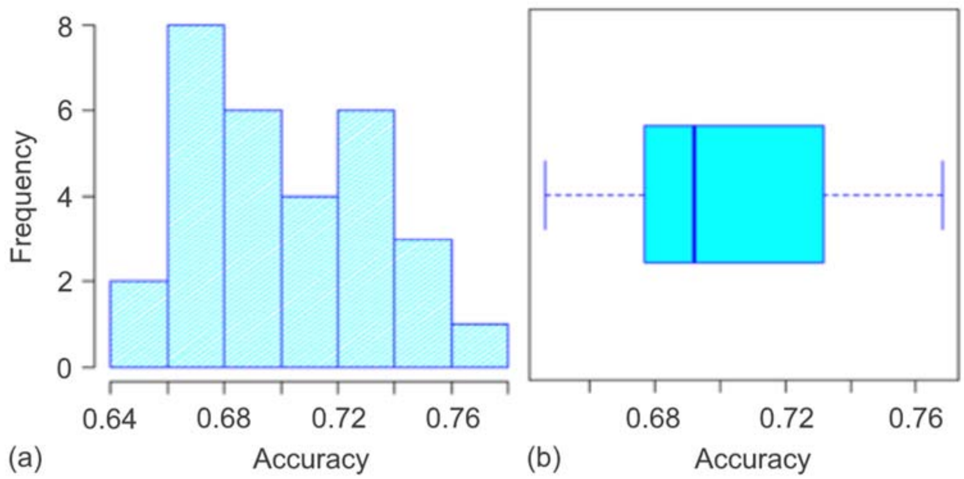

Figure 33. K-fold cross validation accuracy (a) histogram and (b) box-and-whisker plot.

Application Examples

Following are two examples of how this binary LR could be used by an agency. The first example computes the probability of three different concrete bridge decks being associated with the "highest DR" group assuming a specific set of environmental and structural parameters. The second example visualizes the probability of a concrete bridge deck being associated with the "highest DR" group as a function of ADTT and Climatic Region.

Example 1

This example supposes that an agency would like to know the probability that a particular concrete bridge deck is be associated with the "highest DR" group assuming three different scenarios (Table 11).

Table 11. Example 1 scenarios.

Variable Name	Scenario 1	Scenario 2	Scenario 3
ADTT	1500	800	10
Climatic Region	Boston, MA (climatic region: cold)	Houston, Tx (Climatic region: Very hot)	Los Angeles, CA (Climatic region: Hot Marine)
Functional Classification of Inventory Route	Urban	Urban	Rural
Distance from Seawater (DSW)	0.01 miles (0.016 km)	10 miles (16 km)	60 miles (96.5 km)
Type of Design and Construction	Truss – through	Box beam or girders – multiple (BBS)	Channel beam (CB)
Maintenance Responsibility	County Highway Agency (CHA)	State Highway Agency	Town Highwat Agency

Based on the final LR model, the coefficients in Table 8, Column 5 as well as the values given from the example are substituted in Eq. 2, leading to the following probability predictions:

Scenario 1: $$p(X) = \frac{e^{-1.82+\left(\frac{2.41}{10^4}*1500\right)+(1.74)+\left(\frac{2.2}{10}\right)-\frac{3.99}{10^5}(0.016)+(1.02)+\left(\frac{4.85}{10}\right)}}{1+e^{-1.82+\left(\frac{2.41}{10^4}*1500\right)+(1.74)+\left(\frac{2.2}{10}\right)-\frac{3.99}{10^5}(0.016)+(1.02)+\left(\frac{4.85}{10}\right)}} = 0.88 \quad \text{Equation 16}$$

Scenario 2: $$p(X) = \frac{e^{-1.82+\left(\frac{2.41}{10^4}*800\right)+\left(\frac{2.2}{10}\right)-\frac{3.99}{10^5}(16)+(1.65)}}{1+e^{-1.82+\left(\frac{2.41}{10^4}*800\right)+\left(\frac{2.2}{10}\right)-\frac{3.99}{10^5}(16)+(1.65)}} = 0.56 \quad \text{Equation 17}$$

Scenario 3: $$p(X) = \frac{e^{-1.82+\left(\frac{2.41}{10^4}*10\right)+(2.86)-\frac{3.99}{10^5}(96.5)-\left(\frac{7.81}{10}\right)-\left(\frac{9.94}{10}\right)}}{1+e^{-1.82+\left(\frac{2.41}{10^4}*10\right)+(2.86)-\frac{3.99}{10^5}(96.5)-\left(\frac{7.81}{10}\right)-\left(\frac{9.94}{10}\right)}} = 0.32 \quad \text{Equation 18}$$

Based on these predictions, Scenario 1 has the highest probability (= 0.88) of a concrete bridge deck being associated with the "highest DR" group, followed by Scenarios 2 and 3. There are several reasons why Scenario 1 has the highest probability: 1) It has the highest ADTT, 2) it is in the coldest region, 3) it is the closest to seawater, and 4) it includes the structural parameter observed to increase the probability of it being associated with the "highest DR" group.

Example 2

A bridge owner would like to know how increasing the ADTT affects the probability of a certain concrete bridge deck being associated with the "highest DR" group while considering the climatic effects "Hot", "Average", "Cold", and "Very Cold". The bridge is assumed to be 100 km (62.1 miles) away from seawater, has a tee beam design, "Urban" functional classification, and is maintained by the county highway.

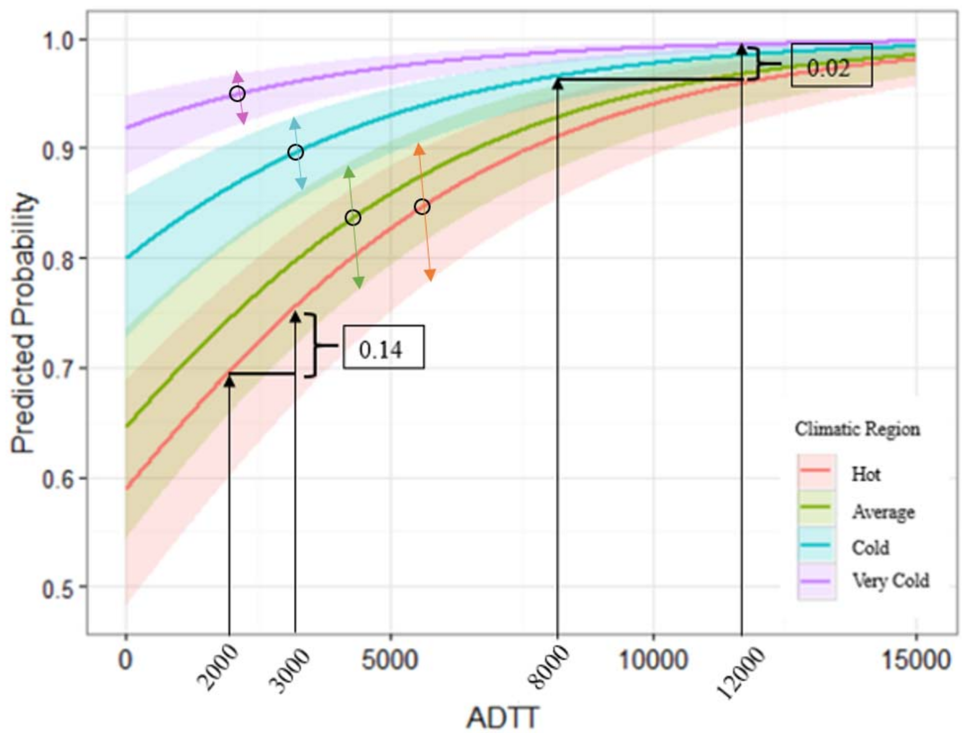

Figure 34. Predicted mean probabilities of a bridge deck being associated with the “highest DR” group with 95% confidence intervals for Example 2.

Figure 34 shows the mean probabilities for four select climatic regions, and the 95% confidence intervals, as ADTT increases from 0 to 15,000. As can be observed, as the climatic region becomes colder the probability of a concrete bridge deck being associated with the “highest DR” group increases. This is plausible because colder regions experience more snow and freeze-thaw, and possibly use of deicers, all of which play a critical role in deck performance. Further, as ADTT increases, so does the probability of the deck being associated with the “highest DR” group. It can also be observed that the difference of the climate diminishes with increasing ADTT. Two numerical illustrations are shown in Figure 34: first, an increase in ADTT from 2000 to 3000 (by 50%) for a bridge deck in a “Hot” climatic region leads to a 14% increase in the probability of it being associated with the “highest DR” group. Second, if ADTT is increased from 8000 to 12000 (also by 50%) for a bridge deck in a “Cold” climatic region there is 2% increase in the probability of it being in the “highest DR” group.

Summary and Conclusions

The objective of this study was to examine how environmental and structural parameters affect the performance of concrete bridge decks by means of binary logistic regression (LR). The model is used to predict the likelihood for a concrete bridge deck being associated with the “highest deterioration rate (DR)” group, which is the worst performing set of bridge decks. The LR model development is based on 3,262 observations extracted from a nationwide database, which was developed by the authors previously (Chapter 3). In the final model, the DR was used as the dependent variable, while ADTT, Climatic Region, Functional Classification of Inventory Route, Distance from Seawater, Type of Design and/or Construction, and Maintenance Responsibility were used as independent variables (= predictors). A log likelihood test was performed to validate the model were the p-value was less than 0.05, indicating that the final model fits significantly better than the restricted model. Further, a K-fold cross validation based on 30 predicted accuracies showed an average of 70.2%, which was considered as acceptable. Finally, parameters were ranked in order of their relative importance in the model. Based on the odds ratio and elasticities it was found that bridge decks 1) with higher ADDT, 2) in colder climatic regions, 3) further away from seawater, and 4) categorized as "Urban" have higher odds/probabilities of being associated with the "highest DR" group. Type of construction and maintenance responsibility are additional parameters affecting bridge deck performance. Finally, two practical examples are illustrated to demonstrate how a binary LR model could be used by agencies to answer specific questions regarding bridge deck performance.

In the future, additional parameters could be added such as structural design characteristics (e.g., minimum deck thickness, reinforcement bar size, bar spacing), construction practice (e.g., concrete temperature, placement procedure, curing practice), specifications (e.g., water-to-cement ratio and minimum cementitious material content), and other notable factors (e.g., application of deicers and freeze-thaw cycles). It is recommended that upcoming studies use this methodology to model those additional independent variables on their effect on bridge deck performance.

CHAPTER 5 - BAYESIAN SURVIVAL ANALYSIS FOR US CONCRETE HIGHWAY BRIDGE DECKS

Authors: Adam Fleischhacker, Omar Ghonima, and Thomas Schumacher

Note: This chapter was submitted to the *ASCE Journal of Infrastructure Systems* and is currently under review. Please look for the peer-reviewed journal publication version of this chapter entitled "Bayesian Survival Analysis for US Concrete Highway Bridge Decks" under the following link: https://ascelibrary.org/journal/jitse4.

Introduction and Background

Deterioration modeling of concrete highway bridge decks is of significant importance as they incur the largest cost for maintenance and repair. In order for agencies to make informed decisions using limited funds, asset management strategies are critical. The national bridge inventory (NBI) represents the largest comprehensive database containing deck condition data from 1992 to date offering opportunities to create deterioration models. Subsequently, relevant work that has developed deterioration models for concrete bridges and bridge decks is presented in more detail.

Hatami and Morcous (2011) used simple curve fitting of the mean condition ratings (CR) for State-owned bridges in Nebraska to study the correlation of various NBI items such as bridge age, type of wearing surface, average daily truck traffic (ADTT), highway agency district, type of deck protection, and use of membranes. This study considers one variable at a time and some limited discussion about the combined effects of the variables on the CR is included. The paper further discusses a probabilistic approach, which determines future CR based on a simple Markovian model. This approach only takes into consideration current CR, which can be adverse, given that the time elapsed from a bridge's initial CR is ignored. Bolukbasi et al. (2004) undertook a similar deterministic study on all bridges in Illinois employing third-order polynomial curve fitting to create mean deterioration curves based on CR vs. bridge age. A more advanced approach was proposed by Nasrollahi and Washer (2015) that utilizes a probabilistic approach to estimate CR-based inspection intervals needed for concrete, steel, and prestressed concrete superstructures using NBI data for the State of Oregon. Their analysis is based on the duration a specific CR remains constant before it changes, referred to as a time-in-condition rating (TICR). A Weibull probability density distribution (PDF) was found to best represent TICR for each CR. Cumulative distribution function (CDF) graphs were developed based on the created PDF for each CR. These CDF were used to develop probability-based inspection intervals in lieu of the standard 24-month intervals mandated by the FWHA. TICR values were considered for both cases where the CR went to a lower or a higher level at the end of the TICR, effectively neglecting the effect of maintenance, which is marked by an increase in the CR.

Dekelbab et al. (2008) used NBI data from 1983 to 2006 to compute survival curves for concrete bridge decks. The authors define maintenance, rehabilitation, or reconstruction as observed improvement, which is the improvement of the observed bridge condition from one year to the next. The research found that bridges have an average of 7 years before the first condition improvement. Without observed improvement was defined as bridges that do not have any form of maintenance, i.e. there is no observable improvement in the bridge condition rating from one year to the next. Based on those definitions, the authors' performed a time-series data analysis based on the Kaplan-Meier method. Survival functions for decks in different conditions with and without observed improvement were plotted. These survival function curves show the percentage of bridge decks maintaining a specific CR vs. the time in that condition. Although this represents a new approach analyzing CR, effects of NBI parameters such as membrane type, deck protection, or protective measures were not studied. Tae-Hoon et al. (2006) determined the end of service-life for concrete cast-in-place and concrete pre-cast panel bridge decks for 30 Department of Transportations (DOTs) based on NBI data. The deterioration model was based on six linear regressions of the CR for all bridges reconstructed between 1950 and 2000. The six linear regression models only used bridge age as the explanatory variable. The criteria in accepting a regression model were: 1) high R-squared value and 2) a significance value of more than 95%. Tabatabai et al. (2011) developed a two-parameter hypertabastic PDF to determine the service life of bridge decks in Wisconsin using 2005 NBI data. Deck CR of 4 and 5 were defined as the end of service life. The NBI items used included: type of superstructure (concrete or steel), age of deck, deck area, and ADT. This study took into consideration a few NBI items in its model without justification why others were omitted. Work by Abed-Al-Rahim and Johnston (1995) developed an equation based upon the average change from a specific CR in order to plot deck deterioration.

Most studies do not discuss the important effect of bridge deck condition history on future CR (Dekelbab et al., 2008). Also, most studies that use NBI data have been done on specific states rather than nationwide. Finally, to the best of the authors' knowledge, no study has considered censored data. Censoring of bridge deck survival times occurs because often the true amount of time that a bridge deck would have lasted in a certain CR cannot be observed. For example, one bridge might reflect a given CR for three consecutive years and then it increases. In this scenario, the bridge survived in that CR for at least three years but it is unknown whether the bridge would have continued in its current rating or deteriorated had the maintenance not been performed. Similarly, CR data for all of the bridge decks at the beginning or end of the observed period represent data that may be censored. In survival analysis, exclusion of censored observations leads to an underestimation of survival time and probabilities (Leung et. al., 1997). Logically, if only bridge deck data for which we observe the entire TICR are included, then the dataset most certainly over represents shorter duration observations.

The goal of this study was to employ an advanced statistical model for the entire country that is capable of considering censored data. This proposed methodology is often used in medical survival analysis studies. For example, Peltola et al. (2014) used the same computational algorithms and software to model the duration for which diabetic patients may go without a cardiovascular event. As in this dataset, which observed bridges over a 23 year period, medical observations are also censored in that patients are only followed for a certain duration (e.g. 15 months following study start time).

Data Used in this Study

The data used in this study comes from a nationwide dataset mainly based on National Bridge Inventory (NBI) data and referred to as the Nationwide Concrete Highway Bridge Deck Performance Inventory (NCBDPI) that the authors developed previously (Chapter 3), consisting of 150,136 unique concrete highway bridge decks. The main advantage of this dataset is that it is nationwide and easily accessible. Once the research project is completed, the NCBDPI will be made accessible by the authors to the public. Questions have been raised regarding subjectivity of the CR and their accuracy to represent the actual condition of a bridge deck. The authors discuss additional challenges regarding meaningfulness of recorded parameters (or items) for modeling performance in Chapter 3. In summary, parameters found to affect bridge deck performance such as actual as-built properties (fresh concrete properties, early-age cracking, curing procedures, concrete cover), in-service parameters (freeze-thaw conditions, bridge cleaning, use of deicers), and actual traffic conditions (number and weight of heavy trucks) are not currently captured in the NBI database. Hence, for this study, specific deterioration mechanisms were not considered. The aim was, rather, to employ an advanced statistical analysis to provide a more global view of concrete highway bridge deck performance in the US.

Figure 35. Histograms of model variables with codes (see Table A1 for code descriptions). Note: most plots use a log scale. Note: Climatic Region, Distance from Seawater, and TICR were developed and added by the authors, the other variables come from the NBI database.

The covariates used in this study are based on select parameters available in the NBI database and three additional ones developed and added by the authors (see Chapter 3), and consist of eight categorical variables and one numerical variable. The independent variable referred to as time-in-condition rating (TICR) was derived from the condition ratings (CR), which were available for the years 1992 to 2014. Histograms of the modeled covariates along with a histogram of the dependent variable (= TICR) are shown in Figure 35. Censored data (light green) are sequences of bridge deck CR where only a lower-bound on TICR are available, while (fully) observed data (dark green) are sequences of ratings where the change in condition is due to deterioration. Note that excluding censored observations would throw away over half of the dataset. Relevant code descriptions are provided in Table 12.

Table 12. Code descriptions for used variables (ordered alphabetically).

Code	*Description*		*Code*	*Description*
ADTT (NBI Item 109)			**Deck Structure Type (NBI Item 107)**	
N.A.	Numerical		– Code 1	Concrete Cast-in-Place
			– Code 2	Concrete Precast Panels
Climatic Region				
– Code 2	Region 2 – Very Hot		**Distance from Seawater**	
– Code 3	Region 3 – Hot		– Code 0	Sea Less Than 3 km Away
– Code 4	Region 4 – Average		– Code 1	Sea GreaterThan 3 km Away
– Code 5	Region 5 – Cold			
– Code 6	Region 6 – Very Cold		**Functional Class (NBI Item 26)**	
– Code 7	Region 7 – Extremely Cold		– Code 1	Rural
– Code 8	Region 8 – Subartic		– Code 2	Urban
– Code 9	Region 9 – Average Marine			
– Code 10	Region 10 – Hot Marine		**Maintenance Responsibility (NBI Item 21)**	
			– Code 1	State Highway Agency
Deck Condition Rating (NBI Item 58)			– Code 2	County Highway Agency
– Code 3	CR = 3		– Code 3	Town or Township Highway Agency
– Code 4	CR = 4		– Code 4	City or Municipal Highway Agency
– Code 5	CR = 5		– Code 26	Private (Other Than Railroad)
– Code 6	CR = 6		– Code 31	State Toll Authority
– Code 7	CR = 7			
– Code 8	CR = 8		**Structure Type (NBI Item 43A)**	
– Code 9	CR = 9		– Code 1	Concrete – Simple Span
			– Code 2	Concrete – Continuous
Deck Protection (NBI Item 108C)			– Code 3	Steel – Simple Span
– Code 0	None		– Code 4	Steel – Continuous
– Code 1	Epoxy-Coated Reinforcing		– Code 5	Prestressed Concrete – Simple Span
– Code 2	Galvanized Reinforcing		– Code 6	Prestressed Concrete – Continuous
– Code 3	Other Coated Reinforcing			
– Code 4	Cathodic Protection		**Time-in-Condition Rating**	
– Code 6	Polymer Impregnated		N.A.	Numerical
– Code 7	Internally Sealed			
– Code 8	Unknown			
– Code 9	Other			

Subsequently, each variable is briefly introduced. A more detailed discussion along with details regarding preprocessing and filtering of the variables can be found in (Chapter 3).

Average Daily Truck Traffic (ADTT)

ADTT is defined as the daily average number of trucks that pass over a bridge in one day. This variable was generated from NBI Item 109 (FHWA, 1995). It represents the only numerical variable in the model.

Climatic Region
Climatic regions are based on the International Energy Conservation Code (International Code Council, 2009), comprising eight temperature areas ranging from Zone 1 (hottest) to Zone 8 (coldest), and three moisture regimes, marine, dry, and moist, designations allowing for up to 16 different combinations. Because this study is mainly concerned with the effects of ice and snow on concrete bridge decks, not all 16 combinations were considered. Following are the assumptions used to generate this categorical variable:

- Zone 1 consisted of three counties in Florida, Hawaii, and Puerto Rico. Because those regions had very few TICR data points, they were combined with Zone 2.
- Of all moisture regimes, only that of marine was considered, as this moisture regime has little snow for most climatic zones. For example, although the Marine region for Oregon and Washington falls in Zone is 4, it snows much less as compared with Delaware which is also in Zone 4.
- Zones 2 and 1 were considered as “very hot,” 3 as “hot,” 4 as “average,” 5 as “cold,” 6 as “very cold,” 7 as “extremely cold,” and 8 as “subarctic.” Marine areas of Zone 4 were labeled as “average marine,” and those of Zone 3 labeled “hot marine.”

Deck Condition Rating (CR)
This categorical variable corresponds to NBI Item 58 (FHWA, 1995). Assigned CR range from 0 (failed condition) to 9 (excellent condition). Due to lack of sufficient data, only CR ranging from 3 to 9 were included in this study. Figure 36 illustrates three example cases of bridge deck CR records. Indicated are example instances of deterioration and maintenance, corresponding to a decrease and increase in CR, respectively. The treatment of missing data is explained in detail in (Chapter 3).

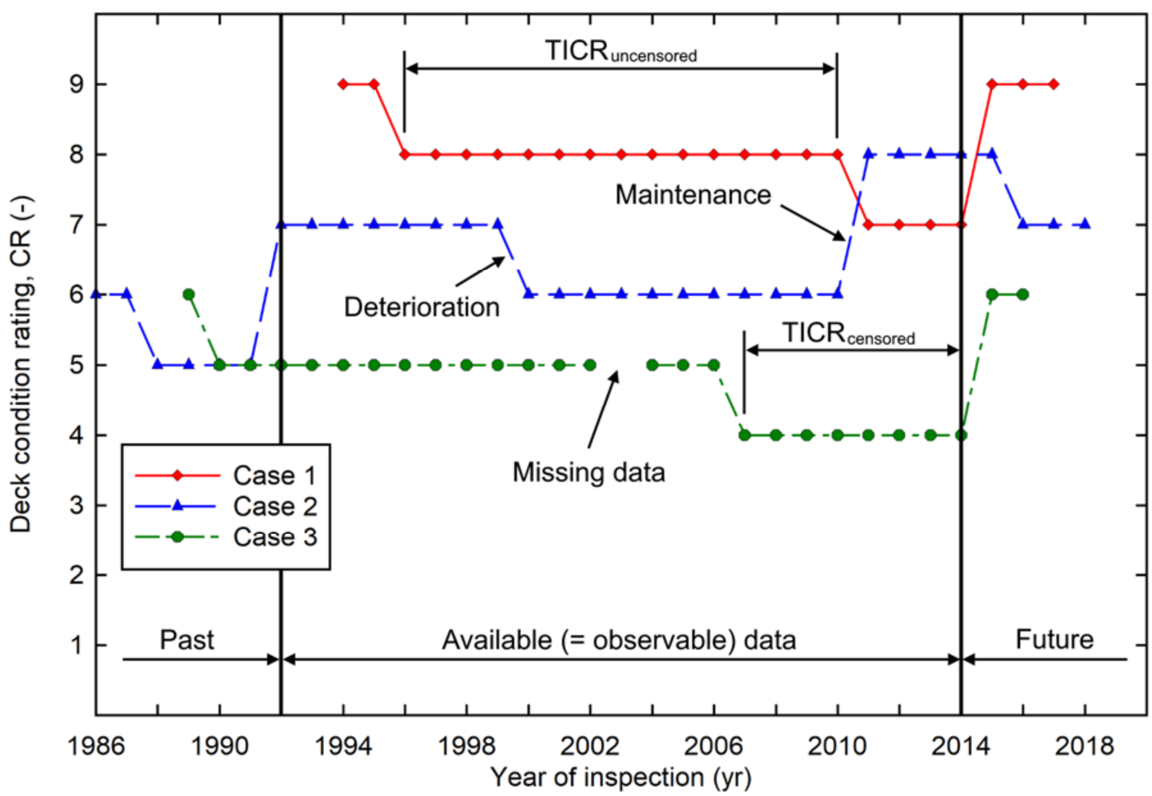

Figure 36. Three sample bridge deck CR. Available NBI data includes 23 years from 1992 to 2014.

Deck Protection

This categorical variable corresponds to NBI Item 108C (FHWA, 1995) and describes the corrosion protection measure, if any, present in a concrete bridge deck.

Deck Structure Type

Only the first two categories from this categorical variable were used to exclude non-concrete bridge decks. It corresponds to NBI Item 107 (FHWA, 1995).

Distance from Seawater

This categorical variable was generated by the authors and is discussed in detail in Chapter 3. In this study, two cases were considered: bridge decks located less than 3 km or more than 3 km from seawater. The distinction was guided by (Stewart and Rosowsky, 1998).

Functional Class

This categorical variable was generated based on NBI Item 26 (FHWA, 1995) and was condensed to distinguish bridge decks located on rural and urban highways.

Maintenance Responsibility

This categorical variable names the agencies responsible for maintaining the bridge deck and is based on NBI Item 21 (FHWA, 1995). Due to lack of sufficient data for some codes, only the six categories with the most data were included in this study.

Structure Material

This categorical variable corresponds to NBI Item 43A (FHWA, 1995) and describes the material and determinacy (simple span vs. continuous) of the structure supporting the bridge deck.

Time-In-Condition Rating (TICR)

TICR as proposed by Nasrollahi and Washer (2015) represents the number of years a bridge member is assigned the same CR regardless of the preceding and subsequent CR. TICR used in this study differs in that the authors only consider those cases where the CR decreases. The reason for this is to capture true deck deterioration, on the assumption that when a higher CR is assigned, maintenance must have occurred. The available data derived from the 150,136 decks includes 670,760 observations of consecutive TICR. This includes 211,908 uncensored observations and 458,852 censored ones. Censorship occurs for four reasons: (1) data is censored as its CR prior to 1992 is unknown, (2) data is censored as its CR after 2014 is unknown, (3) data is censored due to missing observations in the dataset, and (4) data is censored due to an increase in CR from one year to the next, which is considered maintenance. All censoring provides us with a lower bound on survival time in a specifc CR and hence, data is right-censored only. In Figure 36, the only uncensored TICR is the one labeled; all other TICR are considered censored because they cannot be fully observed.

Methodology

The methodology used in this study is Bayesian survival analysis (e.g., Peltola et al., 2014) to the TICR ratings of bridge decks. Since our dataset is limited to 23 years of observations, the Bayesian approach provides a coherent method of handling censored observations. The four types of censorship are described in the previous section. All censoring provides thus a lower bound on survival time in a specific CR and hence, data is right-censored only.

As shown in Figure 37, we let observation t_i represent either the observed time in condition T_i or the censoring time C_i. The event indicator $v_i = 1$ when data is observed. All censored points have event indicator v_i=0 and censoring is such that $T_i > C_i$. We let x_i represent a J×1 column vector of predictors (i.e., condition rating, climatic region, etc.) that influence the expected time in condition for the i^{th} observation and β_i represent the corresponding J×1 vector of regression coefficients. μ represents the intercept. Despite our observations t_i being on a yearly scale (i.e., interval-censored), we assume a continuous time model for interpretability and to ease the computational burden. Mid-point imputation is assumed and has been shown to be a reasonable procedure in other survival analysis studies (e.g., Law and Brookmeyer, 1992).

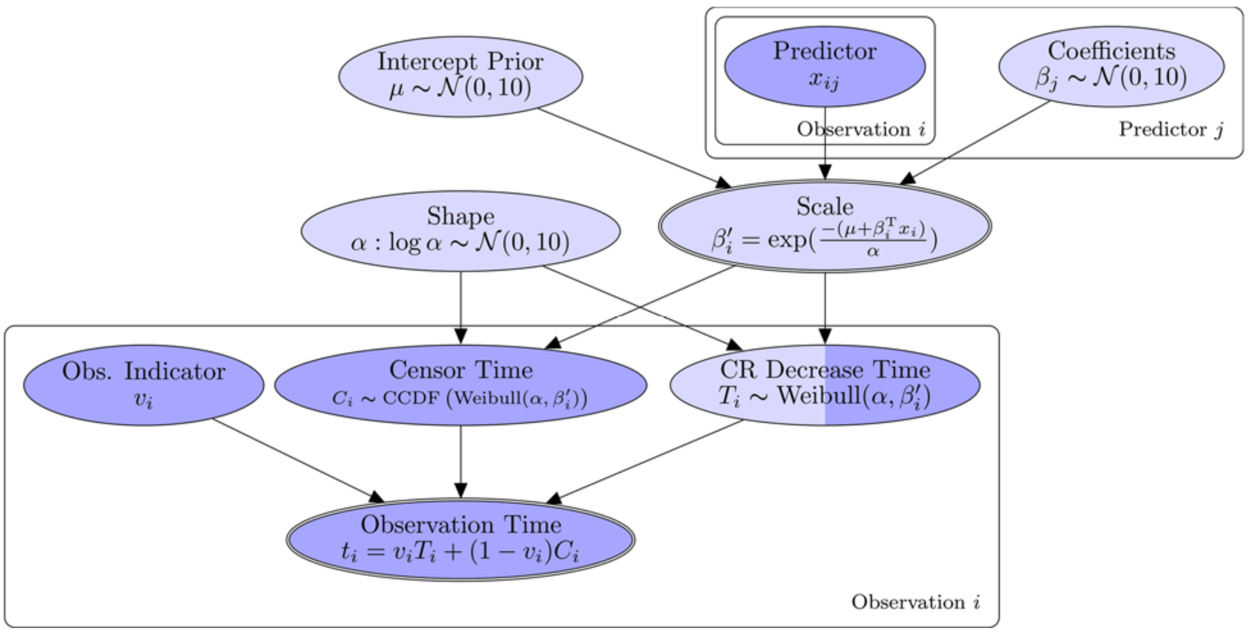

Figure 37. Plate notation of observation model. The darker fill represents observed values while the lighter fill represents unobserved variables/parameters. The presence of both fills indicates a censored variable.

The observations are assumed to come from a Weibull distribution. Note that Figure 37 reflects a Weibull parameterization that is atypical in survival analysis, but one which is consistent with the Stan modelling language (Stan Development Team, 2016, page 526). Expressed mathematically, computed estimates reflect the following censored Weibull probability density function (Peltola et al., 2014):

$$p(t_i|x_i, v_i, \beta_i, \alpha) = \alpha^{v_i} t_i^{v_i(\alpha-1)} \exp\left(v_i(\mu + \beta_i^T x_i) - t_i^{\alpha} \exp(\mu + \beta_i^T x_i)\right).$$

Equation 19

As described in Nasrollahi and Washer (2014), the Weibull distribution is particularly well suited for this type of application as it allows one to model a failure rate that increases with time. For bridge decks, it is obvious that the longer the deck is in operation, the less likely it will be in maintaining a constant condition rating.

Results

Parameter Estimates

Estimates for Weibull parameters in Equation 19 were derived using the Hamiltonian Monte Carlo algorithm (Betancourt, 2017) as implemented in the Stan software and accessed via R (Stan Development Team, 2016). Four chains of 1,000 samples each were verified for convergence and fit was verified using the diagnostics of shinystan (Stan Development Team, 2016). A graphical representation of the covariate estimates given in terms of their probability density functions (PDF) are shown in Figure 38.

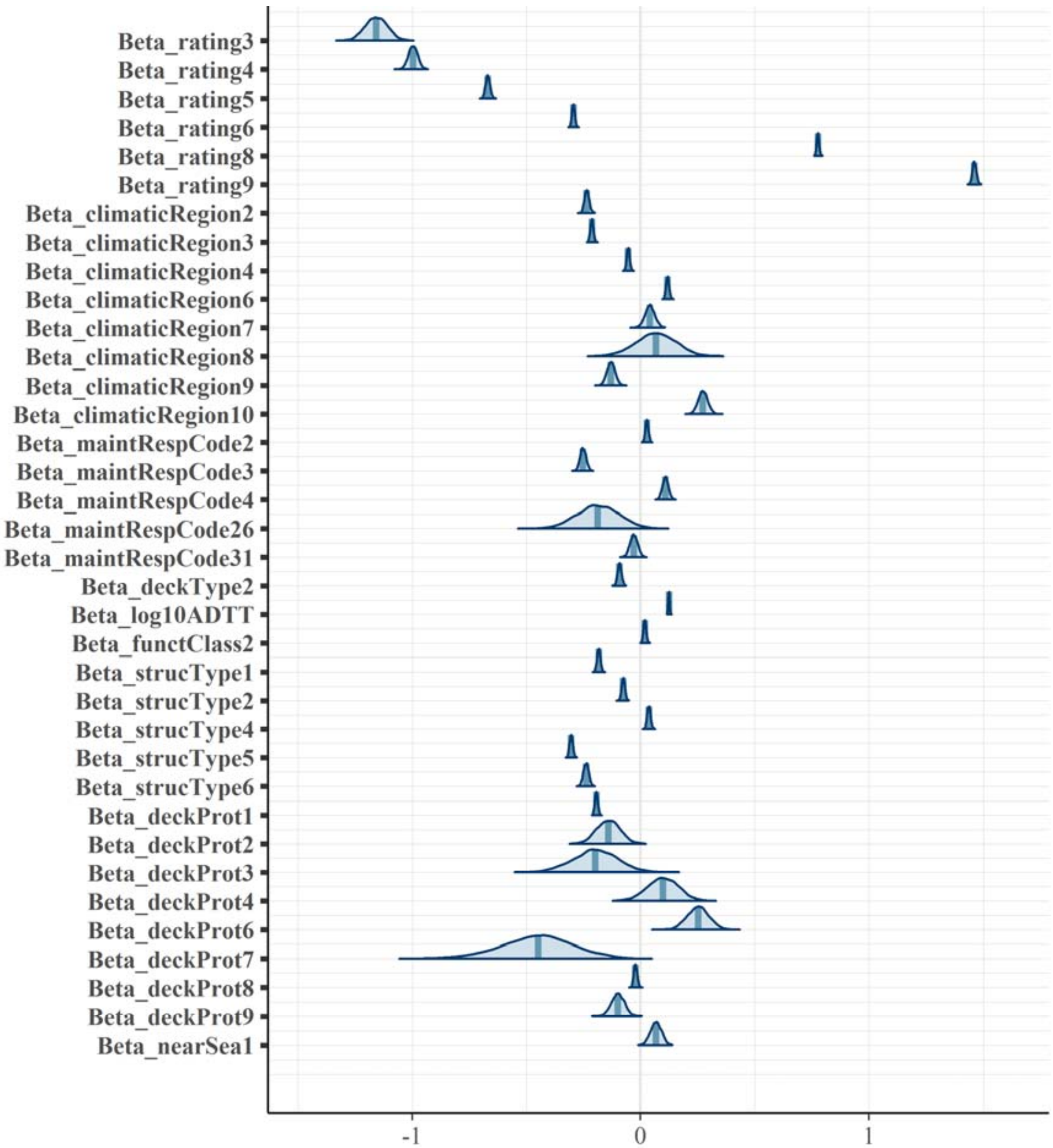

Figure 38. Marginal posterior distributions for estimated parameters.

Narrow and wide PDFs indicate high and low precision for the given estimate, respectively. Distributions located below and above a value of zero mean that the bridge deck is more and less likely to be assigned a lower CR at any given time compared to the referent case, respectively, which is highlighted in Table 1.

For example, a bridge deck supported by prestressed concrete girders (simple-span) (= Beta_strucType_5) is less likely to be assigned a lower CR compared to a bridge deck that is supported by steel girders (simple-span) (= Beta_strucType_3, referent). In other words, concrete bridge decks supported by prestressed concrete girders appear to perform better than when they are supported by steel girders.

Numerical values for the estimated coefficients illustrated in Figure 38 are provided in Table 13.

The mean estimate of the shape parameter $\alpha = 1.486$. By analyzing Equation 19, the significance of this parameter is revealed by assessing whether it is greater or less than one; any shape parameter greater than one indicates a failure rate that increases in time, and as expected, bridge decks are more likely to be assigned a lower CR the longer they remain in a given CR. In contrast, we would expect $\alpha < 1$ in cases where failure rate decreases with TICR (e.g. a business that has lasted 20 years is less likely to go bankrupt than one that has lasted 2 months).

Table 13. Parameter estimates.

Term	*Estimate*	*Std.error*	*Conf.low*	*Conf.high*	*rhat*	*ess*
alpha	1.486	0.002	1.482	1.491	1.000	4000
mu	-3.881	0.012	-3.904	-3.858	1.002	2447
Beta_rating3	-1.157	0.048	-1.248	-1.065	0.999	4000
Beta_rating4	-0.996	0.020	-1.035	-0.956	1.000	4000
Beta_rating5	-0.669	0.010	-0.688	-0.649	0.999	4000
Beta_rating6	-0.294	0.007	-0.307	-0.281	1.000	4000
Beta_rating8	0.776	0.005	0.766	0.787	1.000	4000
Beta_rating9	1.462	0.009	1.444	1.478	1.000	4000
Beta_climaticRegion2	-0.235	0.010	-0.254	-0.215	0.999	4000
Beta_climaticRegion3	-0.213	0.007	-0.226	-0.200	1.001	4000
Beta_climaticRegion4	-0.054	0.006	-0.067	-0.041	1.000	4000
Beta_climaticRegion6	0.119	0.007	0.106	0.132	1.000	4000
Beta_climaticRegion7	0.041	0.021	-0.003	0.083	1.000	4000
Beta_climaticRegion8	0.067	0.087	-0.107	0.231	1.000	4000
Beta_climaticRegion9	-0.130	0.018	-0.165	-0.094	1.000	4000
Beta_climaticRegion10	0.273	0.021	0.232	0.313	1.001	4000
Beta_maintRespCode2	0.028	0.007	0.015	0.042	1.001	3090
Beta_maintRespCode3	-0.252	0.013	-0.278	-0.226	1.000	4000
Beta_maintRespCode4	0.109	0.013	0.084	0.134	1.000	4000
Beta_maintRespCode26	-0.187	0.091	-0.365	-0.011	0.999	4000
Beta_maintRespCode31	-0.030	0.017	-0.063	0.004	1.000	4000
Beta_deckType2	-0.092	0.009	-0.109	-0.074	1.000	4000
Beta_log10ADTT	0.125	0.003	0.119	0.130	1.001	3444
Beta_functClass2	0.019	0.006	0.007	0.031	1.000	4000
Beta_structType1	-0.183	0.007	-0.197	-0.169	1.000	3026
Beta_structType2	-0.075	0.007	-0.090	-0.062	1.000	4000
Beta_structType4	0.036	0.007	0.022	0.051	1.001	4000
Beta_structType5	-0.303	0.007	-0.318	-0.290	1.000	3039
Beta_structType6	-0.239	0.012	-0.261	-0.216	0.999	4000
Beta_deckProt1	-0.193	0.007	-0.206	-0.180	1.001	4000
Beta_deckProt2	-0.142	0.051	-0.242	-0.043	1.000	4000
Beta_deckProt3	-0.199	0.098	-0.396	-0.009	0.999	4000
Beta_deckProt4	0.097	0.067	-0.036	0.227	1.000	4000
Beta_deckProt6	0.252	0.048	0.159	0.344	1.000	4000
Beta_deckProt7	-0.454	0.158	-0.784	-0.155	0.999	4000
Beta_deckProt8	-0.022	0.008	-0.037	-0.007	0.999	4000
Beta_deckProt9	-0.099	0.029	-0.156	-0.043	1.000	4000
Beta_nearSea1	0.067	0.024	0.020	0.112	1.000	4000

Hazard Ratios

A convenient interpretation of the covariate coefficients is based on the calculated hazard ratios, shown in

Table 14 along with their 95% percentile intervals. Coefficients are interpreted using a proportional hazards model with hazard function:

$$h(T_i) = \alpha T_i^{\alpha-1} \exp(\mu + \beta^T x_i). \qquad \text{Equation 20}$$

For each categorical coefficient, the hazard ratio represents the ratio of the chance of a CR decrease in the presence of the categorical variable to the chance of a CR decrease of the referent bridge deck CR. Referents were selected to represent a common case. For example, a bridge in Climatic Region 6 is between 11.1% and 14.1% more likely to be assigned a lower CR at any given time than a similar bridge in Climatic Region 5. For the numerical variable, namely $\log_{10}$(ADTT), a 10-fold increase in traffic volume leads to an approximately 13.3% chance of a CR decrease. Ratios of less than 1 indicate that the considered bridge deck in this category is less likely to be assigned a lower CR at any given time.

Table 14. Hazard ratio estimates. Code descriptions are listed in Table 15.

Variable	Mean	95% interval		Variable	Mean	95% interval
ADTT				**Deck Structure Type**		
– $\log_{10}$(ADTT)	1.133	1.126 - 1.139		– Code 1	Referent	
				– Code 2	0.912	0.897 - 0.929
Climatic Region						
– Region 2	0.790	0.775 - 0.807		**Distance from Seawater**		
– Region 3	0.808	0.797 - 0.819		– Sea > 3 km away	Referent	
– Region 4	0.948	0.936 - 0.960				
– Region 5	Referent			**Functional Class**		
– Region 6	1.126	1.111 - 1.141		– Code 1	Referent	
– Region 7	1.042	0.997 - 1.086		– Code 2	1.019	1.007 - 1.031
– Region 8	1.073	0.898 - 1.260				
– Region 9	0.879	0.848 - 0.910		**Maintenance Responsibility**		
– Region 10	1.314	1.262 - 1.368		– Code 1	Referent	
				– Code 2	1.029	1.015 - 1.043
Condition Rating				– Code 3	0.778	0.758 - 0.798
– CR = 3	0.315	0.287 - 0.345		– Code 4	1.115	1.087 - 1.144
– CR = 4	0.369	0.355 - 0.384		– Code 26	0.833	0.694 - 0.989
– CR = 5	0.513	0.503 - 0.523		– Code 31	0.971	0.939 - 1.004
– CR = 6	0.745	0.736 - 0.755				
– CR = 7	Referent			**Structure Type**		
– CR = 8	2.174	2.151 - 2.198		– Code 1	0.833	0.821 - 0.845
– CR = 9	4.313	4.239 - 4.384		– Code 2	0.927	0.914 - 0.940
				– Code 3	Referent	
Deck Protection				– Code 4	1.037	1.022 - 1.053
– Code 0	Referent			– Code 5	0.738	0.728 - 0.749
– Code 1	0.824	0.814 - 0.835		– Code 6	0.788	0.770 - 0.805
– Code 2	0.869	0.785 - 0.958				
– Code 3	0.823	0.673 - 0.991				
– Code 4	1.105	0.965 - 1.254				
– Code 6	1.287	1.173 - 1.411				
– Code 7	0.643	0.457 - 0.857				
– Code 8	0.978	0.964 - 0.993				
– Code 9	0.906	0.855 - 0.958				

Survival Curves

The survival function for bridge deck i is given by the following formula:

$$S(T_i) = \exp\left(-T_i^{\alpha}\exp(\mu + \beta^T x_i)\right) \qquad \text{Equation 21}$$

Visualizing this function by varying covariate values is a useful way to compare the effect of covariate values on the probability that a given CR is maintained (or survived). Using referent values (see Table 1) for all categorical variables and assuming ADTT = 100, survival probability comparison plots using mean estimates are provided in Figure 39 to Figure 47 (confidence intervals are not shown).

To give an example of how to interpret and use these survival plots, Figure 39 is used. The question can be asked: What are the probabilities that a highway concrete bridge deck will be assigned CR = 7 (= referent) for more than 10 years, i.e. TICR ≥ 10 yr, for ADTTs of 10 and 10,000? Answer: The probabilities that a bridge deck assigned a CR = 7 has a TICR ≥ 10 yr are 48.8% and 35.3% for ADTT = 10 and 10,000, respectively.

From Figure 39, it is also obvious that lower ADTTs lead to higher survival probabilities, i.e. a lower chance that a bridge deck is assigned a lower CR, which makes sense.

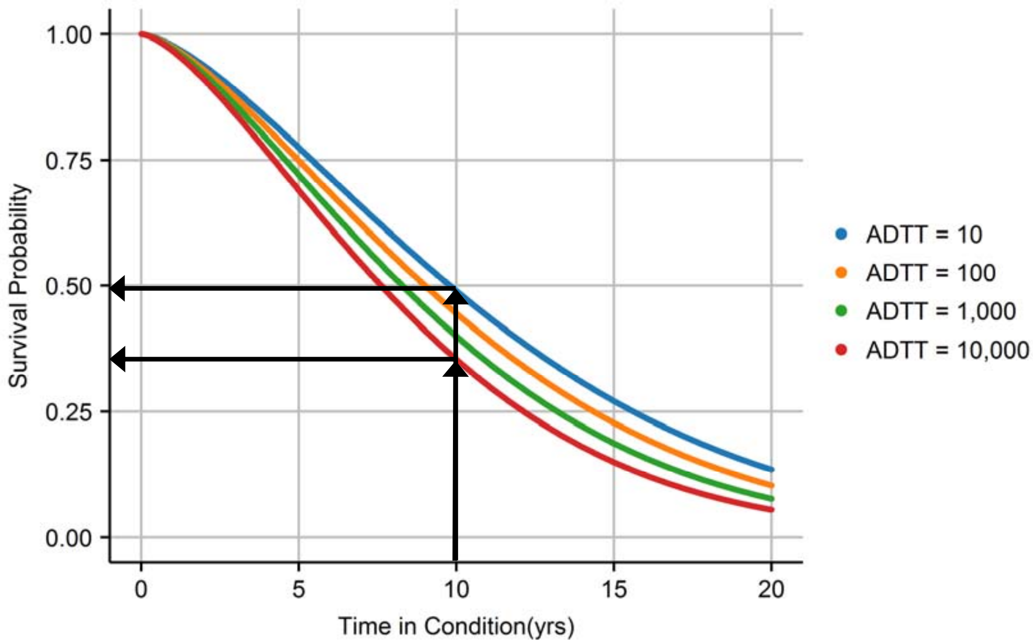

Figure 39. Comparison of select ADTT values. Note: arrows correspond to example presented above.

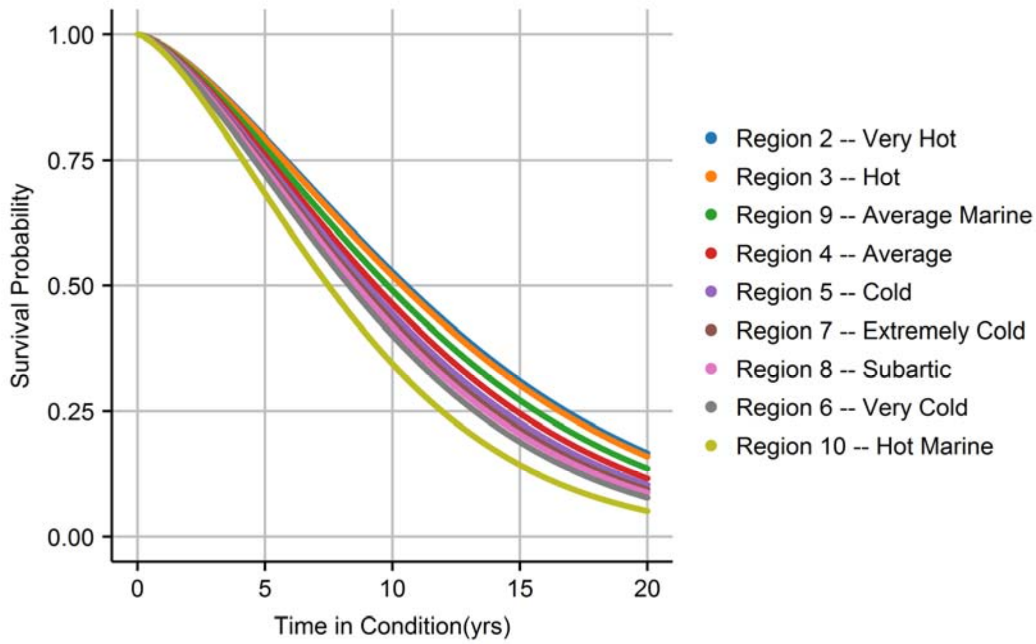

Figure 40. Comparison of Climatic Region values.

Figure 40 shows the effect of different environments following IECC Climatic Regions. Overall, it can be observed that colder climates are associated with higher survival probabilities, which is reasonable. The lowest survival probability is associated with Region 10 (hot marine). Figure 41 is interesting as it differs from what the authors (and other researchers) have found: there is a clear trend for higher CR to be associated with lower survival probabilities. The reason for this is that the analysis discussed here is capable of considering censored data, i.e. data that cannot be fully observed (see Figure 36).

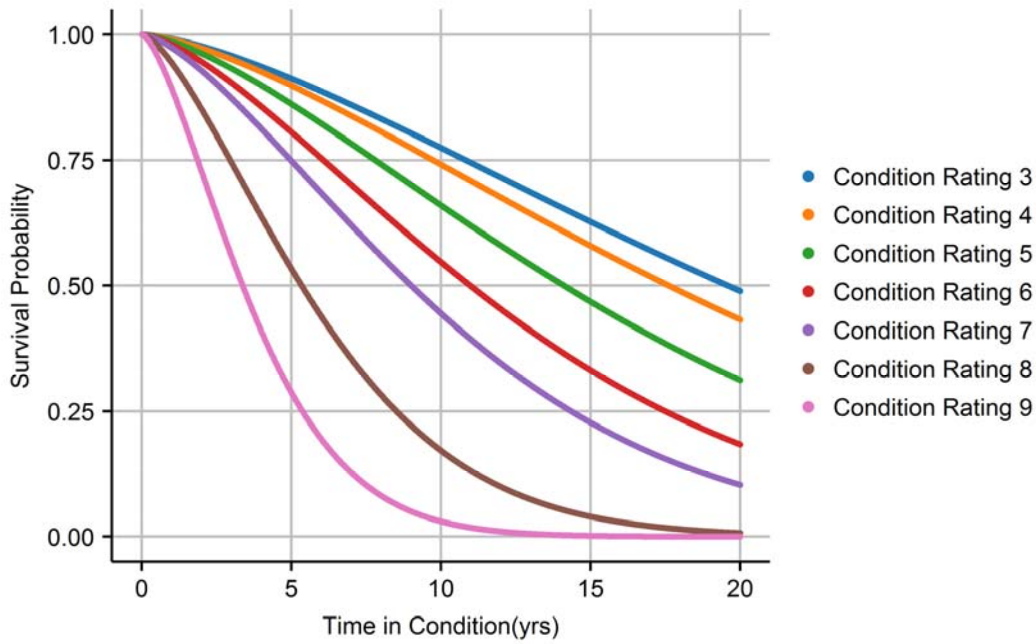

Figure 41. Comparison of deck CR values.

In Figure 42, the effect of protective measures on survival probabilities is illustrated. As can be observed, some protections measures appear helpful, others not. For example, both epoxy-coated as well as galvanized rebars appear to increase survival probability compared to when black rebars (= None) are used. The best performing measure is internally sealed, but that particular one also has a low precision (see Figure 38). Figure 43 suggests that precast concrete decks perform slightly better than reinforced concrete ones. In the next section, the uncertainty in these estimates is explored in more detail to highlight that this slight difference seems significant

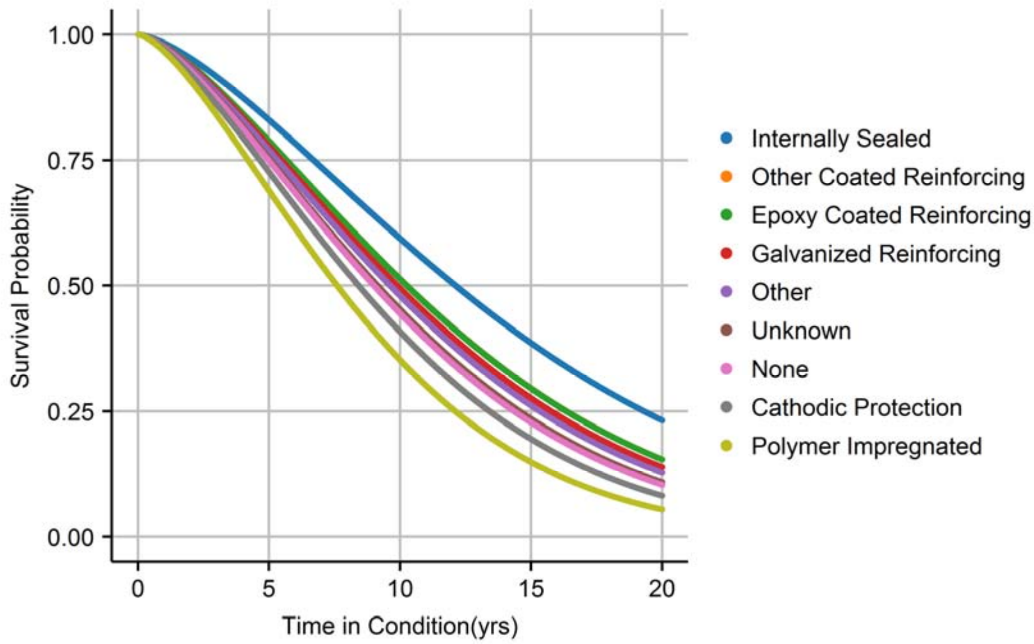

Figure 42. Comparison of Deck Protection values.

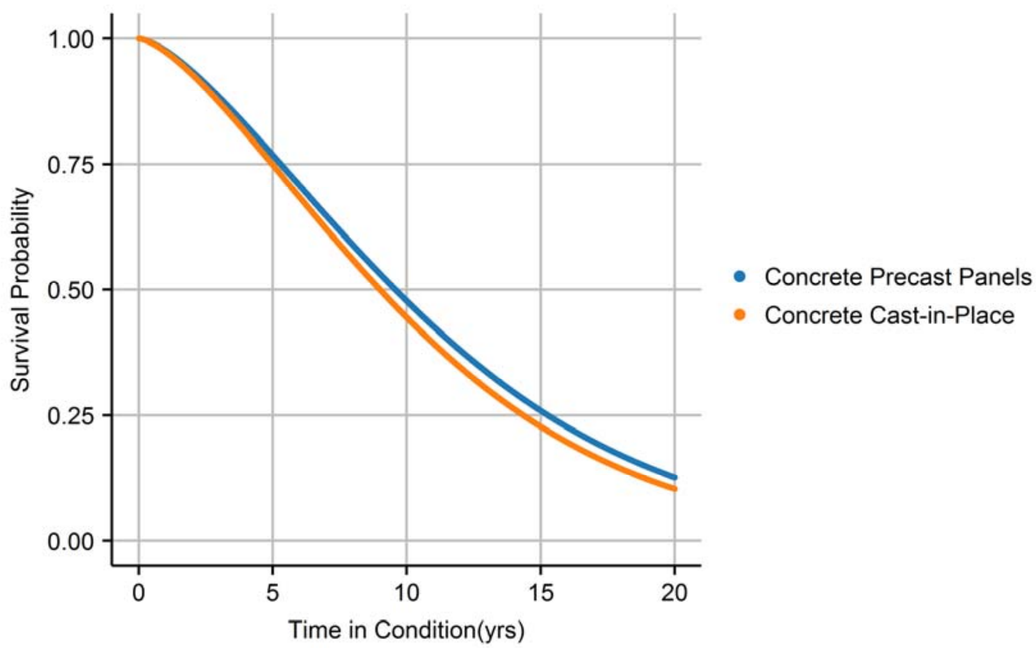

Figure 43. Comparison of Deck Structure Type values.

In Figure 44, the proximity of a bridge deck to seawater is explored. Surprisingly, bridge decks located closer to seawater appear to exhibit a slightly higher survival probability compared to when they are located further away. The reason for this could be several fold. First, the data is heavily skewed toward bridge decks located more than 3 km away. Figure 45 shows that there is no significant different difference between bridges located in urban vs. rural areas.

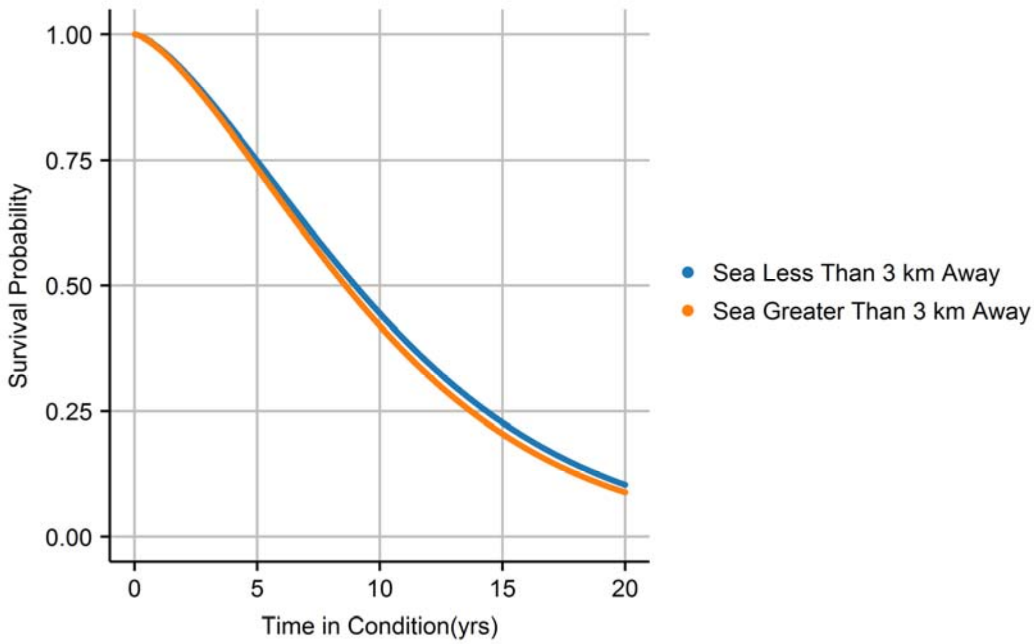

Figure 44. Comparison of Distance from Seawater values.

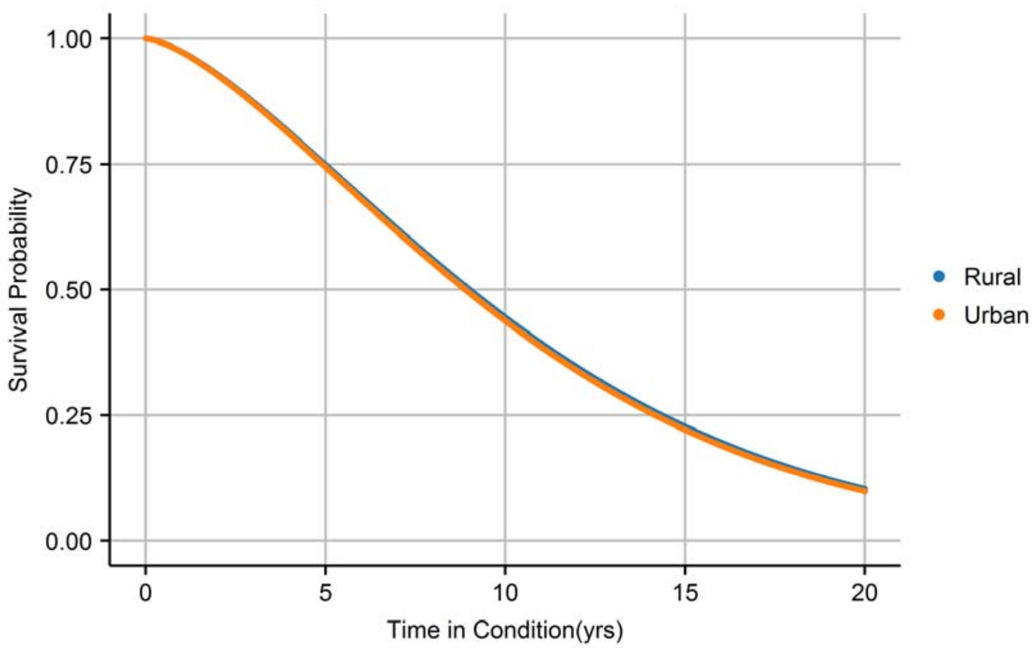

Figure 45. Comparison of Functional Class values.

In Figure 46, the effect of who is responsible for maintaining a bridge deck on survival probability is illustrated. There appears to be a trend for bridge decks located in smaller local entities to perform better than when they are maintained by larger entities, or states. While private entities appear to have well-performing bridge decks, this category also exhibits large spread (see Figure 38). Finally, Figure 47 shows the effect of the type and material of the structure supporting the bridge deck on its performance. Overall it can be observed that simple-span bridges have bridge decks with higher survival probabilities compared to continuous span bridges. This can be explained by the fact that simple-spans do not have negative bending regions and thus the bridge deck is less likely to develop cracking. In terms of material of the supporting structure, prestressed concrete appears to perform better than steel and reinforced concrete.

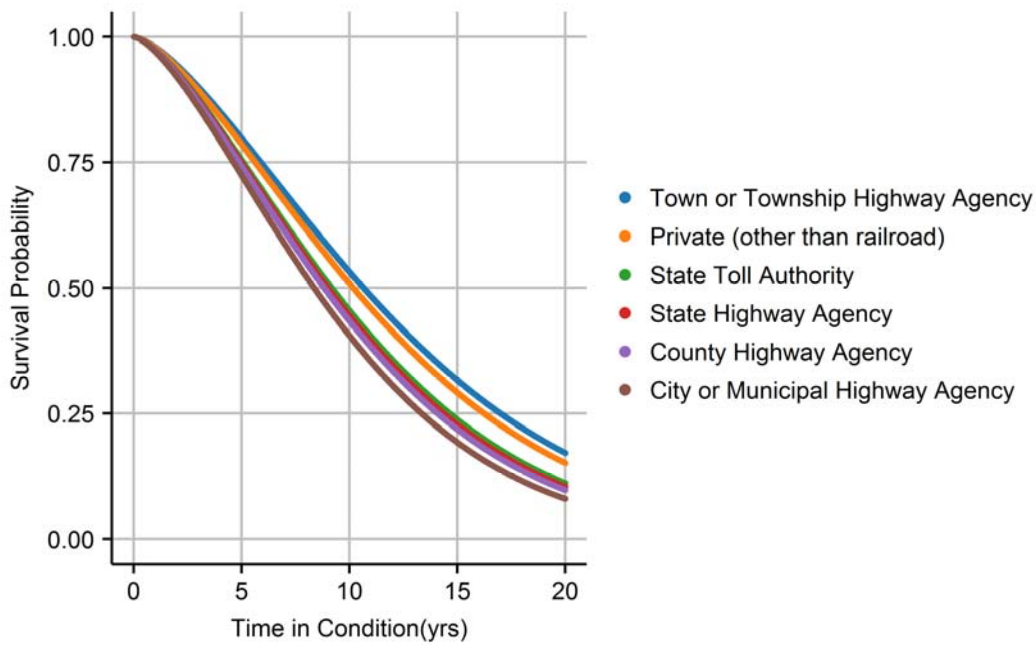

Figure 46. Comparison of Maintenance Responsibility values.

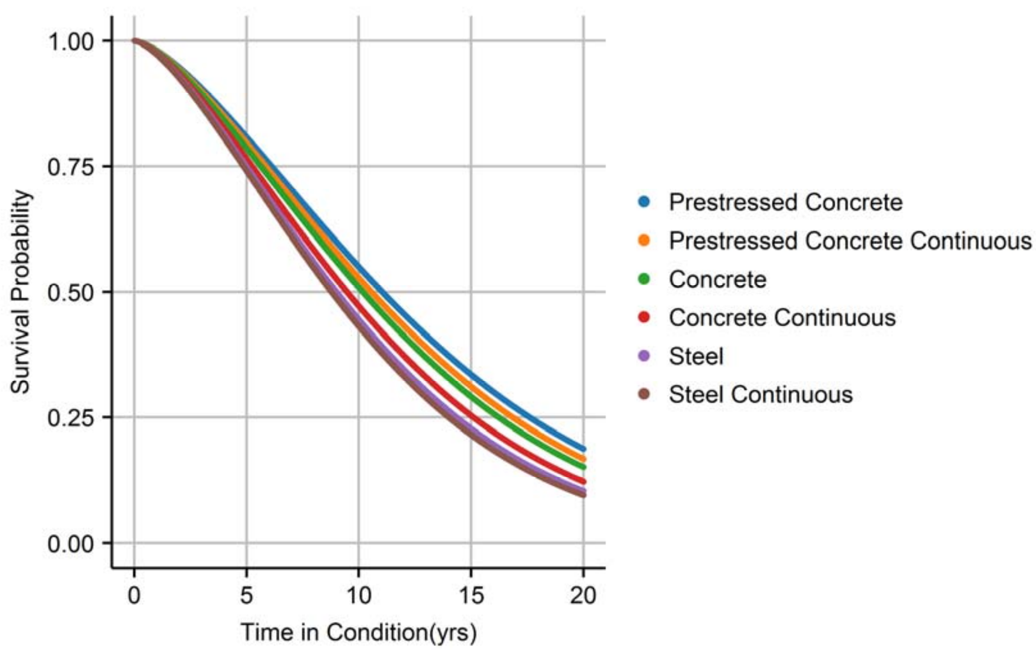

Figure 47. Comparison of Structure Type values.

Interpreting and Modelling Estimate Uncertainty

While the survival curves (Figure 39 to Figure 47) of the previous section reflect differences in mean estimates of survival probability, they do not capture the uncertainty in the estimates shown in Table 14 via confidence intervals and reflected in Figure 38. While Figure 38 hints at whether estimates are plausibly different by seeing whether their confidence intervals overlap, the practical relevance of those differences is difficult to assess. To show how estimate uncertainty can be made more interpretable, the posterior density estimates for 5-year survival probabilities are computed from sampling the posterior distribution output from the Stan modeling language. Figure 48 shows the density figures for the Deck Protection parameter.

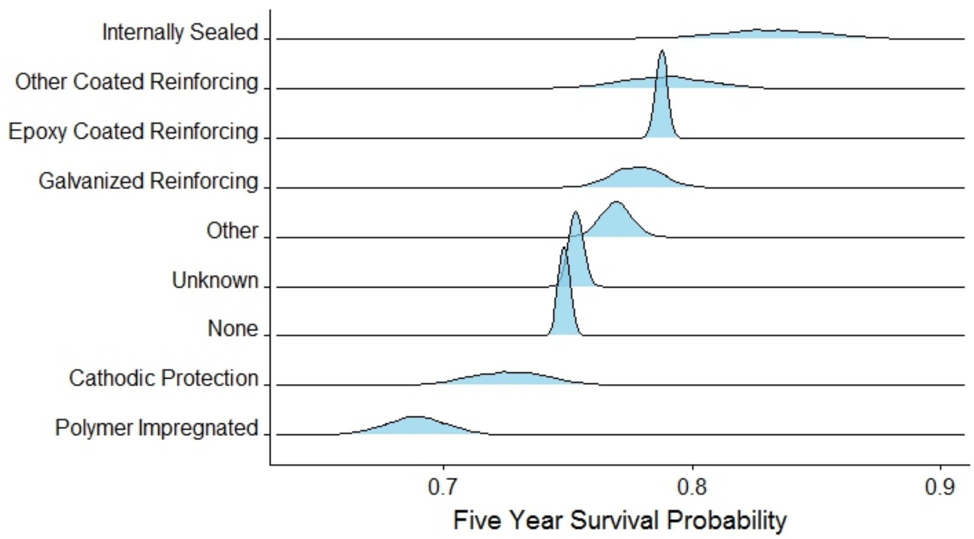

Figure 48. Density estimates showing uncertainty in 5-Year survival probability, ordered in descending order of mean probability, using referent values, and varying Deck Protection values.

Conclusions

This paper presents Bayesian survival analysis applied to time-in-condition rating (TICR) data computed from NBI condition ratings (CR). The objective was to employ a more advanced analysis procedure capable of considering both observed as well as censored data, which has not been previously done. The data used in the model includes five select variables from the NBI data and three additional parameters generated and added by the authors, The observed variable (= TICR) was computed from the CR and assumed to come from a Weibull distribution, which is convenient as it allows modeling the probability of CR decrease to increase with increasing TICR. A convenient way to visualize and explore the estimated parameters is by means of survival plots. Assuming certain values for all select variables, the effect of one covariate can be visualized as a function of TICR. These plots are useful to gain an understanding of bridge deck performance and when bridge maintenance is best performed.

Table 15. Parameter estimates.

Term	*Estimate*	*Std.error*	*Conf.low*	*Conf.high*	*rhat*	*ess*
alpha	1.486	0.002	1.482	1.491	1.000	4000
mu	-3.881	0.012	-3.904	-3.858	1.002	2447
Beta_rating3	-1.157	0.048	-1.248	-1.065	0.999	4000
Beta_rating4	-0.996	0.020	-1.035	-0.956	1.000	4000
Beta_rating5	-0.669	0.010	-0.688	-0.649	0.999	4000
Beta_rating6	-0.294	0.007	-0.307	-0.281	1.000	4000
Beta_rating8	0.776	0.005	0.766	0.787	1.000	4000
Beta_rating9	1.462	0.009	1.444	1.478	1.000	4000
Beta_climaticRegion2	-0.235	0.010	-0.254	-0.215	0.999	4000
Beta_climaticRegion3	-0.213	0.007	-0.226	-0.200	1.001	4000
Beta_climaticRegion4	-0.054	0.006	-0.067	-0.041	1.000	4000
Beta_climaticRegion6	0.119	0.007	0.106	0.132	1.000	4000
Beta_climaticRegion7	0.041	0.021	-0.003	0.083	1.000	4000
Beta_climaticRegion8	0.067	0.087	-0.107	0.231	1.000	4000
Beta_climaticRegion9	-0.130	0.018	-0.165	-0.094	1.000	4000
Beta_climaticRegion10	0.273	0.021	0.232	0.313	1.001	4000
Beta_maintRespCode2	0.028	0.007	0.015	0.042	1.001	3090
Beta_maintRespCode3	-0.252	0.013	-0.278	-0.226	1.000	4000
Beta_maintRespCode4	0.109	0.013	0.084	0.134	1.000	4000
Beta_maintRespCode26	-0.187	0.091	-0.365	-0.011	0.999	4000
Beta_maintRespCode31	-0.030	0.017	-0.063	0.004	1.000	4000
Beta_deckType2	-0.092	0.009	-0.109	-0.074	1.000	4000
Beta_log10ADTT	0.125	0.003	0.119	0.130	1.001	3444
Beta_functClass2	0.019	0.006	0.007	0.031	1.000	4000
Beta_structType1	-0.183	0.007	-0.197	-0.169	1.000	3026
Beta_structType2	-0.075	0.007	-0.090	-0.062	1.000	4000
Beta_structType4	0.036	0.007	0.022	0.051	1.001	4000
Beta_structType5	-0.303	0.007	-0.318	-0.290	1.000	3039
Beta_structType6	-0.239	0.012	-0.261	-0.216	0.999	4000
Beta_deckProt1	-0.193	0.007	-0.206	-0.180	1.001	4000
Beta_deckProt2	-0.142	0.051	-0.242	-0.043	1.000	4000
Beta_deckProt3	-0.199	0.098	-0.396	-0.009	0.999	4000
Beta_deckProt4	0.097	0.067	-0.036	0.227	1.000	4000
Beta_deckProt6	0.252	0.048	0.159	0.344	1.000	4000
Beta_deckProt7	-0.454	0.158	-0.784	-0.155	0.999	4000
Beta_deckProt8	-0.022	0.008	-0.037	-0.007	0.999	4000
Beta_deckProt9	-0.099	0.029	-0.156	-0.043	1.000	4000
Beta_nearSea1	0.067	0.024	0.020	0.112	1.000	4000

CHAPTER 6 – CONCLUSIONS

This chapter presents the overall conclusions for the performed work. For details regarding which parameters were found influential, please see the conclusion sections in Chapters 3 to 5. Overall, the following conclusions are made:

- The performance parameters DR and TICR do not follow a normal distribution, which means that an analysis of variance (ANOVA) cannot be used. Instead, the Kruskal-Wallis test was used for the initial prescriptive statistical analysis. This showed some initial trends and relationships (see Chapter 3).
- Different modeling approaches will produce slightly different rankings in terms of strength of influence of a parameter on deck performance (compare conclusions Chapters 3 to 5).
- Considering censored data, as is possible by using a Bayesian survival analysis (see Chapter 5), is perhaps the most suitable way to treat this type of data. By not considering censored data (i.e. by discarding it or considering it uncensored), significant bias is introduced into the analysis. This manifests most clearly for the case where TICR is analyzed separately for each CR (compare Figure 24 and Figure 41).
- After having analyzed this large dataset in a number of ways, it became clear that it is best to answer specific questions by fixing certain parameters rather than trying to reveal overall underlying trends and relationships. There are simply too many parameters, which have bias and uncertainty associated with them, which makes it difficult to obtain strong relationships and avoid interrelationships.

Based on the overall findings and lessons learned, the following future work is recommended:

- Analyses using this kind of data are most meaningful on a statewide basis and for one type of agency responsible for preservation activities. The reason for this is that this kind of information is not available in a consistent format.
- Parameters that are known to control service-life performance should be created (if unavailable) and included in future analyses. These include information regarding construction activities (e.g. presence early-age cracking, curing activities, fresh concrete properties), actual on-site environmental conditions (e.g. freeze-thaw cycles, exposure to deicers, chloride content), and as-built properties of the deck (e.g. concrete cover, rebar spacing).
- An analysis that considers multiple parameters, e.g. multiple-parameter regression, should be attempted to estimate relationships between parameters.
- The ultimate goal should be to integrate the performance metrics into asset management methodologies.

CHAPTER 7 – REFERENCES

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