STATISTICAL MODELING OF UNITED STATES HIGHWAY CONCRETE BRIDGE DECKS

by

Omar Ghonima

A dissertation submitted to the Faculty of the University of Delaware in partial fulfillment of the requirements for the degree of Doctor of Philosophy in Civil Engineering

Spring 2017

STATISTICAL MODELING OF UNITED STATES HIGHWAY CONCRETE BRIDGE DECKS

by

Omar Ghonima

Approved: ____
Harry W. Shenton III, Ph.D.
Chair of the Department of Civil and Environmental Engineering

Approved: ____
Babatunde A. Ogunnaike, Ph.D.
Dean of the College of Engineering

Approved: ____
Ann L. Ardis, Ph.D.
Senior Vice Provost for Graduate and Professional Education

I certify that I have read this dissertation and that in my opinion it meets the academic and professional standard required by the University as a dissertation for the degree of Doctor of Philosophy.

Signed: ______________________________
Thomas Schumacher, Ph.D.
Professor in charge of dissertation

I certify that I have read this dissertation and that in my opinion it meets the academic and professional standard required by the University as a dissertation for the degree of Doctor of Philosophy.

Signed: ______________________________
Sue McNeil, Ph.D.
Member of dissertation committee

I certify that I have read this dissertation and that in my opinion it meets the academic and professional standard required by the University as a dissertation for the degree of Doctor of Philosophy.

Signed: ______________________________
Nii O. Attoh-Okine, Ph.D.
Member of dissertation committee

I certify that I have read this dissertation and that in my opinion it meets the academic and professional standard required by the University as a dissertation for the degree of Doctor of Philosophy.

Signed: ______________________________
Adam Fleischhacker, Ph.D.
Member of dissertation committee

I certify that I have read this dissertation and that in my opinion it meets the academic and professional standard required by the University as a dissertation for the degree of Doctor of Philosophy.

Signed: ____

Avinash Unnikrishnan, Ph.D.
Member of dissertation committee

ACKNOWLEDGMENTS

No project of this size can be accomplished without a great deal of support along the way. Therefore, I would like to express my sincere gratitude to Dr. Thomas Schumacher for providing me with the opportunity to study under his guidance and for believing in me. His constant motivation and supervision while serving as chair of my academic committee helped bring this research to fruition. Sincere thanks as well to my committee member, Dr. Fleischhacker, for his valuable input and support with my Bayesian model. Additionally, thanks go to the other members of my doctoral committee, Dr. Sue McNeil and Dr. Nii Attoh-Okine, for their insight and support of this study. I also wish to recognize my fellow student and friend Matija Radovic for his invaluable assistance with the clustering modeling portions of this study. Daniel Clem from TY Lin International generously provided professional input regarding how the Delaware and Pennsylvania Departments of Transportation rate their concrete bridges. Gratitude is also extended to Dr. Daniel Lees for his continuous encouragement and donation of his valuable time to proofread this dissertation.

Next, I would like to offer my sincere thanks to the Federal Highway Administration who provided input during my work and for their financial support of the research. I would like to express gratitude to the Civil and Environmental Engineering Department at Portland State University for hosting me as a visiting scholar and financial support, in particular Dr. Avinash Unnikrishnan for his guidance in this research. Dr. Joseph Broach of Portland State's Urban Studies and Planning department furnished me with help and sincere interest in this research. Lastly, a big

thank you to my wider support system, my family, friends, colleagues and the staff at the University of Delaware, all of whom helped make my PhD years memorable. I must also praise God for His blessing and guidance throughout my doctoral journey.

DEDICATION

I dedicate this dissertation to my loving parents Amany Essawy and Dr. Sherif Ghonima, my backbone and greatest influence in my life. I thank them for their sacrifice that provided me with this opportunity to pursue my doctorate. Mom and Dad, your love and support have sustained me throughout this incredible endeavor. Without the determination and work ethic that you have instilled in me, this work would not have been possible. Moreover, your encouragement and push for tenacity made sure that I gave all it takes to finish what I started here. I could not have asked for better role models.

TABLE OF CONTENTS

Chapter

Appendix

LIST OF TABLES

LIST OF FIGURES

ABSTRACT

As the backbone of the US transportation system, bridges are also its most visible part. There are over 600,000 bridges across all US states ensuring network continuity. In order to optimize such activities and use the available monies most 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. Recently there has been a growing interest in analyzing the NBI database. The NBI uses visual inspection, a commonly practiced damage detection method, to rate bridge decks. Focusing on concrete highway bridge deck performance, the present study developed a nationwide database based on NBI data and other critical parameters, such as bridge age, deck area, climatic regions, and distance from seawater. Additionally, two new 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 to form a nationwide database, filtering and processing were performed. Approaches to dealing with inconsistencies and missing data are proposed as well. After developing the nationwide database this research presents network-level, one-way statistical relationships to get a better understanding of the parameters.

Next, a data mining technique on the nationwide database was used to analyze the data. Data mining is a discovery procedure to explore and visualize useful but less-

than-obvious information or patterns embedded in large collections of data. Given the amount and variety of parameter types in a large data set such as that of the nationwide database, using traditional clustering techniques for discovery is impractical. As a consequence, this research has applied a novel data discovery tool called two-step cluster analysis to visualize associations between concrete bridge deck design parameters and bridge deck condition ratings. Two-step cluster analysis is a powerful knowledge discovery tool that can handle categorical and interval data simultaneously and is capable of reducing dimensions for large data sets. The two-step cluster analysis is a useful tool for bridge owners and agencies to visualize general trends in their concrete bridge deck condition data and support them in their decision-making processes to effectively allocate constrained funds for maintenance, repair, and design of bridge decks.

Understanding the attributes of bridge deck performance is central to asset management. This research attempts to characterize how various environmental and structural parameters affect bridge deck performance by employing a binary logistic regression. The logistic model shows the relationship between a dependent variable (lowest vs. highest bridge deck deterioration) and the relative importance of a number of independent variables selected for this study (predictor variables). Observations of extreme bridge deck deterioration taken from the nationwide database were used in the model. Bridge deck deterioration was computed as the decrease in CR over time. Maintenance responsibility fulfillment, functional classification of inventory route, design and construction type, average daily truck traffic, climatic regions, and distance to seawater, were all used as independent variables. Our application of a binary logistic regression model for bridge deck deterioration provides practical insight regarding how certain parameters influence bridge deck performance.

A leading factor in structural decline of highway bridges is the deterioration of concrete decks. Thus, a method to forecast bridge deck performance is vital for transportation agencies to allocate future repair and rehabilitation funds. The objective of this study was the development of a nationwide CR deterioration model based on the nationwide database through the use of a Bayesian statistical approach that predicts probability of CR decrease. In addition to CR data, the impact of other governing factors on CR decrease are shown in the paper, such as average daily truck traffic (ADTT), maintenance responsibility fulfillment, deck structure type, and regional climate effect. One singular advantage of this method is that it can be continually updated as additional NBI information becomes available. Moreover, the results of this model can be used as prior data in future Bayesian studies. The results presented in this study, by providing a better idea of how US concrete bridge decks are performing based on the NBI data, are intended to furnish a progressive bridge management system.

Results yielded by each of the analysis above will encourage future researchers to add other crucial parameters not contained in the nationwide database such as structural design characteristics (e.g., minimum deck thickness), construction practices (e.g., curing practices), specifications (e.g., water-to-cement ratio), and other notable factors (e.g., application of deicing salts). Furthermore, analyze the nationwide database in various statistical application areas leading to more accurate understating of the factors affecting bridge deck deterioration and enhanced deck deterioration prediction models.

Chapter 1

INTRODUCTION

Bridge design follows two criteria, *strength and serviceability*, which ensure structural integrity and functionality, respectively. With limited funding available to keep all bridge decks in a state of good repair, reliable tools are needed to estimate service-life and life-cycle costs so that informed decisions can be made as to which decks should be repaired first and what repair techniques should be employed (38). Additionally, these tools can also assist during the design process to estimate the expected service-life limit of new concrete bridge decks. Currently, state DOTs have their own criteria as to when to repair or rehabilitate a bridge deck (39).

According the American Society of Civil Engineers, 9.1 % of the nation's bridges in 2016 are structurally deficient leading to an average of 188 million daily trips across those bridges. Of the structurally deficiencies, 6.3% belong to bridge deck area (1). 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). According to the Federal Highway Administration (FHWA), two billion dollars are spent annually for maintenance and capital costs for concrete bridge decks (53). Moreover, the main reason for bridge superstructure repair and rehabilitation is deterioration of concrete decks (2). There are 614,386 bridge decks in the United States, of which 425,671 are concrete (54). Although corrosion is usually considered a main contributor to deterioration of concrete decks, many other factors (such as average daily truck traffic, distance from seawater, maintenance responsibility, deck structure type and so on) play a major role in bridge deck deterioration. Therefore, understanding environmental and structural factors that affect concrete bridge deck deterioration and modeling such deterioration is of considerable interest to departments of transportation and the FHWA.

1.1 Outline of the Dissertation

The dissertation is divided into eight chapters. The dissertation has been organized in a specific order, such that it provides an overall introduction of concrete bridge decks, followed by the compilation of the nationwide database, followed by various statistical models analyzing the nationwide database, and concluding with a model that can be used to predict the probability of CR decrease (Fig.1.1).

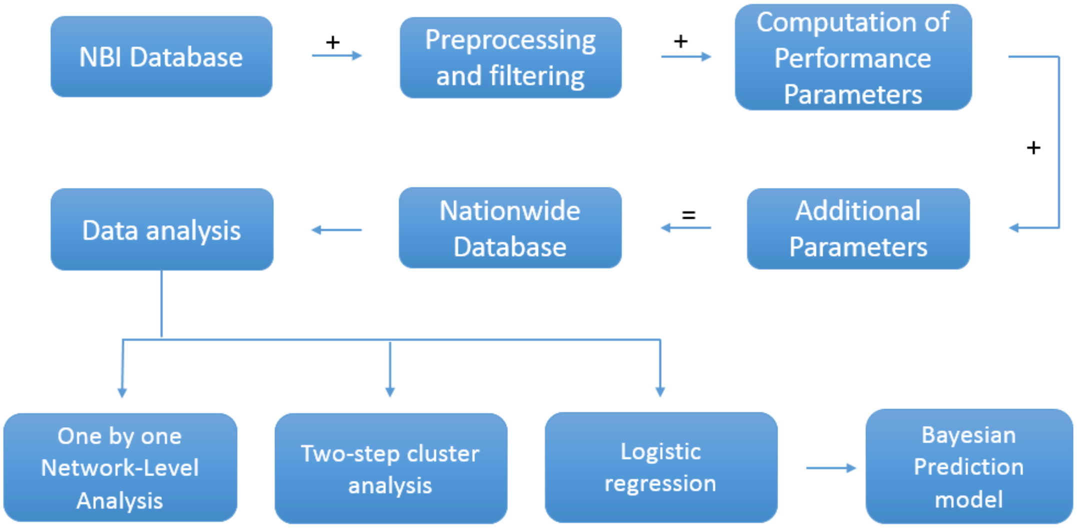


Figure 1.1: Research overview.

1.2 Chapter summary

Chapter 1: Introduces the problem described in this research; discusses the importance of analyzing concrete bridge decks.

Chapter 2: An overview of concrete bridge decks; the factors affecting them; and the methods for the protection, repair, and rehabilitation of these decks. An introduction to the National Bridge Inventory data and a field inspection report of bridge deck condition ratings of a sample of bridges across Delaware is also presented. The chapter concludes with a literature review of deck decoration studies. The aim of this chapter was to give the reader a better understanding of concrete bridge decks, their deterioration and inspection process.

Chapter 3: The motivation and primary objective behind this research.

Chapter 4: The process of compiling a nationwide database for concrete bridge decks based on the NBI and additional computed parameters. Some illustrative network-level, one-way statistical analysis of various parameters of the nationwide database are provided for a better understanding of the effects of such parameters on concrete decks.

Chapter 5: A two-step cluster data mining technique used as a data mining discovery procedure in order to visualize useful but less-than-obvious information. Advantages of this tool are discussed.

Chapter 6: Using Binary Logistic Regression on the nationwide database, showing the relationship between least and highest deteriorated bridge decks and the relative importance of various environmental and structural categories. The binary logistic model predicts the likelihood of bridge decks to be associated with the highest deterioration. Two examples of how this model could be used were also presented in this chapter.

Chapter 7: A preliminary Bayesian model to look at how long concrete bridge decks in the United States remain in CR rating before deteriorating. The impact of other deterioration factors is shown and the influence of prior information on the Bayesian posterior results discussed.

Chapter 8: Conclusion. Summary and implications of limitations of nationwide database along with future research recommendations provided.

Chapter 2

CONCRETE BRIDGE DECKS

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 next 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 reviewed. A brief introduction to the National Bridge Inventory (NBI) and its system of concrete bridge deck rating is then presented. The chapter includes a narrative of a field trip that I undertook with an inspector of bridges in order to get a better idea of the inspection process. A literature review of concrete bridge deck studies concludes the chapter.

2.1 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 (13). 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(14). Furthermore, most concrete decks are composite cast-in-place as opposed to precast concrete panels(5,53). Composite decks have significant advantages, because they are working with the superstructure members to resist load. Some of the advantages are as follows (14):

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

2.2 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 define 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(4)

According to the *Design Guide for Bridges for Service Life* report, two general design approaches predict service life: *finite service-life approach* and *target service-life approach* (5).

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 (5).

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 (5). There is no interference with the deck until it reaches failure (Fig. 2.1).

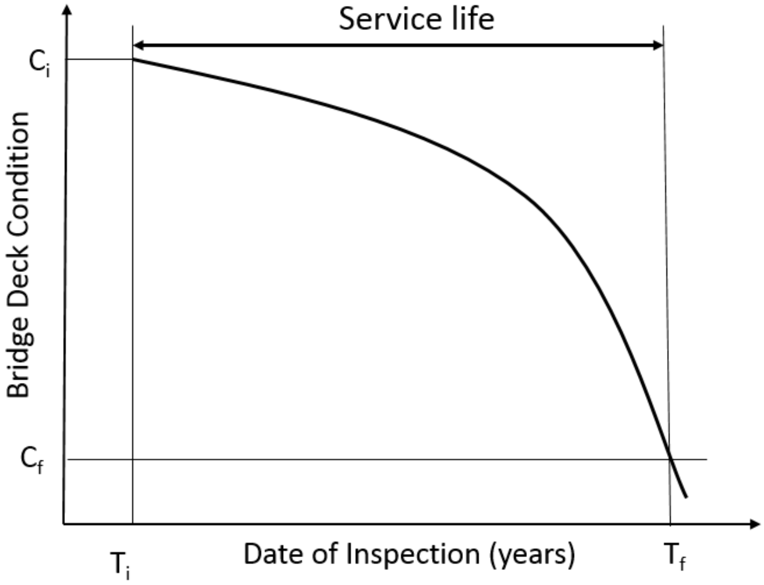


Figure 2.1: Hypothetical bridge deck deterioration.

However, a deck undergoes maintenance, repair, and rehabilitation, which will restore its condition to a higher level (Fig. 2.2). The goal of asset management strategies is to optimize the time of interference (maintenance) to get the highest benefit from the investment.

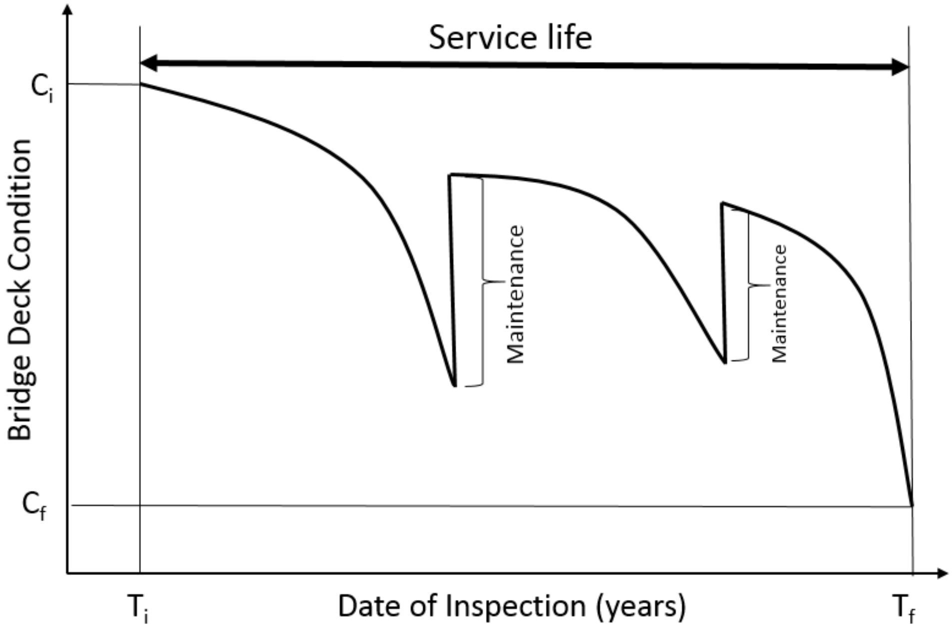


Figure 2.2: Hypothetical bridge deck condition deteriorating including maintenance.

Such smooth deterioration, however, is not always the case. Based on the National Bridge Inventory database (see discussion in Chapter 3) the change in condition rating of bridge decks differs vastly from the merely hypothetical (Fig. 2.3) . A sample of three bridges deck ratings from the NBI for the state of Oregon is shown in Figure 2.3.

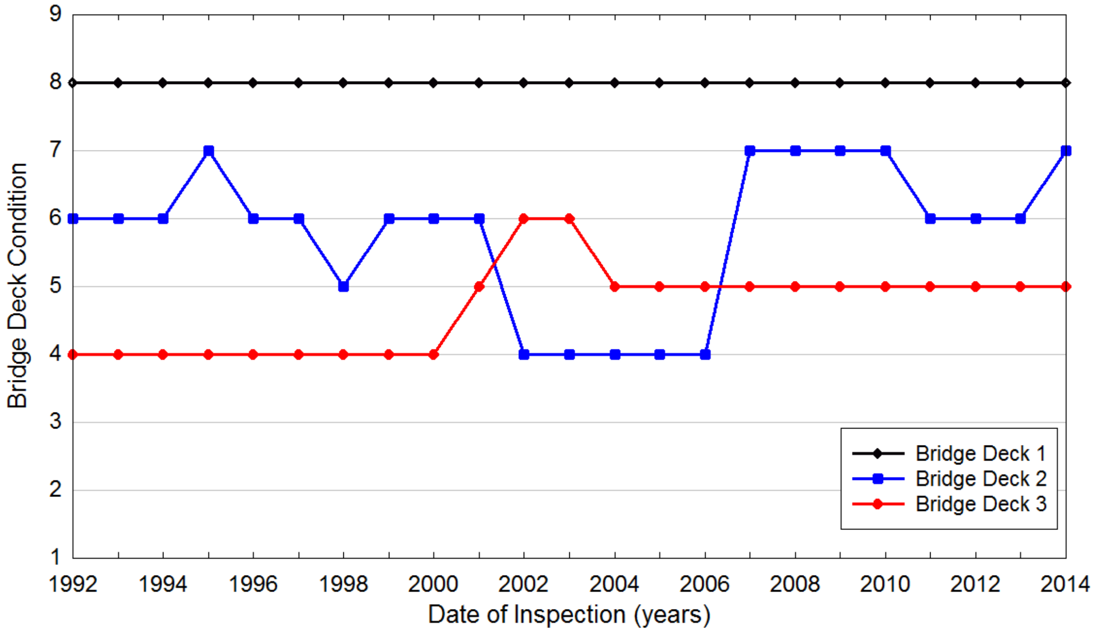


Figure 2.3: Three samples of deck condition rating (CR) vs. date of inspection from NBI data for the State of Oregon.

Smooth deterioration depicted (Fig.2.2) are not supported by the visual inspection data behind the condition ratings of the NBI database.

2.3 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 factors in affecting deck deterioration is explained in more detail.

2.3.1 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 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 (15,16). Once corrosion has initiated, the process will cause the concrete cover to crack, in turn resulting in increased chloride penetration, which further accelerates corrosion (3). 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 (6). Increasing concrete cover depth invokes a trade-off, requiring designers to stay within certain limits while still providing minimum depth to prevent rapid chloride diffusion.

2.3.2 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 (17, 4). Reducing w/c ratio decreases capillary porosity, resulting in decreased permeability (11). 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 (11):

$$D \sim 10^{-10+4.66 w/c} \tag{2.1}$$

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

2.3.3 Compressive strength

Compressive strength affects chloride concentration, and hence bridge deck deterioration. Steware and Rosowsky 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 (11).

2.3.4 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 (19).

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 (19). Up until now there have only 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 (15). Moreover, other research results suggests that epoxy coatings lose the adhesion of their coating when exposed to moisture. (19). 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 (19).

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 (19). 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 (8).

2.3.5 Distance from seawater

The distance of bridge decks from sea 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 (17). In time, chloride content increases from a constant transfer of sea salt (6). 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 (17):

$$C_0(d) = 2.95\ {}^{kg}/_{m^3} \qquad d < 0.1\ km \tag{2.2}$$

$$C_0(d) = 1.15 - 1.81\ log_{10}(d) \qquad 0.1\ km < d < 2.84\ km \tag{2.3}$$

$$C_0(d) = 0.03\ {}^{kg}/_{m^3} \qquad d > 2.84\ km \tag{2.4}$$

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 (6).

2.3.6 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 (13) (usually caused when concrete is in a plastic stage undergoing differential concrete settlement). Initial cracks expedite chloride ingression, leading to early corrosion initiation. Moreover, crack width is significant: according the National Cooperative Highway Research Program crack widths of 0.002 inch or wider can cause salt contaminants containing chloride to pass through a deck cover (55). Another study suggests that corrosion initiation is affected by surface cracks larger that 0.3-0.6 mm (0.012-0.024 in) (11).

2.3.7 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 cracks (19). According to Krauss and Rogalla, cement used nowadays causes concrete to gain strength more rapidly, resulting in higher modules of elasticity and compressive strength, in turn causing the concrete to have a higher chance of early cracking (19). Hadidi and Saadeghraziri recommended the following mix design in order to reduce deck cracking (19):

- 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
- Water reducers
- Largest maximum aggregate size and the maximum aggregate content
- Avoidance of concrete mixes that have a tendency for cracking

2.3.8 Type of restraint

Bridge decks can be restrained when cast over already dried concrete or steel girder causing tensile stresses to develop. Moreover, boundary conditions of a bridge deck can cause additional axial forces on the deck. Girders, parapet, abutment, and so forth. all play a role in causing axial forces or tensile stress on the deck (5). According to Krauss and Rogalla, 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 (76,19).

2.3.9 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 (5).

2.3.10 Construction practices

Poor concrete placement and curing practices can affect the service life of bridge decks (5). 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 cement (4). 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 (5).

2.3.11 Design practices

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 deterioration (5).

2.3.12 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 (6), making deicing salts one of the main factors in 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 (8).

2.3.13 Traffic and load

Deck-rehabilitation decisions are often based on a bridge's worst-span lane (usually the right hand lane) the one receiving the most traffic (3). 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 (5)

- **Fatigue:** Structural damage to an element due to cyclic loading from traffic resulting in the initiation of cracks and subsequent chloride ingression.
- **Overload:** 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.

2.3.14 NCHRP 333 report

This report discusses the effects of material and mix design on the durability of 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 on research this report concluded that the use of the following materials and practices enhances the performance of concrete bridge decks (19):

1. 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.

2. Reinforcement Materials

   - Epoxy-coated reinforcement in both layers of deck reinforcement and

   - minimum practical transverse bar size and spacing.

3. 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.

2.4 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 how bridge decks corrode. The process can be broken down into several steps (Fig. 2.4):

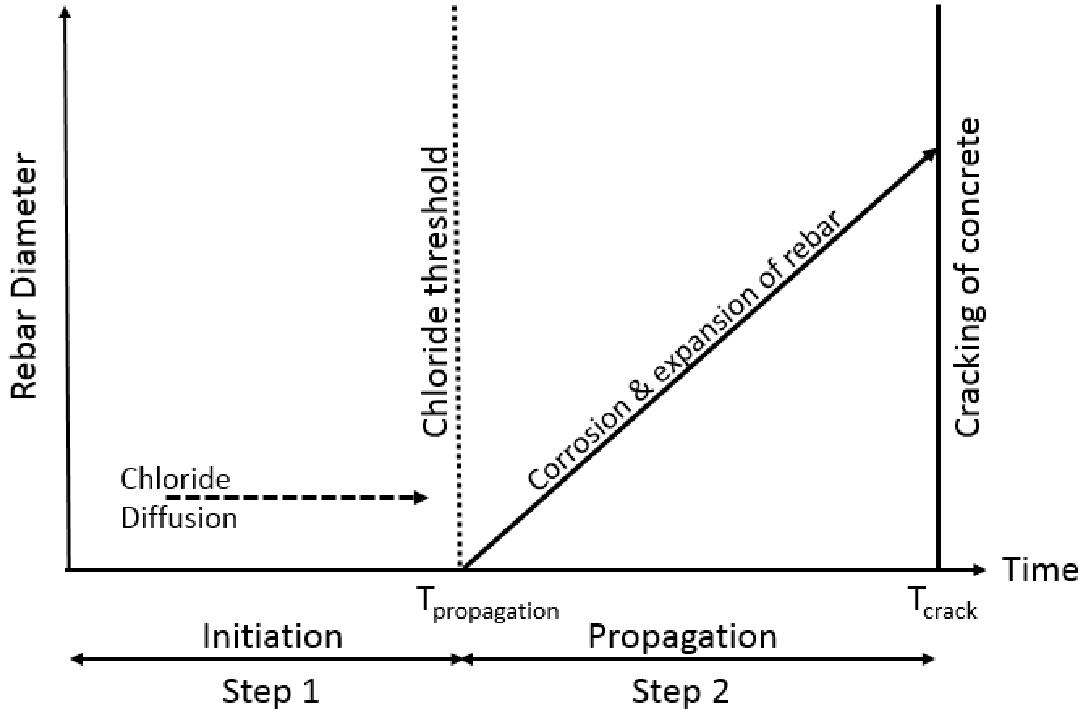


Figure 2.4: Corrosion process of steel reinforcement.

2.4.1 Step1 – Chloride initiation

Corrosion cannot begin until the passivity layer protecting the steel is deactivated (7). 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 (8). 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. There is no agreed upon set value for chloride concentration at which corrosion occurs when that value is surpassed (9). Isgor argues 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 (31). 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 (8).

2.4.2 Step 2 – Corrosion Propagation

After the initiation process comes corrosion propagation where the steel rebars start to corrode causing them to rust and increase in area resulting in a loss of bond (Fig. 2.5).

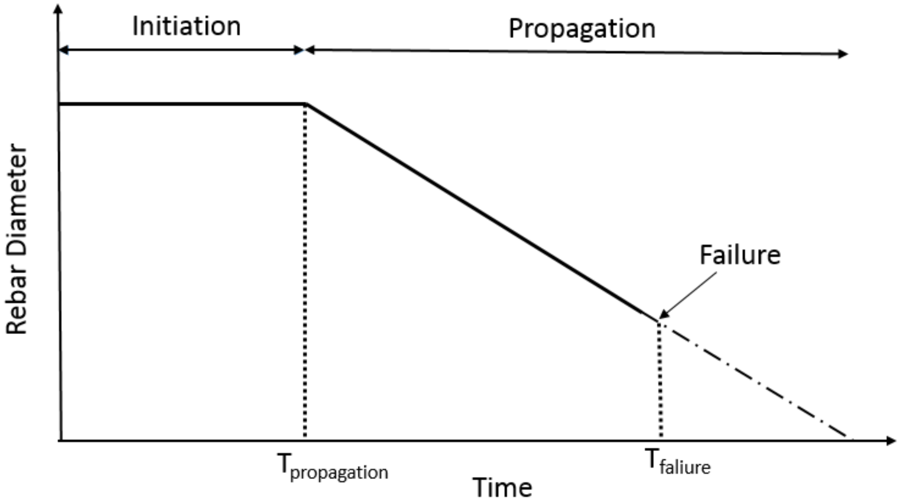


Figure 2.5: Concrete bridge deck corrosion process.

According to Stewart et al., once the propagation period occurs, the rebar loss of area can be modeled as a uniform reduction by the following equation:

$$D(t) = \begin{Bmatrix} D_i & t \leq T_i \\ D_i - 2\lambda(t - T_i) & T_i < t \leq T_i + ({}^{D_i}/_{2\lambda}) \\ 0 & t > T_i + +({}^{D_i}/_{2\lambda}) \end{Bmatrix}. \tag{2.5}$$

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 (11).

Figure 2.6: Corrosion of reinforcing steel.

Cracking in concrete is caused by iron oxides (rust) (Fig. 2.6) 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 (11). Life 365 uses a propagation period of six years for bare steel, while ACI suggests a higher value (10) ; Williamson suggests sixteen years, and Weyers between two and five (8). 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 (section 2.3) that influence deterioration into consideration.

2.5 Deck Protection Methods

Deck protection methods are used in the initial design of bridge decks in order to extend a deck's service life. The type of steel and the concrete properties (such as type of cement and permeability of concrete methods) mentioned earlier in section 2.3 are examples of such protective methods. Other types of protection methods include the following:

2.5.1 Cathodic prevention

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 steel in the negative direction, causing the reinforcement to become cathodic, thereby preventing corrosion. However, there are some disadvantages to it (8,19,22,23):

- High cost.
- Need for periodic adjustment and constant monitoring.
- A 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 2.6) once a structure is already experiencing corrosion and would then be called cathodic protection.

2.5.2 Membranes

These are usually placed on top of the concrete and protected by another material (usually asphalt) that functions as the riding surface (5, 19). 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 (5).

2.5.3 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 2mm) 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. Deck sealers effectiveness depends on the permeability of concrete (8,5).

2.5.4 Corrosion inhibitors (CI)

Various liquid admixtures are used in bridge decks in order to hinder the corrosion process. The idea behind using CI is to raise the chloride threshold of the steel, which will slow the rate of corrosion (19). Calcium nitrate admixtures are the most widely used CI(5). 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 on the concrete mixture or on the surface directly. However, it is usually applied to 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 (19,8,5).

2.6 Deck Repair and Rehabilitation Methods

There are many different definitions of bridge deck repair and rehabilitation. Weyers (56) et al. 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 (8) 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; below are the different methods:

2.6.1 Deck patching (deck repair method)

Patching is normally used to replace areas of a deck that has 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 is corroded). Portland cement concrete, quick-set hydraulic mortar and concrete, and polymer mortar and concrete are used for deck patching (56). 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 2.92, Fig. 2.15) (23). This might be triggered by the low chloride presence in patches that causes them to become cathodic, resulting in higher corrosion rate of surrounding steel (8). Most studies conclude that patching is a questionable method of repair, is costly and involves frequent traffic disturbances, and is only a short term solution (8,22,23).

2.6.2 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 (8). The purpose of overlay is to create low permeability protective layer over the concrete deck that reduces chloride ingression (due to increased cover and low permeability overlay) (5). 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 (8).

Various types of deck overlays (19):

- 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.

2.7 Service Life Software Packages

2.7.1 Life-365

Life-365 is a service life and life cycle program that can be used to model marine structures, parking garages, bridge decks, and transportation infrastructure. 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 damages 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 be changed by the user. The initiation period is calculated using either one or two dimensional Fickian diffusion modeling (25). Fick's second law of diffusion can be expressed most simply by

$$\frac{\partial C}{\partial t} = D_c \frac{\partial^2 C}{\partial x^2} \tag{2.6}$$

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 (20). Inputs required for Life 365 are (20)

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 a project (25).The outputs of the Life 365 are (25)

- time to reinforcement corrosion initiation,
- the 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.

2.7.2 STADIUM

Is a more advanced service life commercial program that was produced by SIMCO Technologies. STADIUM is a multi-mechanistic tool; however, its main usage is for chloride diffusion modeling. The program is considered an asset management system. There are three main applications of STADUIM: 1) Optimize the service life, 2) Extend the service life, 3) Provide information to guide decision-making (26). Stadium has a longer list of inputs compared to life-365 (27):

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 imputing those 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 electrodiffusion 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 (26).

The difference between most commercial programs and Stadium is that commercial programs only consider chloride contamination exclusively, while Stadium takes into consideration all these ionic species: OH^-, Na^+, K^+, S O_4^{-2}, $CA^{2+,}$, Cl^-, K^+,

Mg^{2+}, $H_2Si\ O_4^{-2}$, $Al(OH)_4^-$, $Fe(OH)_4^-$, HCO_3^- and NO_2^-. Moreover, the model accounts for the effect of cement and supplementary cementing materials hydration on 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 (26).

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 (8).

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 (26).

2.8 National Bridge Inventory (NBI)

The collapse of the Silver Bridge in Ohio in 1967 resulted in 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 (29). 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 (1). The NBI database allows DOTs to monitor bridge performance and condition and identify what should be done. Based on the 2016 NBI census there 425,671 concrete bridge decks in the United States (54).

2.8.1 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 (29)

2.8.2 Rating

Certified trained inspectors assess structural components and operational characteristics and rate them from 0 to 9 (Table 2.1) According the FHWA recording and coding guide (30), 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 (30). 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 2.1: Deck condition ratings (30).

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 definition for bridge deck conditions (Table 2.1) which makes it hard to differentiate the CR based on the descriptions. However, most DOTs have similar-in depth description of the CR which makes it easier to differentiate (Table 2.2).

Table 2.2: Concrete bridge deck condition rating based on the Minnesota Department of Transportation (77).

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.
N	Not Applicable: Use for culverts, roadway tunnels, or filled spandrel arch bridges
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.

2.9 Understanding the deck rating process (field inspection report)

While developing this dissertation, I conducted a field trip to selected bridges across Delaware with a certified bridge inspector, Mr. Daniel Clem 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 within a ±1 range against the actual 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.

2.9.1 First inspected bridge

Location: Newark DE, **Latitude**: 39 39’ 46’’and, **longitude**: 075 45’ 20’’
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 2.7.

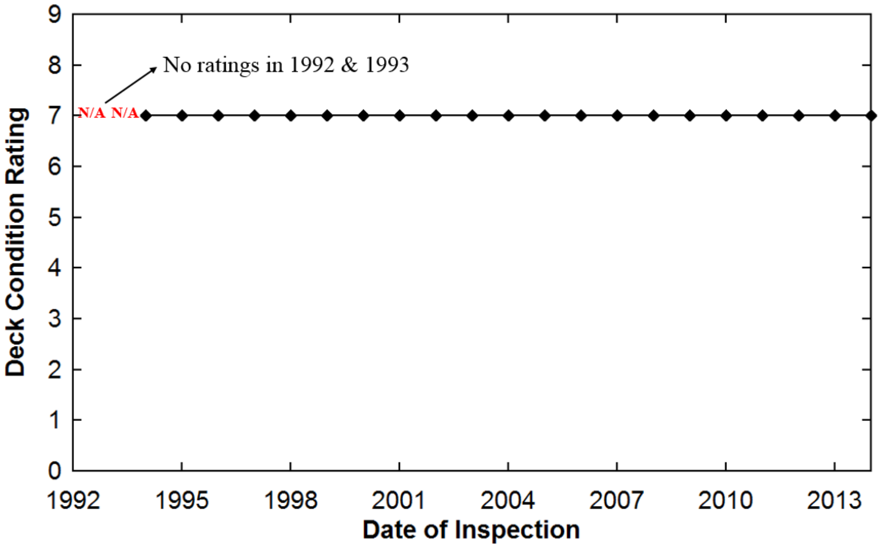


Figure 2.7: Deck condition rating for bridge structure Number 1282366.

Figure 2.8: Bridge deck from both sides of approaching traffic.

Figure 2.9: Approach slab and joint.

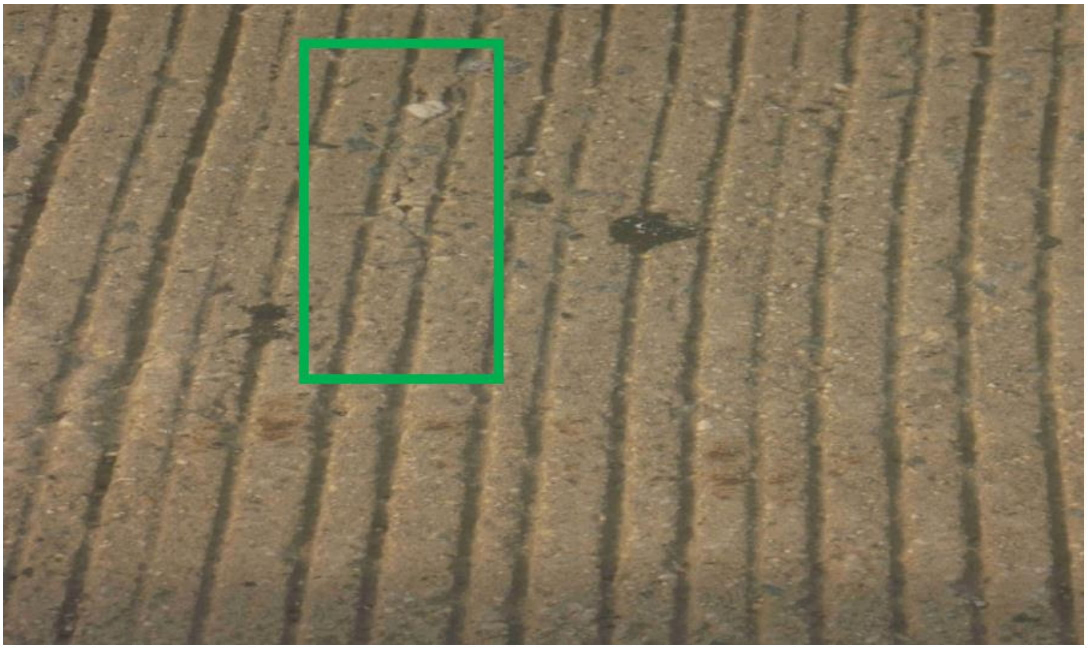


Figure 2.10: Example of shrinkage and creep cracks.

Upon the my 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 a CR of 7. In Clem's experience, bridge decks having a rating of 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 shrinkage and creep crack.

2.9.2 Second inspected bridge

Location: Newark, DE, **Latitude:** 39 40’ 50’’, and **longitude:** 075 35’ 25’’
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 2.11.

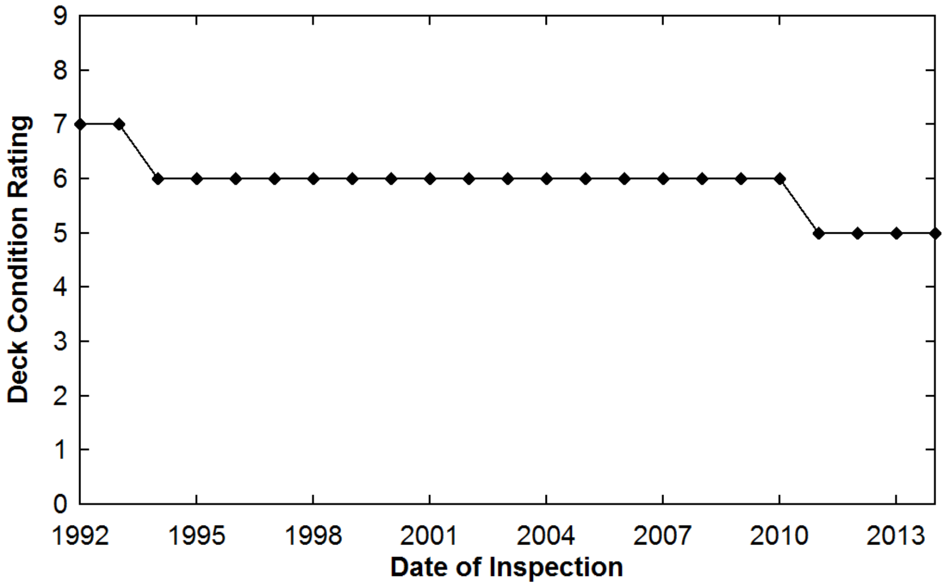


Figure 2.11: Deck condition rating for bridge structure number 1680006.

Figure 2.12: Bridge deck from both sides of approaching traffic.

Figure 2.13: Examples of corrosion cracks.

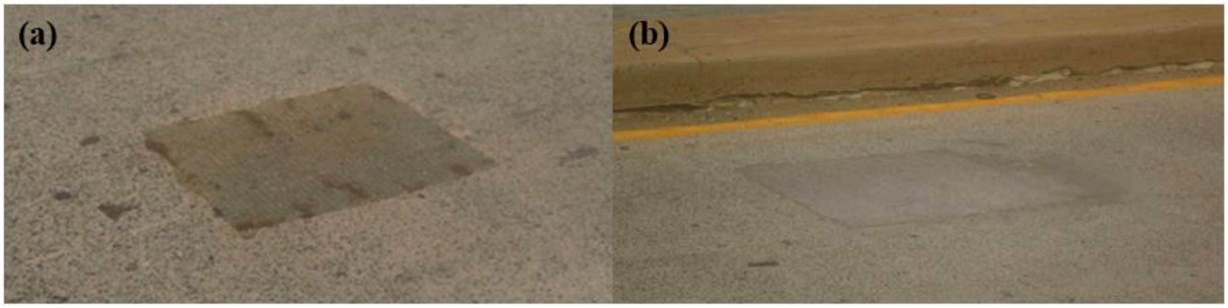


Figure 2.14: Example of (a) old bituminous patch on the concrete deck and (b) new concrete deck patch.

Figure 2.15: Two example of corrosion seepage between deck patch and original deck.

Figure 2.16: Example of blocked scupper.

This bridge was quite deteriorated and had many (deck) patches, some new and others old. Following my own inspection of the deck, my initial thought was that it would have a CR of 5 or 4. The report had indeed assigned the deck a CR of 5; however, this inspection took place on 5/30/2014. According to Inspector Clem, 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 Clem, 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 (Fig. 2.15). 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.

2.10 Concrete Bridge Deck Studies

This section, a literature review of NBI statistical analyses, also includes a review of deck deterioration studies that used both NBI and other databases.

The NBI database, perhaps the most comprehensive and consistent accessible dataset of bridge parameter records and bridge condition across the US. The use of this database in combination with recent advances in data mining and statistical methodologies is perhaps the reason for the growing interest in NBI studies in general. Studies relevant to the present research are summarized here.

Morcous (33) used simple curve fitting of the condition ratings (CR) for State-owned bridges in the Nebraska to study the effects 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 only considers one item at a time, and little discussion about combined effects of items on the CR decrease is included. The same paper discusses a probabilistic approach based on a simple Markovian model to determine future CR. This approach only takes into consideration current CR, which can be adverse, given that a bridge's service time from its initial CR is ignored (46). Bolukbasi et al. undertook a similar deterministic study on all bridges in Illinois, employing third-order polynomial curve fitting to create deterioration curves based on CR vs. bridge age (45). A more advanced approach has been developed by Nasrollahi and Washer (36) that utilizes a probabilistic methodology 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 that 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 graphs were used to develop probability-based inspection intervals in lieu of the standard 24-month intervals mandated by the FWHA. Maintenance effects that lead to increases in CR were not considered in the analysis. Work by Abed-Al-Rahim and Johnston develops an equation based upon the average change from a specific condition rating within 1-year period in order to plot deck deterioration (50). Deterioration curves were done for North Carolina based on the NBI condition ratings for bridge decks, superstructures, and substructures for the years 1980 through 1989.

Dekelbab and Al-Wazeer (46) used NBI data from 1983 to 2006 to come up with survival curves for concrete bridge decks. The authors define maintenance and 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 a first condition improvement. “Without observed improvement” (i.e., no observable improvement in bridge condition rating from one year to the next) was defined for bridges not having any form of maintenance. Based on those situations the authors used a time-series data analysis based on the Kaplan-Meier method. Survival functions for decks in different conditions, i.e., without observed improvement and having observed improvement, were plotted. These survival function curves show the percentage of bridge decks maintaining a specific CR versus their time in that condition. Although this represents a new approach in analyzing CR, effects of other parameters in the NBI such as maintenance responsibility, deck protection methods, or ADTT were not studied. Tae-Hoon et al. (47) determined the end-of-service-life for concrete cast-in-place and concrete pre-cast panel bridge decks for 30 DOTs based on NBI data. A deterioration model was based on six linear regressions of the CR for all bridges reconstructed between 1950 and 2000. The linear regression technique used by the authors only used bridge age as the explanatory variable. Criteria for accepting a regression model were 1) high R-squared value, and 2) a significance value of more than 95%. Using 2005 NBI data, Tabatabai and Tabatabai (48) developed a two-parameter hypertabastic PDF to determine the service life of bridge decks in Wisconsin. Deck CRs 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, but without justification as to why others were omitted.

A study by Agrawal et. al (44) used the New York State Department of transportation's inventory of 17,000 highway bridges to come up with a deterioration model for bridge structural members. The authors compared two deterioration models, one based on a Weibull distribution approach and the other on a Markov chains approach, concluding that the Weibull approach performs better with regard to CR prediction. Morcous et al.(52) employed artificial intelligence (AI) to predict a deterioration model for bridge decks using data from the database of the Ministry of Transportation of Quebec (MTQ). The model in the paper used case-based reasoning for modeling infrastructure deterioration (CBRMID), which is a new CBR system used to determine future conditions. The paper goes on to evaluate the performance of the CBR model versus the current deterioration models used by Bridge Management

Systems. Other studies modeled the effects of chloride ingress in concrete, assuming bridge deck corrosion as the sole factor in concrete bridge deck deterioration (8,15,63,10).

In conclusion, while many studies introduce a variety of new deterministic and stochastic models for CR, few discuss the parameters causing deterioration. While many studies have investigated bridge deck performance, most have attempted to predict end of bridge deck service life (9, 27). Although these methodologies may be helpful to model behavior of individual bridge decks using detailed project and site-specific parameters, such data are not consistently available for large numbers of bridges.

Chapter 3

MOTIVATION AND OBJECTIVE OF THE RESEARCH

3.1 Motivation

Although many studies predict probability of condition rating change over time, not all of these studies are concentrated on concrete bridge decks. Moreover, all such studies have been limited to specific states within the United States. Our motive was to do a statistical study for concrete bridge decks for the entire country, something never before undertaken.

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 neither take into consideration nor discuss maintenance of decks. 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. Our goal, therefore, was to develop a model of the actual deterioration process for concrete bridge decks. To accomplish that we develop a database for the United States that captures the true deterioration of bridge decks. The database contains 21 critical structural and environmental parameters, tests their statistical significance, analyzes the effects of those parameters on concrete bridge decks performance, and understand how long CR last for bridge decks in the US. A rigorous analysis of some of those parameters is unprecedented to the best of the author's knowledge.

3.2 Objectives

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

This report aims to answer the following main questions with respect to the US concrete bridge decks:

- Can certain relationships and trends of concrete bridge deck conditions be visualized?
- What are the parameters that affect deck deterioration?
- Do certain environmental or structural parameters promote higher deterioration rates?
- How long do CRs of concrete bridge decks in the United States remain constant before they are assigned a lower CR?
- How do maintenance responsibility, ADTT, deck structure type, and other structural and environmental parameters, affect the duration of a CR?

The novelty of this research is that it provides

1. a first-of-its-kind nationwide database for concrete bridge decks in combining NBI data with additional pertinent parameters,
2. an understanding of how relevant environmental and structural parameters affect concrete highway bridge decks,
3. an analysis of the worst and best performing bridge decks in the United States, and

4. a holistic view of how CR of concrete bridge decks in the United states remain constant before they are assigned a lower CR .

Chapter 4

A NATIONWIDE ENHANCED NATIONAL BRIDGE INVENTORY DATABASE TO STUDY CONCRETE HIGHWAY BRIDGE DECK PERFORMANCE

This chapter has been prepared as a paper for the journal of Bridge Engineering.

4.1 Motivation and Objectives

While many studies introduce a variety of new deterministic and stochastic models for condition rating (CR), few discuss the parameters causing these deteriorations. Furthermore, most authors neither take into consideration nor discuss maintenance of decks. While many studies predict probability of condition rating change over time, not all of these studies are concentrated on concrete bridge decks. Moreover, all such studies have been limited to specific states. The objective of this research was to develop a nationwide database for the United States that excludes concrete bridge decks that have been maintained and focuses on the actual deterioration process, something previously not considered. The nationwide database 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 (e.g., deck area, National Oceanic and Atmospheric Administration Climatic Regions, 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). Network-level, one-way statistical analyses of various parameters in the new nationwide database were performed to get a better picture of the effects of important parameters on concrete bridge deck performance.

4.2 The NBI Database

4.2.1 Background and Overview

A unified method of national bridge inspection standards (NBIS) for all public highway bridges across the country with a span length of more than 20 feet was established in the 1970s. The associated data consisting of 116 parameters (or “items”) are stored in the National Bridge Inventory (NBI). This dataset was downloaded from the FHWA web site (72) for all 50 States, Washington, D.C., and Puerto Rico. The 116 parameters, referred to as “items” in the NBI, were imported from the NBI database using MATLAB. This analysis was performed for the whole country. Based on the 2016 NBI census there are 614,386 bridges in the US (54).

4.2.2 Inspection 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 a bridge’s substructure, superstructure, and deck. Table 4.1 shows an example from Michigan DOT’s (74) evaluation of CR for bridge decks. Bridge deck inspections and assessments are performed by State DOTs for state and local bridges and recorded in the NBI database. **Concrete highway bridge decks** was the focus of this research, and CR between 1992 through 2014 were investigated.

Table 4.1: Bridge deck CR (NBI Item 58) per Michigan NBI rating guide (74).

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).

After reviewing state deck rating guides and having multiple discussions with bridge inspectors, the following observations can be summarized:

- Bridge decks are rarely ever assigned a CR of 9, except when new. If a bridge deck is given that rating it does not usually remain there more than one or two years depending on the next inspection cycle.

- Inspections may be biased as it is often the practice for a bridge inspector to review the previous report and consider the preceding rating assigned in the subsequent rating.

- When the surface of a deck is not visible, i.e., when an asphalt overlay is used, the condition of the deck is often inferred by looking at the overlay and any observable concrete surfaces, which include curbs, deck underside, etc.

- States have developed their individual inspection guidelines based on general national guidelines that may include additional means to better quantify the condition such as electrical resistivity or chloride measurements.

4.3 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 (condition ratings) , nondestructive evaluation results for certain bridge, and some material testing results. From the 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(83).

4.4 Proposed Performance Parameters

4.4.1 Pre-Processing of Condition Ratings

The condition ratings (CR) for concrete bridge decks had numerous missing data (e.g., Table 4.2, where “NaN” entries mean “not a number”).

Table 4.2: Sample concrete bridge deck CR 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
NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	7	7	7	7	7
NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	8	8	8	8	8
NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	7	7	7	7	7

Due to inconsistencies in the recorded bridge deck CR data (Table 4.2), 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 (50). Whenever that occurred, the CR was replaced with the CR before the spike (Fig. 4.1).

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 but was slightly modified for this research, as explained in the following section (36):

4.4.2 Time-In-Condition-Rating (TICR)

Proposed by Nasrollahi and Washer (36), 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 4.1. CRs that started in 1992 and were not constant (same) for at least five years was discarded. Moreover, CRs that ended in 2014 and did not have the same CR for the 5 years preceding were was discarded. A sensitivity study performed by Nasrollahi and Washer demonstrated that 5 years was a reasonable cutoff. The range of years they used was 3 to7 years (36). 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.

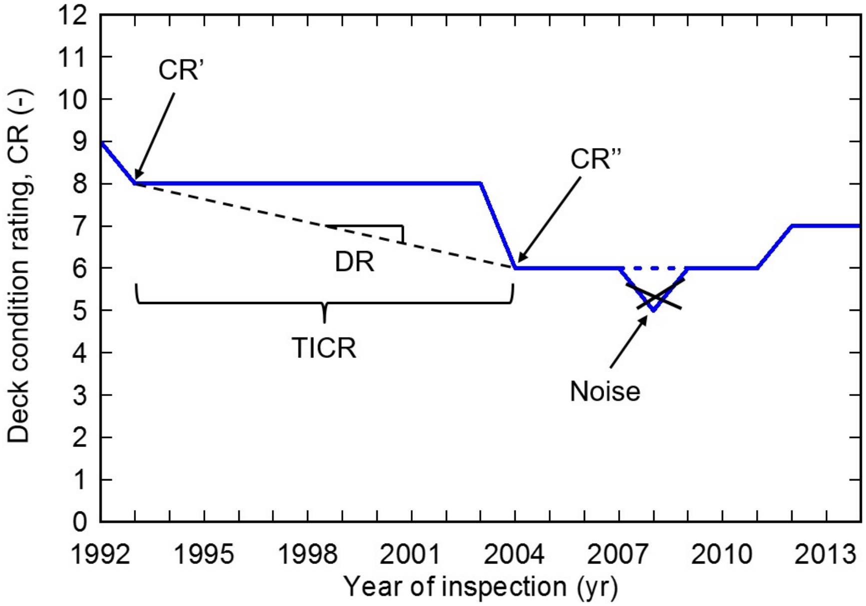


Figure 4.1: Sample bridge deck CR and computed parameters.

A Birnbaum-Saunders distribution, usually used for predictions associated with fatigue processes in materials (59), was found to be the best-fit distribution for TICR for the entire country (Fig. 4.2). 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. The implication of this is that a standard analysis of variance (ANOVA) cannot be used on this data.

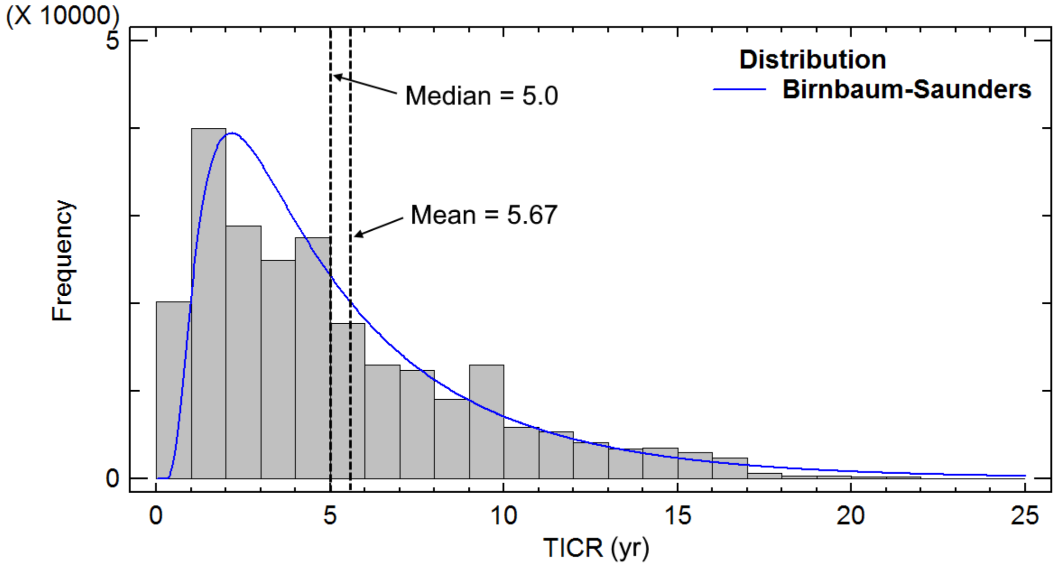


Figure 4.2: Histogram and best-fit distribution for TICR for the entire country (all CR).

Figure 4.3 shows the mean TICR for each state based on all CRs. As can be observed, the result vary drastically between states, which resulted in further exploration of TICR for select CR (see “Preliminary Descriptive Statistical Analysis” section). 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).

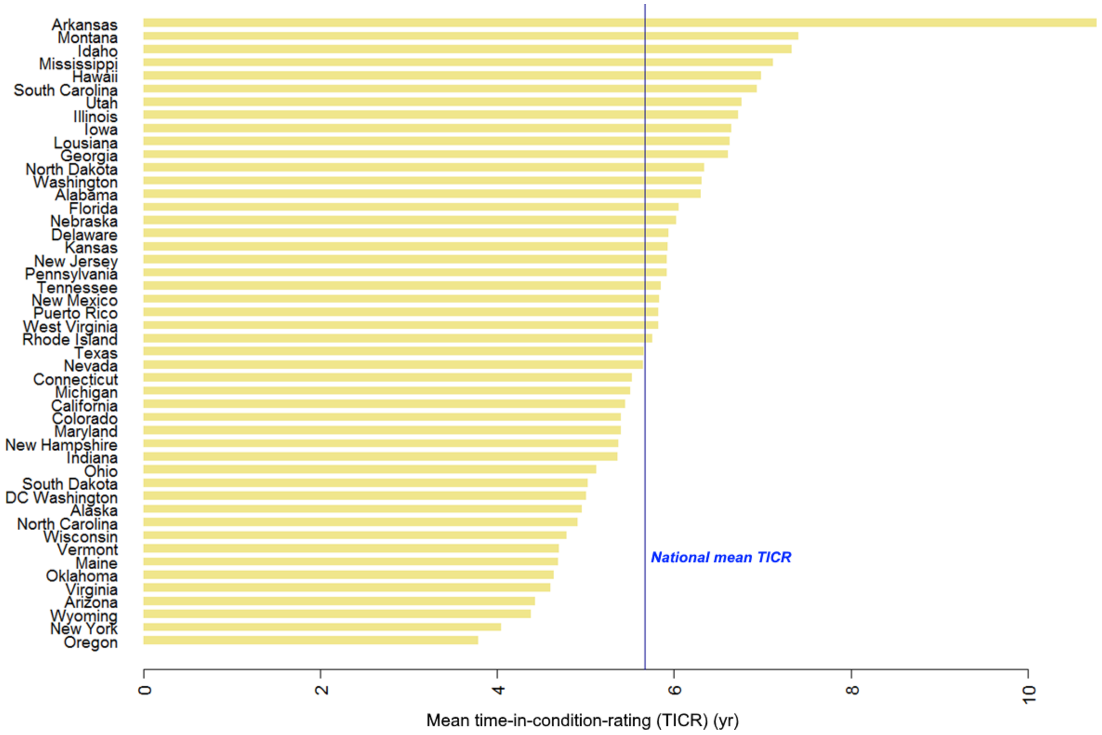


Figure 4.3: Mean TICR for all US states (includes all CR).

4.4.3 Deterioration Rate (DR)

This performance parameter is computed as the change of CR, as illustrated in Figure 4.1. Although this parameter technically represents the change of CR (Fig. 4.1), it is subsequently referred to as deterioration rate (DR). It should be noted that it is based on the change of the condition rating 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 (Fig. 4.1). However, the CR following TICR, i.e., CR”, was also needed in order to calculate the DR. To compute the DR, a 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

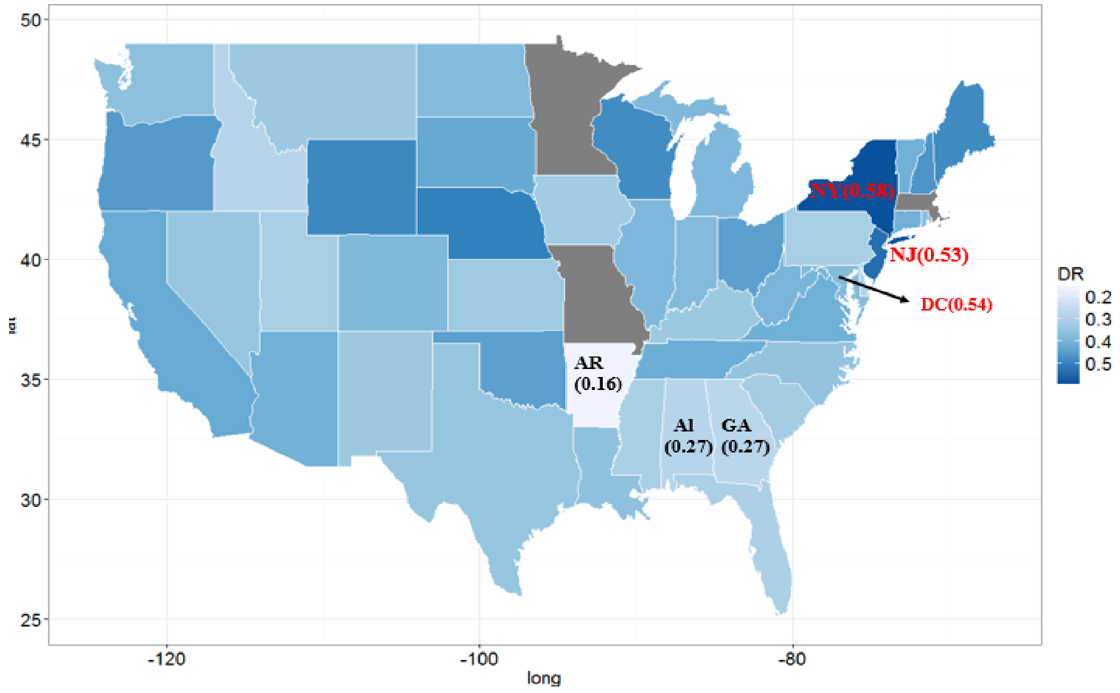


Figure 4.4: Mean DR for all states. Minnesota, Missouri, and Massachusetts had insufficient data.

Figure 4.4 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.

4.4.4 Final Comment

It can be observed 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.

4.5 Creation of Enhanced 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 previously. The subsequent sections contain a list of the parameters that were extracted, processed, and then statistically analyzed.

4.5.1 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.

4.5.2 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)

4.5.3 Additional Parameters

The following additional important parameters that were not originally in the NBI database were developed and included in the new enhanced 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:

$$\text{Deck Area} = \text{NBI Item 49 x NBI Item 51} \tag{4.1}$$

- 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. National Centers for Environmental Information (NCEI) Climatic Regions

The NCEI of the National Oceanic and Atmospheric Administration (NOAA) (49) has identified nine climatically consistent regions within the contiguous US (58). These regions have distinct climatic characteristics such as temperature, humidity, freeze-and-thaw cycles, and precipitation levels, which are known to affect bridge deck performance. Figure 4.5 shows the 9 climatic regions based on NOAA's National Centers for Environmental Information (75) and Figure 4.6 shows the histograms.

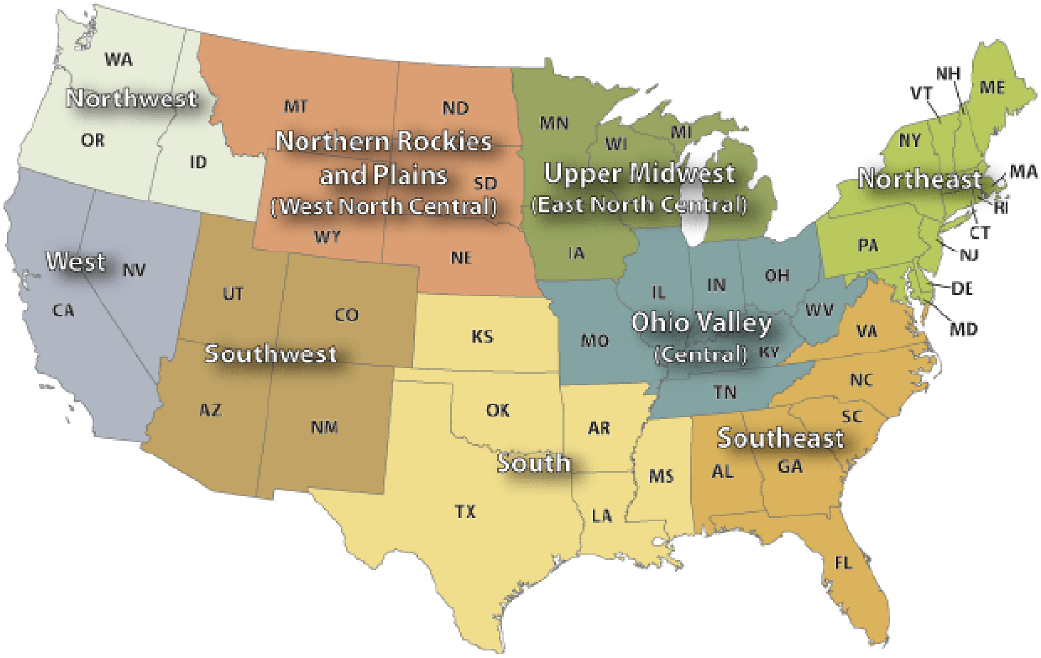


Figure 4.5: Nine U.S. Climatic Regions Map from NOAA's National Centers for Environmental Information [(75)].

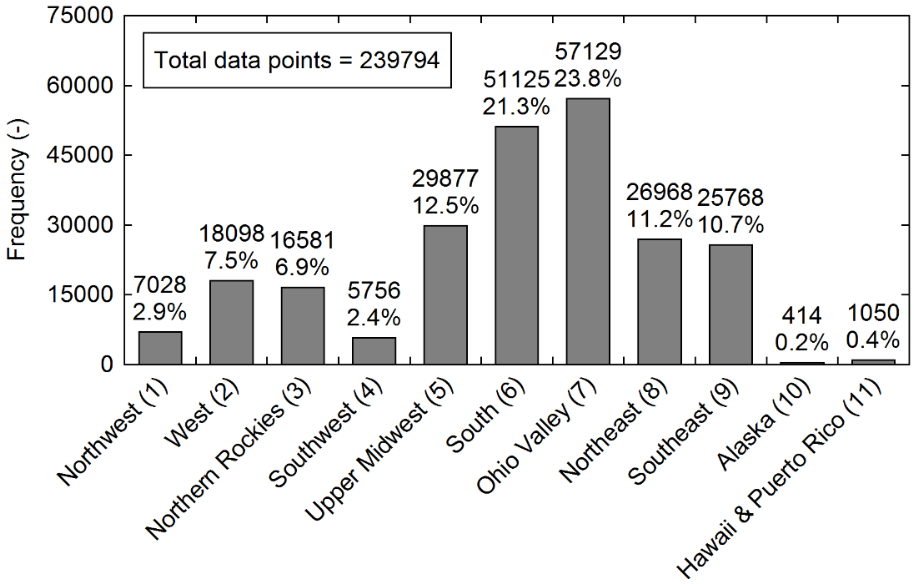


Figure 4.6: Histogram for NCEI Climatic Regions. Numbers in parentheses represent a group code.

4. International Energy Conservation Code (IECC) Climatic Regions

Climate regions were based on US Department of Energy designations (57), comprising eight temperature areas ranging from Zone 1 (hottest) to Zone 8 (coldest), and three moisture regimes, marine, dry, and moist (Fig. 4.7), 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 (Fig. 4.7). 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.”

The nine resulting IECC Climatic regions and regimes are visualized in Figure 4.7 and Figure 4.8 shows their distribution.

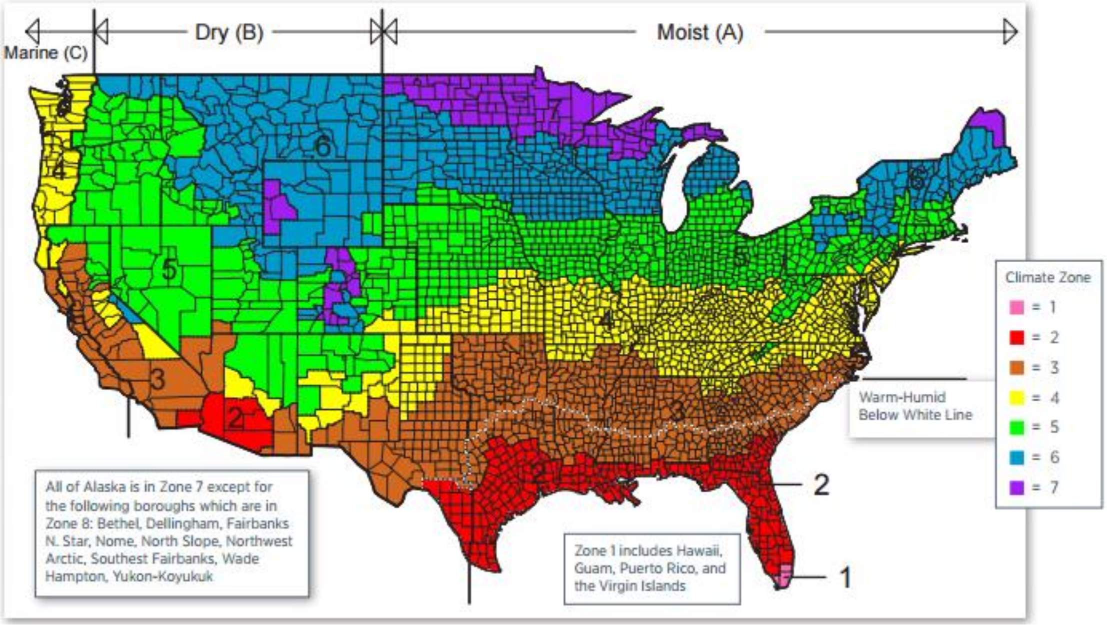


Figure 4.7: IECC Climatic Regions (57).

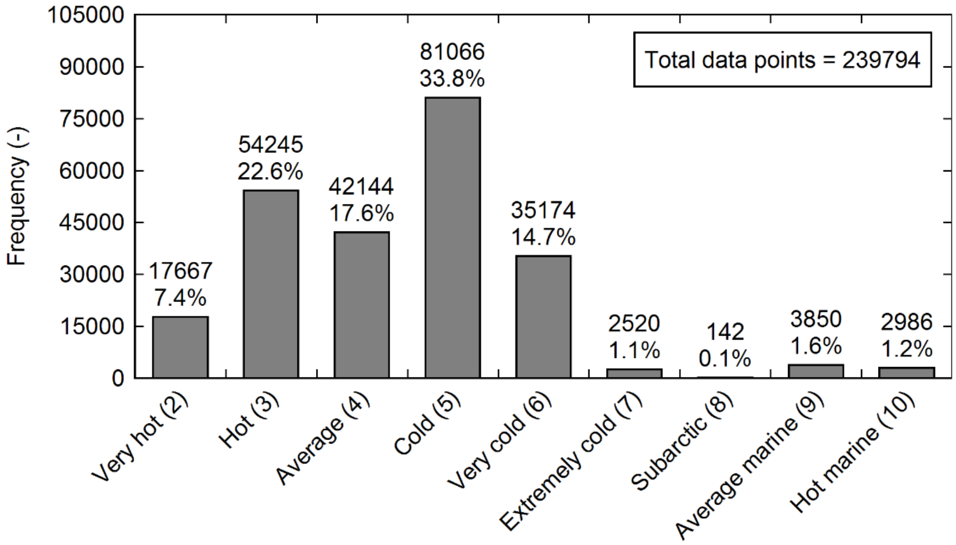


Figure 4.8: Histogram for IECC Climatic Regions. Numbers in parentheses represent a group code.

5. 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 McGee (17):

- *x* < 1 km (0.62 miles)
- 1 km (0.62 miles) < *x* < 2 km (1.24 miles)
- *x* > 2 km (1.24 miles)

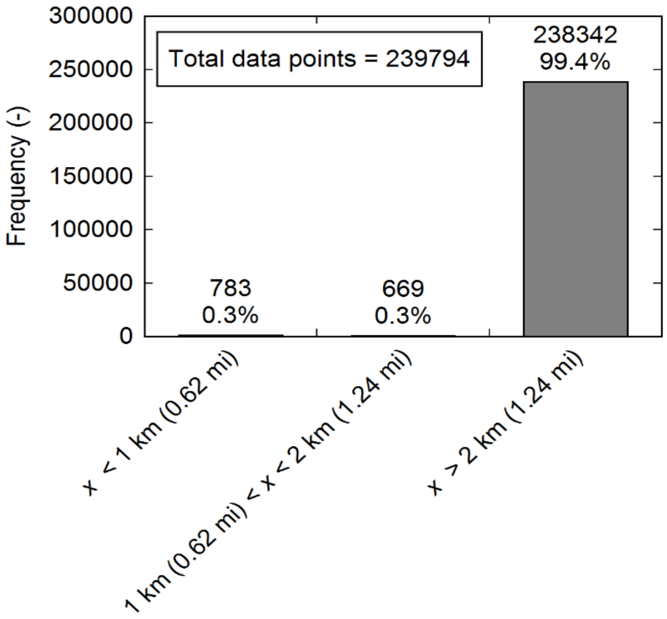


Figure 4.9: A histogram for distance to seawater.

6. Bridge age

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

$$\text{Bridge age} \\ = 2014 - [\text{larger of (NBI Item 27 or NBI Item 106)}], \tag{4.2}$$

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 (Fig. 4.10). The mean and median bridge age correspond to 40.2 and 39.0 years, respectively.

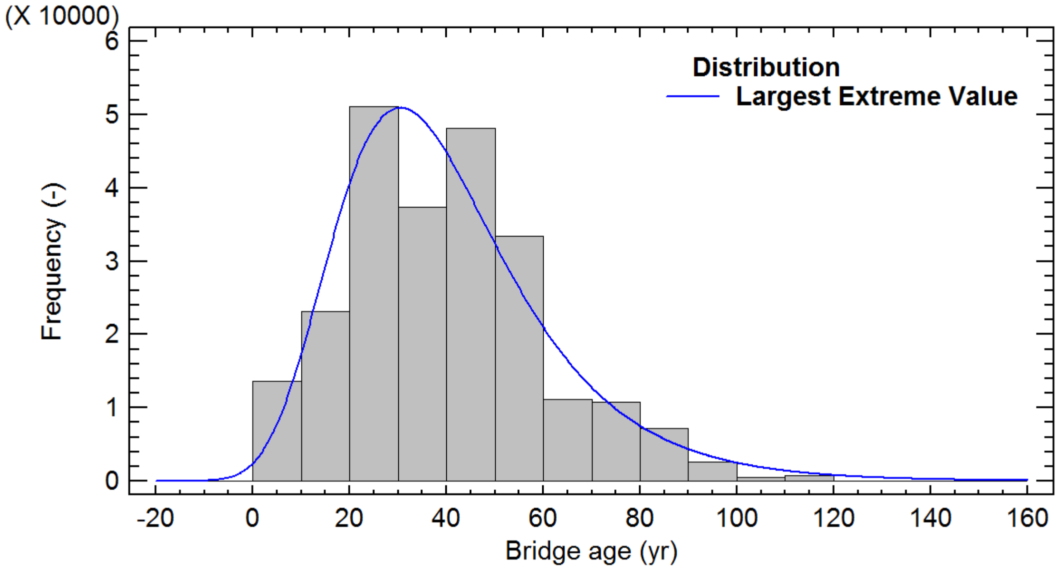


Figure 4.10: A histogram and best-fit distribution for bridge age.

4.5.4 Parameters not Included in the New Database

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.

4.5.5 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 size of the extended database after preprocessing was 236,010. The dataset thus lost 3,783 of the data points, which account for just 1.6% of the data. Appendix A summarizes the preprocessing actions performed on the parameters.

4.6 Preliminary Descriptive Statistical Analysis

A Box-and-Whisker plot of all time in condition ratings (TICR) vs. condition ratings (CR) and summary statistics are presented (Fig. 4.11 and Table 4.3, respectively). Figure 4.11 shows the median (notch), upper and lower quartiles (upper and lower limit of box), lowest and highest values (error bars), outliers (dots) and means with 95% confidence intervals (green dot with green error bars). CR = 1, 2, and 3 are not shown due to lack of sufficient data. It can be observed that the data follows an inverted "bathtub" curve with the highest TICR found at CR = 7. Two groups highlighted with a red box (Figure 4.11) were considered for analysis:

- High (CR = 8): Bridge decks in very good condition with minor signs of deterioration, i.e. requiring no action. This group counts 78,054 data points and therefore a significant portion of all bridge decks.

- Low (CR = 5): Bridge decks in fair condition with significant deterioration, i.e., needing repair. This group counts 12,789 data points and represents bridge decks needing attention.

Summary statistics, tests for normality, and Kruskal-Wallis tests were computed with the commercially available program STATGRAPHICS Centurion (81) and further processed and visualized using the open-source program R(82).

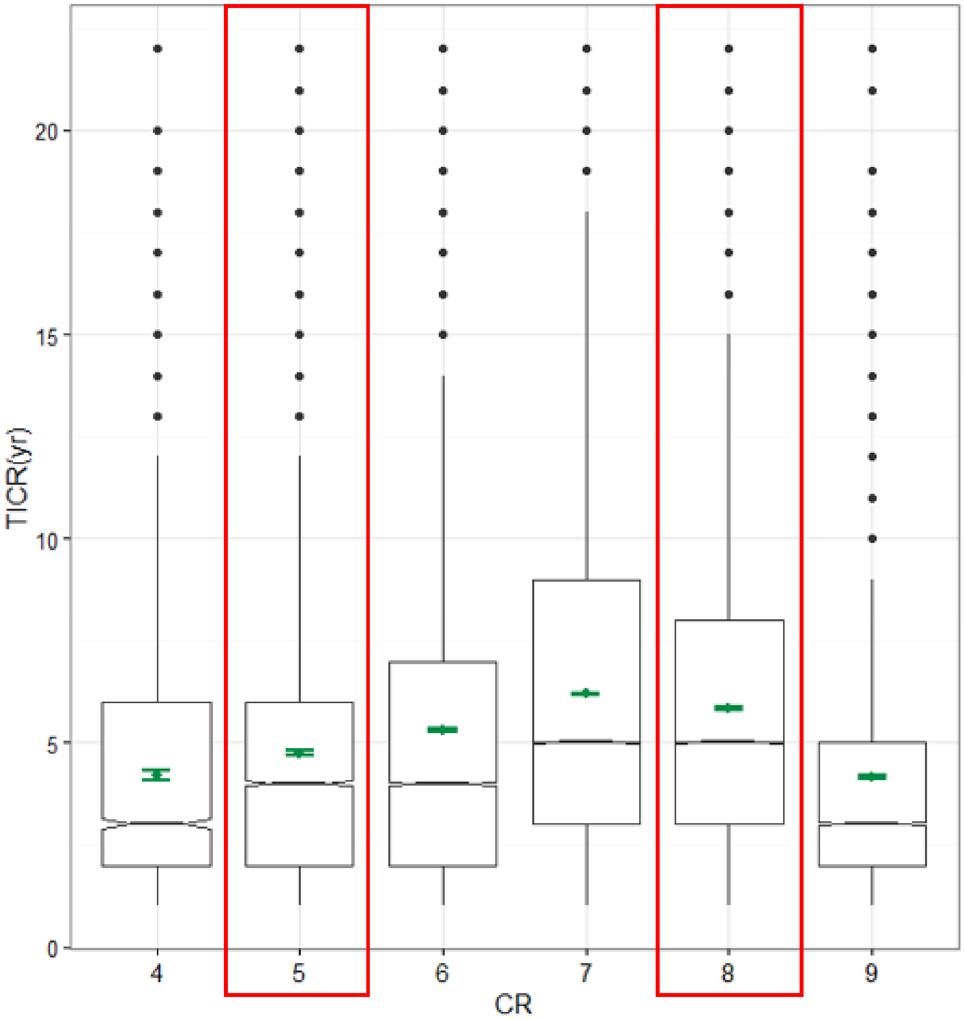


Figure 4.11: A Box-and-Whisker plot and means with 95% confidence intervals for CR.

There were two main reasons behind only looking at CR = 5 and 8, to:

- provide a comparison between a relatively high vs. a relatively low CR (CR = 9 was found not to be a meaningful representative of a high CR as that rating is typically assigned for new bridges and for a short period of time, as discussed earlier) and

- include CRs that had sufficient data points (CR = 2, 3 and 4 did not have sufficient data).

Table 4.3: Summary statistics of CR (groups used in this section are highlighted)..

CR	Count	Average	Median	Standard deviation	Coefficient of variation	Minimum	Maximum	Range
1	1	9.0	9.0	n/a	n/a	9.0	9.0	0
2	35	3.3	2.0	2.9	88.8%	1.0	14.0	13.0
3	397	3.1	2.0	2.5	80.9%	1.0	21.0	20.0
4	2694	4.2	3.0	3.3	78.5%	1.0	22.0	21.0
5	12780	4.7	4.0	3.5	74.3%	1.0	22.0	21.0
6	39649	5.3	4.0	3.9	72.6%	1.0	22.0	21.0
7	84136	6.2	5.0	4.2	67.1%	1.0	22.0	21.0
8	77914	5.8	5.0	4.1	69.4%	1.0	22.0	21.0
9	18404	4.2	3.0	3.4	80.7%	1.0	22.0	21.0
Total	236010	5.7	5.0	4.0	70.9%	1.0	22.0	21.0

A Kruskal-Wallis test showed that there was a statistically significant difference between certain groups at the 95% confidence level. The Kruskal-Wallis test is used to compare data groups that do not follow a normal distribution. The asterisks indicate the groups with a statistical significant difference (Table 4.4). CR = 5 and 8 were statistically different, which justifies the selection of these two CRs. Additional results of the other parameters in the nationwide database are included in Appendix B.

Table 4.4: Kruskal-Wallis results for CR.

Contrast	Sig.	Difference	+/- Limits
3 - 4		2835.29	11125.7
3 - 5		5235.07	10546.8
3 - 6		1000.47	10438.6
3 - 7		-6008.73	10411.2
3 - 8		-2163.01	10413.1
3 - 9		1151.0	10498.1
4 - 5		2399.78	4387.44
4 - 6		-1834.82	4120.5
4 - 7	*	-8844.02	4050.59
4 - 8	*	-4998.3	4055.61
4 - 9		-1684.29	4269.13
5 - 6	*	-4234.6	2105.12
5 - 7	*	-11243.8	1964.78
5 - 8	*	-7398.09	1975.1
5 - 9	*	-4084.07	2382.97
6 - 7	*	-7009.2	1260.67
6 - 8	*	-3163.48	1276.69
6 - 9		150.531	1845.92
7 - 8	*	3845.72	1028.96
7 - 9	*	7159.73	1684.12
8 - 9	*	3314.02	1696.15

The following seven parameters from our new nationwide enhanced database were further explored based on subjective selection supported by the Kruskal-Wallis tests included in the Appendix:

- Maintenance Responsibility
- Functional Classification of Inventory Route
- Structural Material/Design
- Deck Structure Type
- Deck Protection
- Average Daily Truck Traffic (ADTT)

- Distance to Seawater

The next section shows Box-and-Whisker plots and the means with 95% confidence intervals for each of the above parameters for CR = 5 and 8 along with some observed conclusions(Kruskal-Wallis test results for each of those parameters are shown in Appendix B).

4.6.1.1 Maintenance Responsibility

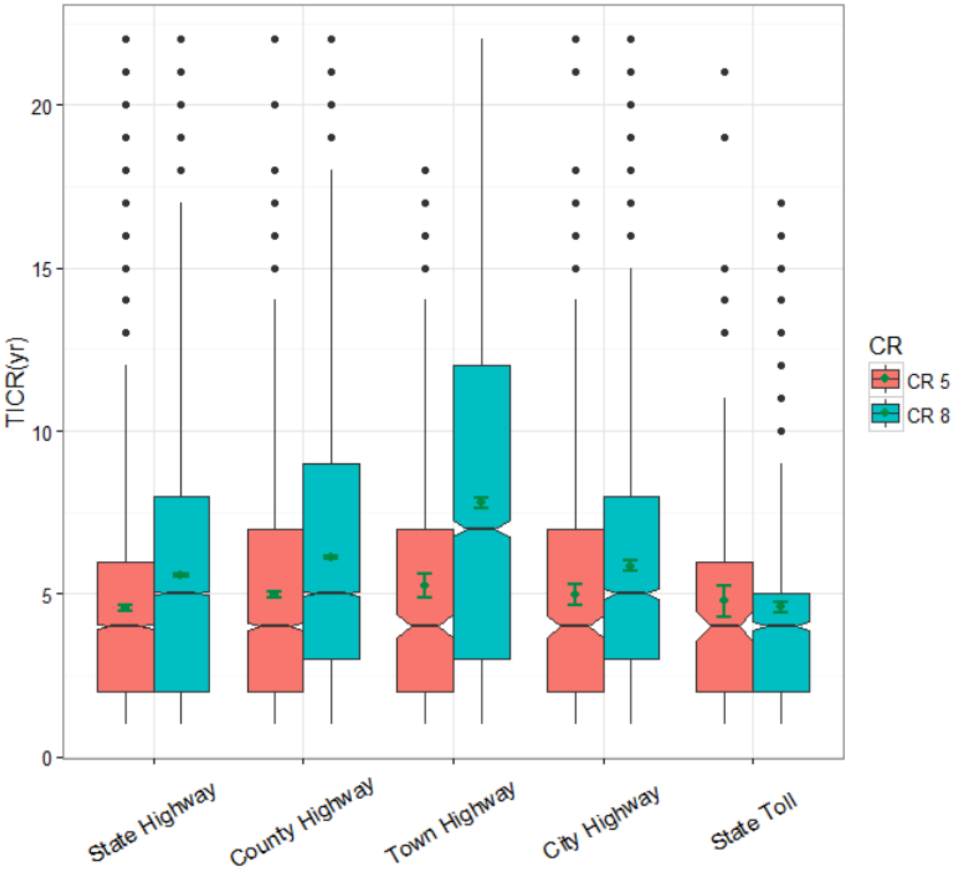


Figure 4.12: A Box-and-Whisker plot and means with 95% confidence intervals for Maintenance Responsibility.

The group Private was excluded from the analysis due insufficient data. The following observations can be made from Figure 4.12:

- Based on the mean, CR = 8 has a higher TICR than CR = 5 for all groups.
- Based on the median, CR = 8 has a higher TICR than CR = 5 for all groups, except for State Toll, where TICR are equal.
- The Town Highway group has the highest TICR for CR = 8 for both mean and median.
- CR = 5 has the same median TICR among all groups.

Overall, the data suggests that concrete bridge decks in county and town highway tend to have higher TICR, concluding that decks outside urban areas tend to perform better. This is true if the bridge is in very good condition, but seems to make no difference if it is in fair condition.

4.6.1.2 Functional Classification of Inventory Route

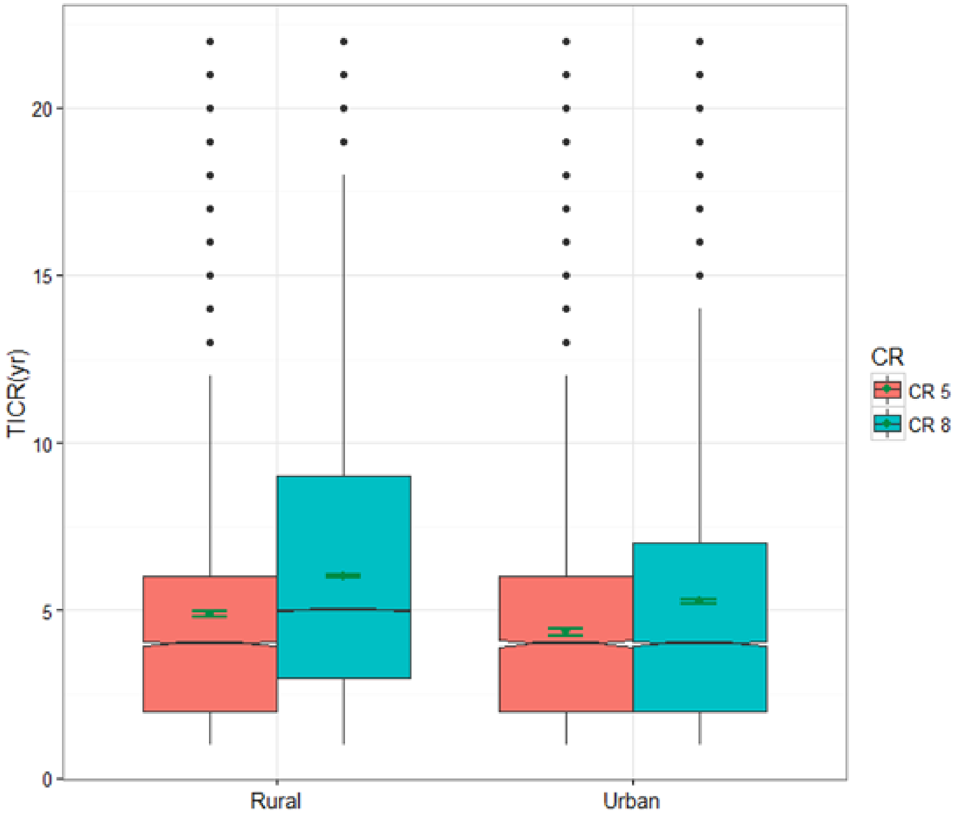


Figure 4.13: A Box-and-Whisker plot and means with 95% confidence intervals for Functional Classification of Inventory Route.

The following observations can be made from Figure 4.13:

- Based on the mean, CR = 8 has a higher TICR than CR = 5 for both groups.
- Based on the median, CR = 8 has a higher TICR than CR = 5 for rural and is equal for urban.
- CR = 8 for rural has a higher TICR than urban for both mean and median.

- CR = 5 for rural has a higher TICR than urban based on the mean and equal based on the median.

Overall, it the data suggests that concrete bridge decks located in rural areas perform better. Moreover, decks in very good condition tend to stay longer in that condition compared to when they are in fair condition.

4.6.1.3 Structural Material/Design

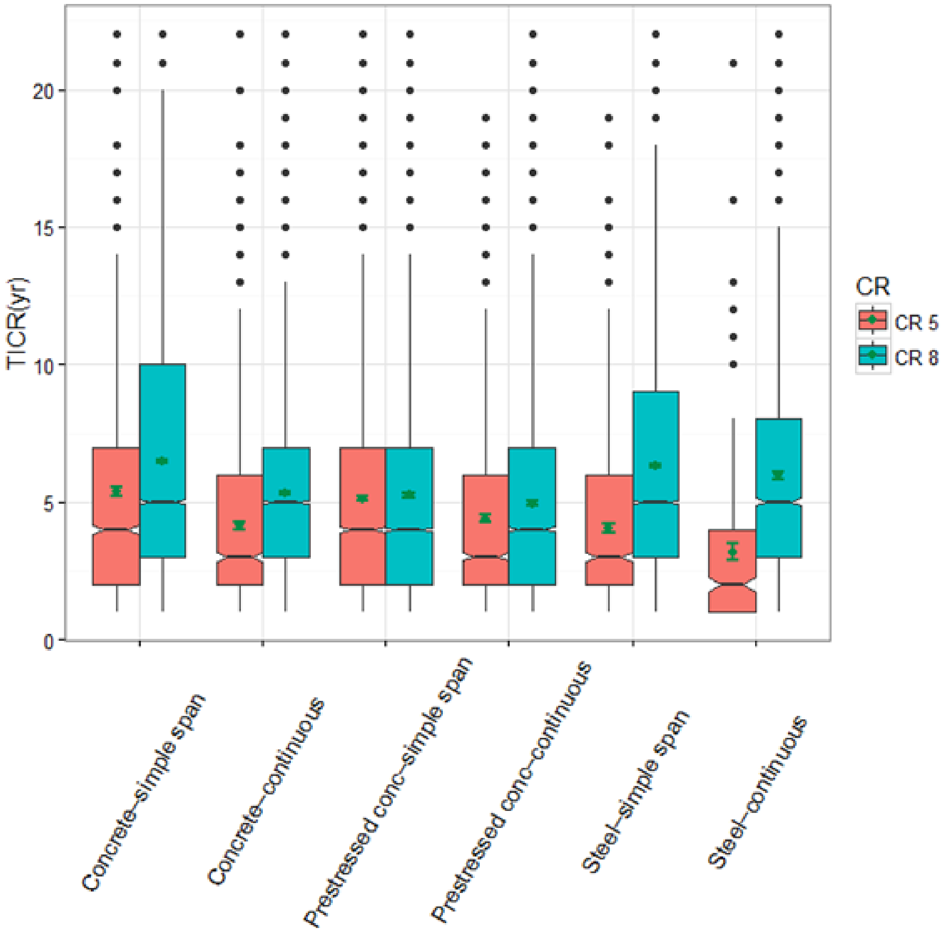


Figure 4.14: A Box-and-Whisker plot and means with 95% confidence intervals for Structural Material/Design.

The following observations can be made from Figure 4.14:

- Based on the mean, CR = 8 has a higher TICR than CR = 5 for all groups.
- Based on the median, CR = 8 has a higher TICR than CR = 5 for all groups except for prestressed concrete-simple span TICR are equal.
- Simple spans for both TICR = 5 and 8 have higher mean TICR than continuous.

Overall, the data suggests simple spans 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.

4.6.1.4 Deck Structure Type

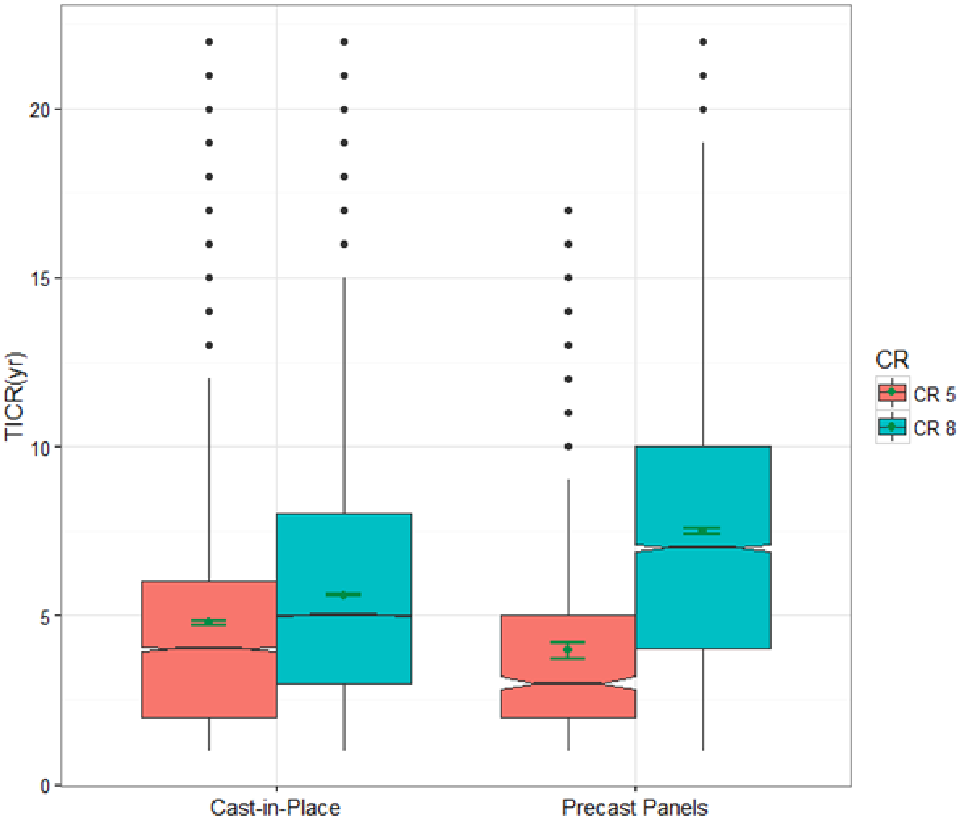


Figure 4.15: A Box-and-Whisker plot and means with 95% confidence intervals for Deck Structure Type.

The following observations can be made from Figure 4.15:

- Based on the mean and the median, CR = 8 for both groups has a higher TICR than CR = 5
- Precast panels have a higher TICR for CR = 8 than cast-in-place but a lower TICR for CR = 5 but a lower TICR for CR = 5 (based on the mean).

Overall, the data suggests that precast panels lead to a better performance for concrete bridge decks that are in very good condition. However, cast-in-place decks appear to perform slightly better once they are assigned a fair condition.

4.6.1.5 Deck Protection

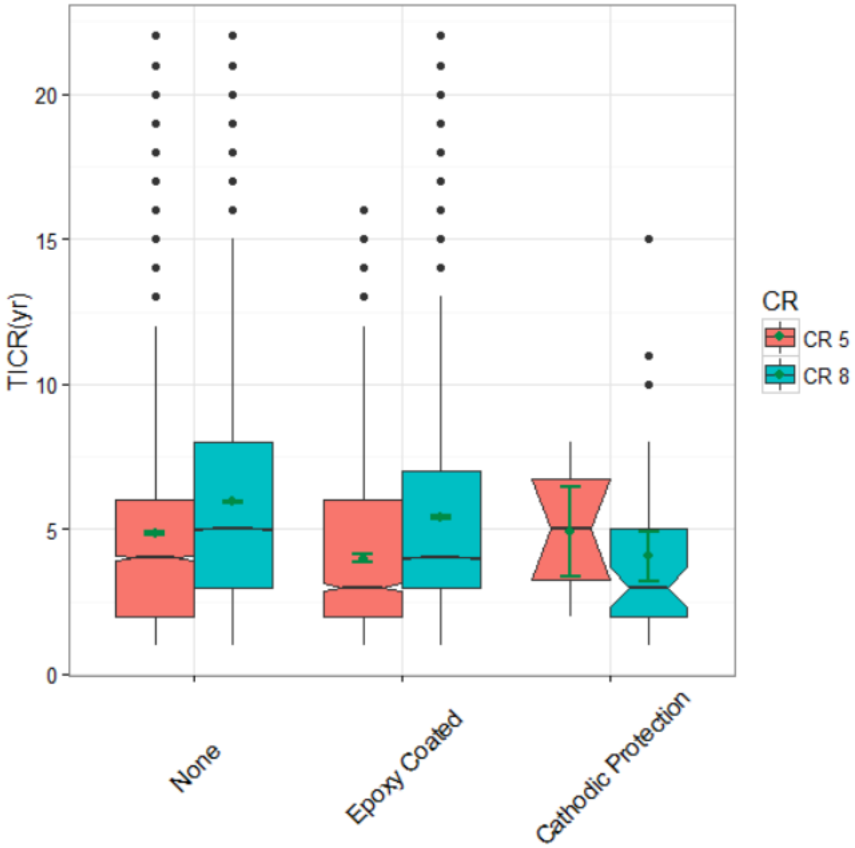


Figure 4.16: A Box-and-Whisker plot and means with 95% confidence intervals for Deck Protection.

Galvanized, internally sealed, and other coated groups were not included due to insufficient data. The following observations can be made from Figure 4.16:

- Based on the mean, the group none (black rebar) has the highest TICR for CR = 8.
- Based on the mean, CR = 8 had a higher TICR than CR = 5 for all groups except cathodic protection.

Overall, the data suggests that concrete bridge decks with regular reinforcing steel (black rebar) perform slightly better compared to when epoxy coating is used. This is independent of the condition. It should be noted that this does not indicate the performance of the reinforcing itself but rather the overall deck performance.

4.6.1.6 Average Daily Truck Traffic (ADTT)

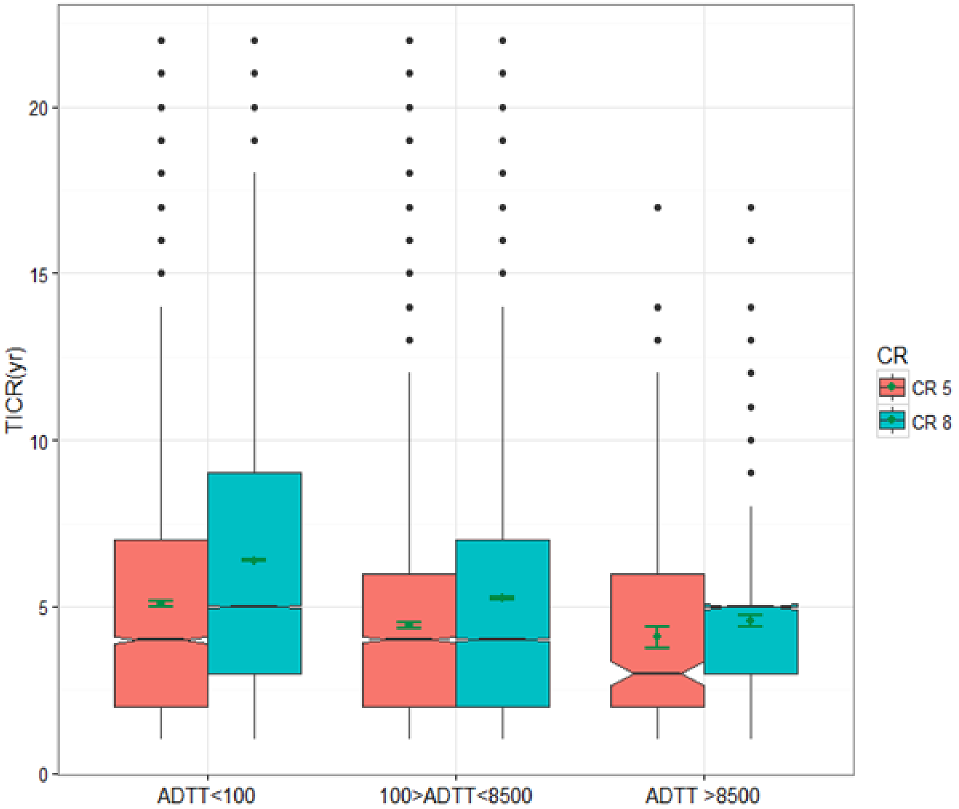


Figure 4.17: A Box-and-Whisker plot and means with 95% confidence intervals for ADTT.

The following observations can be made from Figure 4.17:

- Based on the mean, CR = 8 has a higher TICR than CR = 5 for all groups.

- Based on the median, CR = 8 has a higher TICR than CR = 5 for all groups except for 100>ADTT<8500 are equal.

- For both CR = 5 and 8 as ADTT increases average TICR decreases (based on the mean).

Overall, the data suggests that bridge decks that experience lower r truck traffic perform better. This is true independent of their condition. Intuitively, this makes sense.

4.6.1.7 Distance to Seawater

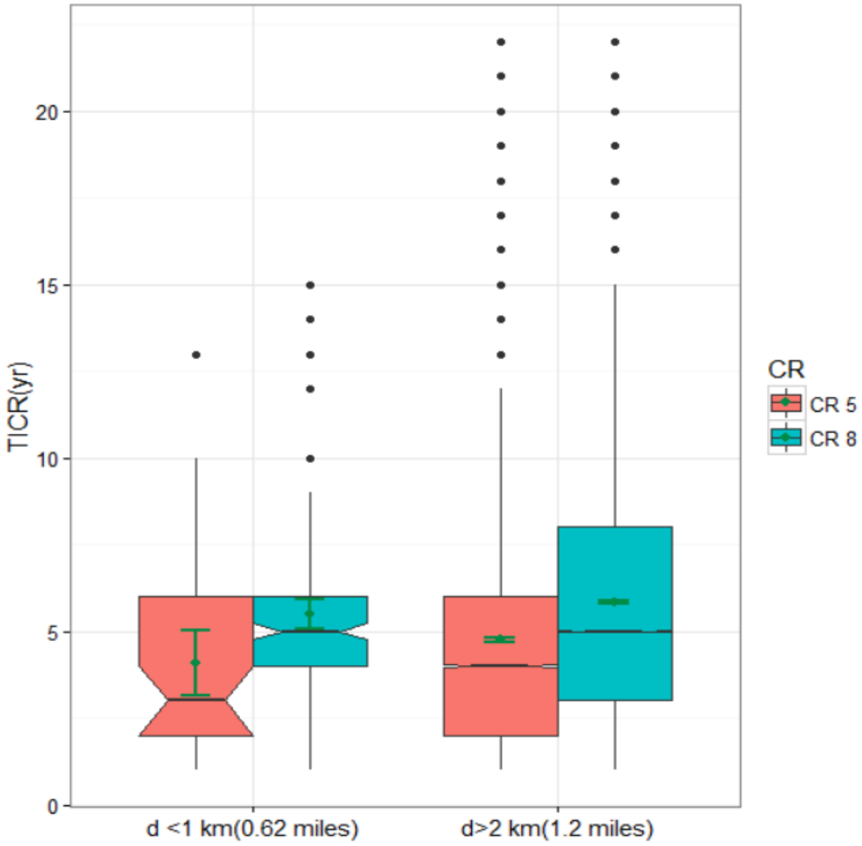


Figure 4.18: A Box-and-Whisker plot and means with 95% confidence intervals of Distance to Seawater.

The following observations can be made from Figure 4.18:

- Based on the mean and median, CR = 8 has a higher TICR than CR = 5 for all categories.
- CR = 8 and CR = 5 have higher TICR for d > 2 km (1.2 miles) than d < 1 km (0.62), respectively (based on the mean).

Overall, the data suggests that bridge decks located in close proximity to seawater perform slightly worse compared to those that are located away from it. Intuitively, this makes sense.

4.7 Conclusion and Future Work

In this research, a nationwide database for concrete highway bridge decks was created based on NBI data and additional computed parameters: state code, deck area, National Centers for Environmental Information (NCEI) Climatic Regions, International Energy Conservation Code (IECC) Climatic Regions, distance to seawater, and bridge age. This nationwide database is based on two performance parameters developed from the NBI concrete bridge deck condition ratings (CR): Time-in-condition rating (TICR) and deterioration rate (DR). In order to come up with those two parameters - filtering and processing was performed on the NBI CR due to the numerous missing data in the NBI CR.

A preliminary descriptive statistical analysis was then performed on a number of select parameters where Box-and-Whisker plots and means with 95% confidence were computed for certain groups of the nationwide database. The following conclusions were reached:

- As CR decreases from (7 to 4) DR increases and TICR decreases. With the exception of CR = 9 where the TICR is significantly lower and DR is significantly higher for any of $6 < CR < 8$. Moreover, CR = 8 average TICR was slightly less than CR 7.

- CR = 8 has a higher TICR than CR = 5 for nearly all groups, which may be interpreted as bridge decks with lower CR deteriorate faster compared to ones with higher CR.

Furthermore, concrete bridge decks with CR = 8 and 5:

- In county and town highway tend to have higher TICR, concluding that decks outside urban areas tend to perform better.
- Simple spans perform better than continuous.
- Located in rural areas perform better.
- Precast panels lead to a better performance in very good condition (CR 8). However, cast-in-place decks appear to perform slightly better once they are assigned a fair condition (CR 5).
- Regular reinforcing steel (black rebars) perform slightly better compared to when epoxy coating is used.
- That experience lower truck traffic perform better than those with higher truck traffic.
- In close proximity to seawater perform slightly worse compared to those that are located away from it.

Chapter 5

DATA MINING OF BRIDGE CONCRETE DECK PARAMETERS IN THE NATIONAL BRIDGE INVENTORY BY TWO-STEP CLUSTER ANALYSIS

This chapter was published in July 20, 2016 at the ASCE-ASME Journal of Risk and Uncertainty in Engineering Systems and used in this dissertation with permission from ASCE. Section 5.1, part of 5.2 and 5.3 are repeated from chapter 4.

Radovic, M., Ghonima, O., & Schumacher, T. (December 22, 2015). Data Mining of Bridge Concrete Deck Parameters in the National Bridge Inventory by Two-Step Cluster Analysis. *Asce-asme Journal of Risk and Uncertainty in Engineering Systems, Part A: Civil Engineering,* 12.)

5.1 Introduction

Inspecting and maintaining infrastructure elements such as bridges are the primary responsibility of Department of Transportation (DOT) agencies. Owing to the fiscal constraints of recent years, making well-informed decisions on fund allocations for rehabilitation or maintenance of bridges has become a major concern for these agencies, requiring bridge owners to employ comprehensive asset management strategies. Recently, researchers have started analyzing bridge records found in the National Bridge Inventory (NBI), a database with detailed information of more than 600,000 public highway bridges in the United States (30). This inventory comprises 116 parameters, called *items*, categorized in eight groups: general description; functional or operational capacity; design; geometric information; waterway and approach data, work recommendations and projected costs; and bridge loading and structural condition ratings. The structural condition ratings are created every two years by trained and certified bridge inspectors, as mandated by the Federal Highway Administration (FHWA) (30). These inspectors evaluate the bridge structural components and assign them a value on a 0–9 scale, as presented in Table 5.1, where a rating of 9 implies new and 0 a failed bridge component. The condition ratings are assessed separately for bridge substructure, superstructure, and deck. It has been known that the main impetus for bridge superstructure repair and rehabilitation is bridge deck deterioration (1). Additionally, concrete decks rated 4 or below require substantial financial outlays in order to be remediated to an acceptable condition (64). Accordingly, bridges having deck ratings of 8 and 9 are bridges in very good and excellent condition, respectively (Table 5.1), and require small or insignificant financial outlays for their maintenance or rehabilitation.

Many factors affect bridge deck deterioration such as climate, daily traffic volume, age, frequency of maintenance, type of maintenance work performed, and deck design parameters. Deck design parameters refer to a set of variables used in the designing of the bridge concrete deck. For example, type of concrete mix used in the bridge deck, type of wearing surface used for deck protection, or type of deck structure are some of the deck design parameters. Many studies have investigated bridge deck deterioration and have attempted to predict when a bridge deck will reach an unacceptable condition (48,65,66, 44). However, there is a lack of studies that has explored associations between deck design parameters and deck condition ratings. Additionally, while methodologies employed in the previously mentioned studies may be helpful to model the behavior of individual bridge decks using detailed project and site-specific parameters, they are not adequate for analyzing network-level behavior.

Therefore, a wholly different analytical approach, such as is found in data mining, has to be employed.

Table 5.1: Deck Ratings According to "Recording and coding guide for the structure inventory and appraisal of the nation's bridges" (30).

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 back in light service.
0	**Failed condition:** out of service - beyond corrective action.

In this paper the authors present the motivation and objectives of this study, describe the main factors that influence concrete bridge deck deterioration, and introduce Two-step cluster analysis, the methodology used in this study. Finally, the authors discuss the results from the analysis applied to a large data set and make recommendations for future use.

5.2 Motivation and Objective

Data mining is a discovery procedure to find useful, but less- than- obvious, information or patterns in large collections of data (an introduction to the subject can be found in *Introduction to data mining* (67)). While the NBI database is considered exceptionally large in terms of its size, it contains complex multidimensional data not easily processed using traditional statistical or research tools. Motivation for this study was to help bridge owners utilize data mining tools in their decision-making processes to effectively allocate limited funds for maintenance, repair, and design of bridge decks. The objective of this study was to evaluate specific data mining tools used for the analysis, exploration, and visualization of associations between concrete bridge deck design parameters and deck condition ratings recorded in the NBI database. The advantages of using this method are that it can efficiently handle large data sets, deal with data sets consisting of both parametric (categorical and ordinal) and interval data, and effectively visualize these associations.

5.3 Factors Affecting Concrete Bridge Deck Condition

There were three main factors affecting bridge deck condition that were evaluated in this study:

- Climate;
- Traffic volume; and
- Concrete deck design parameters.

5.3.1 Climate

Environmental factors, represented by climate characteristics of the region in which the bridge is located, may affect bridge deck condition. Grouping bridges based on climate region provides a control over the variability of environmental effects, as the majority of bridges are being exposed to the same or similar environmental conditions. The National Climatic Data Center (49) has identified nine climatically consistent regions within the contiguous United States as shown in Figure 5.1. These nine climate regions have distinct climate characteristics such as temperature, humidity, freeze-and-thaw cycles, and precipitation levels. All these climate characteristics are known to affect deck condition. For the scope of this study, only the concrete decks of bridges located in the Northeast climatic region were analyzed.

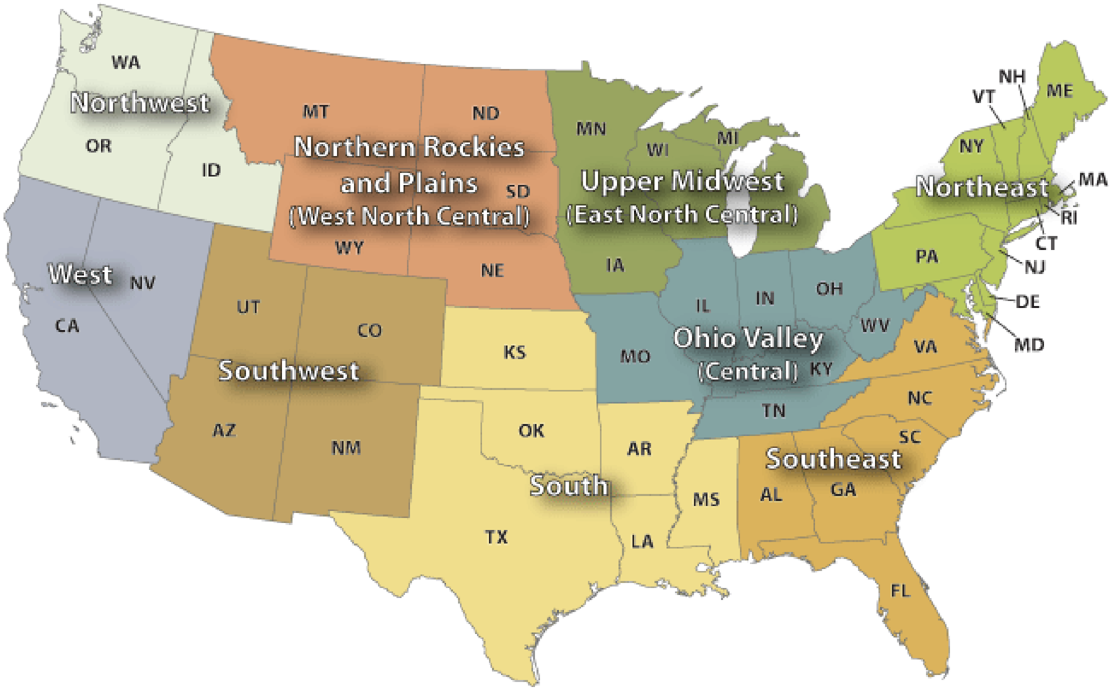


Figure 5.1: Nine U.S. Climatic Regions Map from NOAA's National Centers for Environmental Information (image courtesy of NOAA and NCEI 2015).

5.3.2 Traffic Volume

The traffic volume, represented by average daily truck traffic (ADTT), is another factor known to affect bridge deck condition. A study conducted in the state of Nebraska (33), compared the bridge deck ratings over a period of 12 years (1998–2010) with three different levels of ADTT (<100, 100 ADTT < 500, >500). The researchers concluded that in general, decks with lower condition ratings usually have higher ADTT and vice versa. For the scope of this study, all bridges were grouped based on the ADTT quartile ranges.

5.3.3 Deck Design Parameters

There are four concrete deck design parameters currently available in the NBI data set (deck reinforcement protection, membranes, wearing surfaces, and deck types) that were considered in this study. While a Transportation Research Board (68) report identified other concrete deck design parameters that could affect deck condition (such as water-to-cement ratio, cement type, admixtures found in bridge deck concrete mixes, and concrete cover depth), these parameters are not recorded in the NBI data set and therefore could not be included in this analysis.

1. Deck reinforcement protection

   Reinforcing steel bar (or rebar), is the predominant reinforcement in bridge concrete decks, and it is corrosion's main target. In order to protect development of the corrosion in the concrete deck reinforcement, various types of the protection methods are suggested. Currently, the NBI lists the following deck protection methods for bridge concrete decks (30): epoxycoated reinforcement, galvanized reinforcement, other reinforcement coatings, cathodic protection, polymer impregnated, internally sealed, other, and none.

2. Membranes

Membranes are nonstructural materials placed on top of the concrete and protected by another material (usually asphalt) that functions as the riding surface (19). The membrane's main purpose is to shield the concrete deck from water, aggressive agents such as deicing salts, and freeze-and-thaw cycles. The literature suggests an average membrane requires periodic rehabilitation every 10 to 20 years (5). There are six different deck membranes categories in the current NBI data set: built-up, preformed fabric, epoxy, unknown, other, and none.

3. Wearing surfaces

   The wearing surface is the uppermost roadway layer placed over the bridge deck to form the riding surface. The type of wearing surface is another important deck design parameter that may affect deck condition. The NBI identifies 10 items related to the wearing surface: monolithic concrete (concurrently placed with structural deck), integral concrete (separate, nonmodified layer of concrete added to structural deck), latex concrete or similar additive low-slump concrete, epoxy overlay, bituminous, wood or timber, gravel, other, and none (no additional concrete thickness or wearing surface included in the bridge deck).

4. Deck type

   Bridge decks are integral load-bearing components of the bridge structure. The NBI data set lists nine bridge deck types: concrete cast-in-place (CIP), concrete precast panels (PC), open grating, closed grating, steel plate, corrugated steel, aluminum, wood or timber and other. CIP and PC decks are the two most commonly used concrete bridge deck types. CIP decks are low-cost/low-maintenance decks, but they are susceptible to cracking. Alternatively, PC deck systems are typically prestressed to control cracking, but have a higher initial cost (5).

5.4 Two-Step Cluster Analysis

Using data mining and big data analytics tools for decision making is a growing trend in civil infrastructure studies (69). The unsupervised learning concept in data mining consists of organizing sets of data into groups without advance knowledge of group attributes. One commonly used unsupervised learning method in data mining is that of cluster analysis, the process of grouping data into subsets (clusters) that reflect the essential structure of the data, based on similarity of groups within the data. Ideally, cluster analysis minimizes the difference of cases within a cluster while maximizing the difference between clusters (67). Cluster analysis typically consists of the following four major steps:

1. Select clustering method;
2. Select measuring algorithm;
3. Determine the number of clusters; and
4. Interpret the clustering groups.

While clustering methods such as K-means and hierarchical clustering (67) have been widely used in other scientific fields, they are rarely implemented for the analysis of bridge condition data, specifically in the analysis of NBI data, for a few reasons. First, hierarchical clustering cannot be used on large data sets because of its computationally expensive algorithms. Additionally, hierarchical clustering is sensitive to outliers and cannot combine categorical (nominal) and interval data simultaneously. On the other hand, K-means is a computationally inexpensive algorithm, but can only deal with an interval data. This approach is also sensitive to an initial seeds setting and how pre-specified numbers of clusters are determined.

In order to mitigate constraints imposed both by hierarchical algorithms and K-means, a novel data mining method called *Two-step cluster* analysis is proposed and presented in this study. The approach works well for large data sets and is able to cluster all three types of data-categorical, ordinal, and interval-simultaneously. The Two-step clustering algorithm is efficient in that it forms clusters on the basis of either categorical or continuous data and does so for a varying number of clusters. This algorithm is based on a log-likelihood distance measure that gives the most accurate results when all variables are statistically independent and when continuous and categorical variables follow normal and multinomial distributions, respectively (70). The disadvantages of the Two-step clustering algorithm is that it requires a complete data set; i.e., it is not able to handle sets with missing or incomplete data. Another disadvantage of this method is that ordinal variables have to be treated as continuous or categorical, which can lead to non-unique clustering results in some cases. Additionally, data sets with categorical and interval variables need to be normalized before a clustering algorithm is applied. The normalization favors categorical over interval variables to define clusters. Therefore, categorical variables may dominate the results because differences in categorical variables are given a higher weight than differences in continuous variables. However, a majority of these issues have been addressed for the Two-step cluster algorithm used in this study, as reported in the paper by Bacher et al. (71).

Two-step cluster analysis starts by scanning all data entries and measuring the distance between them. The distance measure, based on some threshold distance criterion (71), is a mathematical tool to determine which data entries are going to form pre-clusters. If a data set contains a mix between categorical and continuous variables, only the log-likelihood distance measure can be used. The log-likelihood distance measure, d, between two clusters, i and j, is defined by the following four equations:

$$\mathrm{d}(\mathrm{i},\mathrm{j}) = \varepsilon_{\mathrm{i}} + \varepsilon_{\mathrm{j}} - \varepsilon_{\langle \mathrm{i},\mathrm{j} \rangle} \tag{5.1}$$

$$\varepsilon_{i} = -n_{i}\left(\sum_{k=1}^{p}\frac{1}{2}\log\left(\hat{\sigma}_{ik}^{2} + -\hat{\sigma}_{k}^{2}\right) - \sum_{k=1}^{q}\sum_{l=1}^{m_k}\hat{\pi}_{ikl}\log\left(\hat{\pi}_{ikl}\right)\right) \tag{5.2}$$

$$\varepsilon_{j} = -n_{j}\left(\sum_{k=1}^{p}\frac{1}{2}\log\left(\hat{\sigma}_{jk}^{2} + -\hat{\sigma}_{k}^{2}\right) - \sum_{k=1}^{q}\sum_{l=1}^{m_k}\hat{\pi}_{jkl}\log\left(\hat{\pi}_{jkl}\right)\right) \tag{5.3}$$

$$\begin{aligned}\varepsilon_{\langle i,j\rangle} = -n_{\langle i,j\rangle}\Bigg(&\sum_{k=1}^{p}\frac{1}{2}\log\left(\hat{\sigma}_{\langle i,j\rangle k}^{2} + -\hat{\sigma}_{k}^{2}\right)\\ &- \sum_{k=1}^{q}\sum_{l=1}^{m_k}\hat{\pi}_{\langle i,j\rangle kl}\log\left(\hat{\pi}_{\langle i,j\rangle kl}\right)\Bigg)\end{aligned} \tag{5.4}$$

where ε can be interpreted as a variance within a cluster, $\hat{\sigma}_{jk}^{2}$ represents variance of continuous variables and $\hat{\pi}_{ikl}$ represents probability of categorical variables. If only continuous interval data are clustered, the Euclidian distance can be used as the distance measure. Once pre-clusters are formed, the dataset is ready for a second step.

In the second step, pre-clusters formed in the first step are grouped into new clusters using an agglomerative clustering algorithm (a bottom-up approach). Agglomerative clustering starts by treating pre-clusters determined in the previous step as single entries. In each following iteration, the algorithm merges the closest pair of pre-clusters by satisfying a co-occurrence similarity criterion, until all data are placed within a single cluster. If a desired number of clusters is not predetermined, the algorithm uses Schwarz's Bayesian Criterion (BIC) or the Akaike Information Criterion (AIC) as a clustering standard to determine the optimal number of clusters (70).

5.5 Methodology

This section details how data used in this study were extracted from the NBI database and filtered before used in the proposed Two-step cluster analysis. In addition, this section outlines how variables such as climate characteristics and traffic volumes were organized in order to control effects they have on bridge deck condition.

5.5.1 Data Extraction

The NBI data set contains information on more than 600,000 highway bridges in the United States, collected over a 22-year period. This data set is downloaded from the FHWA website (72) for all 50 states and Washington, DC. The following items (30) were extracted from the NBI database and used in this analysis:

1. Item 27-Deck condition rating (a range from 0 to 9).
2. Item 107-Deck structure type [cast-in-place (CIP) or precast (PC)].
3. Item 108-Wearing surface/protective system:
    - Type of wearing surface: monolithic concrete, integral concrete, latex concrete or similar additive, low-slump concrete, epoxy overlay, bituminous, gravel, timber, other, none;
    - Type of membrane: built-up, preformed fabric, epoxy, unknown, other, none; and
    - Deck protection: epoxy-coated reinforcing, galvanized reinforcing, other coated reinforcing, cathodic protection, polymer impregnated, internally sealed, unknown, other, none.
4. Item 109-Average daily truck traffic (ADTT; i.e., a count of the average number of trucks that pass over the bridge in one day). All bridges that had an ADTT = 0 were filtered out of the data set.

Following a review of all data sets, the most comprehensive set, in this case the one for the year 2014, was selected (Table 5.4). Furthermore, because this study was only interested in exploring bridges with concrete decks, bridges with decks of different types were filtered out from the data sets. Conceptual illustration of the data set in question is presented in Table 5.2.

The remaining bridge records were grouped according to two criteria:

1. Geographical location: Bridges were grouped into nine different climate regions (Fig. 5.1).
2. Deck condition: All bridges having a deck rating below 5 were grouped into one group [*bad decks* (BD)], and all bridges above 7 were grouped into second group [*good decks* (GD)]. Bridges with deck condition ratings 5, 6, and 7 were excluded from further analysis in order to have clear separation between bridge decks in good and bad condition. Hence, each climate region would have two data sets; i.e., BD and GD. To control the effect that traffic volume has on deck condition,

GD and BD data sets were further divided into subsets based on quartile limits of ADTT data, such limits seeming to provide the best distinction by creating subsets of meaningful sizes.

Table 5.2: Conceptual Representation of Sample Data Structure of Dataset for Bridges with Concrete Decks Extracted from National Bridge Inventory (NBI) Dataset (79).

Deck Rating	ADTT	Deck Type	Wearing Surface	Membrane Type	Deck Protection	Climatic Region
Very Good Condition = 8	4	Precast Panels	Bituminous	Other	Epoxy Coated Reinforcing	North East
Very Good Condition = 8	5.2	Cast-in-Place	Bituminous	Other	Epoxy Coated Reinforcing	North East
Very Good Condition = 8	5.6	Precast Panels	Bituminous	Other	Epoxy Coated Reinforcing	North East
Fair Condition =5	63	Precast Panels	Bituminous	Preformed Fabric	Epoxy Coated Reinforcing	North East
Excellent Condition= 9	3540	Precast Panels	Bituminous	Other	Epoxy Coated Reinforcing	North East
Excellent Condition= 9	14300	Cast-in-Place	Bituminous	Other	Epoxy Coated Reinforcing	North East
Serious Condition = 3	7663.5	Cast-in-Place	Bituminous	None	None	North East
Serious Condition = 3	53.56	Cast-in-Place	Bituminous	None	Other Coated Reinforcing	North East
Serious Condition = 3	1	Cast-in-Place	Bituminous	None	Unknown	North East
Serious Condition = 3	80	Cast-in-Place	Bituminous	None	Unknown	North East
Fair Condition =5	63.04	Cast-in-Place	Epoxy Overlay	None	Epoxy Coated Reinforcing	North East
Fair Condition =5	63	Precast Panels	Latex Concrete	None	Epoxy Coated Reinforcing	North East
Excellent Condition= 9	0.5	Cast-in-Place	Monolithic Concrete	Other	Epoxy Coated Reinforcing	North East
Excellent Condition= 9	15.12	Cast-in-Place	Monolithic Concrete	Other	Epoxy Coated Reinforcing	North East

5.5.2 Cluster Analysis Procedure

A total of eight subsets (four each for BD and GD groups) were analyzed using the proposed Two-step cluster analysis (available in the SPSS [v19] statistical software package).

This software was written in Java with a user-friendly interface. The program can be executed by all three major operating systems (Windows, Mac, and Linux) and does not have any specific CPU or GPU requirements.

Four deck design parameters (deck protection, deck wearing surface, deck membrane, and deck type) were used as grouping variables, while a total of 28 deck design parameters [nine from deck protection, ten from deck wearing surface, six from deck membrane, and two from deck type (PC and CP)] were used as clustering categories. Because only categorical variables were used for clustering, log-likelihood was selected as the distance measure.

Cluster cohesion and separation were assessed by the so called silhouette measure, a representation of a poor, fair, or good cluster structure, which is numerically represented by the silhouette coefficient (SC), and calculated as follows (73):

$$s(i) = \left\{ \begin{matrix} 1 - \frac{a(i)}{b(i)} \text{ if } a(i) < b(i) \\ 0 \text{ if } a(i) = b(i) \\ \frac{b(i)}{a(i)} - 1 \text{ if } a(i) > b(i) \end{matrix} \right\} \qquad (5.5)$$

where $a(i)$i is the measure of how case i is dissimilar [based on the distance measure d (i, j)to other cases in the same cluster; i.e., a smaller a indicates a more cohesive cluster], and b(i) is the measure of how case i is dissimilar to other clusters that i is not part of (a large b indicates poor cluster separation). Poor cluster structures are considered to have an SC ranging between -1 and 0.2, fair cluster structures are considered to have an SC between 0.2 and 0.5, and good cluster structures have an SC between 0.5 and 1. Conceptually speaking, an SC of 1 indicates a perfect cluster structure, in which all cases in the data sets are located at their cluster centers. Accordingly, an SC of 1 means that all cases identified in one cluster are located on the cluster centers of some other cluster. A cluster structure having an SC of 0 indicates that, on average, cases are equally located between their own cluster center and the nearest other cluster (70). In this study, five out of eight subset clusters had good cluster structures ($SC \geq 0.5$) while the remaining three subset clusters had a fair cluster structure ($SC=0.4$).

5.6 Results

From the analysis of a total of 9,809 concrete highway bridge decks in the Northeast climatic region, results show that Two-step cluster analysis was able to effectively differentiate deck design parameters between BD and GD groups across all ranges of ADTT. Furthermore, the next sections of this paper report in detail climate characteristics, traffic volumes, and distribution of deck design parameters used in the analysis.

5.6.1 Climate Characteristics

A randomly selected climate region, Northeast, was analyzed in this study. The region consists of 11 states: Maine, Massachusetts, Vermont, Pennsylvania, Rhode Island, Connecticut, New Hampshire, New York, New Jersey, Maryland, and

Delaware. According to the Global Change Report for 2014 (75), the Northeast region is characterized by a diverse climate, with cold and frozen precipitation during winter and warm and humid summers with frequent storms. Average annual precipitation varies by about 20 in. across the regions (from Maine to Maryland), and the average annual temperature ranges from 28.4°F in January to 66.5°F in July.

5.6.2 Traffic Volumes

The records of 2,546 and 7,263 bridges with deck condition ratings below 5 (= BD) and above 7 (= GD) were analyzed. The average (± , one standard deviation) ADTT of the bridges in the BD group was 952 (± 2,224) with the maximum ADTT being 21,210. The value of the first, second, and third quartile were found to be 36.5, 180, and 680, respectively. The average (± one standard deviation) ADTT of the bridges in the GD group was 878 (±2021) with the maximum ADTT being 24,700. The value of the first, second, and third quartile was found to be 34.9, 185, and 714, respectively. Quartile limits were used to create eight subsets of data, four for GD and four for the BD data set. A typical structure of the newly created data set is: subset #1 contains all bridges from BD group that have ADTT less than or equal to 36.5, subset #2 contains all bridge from GD that have ADTT ≤ 34.9, subset #3 contains all bridges from BD group that have ADTT > 36.5 and ≤ 180, and so on. Data dispersion measures (mean, standard deviation and median) of the newly created subsets showed a fairly low average overall percent difference (less than 9.5%) (Table 5.3). The results show that, in general, dividing BD and GD data sets based on ADTT quartile limits is an appropriate differentiation method for this data.

Table 5.3: ADTT Data Dispersion Measures for GD and BD subsets.

Quartile	GD			BD		
	Mean	SD	Median	Mean	SD	Median
First Quartile	12.4	10.1	10.1	15.6	10.4	14.8
Second Quartile	93.7	43.1	85.0	89.5	39.9	82.3
Third Quartile	402	152	381	381	139	360
Fourth Quartile	3005	3194	1814	3323	3495	1767

5.6.3 Deck Design Parameters Distribution

The most frequent deck protection feature in the BD group is *none* (93.4%) while the most frequent deck protection feature in GD group is *epoxy-coated reinforcing* (67.2%). Accordingly, the most frequent wearing surface feature is *bituminous* (77.5%) and *monolithic concrete* (33.3%) for the BD and GD groups, respectively. The most frequent deck membrane type was *none* for both data sets (80.3% and 70.6%, respectively), and the most frequent deck type was *cast-in-place* for both data sets (98.3% and 92.9%, respectively) (Fig. 5.2).

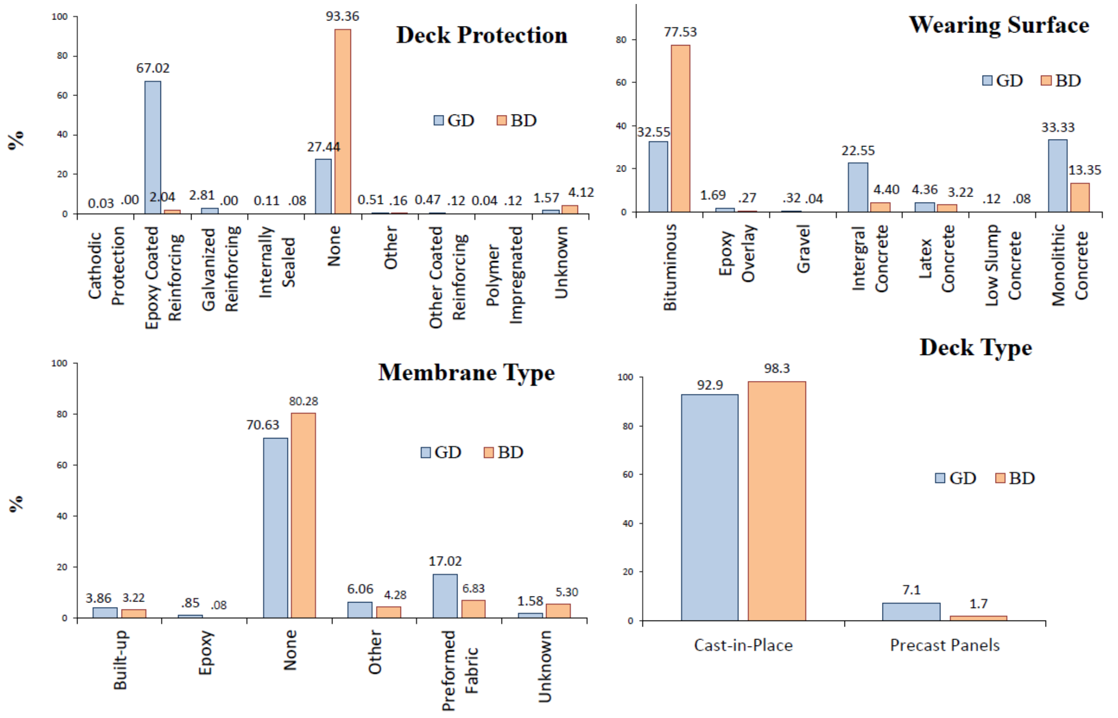


Figure 5.2: Deck design parameter distributions for bridges in the northeast climatic region (expressed in percent).

5.6.4 Two-Step Cluster Analysis

Two-step cluster analysis was used to group deck-design parameters and find their association with low and high bridge deck condition ratings. Design parameters of bridge decks with ratings below 5 (BD group) were compared with those of bridges with deck condition ratings of above 7 (GD group), and are shown in Figure: 5.3 and 5.4, respectively. Parameters relating to climate and traffic were kept within controlled ranges. In a typical outcome of a Two-step cluster analysis, data are grouped by the clustering category n(deck design feature) into clusters at each assembly (= deck design parameter). For example, the BD subsets show all clusters are grouped by the bituminous feature for the wearing surface assembly (Fig. 5.3). One of the clusters is considerably larger than the other, meaning that the larger cluster (blue circle) captured more cases of decks having a bituminous wearing surface than the smaller cluster, which captured less cases of decks having monolithic concrete as wearing surface (red circle).

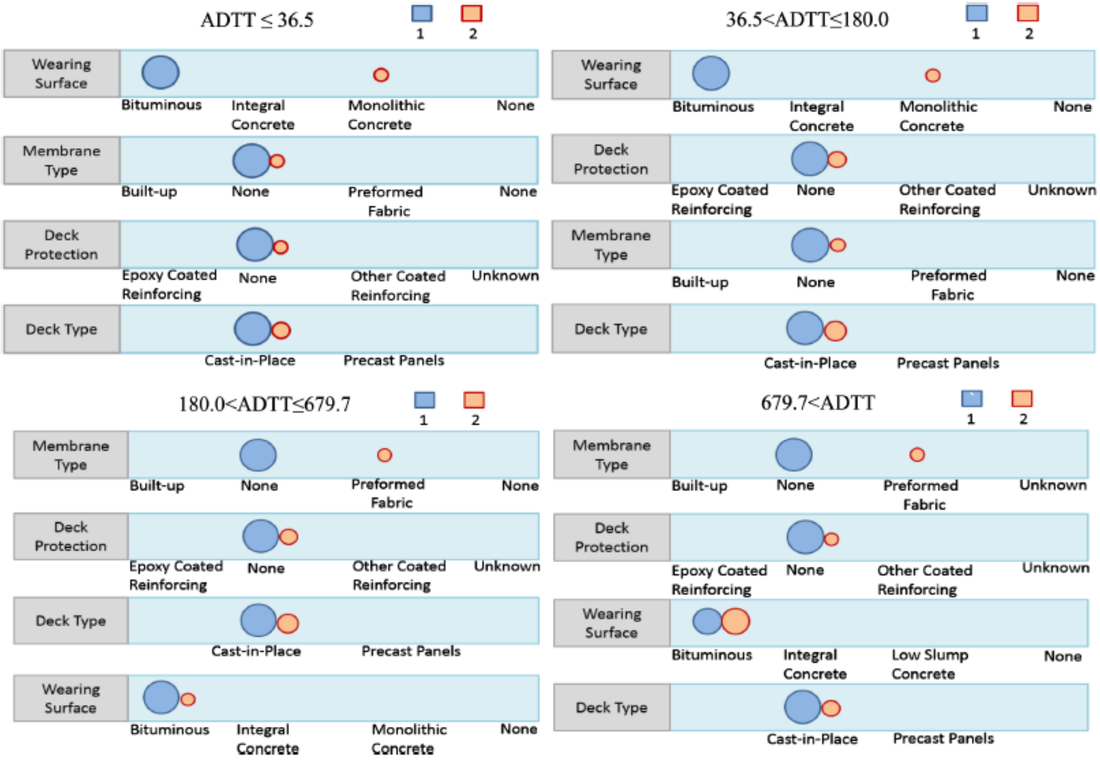


Figure 5.3: Graphical representation of Two-step cluster analysis for deck parameters BD Group.

The order of the assemblies (= deck design parameters) is also important. Because assembly ranking is based on its importance in forming clusters, the assembly listed on the top of the cluster has the most importance in forming the cluster. For example, the membrane type assemblies are at the top of the clusters for the third ADTT quartile ranges (180<ADTT≤680) for both GD and BD subsets (Figs. 5.3 and

5.4), meaning that features within the membrane type assembly contribute the most in forming those clusters. Accordingly, features from assemblies ranked last, such as deck type for the BD subset or deck protection for the GD subset, had the least importance in forming the clusters.

The results show that Two-step cluster analysis effectively differentiates deck design parameters between BD and GD groups across all ranges of ADTT. For example, epoxy-coated reinforcing, a deck protection feature, is presented as a grouping variable in all ADTT subsets of the GD group regardless of the ADTT on the bridge. This indicates that there is a strong association between bridge decks that are in good condition (GD group) and bridge decks having epoxy-coated reinforcing. Conversely, there is a strong association between bridge decks being in poor conditions and bridge decks lacking deck reinforcement protection. Furthermore, it seems that some deck design parameters are influenced by the ADTT more than others. For instance, integral concrete wearing surface is shown as a grouping variable only in the GD bridges having a large ADTT (> 714). In all other GD cases, monolithic concrete or bituminous as wearing surfaces prevail as grouping variables. In addition, it seems that certain sets of deck-design parameters are associated with the BD group regardless of the ADTT, such as cast-in-place bridge decks that have a bituminous wearing surface but have neither a deck membrane nor deck reinforcement protection. Accordingly, certain sets of deck-design parameters are associated with the GD group regardless of the ADTT, such as cast-in-place bridge decks that that have a bituminous wearing surface, preformed fabric membrane, and epoxy-coated reinforcement protection.

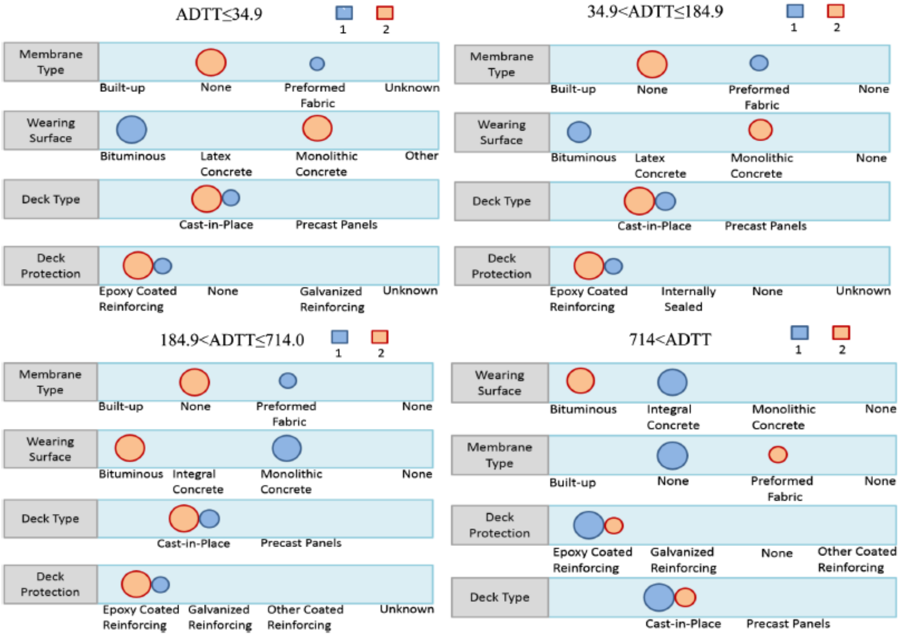


Figure 5.4: Graphical representation of Two-step cluster analysis for deck parameters GD Group.

It is also important to note that certain deck design parameters are present as clustering variables in both groups (BD and GD), such as monolithic concrete and preformed fabric membranes. However, only when these deck design parameters are combined with other deck design parameters, do they tend to be uniquely associated with the BD or GD groups. For instance, cast-in-place bridge decks with monolithic concrete as a wearing surface with no membrane and no deck protection are clustered together in the BD group for an ADTT range between 36.5 and 180 (second quartile range). On the other hand, cast-in-place bridge decks with monolithic concrete as a wearing surface and with no membrane but having epoxy-coated reinforcing/reinforcement as deck reinforcing protection are clustered together in the GD group for the same quartile range (Fig. 5.4). These results show a strong association between a deck having a good (or bad) condition and having a specific set of deck-design parameters rather than just one.

5.7 Conclusions

Due to the complex multidimensionality of the NBI database, analyzing data using traditional methods can become challenging if not futile. This study suggests that by applying data mining tools to the NBI database, bridge owners can explore this complex data set in a more comprehensive way. More specifically, this study recommends using a Two-step cluster analysis, a powerful knowledge discovery tool that can handle categorical and interval data simultaneously. Using this data mining tool, the authors were able to discover associations between sets of deck design parameters and bridge decks with either high (above 7) or low (below 5) condition ratings. The study suggests grouping bridges based on climate region (to provide control over the variability of environmental effects) and ADTT (to provide control over traffic volumes), before conducting Two-step cluster analysis on sample data sets. Once cluster analysis was performed and cluster groups formed, the relationships between deck-design parameters and deck-condition ratings could be further explored and visualized. Two-step cluster analysis can be also used as the data set dimension reduction tool. For example, given the four deck design parameters that are chosen (deck protection, wearing surface, deck membrane, and deck type), a total of 28 different factors needed to be analyzed. Analyzing all these factors would subsequently yield to 960 different deck design combinations. Using Two-step cluster analysis, researchers would be able to reduce this number to a meaningful, relatively small number of deck design combinations that could capture most of the variations and associations between parameters in the data set. In this study the authors were able to differentiate two distinguished deck design combinations. After reducing the data set to a manageable size, further traditional statistical analysis could be conducted for verification or forecasting of discovered trends.

From the analysis of a total of 9,809 concrete highway bridge decks in the Northeast climatic region, it was discovered that bridges with cast-in-place bridge decks that have a bituminous wearing surface, a preformed fabric membrane, and epoxy-coated reinforcement protection, are strongly associated with the *good* bridge deck condition ratings regardless of the average daily truck traffic (ADTT). Additionally, results also show that bridges with cast-in-place bridge decks that have a bituminous wearing surface but have neither a deck membrane nor deck reinforcement protection are strongly associated with *bad* bridge deck condition ratings regardless of the ADTT.

Additional parameters that were included in this study, but also having an influence on the selection of design parameters, would include, for example: material and construction costs, construction type, maintenance efforts, and so on. Such information could simply be added to the existing data set and included in the proposed Two-step cluster analysis to complete the picture of how concrete bridge decks perform under realistic conditions. By knowing which of the parameters (type of maintenance, design parameters etc.) lead to *good* bridge decks, bridge owners can stipulate that all future deck designs should conform to *good* deck design parameters. Conversely, knowing which of the parameters lead to *bad* bridge decks, bridge owners can proactively monitor bridges decks that have these design parameters and conduct preventive maintenance if needed. The authors hope that, ultimately, this type of data mining tool will serve as a useful tool for bridge owners in their decision-making, helping them to more efficiently allocate limited funds for design, maintenance, and repair of the bridge decks. Future work on this topic could implement the use of multiway analysis tools such as tensor decomposition, in order to add a temporal dimension to the analysis of the 22 years of records in the NBI database.

5.8 Supplemental Data

Table 5.4 is available online in the ASCE Library (http://www. ascelibrary.org).

Chapter 6

BINARY LOGISTIC REGRESSION TO CHARACTERIZE CONCRETE BRIDGE DECK PERFORMANCE USING THE NATIONWIDE DATABASE

This chapter has been prepared as a paper for the journal of Bridge Engineering. Section 6.1 and part of 6.2 are repeated from chapter 4.

6.1 Introduction

As a result of the Silver Bridge (across the Ohio River) collapse in 1967, which caused 46 deaths and 9 injuries, congress passed the Surface Transportation Assistance Act (STAA), leading to the establishment of the National Bridge Inspection Standards (NBIS) that were later stored in the National Bridge Inventory (NBI) (21,44). In 2016, the NBI contained records of 425,671 concrete bridge decks (54). These bridges were designed in accordance with two criteria, *strength* and *serviceability*, both of which are to ensure structural integrity and functionality, respectively. Decks exposed to freeze and thaw cycles, deicers, and traffic loads, present a bridge’s most susceptible element. The NBI states that concrete bridge deck deterioration is a leading cause for structural deficiency (19). According to the Federal Highway Administration (FHWA), two billion dollars are spent annually for maintenance and capital costs for concrete bridge decks (1). As a direct consequence, Departments of Transportation (DOTs) and the FHWA are committing major resources to investigate concrete bridge deck deterioration.

Many published studies investigates the effects of chloride penetrations on deck deterioration(8,63). Other research concentrate on predicting future bridge ratings by using various deterministic and stochastic models such as multiple regression (45,47), curve fitting(33), Markov models(44,62), and Bayesian models(37). Although promising, such studies are not nationwide and fail to address the effects of environmental and structural factors on bridge deck deterioration, a complex phenomenon influenced by numerous factors such as average daily truck traffic, reinforcement corrosion, cracking, distance to seawater, bridge age, creep, shrinkage, to name the commonest. Therefore, applying a logistical model would help identify how these factors effects deck deterioration.

This study uses binary logistic regression applied to a nationwide database that was created in chapter 4. This nationwide database uses parameters based on NBI items and additional parameters/variables (in this study parameters and variables are used interchangeably) not part of the NBI such as climatic regions, distance to seawater, and bridge age. Moreover, two new performances measures, one of which is deterioration rate (DR), were computed and are used in this study.

6.2 Experimental Dataset

Among the 22 parameters from the nationwide database (chapter4) used in this study, deterioration rate (DR) was computed based on the change in in the bridge deck condition rating (CR) (Fig 6.1):

$$DR = {}^{(\mathrm{CR}' - \mathrm{CR}'')}/_{\mathrm{TICR}} \tag{6.1}$$

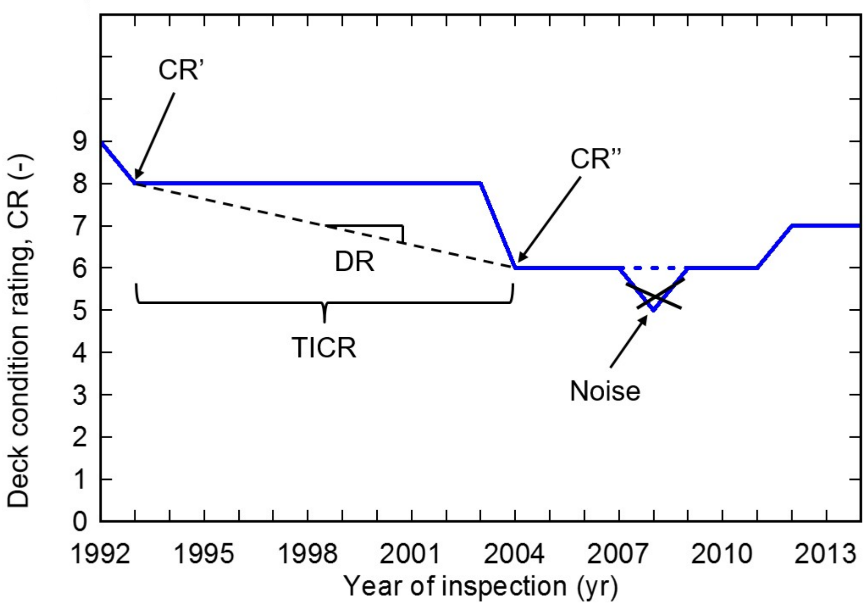


Figure 6.1: Sample bridge deck CR and computed parameters.

DR was used as the dependent variable in the logistic regression and its distribution along with the mean and median are shown in Figure 6.2 for the entire data set.

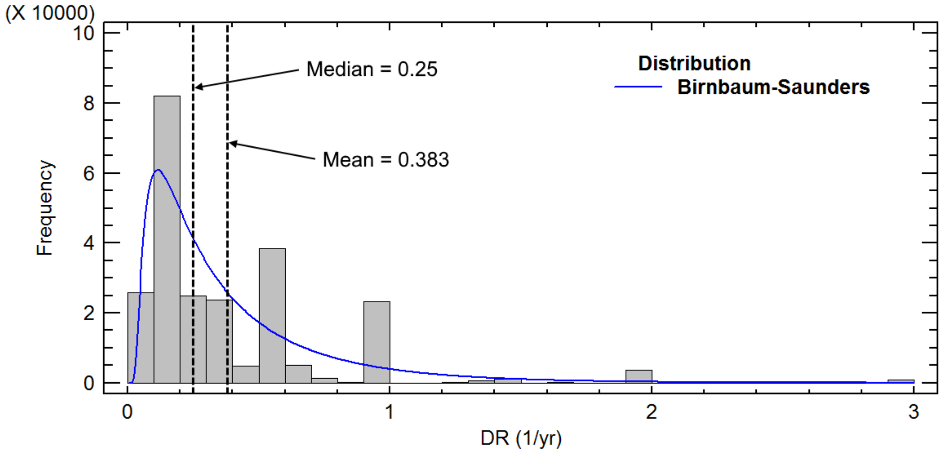


Figure 6.2: Histogram and best-fit distribution for all DR.

This study regarded concrete bridge decks with DR ≤ 0.056 as the lowest deteriorated bridge decks (“lowest DR”) with a total of 1,586 observations. DR = 0.056 means that the bridge deck was assigned the same CR for approximately 18 years before experiencing a one-unit CR decrease. Concrete bridge decks assigned a DR ≥ 2 were considered among the highest deteriorated (“highest DR”) with a total of 1,710 observations. DR = 2 means that the bridge was assigned the same CR for one year before a two-unit CR decrease. The lowest and highest DR were coded as binary variable and assigned 0 and 1, respectively. The reason behind taking these values was to make a clear distinction between the best and worst performing bridge decks. Figure 6.3 shows the histogram of frequency of the lowest (a) and highest (b) bridge deck DR as a function of the CR. Figure 6.4 shows the distribution and best fit for the lowest (a) and highest (b) bridge deck DR.

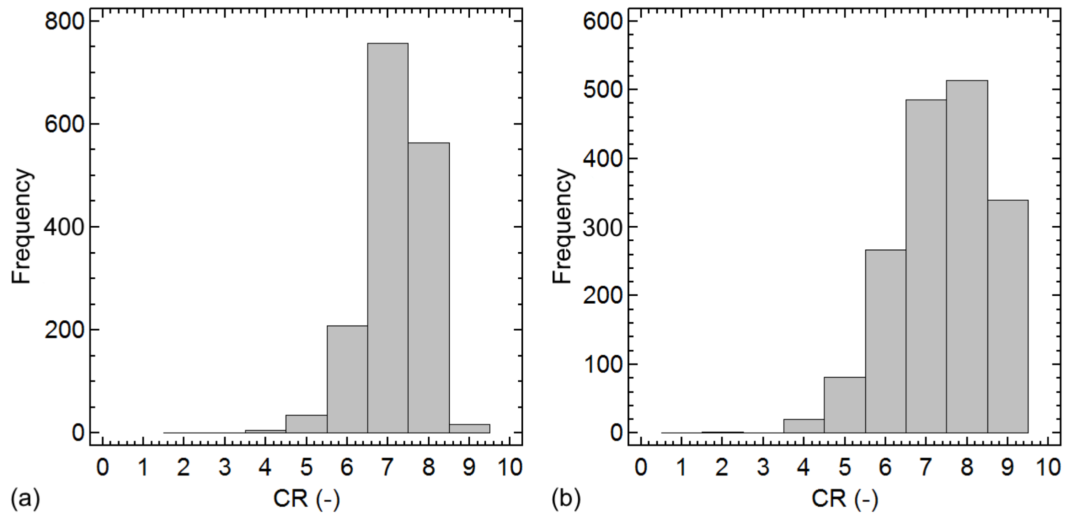


Figure 6.3: Histogram of (a) lowest and (b) highest bridge deck DR for each CR.

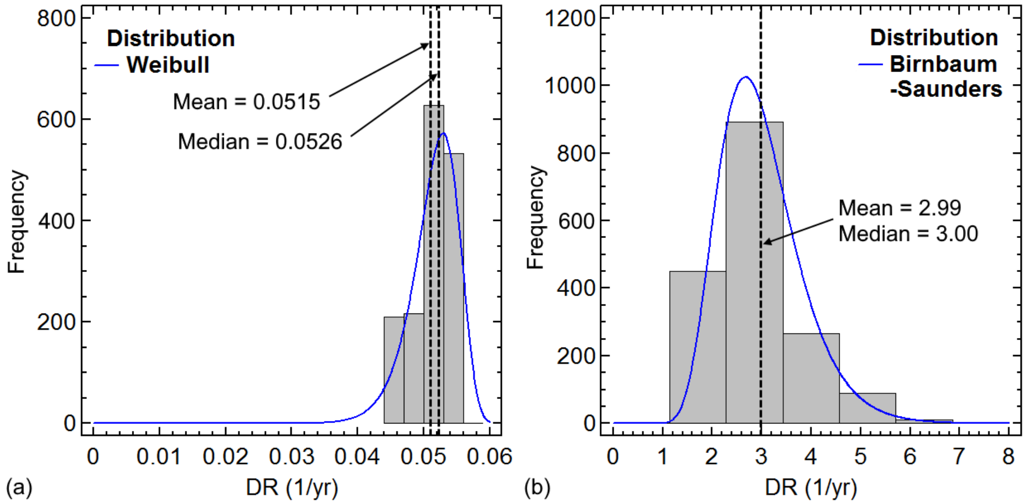


Figure 6.4: Best-fit distributions of (a) lowest and (b) highest bridge deck DR.

Table 6.1 presents a summary of the variables included in the study and/or their frequencies. Climatic regions were defined based on the National Centers for Environmental Information described in chapter 4.

Table 6.1: Summary statistics and counts for the parameters included in the study.

Continuous variables	Minimum	Mean	Maximum
Distance from Seawater (km)	0	5655	16619
Deck Area (ft^2)	2370	74304	4080000
Average Daily Truck Traffic (ADTT)	0	983.49	25432
Bridge Age	0	39.79	122
Number of Lanes	1	1.45	11
Categorical Variable	Categories	Frequency	Percentage
Deck Structure Type	Cast-in-Place	2899	88.0
	Concrete Precast Panels	397	12.0

Table 6.1 Continued

Categorical Variable	Categories	Frequency	Percentage
Structural Material Design	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	Very Hot	215	6.5
	Hot	919	27.9
	Average	553	16.8
	Cold	1045	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	None	2421	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	None	2566	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	None	207	6.3
	Monolithic Concrete	1239	37.6
	Integral Concrete	248	7.5
	Latex Concrete or Similar Additive	131	4.0

Table 6.1 Continued

Categorical Variable	Categories	Frequency	Percentage
	Low-Slump Concrete	59	1.8
	Epoxy Overlay	36	1.1
	Bituminous	1160	35.2
	Timber	88	2.7
	Other	128	3.9
Functional Classification of Inventory Route	Rural	2339	71.0
	Urban	957	29.0
Type of Design and Construction	Slab	664	20.1
	Stringer/multi-beam or girder (SB)	1628	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	State Highway Agency	2134	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

6.3 Analysis

6.3.1 Binary Logistic Regression

Binary logistic regression, a modeling approach that describes the occurrence of an event, is a method of fitting a regression curve, $y = f(x)$, where y (dependent variable) is a categorical binary variable (coded as 0 or 1), for a set of predictors x (independent variables) (12,24). The predictors can be continuous, categorical, or both. The advantage of logistic regression is that it does not take any of the assumptions of linear/multiple regression regarding linearity, normality, and measurement level (24). In this study, deck deterioration (DR) represents the dependent variable, y, where concrete bridge decks associated with "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 (18), e.g., for the parameter climatic regions (Table 6.1). For this case, there are 8 categories and thus 7 dummy variables, with "very hot" being the first category used as the baseline. The probability function that describes the dependent variable as a function of the number of independent variables can be represented as an equation that would lead to an S-shape function (Fig 6.5) where all the probabilities lie between 0 and 1 (28):

$$p(X) = \frac{e^{\beta_0+\beta_1 X}}{1+\ e^{\beta_0+\beta_1 X}} \tag{6.2}$$

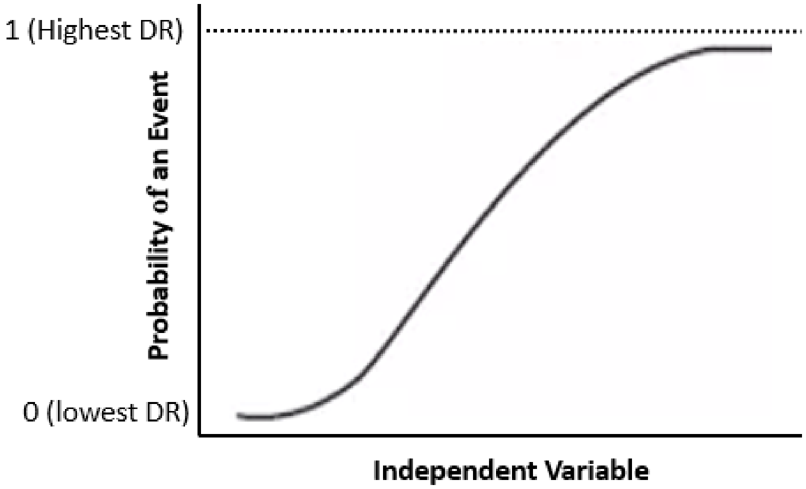


Figure 6.5: Logistic Regression plot.

Equation 6.2 can also be written in the following form, where $\left(\frac{p(X)}{1-p(X)}\right)$ is referred to as the odds:

$$\log\left(\frac{p(X)}{1-p(X)}\right) = \beta_0 + \beta_1 X \tag{6.3}$$

Logistic regression differs from multiple linear regression with respect to the interpretation of the coefficients of the independent variables. The logistic coefficients are typically interpreted using the log of the odds. In other words, the logistic coefficients (β) in Equation 6.3 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})(28,32).

6.3.2 Logistic Regression Coefficients

This study began with a logistic regression for all variables, named the initial model (Table 6.2). The table shows the logistic regression coefficient estimate and the significance at the 95 percentile (bolded numbers mean significant). Although this study sought to consider all parameters that affect bridge deck performance, in the initial model several of the variables were not found as statistically significant, leading to consideration of variable combinations based on their relative importance in overall bridge deck performance. As a result, a final model (parameters highlighted in yellow in Table 6.2) was derived from the first, which consisted of both categorical and continuous variables: maintenance responsibility fulfillment, functional classification of inventory route, design and construction type, average daily truck traffic, climatic regions, and distance to seawater. Those parameters were chosen because 1) they played a role in bridge deck deterioration and 2) they were all significant except the “average marine” category in climatic region and city of municipal highway agency (CMHA) and state toll authority (STA) categories in maintenance responsibility.

Table 6.2: Logistic regression coefficients for initial and final model. Highlighted in yellow are the parameters chosen for the final model.

Parameter	**Parameter Description**	**Initial Model**		**Final Model**		
		Coefficient	Significance	Coefficient	Significance	odds
Intercept		-1.3E+00	**2.01E-05**	-1.8E+00	**6.91E-16**	0.16
Deck Area	continuous variable	-7.41E-08	0.805119			
ADTT	continuous variable	2.22E-04	**6.64E-15**	2.41E-04	< **2e-16**	1.00
Bridge Age	continuous variable	-8.97E-03	0.000383			
Number of Lanes	continuous variable	-5.41E-03	0.921024			

Table 6.2 Continued

Parameter	**Parameter Description**	**Initial Model**		**Final Model**		
		Coefficient	Significance	Coefficient	Significance	odds
Deck Structure Type	Cast-in-Place					
	Concrete Precast Panels	4.22E-01	**0.020054**			
Structural Material Design	Concrete – simple span					
	Concrete – continuous	4.47E-01	**0.007062**			
	Prestressed concrete – simple	1.12E+00	**6.92E-08**			
	Prestressed concrete – continuous	3.99E-01	0.073152			
	Steel – simple span	4.70E-02	0.812376			
	Steel – continuous	1.82E-01	0.509959			
Climatic Region	Very Hot					2.12
	Hot	9.63E-01	**1.35E-05**	7.50E-01	**0.000223**	2.53
	Average	1.14E+00	**4.81E-06**	9.29E-01	**1.50E-05**	5.67
	Cold	2.00E+00	**4.56E-16**	1.74E+00	**< 2e-16**	16.48
	Very Cold (VC)	3.02E+00	**< 2e-16**	2.80E+00	**< 2e-16**	68.24
	Extremely Cold (EC)	4.46E+00	**1.10E-08**	4.22E+00	**3.47E-08**	1.91
	Average Marine (AM)	1.35E+00	**6.96E-08**	6.46E-01	0.104307	17.49
	Hot Marine (HM)	2.93E+00	**3.76E-11**	2.86E+00	**4.71E-08**	
Deck Protection	None					
	Epoxy-Coated Reinforcing	9.50E-01				
	Galvanized Reinforcing	1.52E+00	0.054298			
	Other Coated Reinforcing	1.26E+01	0.961609			
	Cathodic Protection	1.33E+01	0.971902			
	Polymer Impregnated	2.41E+00	**0.023384**			
	Internally Sealed	1.13E+01	0.983174			
	Unknown	1.06E-01	0.687388			
	Other	1.26E+00	**0.013454**			
Type of Membrane	None					
	Built-up	3.88E-01	0.115131			
	Preformed Fabric	-2.05E-02	0.934087			
	Epoxy	8.19E-01	0.16408			
	Unknown	9.74E-01	**7.46E-05**			

Table 6.2 Continued

Parameter	**Parameter Description**	**Initial Model**		**Final Model**		
		Coefficient	Significance	Coefficient	Significance	odds
	Other	-4.13E-01	0.092892			
Type of Wearing Surface	None					
	Monolithic Concrete	-1.43E+00	**2.09E-11**			
	Integral Concrete	-7.30E-01	**0.009224**			
	Latex Concrete or Similar Additive	-1.01E+00	**0.000717**			
	Low-Slump Concrete	-7.68E-01	**0.042375**			
	Epoxy Overlay	-1.31E+00	**0.004699**			
	Bituminous	-1.51E+00	**2.69E-12**			
	Timber	-1.41E+00	**2.21E-05**			
	Other	-1.46E+00	**4.20E-07**			
Functional Classification of Inventory Route	Rural					
	Urban	1.55E-01	0.161068	2.20E-01	**0.032134**	1.25
Distance from Seawater (DSW)	continuous variable	-3.99E-05	**0.000193**	-3.99E-05	**2.36E-05**	1.00
Type of Design and Construction	Slab					
	Stringer/multi-beam or girder (SB)	-6.03E-03	0.975835	4.65E-01	**2.09E-05**	1.59
	Girder and floor beam system	5.25E-01	0.174332	9.52E-01	**0.005068**	2.59
	Tee beam (TB)	9.11E-01	**4.31E-07**	8.07E-01	**1.16E-06**	2.24
	Box beam or girders – multiple (BBM)	6.12E-01	**0.003808**	6.75E-01	**8.94E-06**	1.96
	Box beam or girders – single or spread (BBS)	1.27E+00	**0.011109**	1.65E+00	**0.000331**	5.20
	Truss – through	2.36E-01	0.530937	1.02E+00	**0.001431**	2.76
	Channel beam (CB)	-5.09E-01	0.085461	-7.81E-01	**0.002048**	0.46

Table 6.2 Continued

Parameter	Parameter Description	Initial Model		Final Model		
		Coefficient	Significance	Coefficient	Significance	odds
Maintenance Responsibility	State Highway Agency					
	County Highway Agency (CHA)	4.88E-01	**2.75E-05**	4.85E-01	**3.31E-06**	1.62
	Town or Township Highway Agency	-1.08E+00	**8.69E-06**	-9.94E-01	**4.42E-06**	0.37
	City of Municipal Highway Agency (CMHA)	2.89E-01	0.188847	8.66E-02	0.680019	1.09
	State Toll Authority (STA)	-2.22E-01	0.569985	-4.70E-01	0.185469	0.63

The final model coefficients ($\beta_0, \beta_1, \beta_2, \beta_3$, and so on) can be written as:

$$\begin{aligned} -1.82 &+ \frac{2.41}{10^4} ADTT + \frac{7.5}{10} hot + \frac{9.29}{10} average + 1.74\, cold \\ &+ 2.8\, VC + 4.22\, EC + 2.86 HM + \frac{2.2}{10} urban \\ &+ \frac{-3.99}{10^5} DSW + \frac{4.65}{10} SB + \frac{9.52}{10} girder \\ &+ \frac{8.07}{10} TB + \frac{6.75}{10} BBM + 1.65 BBS \\ &+ +1.02\, truss - \frac{7.81}{10} CB + \frac{4.85}{10} CHA \\ &- \frac{9.94}{10} town \end{aligned} \qquad (6.4)$$

Because every combination of independent variables the authors considered in the logistic regression led to the same sign of the coefficient estimates (Table 6.2, Column 3 and 5), the logistic model used in this study is considered robust. In other words, for a continuous variable such as ADTT, the positive coefficient estimate suggests that if ADDT is increased, then the deck is more likely to be associated with “highest DR”. The negative estimate for the distance from seawater (continuous variable) suggests that if distance from seawater is increased then the bridge is **less** likely to be associated with “highest DR” (i.e., more likely to be in “lowest DR”). Having a different interpretation than continuous variables, the estimates for categorical variables are compared to the first category in a variable. An example of this can be seen for climatic regions (categorical variable); since “very hot” constitutes the first category there is no estimate for it, and all interpretations are performed relative to it. What we can conclude is that “hot”, “average”, “cold”, “very cold”, “extremely cold”, “average marine” and “hot marine” are all more likely to be associated with “highest DR” than to the “very hot” climatic region since all their estimates are positive.

Another way to interpret the estimates is using odds (last column, Table 6.2), calculated by taking the exponential of the estimate. Odds is defined as the probability of an event occurring divided by the probability of it not occurring:

$$odds \ = \frac{P(event\ 1\ occuring)}{1 - \ P(event\ 1\ occuring)} \tag{6.5}$$

In taking ADTT (continuous variable) as an example, and holding all other parameters at a fixed value (constant) , we can observe a 0.024% increase in the odds of ADTT being associated with “highest DR” for a one-unit increase in ADTT , since $e^{(2.2E\text{-}04)}$ = 1.000241. Thus a 1,000 unit increase in ADTT results in a 27.2 % increase in the odds since $e^{(2.41E\text{-}04)}$ = 1.000241. While the interpretations are the same for categorical variables, they are relative to the first category in the variable. Climatic regions can provide an example, where each coefficient estimate for the climatic region categories are relative to the category “very hot”. There is 112 % increase in the odds of being in the “highest DR” for a bridge deck in the “hot” region relative the "very hot" region, since $e^{(7.50E-01)} = 2.12$. Moreover, there is 153 % increase in the odds of being in the "highest DR" for a bridge deck in the "average" region relative to the "very hot" region , because $e^{(9.29E--01)} = 2.53$. The same methodology can be used for the other categorical variables.

6.3.3 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 unit-less measure it captures choice sensitivity to each independent variable (18,34). The calculations for elasticities differs for continuous versus categorical (indicator) variables.

6.3.3.1 Continuous Variables

Elasticities for continuous variables give an average percentage change in probability when the variable experiences a 1% increase (35). The equation used to calculate elasticity is as follows(34):

$$elasticity = \beta_{ik} X_{ikq} (1 - P_{iq}) \tag{6.6}$$

where *i* is the alternative (i.e., in this case the binary outcome 1 when a bridge deck is associated with "highest DR"), *k* is the continuous variable under consideration, q is the observation (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 logistic regression. 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 (43) (Table 6.3).

Table 6.3: Elasticities of continuous parameters.

continuous variable	elasticity
ADTT	0.0614
Distance from seawater	-0.130

As an example of what these values indicate, 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 "highest DR". Continuous variables measure the effect of a 1% change of the variable, which is not applicable for categorical (indicator) variables.

6.3.3.2 Categorical Variables

Calculating the elasticities for categorical variables with multiple indicators is less straightforward. It is much easier to calculate elasticity for categorical variables with two categories such as functional classification (Table 6.2). 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 "highest DR" (Eq. 2) for both "rural" and "urban" while keeping all other variables (ADTT, climatic region, distance from seawater, type of design, and construction and maintenance responsibility) constant. The next step is to subtract the probability of "rural" from "urban" and then divide it by the probability for "rural" for each observation. Once we calculate that we can take the mean, which in this case is 11%. What this tell us is that when we change the functional classification from "rural" to "urban" there is an 11% increase in the probability of a bridge deck being associated with "highest DR".

6.3.4 Statistical Evaluation of the Final Model

To evaluate the logistic regression model, a likelihood ratio test was performed on the final model. In a logistic regression, 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 (42). The equation for the likelihood ratio test is as follows(51):

$$\chi^2 = 2(LL_{restricted} - LL_{unrestricted}) \tag{6.7}$$

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 6.2). The χ^2 is the chi-squared distributed with the number of degrees of freedom equal to the difference in the number of parameters in the restricted and unrestricted models (42). In the likelihood ratio test, the null hypothesis is that the restricted 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 the null hypothesis consequently can be rejected (60) (Table 6.4).

Table 6.4: Likelihood ration 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.

6.3.5 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") from numerous subsets of data split into training sets and testing sets. A binary logistic regression is modeled on the training set and based on the coefficients of the model is tested on the testing set (61). This process is repeated several times in order to see how well the logistic regression predicts the accuracy of the dependent variables ("lowest DR" and "highest DR"). 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 high since accuracies above 65% are generally considered as acceptable (18). Figure: 6.6 shows a histogram and a box-and-whisker plot for the computed accuracies. Looking at the histogram (Fig. 6.6 (a)), it can be observed that measuring the performance of the model on one single set (rather than 30) can be quite deceiving, as accuracies range from 0.64 to 0.76. Here, however, the classifier is doing quite well as all accuracies are all above 0.64 (Fig. 6.6).

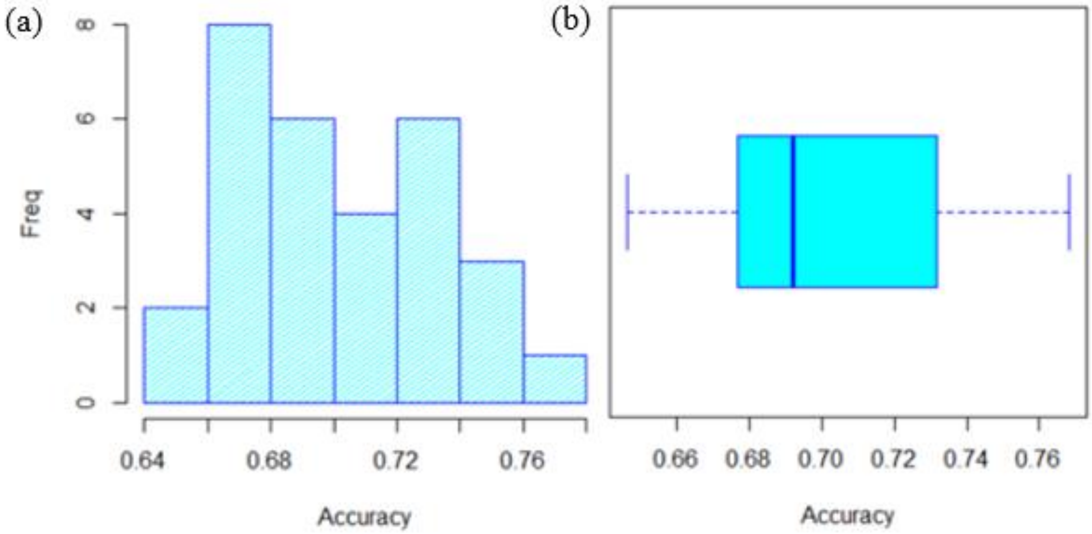


Figure 6.6: K-fold cross validation accuracy (a) histogram and (b) box-and-whisker plot.

6.4 Application Examples

Following are two examples of how this logistic regression can be used by agencies or bridge owners. The first computes the probability of three different concrete bridge deck configurations being associated with "highest DR" assuming certain environmental and structural parameters. The second example visualizes the probability of a concrete bridge deck being associated with "highest DR" as a function of ADTT.

6.4.1 Example 1

The example supposes that an agency would like to know the probability that a bridge deck would be associated with "highest DR" assuming three different scenarios.

Table 6.5 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 Highway Agency

Based on the final logistic regression model, the coefficients of the logistic regression in Table: 6.2 column 5 as well as the values given from the example are substituted in Equation 2, leading to the following equations:

Scenario 1

$$p(X) = \frac{e^{-1.82+\left(\frac{2.41}{10^4}*1500\right)+(1.74)+\left(\frac{2.2}{10}\right)-\frac{3.99}{10^5}(0.016)+\,(1.02)+\,\left(\frac{4.85}{10}\right)}}{1+\ e^{-1.82+\left(\frac{2.41}{10^4}*1500\right)+(1.74)+\left(\frac{2.2}{10}\right)-\frac{3.99}{10^5}(0.016)+\,(1.02)+\,\left(\frac{4.85}{10}\right)}} = 0.88 \tag{6.8}$$

Scenario 2

$$p(X) = \frac{e^{-1.82+\left(\frac{2.41}{10^4}*800\right)+\left(\frac{2.2}{10}\right)-\frac{3.99}{10^5}(16)+\,(1.65)}}{1+e^{-1.82+\left(\frac{2.41}{10^4}*800\right)+\left(\frac{2.2}{10}\right)-\frac{3.99}{10^5}(16)+\,(1.65)}} = 0.56 \qquad (6.9)$$

Scenario 3

$$\begin{aligned} &p(X) \\ &= \frac{e^{-1.82+\left(\frac{2.41}{10^4}*10\right)+(2.86)-\frac{3.99}{10^5}(96.5)-\left(\frac{7.81}{10}\right)-\left(\frac{9.94}{10}\right)}}{1+\ e^{-1.82+\left(\frac{2.41}{10^4}*10\right)+(2.86)-\frac{3.99}{10^5}(96.5)-\left(\frac{7.81}{10}\right)-\left(\frac{9.94}{10}\right)}} \\ &= 0.32 \end{aligned} \qquad (6.10)$$

Based on the results, Scenario 1 has the highest probability (0.74) of a concrete bridge deck being associated with “highest DR”, 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, and 3) it includes the structural parameters that increase the probability of it being associated with “highest DR”.

6.4.2 Example 2

A bridge owner would like to know how increasing the ADTT from 400 to 6,000 affects the probability of a certain concrete bridge deck being associated with “highest DR” for hot, average, cold and “very cold” climatic regions. The bridge is assumed to be 100 km (62.1miles) away from seawater, has a tee beam design, urban functional classification, and is maintained by the county highway.

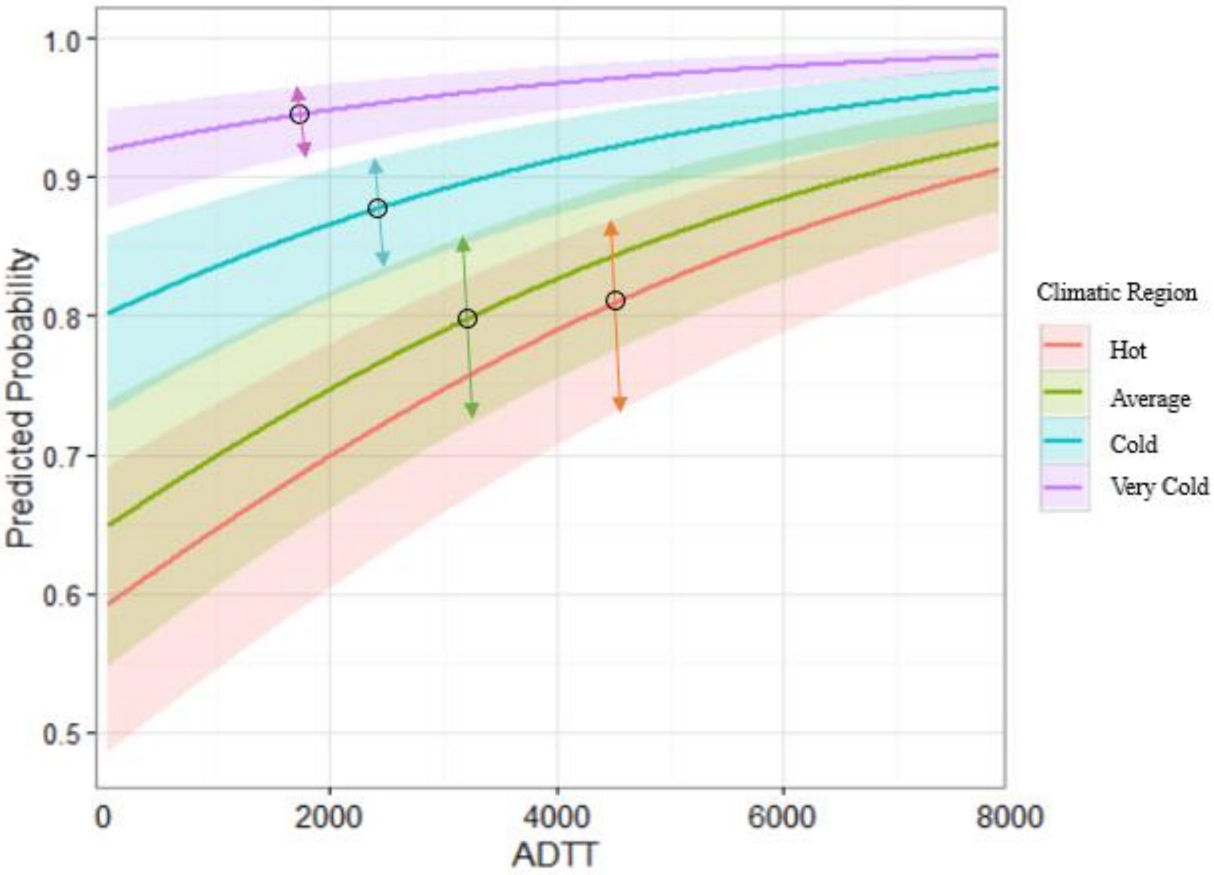


Figure 6.7: Predicted mean probabilities with 95% confidence intervals for Example 2.

Figure 6.7 shows the mean probabilities for 4 select climatic regions, and the 95% confidence intervals, as ADTT increases from 200 to 2000. As can be observed, as the climatic region becomes colder the probability of a concrete bridge deck being associated with “highest DR” 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, also reasonable because an increase in ADTT will likely cause higher stresses in the bridge deck.

6.5 Summary and Conclusion

The objective of this study was to examine how environmental and structural parameters, affect the performance of concrete bridge decks by means of a binary logistic model. The model is used to predict the likelihood for a concrete bridge decks being associated with “highest deterioration rate (DR)”. The logistic regression model development is based on 3,296 observations extracted from a nationwide database, developed in chapter 4. The DR was used as the dependent variable, while ADTT, climatic region, functional classification of inventory route, distance from seawater, type of design and construction and maintenance responsibility were used as independent variables. A log likelihood was performed to validate the model were the p-value was less than 0.05, indicating that 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 is considered as acceptable. The primary conclusions of this study are as follows:

- Based on the odds ratio and elasticities, bridge decks that have higher ADDT or are categorized as “urban” have higher odds/probabilities of being associated with “highest DR”.
- As a climatic region becomes colder, bridge decks have higher odds of being associated with “highest DR”.
- Decks further away from seawater have lower probabilities of being of being associated with “highest DR”.
- Type of construction and maintenance responsibility are additional parameters affecting the model.

This study also illustrates how a binary logistic model can be used by agencies or bridge owners by providing two practical examples. This study was constrained with the NBI items and additional computed items. In the future, additional parameters can be added such as structural design characteristics (e.g., minimum deck thickness, reinforcement bar size, bar spacing), construction practices (e.g., concrete temperature, placement procedure, curing practices), specifications (e.g., water-to-cement ratio and minimum cementitious material content), and other notable factors (e.g., application of deicing salts and thermal climate). It is recommended that upcoming studies use this methodology to model those additional independent variables for their effect on bridge deck performance.

Chapter 7

PREDICTING TIME IN CONDITION RATINGS FOR CONCRETE HIGHWAY BRIDGE DECKS IN THE UNITED STATES

This chapter has been prepared as a paper for the journal of Bridge Engineering. Section 7.1 and part of 7.2 are repeated from chapter 4.

7.1 Introduction

Most studies do not discuss the effect of bridge deck condition history on future CR (33,44,45,46,47). Furthermore, deterministic models omit historic condition ratings in modeling bridge deck deterioration. To the best of the authors' knowledge, most studies that use NBI data have been done on specific states rather than nationwide. The goal of this study was to develop a statistical model for the entire country that predicts the probability of CR decrease, a model that can be updated with new information. Moreover, this study plans to include certain environmental and structural parameters in order to understand their effects on CR decrease.

7.2 Data Needed for the Research

The data used in this paper was taken from the nationwide database (Chapter 4). Five different parameters were used from the nationwide database: 1) time-in-condition-rating (TICR), 2) average daily truck traffic (ADTT), 3) maintenance responsibility, 4) deck structure type, and 5) International Energy Conservation Code (IECC) Climatic Regions.

7.2.1 Time-In-Condition-Rating (TICR)

This parameter, originally proposed by Nasrollahi and Washer(36), represents the number of years a bridge deck is assigned the same CR regardless of the preceding and subsequent CR. Our methodology differs in that we only consider those cases where the CR at the end of the TICR (= CR”) is less than the initial CR (= CR’), as shown in Figure 7.1. The reason for this was to capture true deck deterioration, on the assumption that when the CR” increases maintenance must have occurred. Because deck maintenance can occur at any time during the process of rating deck condition, applying TICR in cases of rating that increase might misrepresent the TICR period before any CR decrease. CR = 5 in Figure: 7.1 can be used as an example: when CR = 5 increases to CR = 8 in 2010 we considered that due to maintenance action. Although the TICR for our study was done for concrete bridge decks based on the entire country we did not use cases such as this one (TICR for CR = 5) because the CR could have remained at a “5” longer had the entity responsible for the bridge decided not to maintain it.

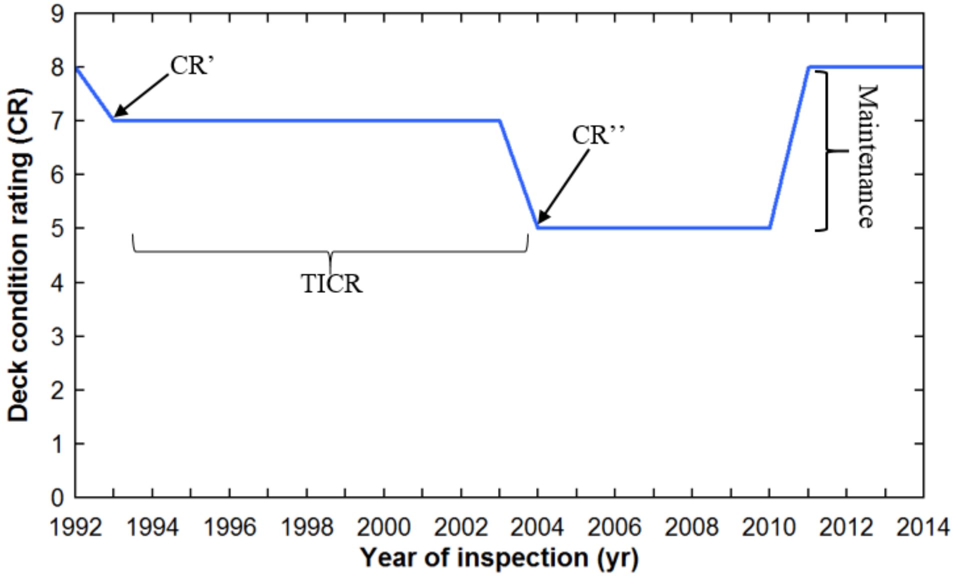


Figure 7.1: Sample bridge deck CR for TICR.

Box-and-Whisker plot and means with 95% confidence intervals of CR. 4 to 9 based on TICR for concrete bridge deck in the US (Fig. 7.2). It can be observed that the TICR is a function of the CR where low and high TICR are correlated with low and high CR, respectively. Two TICR groups as highlighted in Figure 7.2 were considered for further exploratory analysis:

- High (CR = 8): Bridge decks in very good condition with very minor signs of deterioration, i.e. no action is required.
- Low (CR = 5): Bridge decks in fair condition with significant deterioration, i.e. repair is needed.

The data associated with other CRs were excluded from the analysis. There were two reasons behind looking at CR 5 and 8 1) provide a comparison between a relatively high vs. a relatively low (CR 9 wasn't a good representative of a high CR as that rating usually does not last that long as discussed before) 2) Choose CRs that had sufficient data points (CR 2,3 and 4 did not have sufficient data).

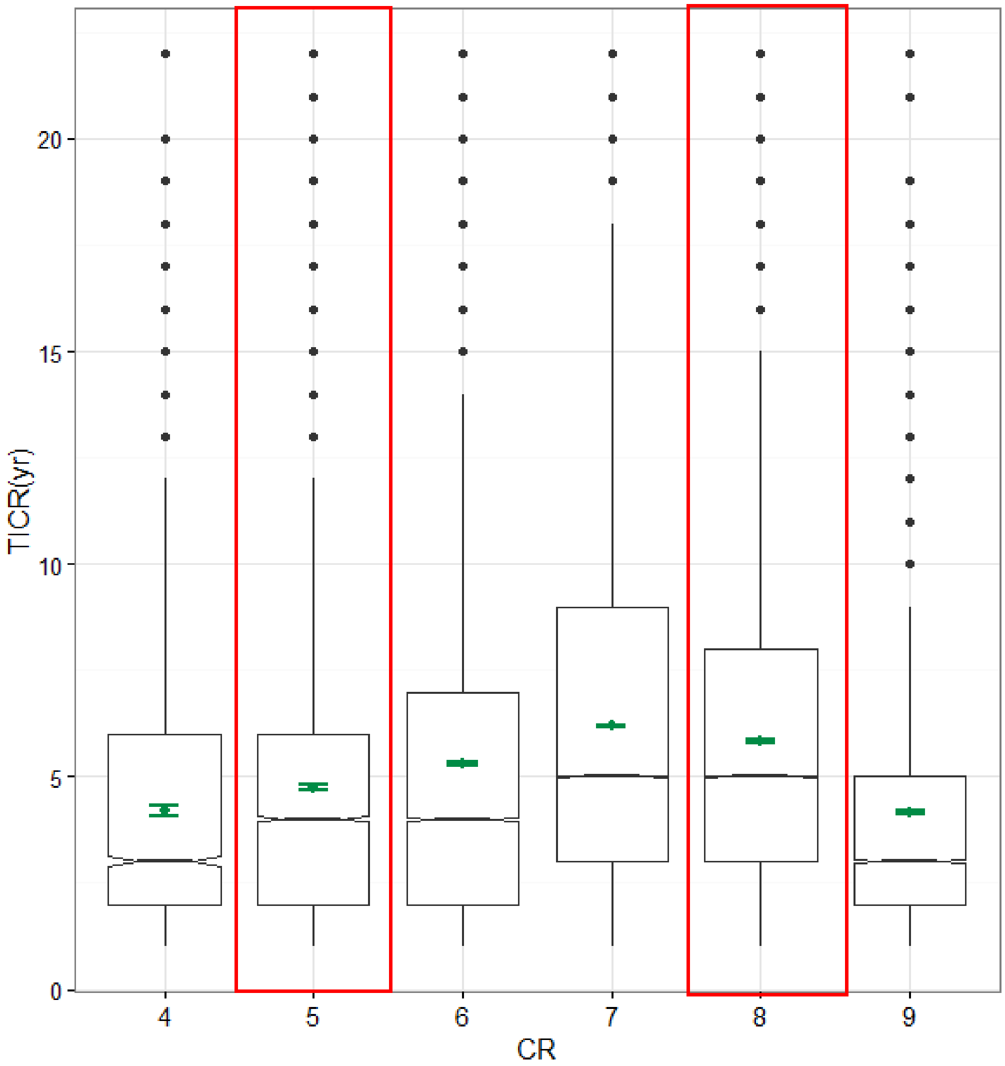


Figure 7.2: Box-and-Whisker plot and means with 95% confidence intervals of for concrete bridge decks for the nation.

7.2.2 Average Daily Truck Traffic (ADTT)

Defined as the daily average number of trucks that pass over a bridge in one day (30). This parameter is derived from the nationwide database.

7.2.3 Maintenance Responsibility

The nationwide database considers four maintenance entities: State Highway Agency, County Highway Agency, Town or Township Highway Agency, City or Municipal Highway Agency, Private agencies (other than railroad), and State Toll Authority. This study considers all these entities except for private ones as there was insufficient data to run the model.

7.2.4 Deck Structure Type

The nationwide database considers two deck structure types: concrete cast-in-place and concrete precast panels.

7.2.5 International Energy Conservation Code (IECC) Climatic Regions

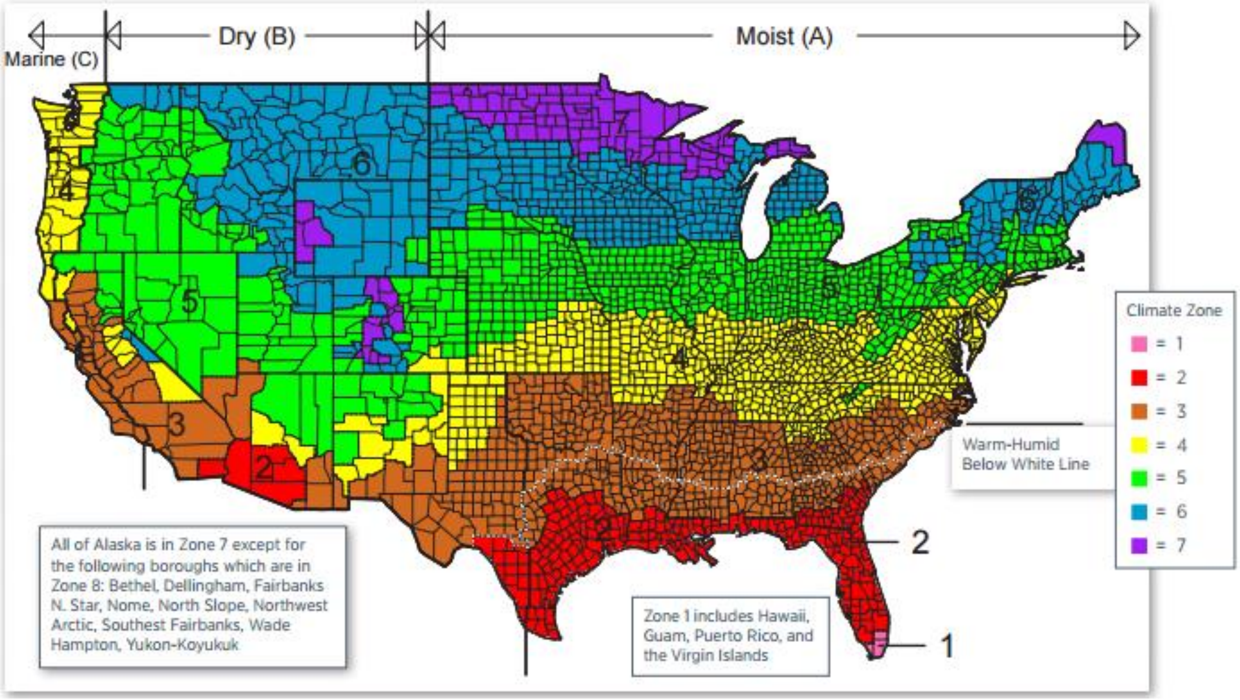
Climate regions were introduced in chapter 4 (section 4.4.3). These were the assumptions used:

- Zone 1 consisted of three counties in Florida, Hawaii, and Puerto Rico (Fig. 7.3). 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.”



All of Alaska is in Zone 7 except for the following boroughs which are in Zone 8: Bethel, Dellingham, Fairbanks N. Star, Nome, North Slope, Northwest Arctic, Southest Fairbanks, Wade Hampton, Yukon-Koyukuk

Zone 1 includes Hawaii, Guam, Puerto Rico, and the Virgin Islands

Figure 7.3: IECC climatic regions(57).

7.2.6 Assumptions

The NBI bridge deck CR are subjective ratings that can be biased depending on the inspector. Structural design characteristics (such as minimum deck thickness, reinforcement bar size, and bar spacing), construction practices (such as concrete temperature, placement procedure, and curing practices), specifications (such as water to cement ratio and minimum cementitious material content), and other notable parameters (such as application of deicing salts and thermal climate) of concrete bridge decks are not included in NBI assessments. Bridge decks of poor design or poor construction and questionable specification characteristics can deteriorate more rapidly than others. Moreover, while modern concrete bridge deck design and durability standards may be responsible for slower deterioration mechanisms than those found in older bridges, deterioration mechanisms for bridge decks are not included in the NBI. Certain bridge decks may have characteristics that make them prone to more rapid deterioration and therefore may not be described correctly by using statistics. All the attributes stated above should be considered in understanding bridge deck deterioration(36). For this study, however, specific deterioration mechanisms were not considered. The aim of this paper was rather to introduce a statistical model that provides a holistic view of concrete bridge deck CR decrease in the United States. This model can be integrated with engineering assessments of particular bridge decks.

7.3 Bayesian Model

7.3.1 Bayesian Approach

A basic Bayesian procedure was adopted based on the Bayes’ rule proposed by English mathematician Thomas Bayes and published 1763. The advantage of the Bayesian technique is that it makes use of new data to improve the statistical parameters of any assumed or calculated distributions. Below is our adaptation of Bayes’ theorem (41):

$$p(\theta|D) = \frac{p(D|\theta) * p(\theta\ )}{P(D)} \tag{7.1}$$

Here P(Θ) is the prior probability, before any new information has been included, and is usually based on expert opinion or prior data; next, p(D│Θ) is likelihood or conditional probability of the data, assuming the parameter is Θ; p(D) is the evidence or marginal likelihood of the model, which is the overall probability of the data according to the model; and p(Θ│D) is the posterior probability based on the new data (D) taken into account (41,78). When we are dealing with continuous variables p(D) is defined as follows:

$$p(D) = \int \mathrm{p(D|\Theta)p(\Theta)d\Theta} \tag{7.2}$$

7.3.2 Methodology

In our model, TICR ranged from 1 to 23 (for the years 1992 to 2014) for CR = 4 to 9, the rest were not considered because there were not many bridges in the US that had CR < 4. An example of this methodology, illustrated for CR = 7 for an extremely cold climatic region, identified 59 bridges with TICR = 1 year before decreasing to a lower CR, 118 bridges with TICR = 2 years before decreasing to a lower CR, and so on (Table 7.1)**.** Next, from the total calculated number of bridges (Table 7.1, Column 2 last row) we subtracted the summation of bridges (Table 7.1, Column 3) to get the Total Number of bridges- Summation of bridges (Table 7.1, Column 4). I explain my reasoning in the next section (7.33-7.3.5).

Table 7.1: Tabulated TICR for CR 7 bridge decks in extremely cold climatic region, highlighting year 6.

TICR	No. of Bridges	Summation of Bridges	Total Number of bridges - Summation of Bridges
1	59	59	733
2	118	177	615
3	67	244	548
4	97	341	451
5	78	419	373
6	99	518	274
7	91	609	183
8	34	643	149
9	26	669	123
10	43	712	80
11	20	732	60
12	19	751	41
13	6	757	35
14	15	772	20
15	6	778	14
16	11	789	3
17	2	791	1
18	0	791	1
19	1	792	0
20	0	792	0
21	0	792	0
22	0	792	0
23	0	792	0
Total no. of bridges	792		

7.3.3 Likelihood Function

The Bernoulli distribution (Eq. 7.1) represents the outcome of a single coin flip, y, which can take the values of 0 or 1. This is a discrete distribution for two values of y:

$$p(y|\Theta) = \Theta^{y}(1-\Theta)^{(1-y)} \tag{7.3}$$

The likelihood for multiple flips, however, can be computed using:

$$\Theta^{z}(1-\Theta)^{(\mathrm{N}-z)}, \tag{7.4}$$

where z is the number of heads and (N-z) is the number of tails. Because the coin flips are assumed independent of one another, the probability is the product of each outcome's (head or tail) probability.

The likelihood is a function of a continuous Θ and is calculated for a continuous variable Θ that varies from 0 to 1 (Eq. 7.4). Our model was similar to the multiple coin-flip example since each TICR was also assumed independent of the other. Moreover, the model relates to the theory in the following manner (41):

- The summation of bridges for the given TICR (Table 7.1, Column 3), was modeled as z (# of heads), which is considered as the number of bridges that failed to have a longer TICR (i.e., representing "failure").
- The total number of bridges minus summation of the number of bridges in TICR (Table 7.1, Column 4), was modeled as N-z (# of tails), or as the number of bridges having a longer TICR (i.e., representing "success").

As an example, considering a TICR = 6 (Table 7.1), the summation of bridges (= 518) is modeled as *z* (= number of bridges that stayed less than or equal to 6 years in CR = 7) and the total number of bridges (*N*) minus summation of bridges, (*z*) (= 792-518) is modeled as *N*-*z* (i.e., bridges that stayed longer than 6 years in CR = 7) (Fig. 7.4).

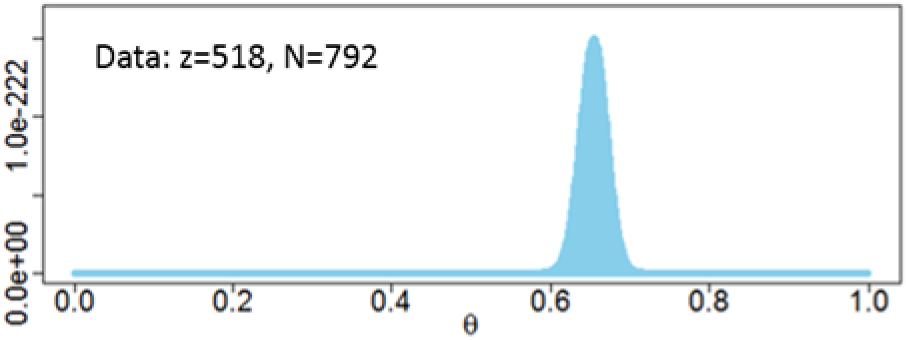


Figure 7.4: Likelihood output of *TICR* = 6 for CR = 7 bridges in extremely cold climatic regions.

7.3.4 Prior Information

Because there was no previous knowledge (or published studies) regarding the distribution of the *TICR* parameter, a Uniform prior was assumed. We decided to use a beta distribution as our prior. There were several reasons behind this choice:

1. A distribution was needed to describe the prior probability for Θ for the interval [0, 1].
2. A function is preferred where the product of p(D | Θ) and p(Θ) results in the same form as the function of p(Θ).

When the likelihood [p(D | Θ)**]** and prior [p(Θ)] combine so that the posterior has the same distribution as the prior distribution, then p(Θ) is called the conjugate prior for

$p(D \mid \Theta)$; and for this case the beta distribution is the conjugate prior of our likelihood. This process allows $\int p(D|\Theta)p(\Theta)d\Theta$ (Equation 7.2) to be solved analytically (41).

The beta distribution has two parameters, *a* and *b*, and is only defined for values of Θ between 0 and 1, as follows (41):

$$\mathrm{beta}(\Theta|\mathrm{a},\mathrm{b}) = \Theta^{(a-1)}(1-\Theta)^{(b-1)} \Big/ B(a,b) \tag{7.5}$$

where *B*(*a*, *b*) is the normalizing constant that ensures the area under the beta curve integrates to 1.0, and is defined as(41)

$$B(a,b) = \int_0^1 \Theta^{(a-1)}(1-\Theta)^{(b-1)}d\Theta, \tag{7.6}$$

For our model we assumed *a* = 1 and *b* = 1, which is essentially a Uniform distribution (Fig. 7.5)

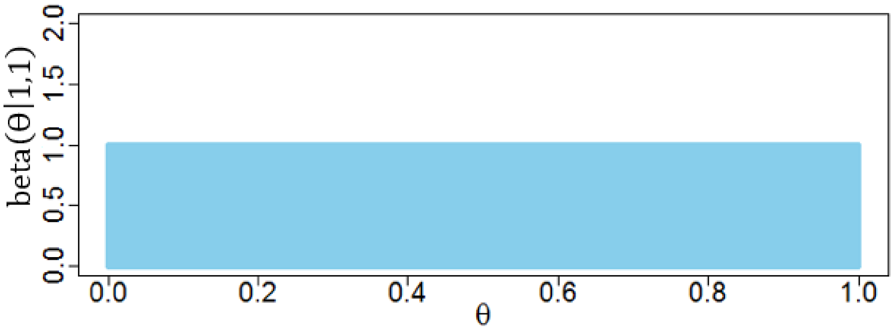


Figure 7.5: A prior based on a Uniform distribution.

7.3.5 Posterior Distribution

Substituting the likelihood function (Eq. 7.4) and the beta prior distribution (Eq. 7.5) into the Bayesian equation (Eq. 7.1) will give us the following (41):

$$p(\Theta|\mathrm{z}, \mathrm{N}) = p(z, N|\Theta)p(\Theta)/p(z, N) \tag{7.7}$$

$$\Theta^{z}(1-\Theta)^{(\mathrm{N}-z)} \frac{\Theta^{(a-1)}(1-\Theta)^{(b-1)}}{B(a,b)} \Big/ p(z,N) \tag{7.8}$$

$$\Theta^{((z+a)-1)}(1-\Theta)^{((\mathrm{N}-z+b)-1)} \Big/ [B(a,b), p(z,N)] \tag{7.9}$$

$$\Theta^{((z+a)-1)}(1-\Theta)^{((\mathrm{N}-z+b)-1)} \Big/ B(z+a, N-z+b)\,. \tag{7.10}$$

While the first step defines the Bayesian equation, the second step substitutes the likelihood function and beta prior, and the third step rearranges the terms. Since the $\Theta^{((z+a)-1)}(1-\Theta)^{((\mathrm{N}-z+b)-1)}$ is the numerator of the beta function, $\mathrm{beta}(\Theta|\mathrm{z}+\mathrm{a}, \mathrm{N}-\mathrm{z}+\mathrm{b})$, then the denominator is the normalizing factor; hence $[B(a,b), p(z,N)]$ was substituted as $B(z+a, N-z+b)$. If we had a prior distribution of $\mathrm{beta}(\Theta|\mathrm{a}, \mathrm{b})$ and there were *z* number of bridges that stayed less than TICR and *N* total bridges, then the posterior distribution is $\mathrm{beta}(\Theta|\mathrm{z}+\mathrm{a}, \mathrm{N}-\mathrm{z}+\mathrm{b})$. The posterior of a TICR = 6 (Table 7.1) case has a beta distribution to which we add *z* and *a* to get a final Beta distribution (Fig. 7.6). Because our prior was non-informative, our posterior is entirely driven by the data.

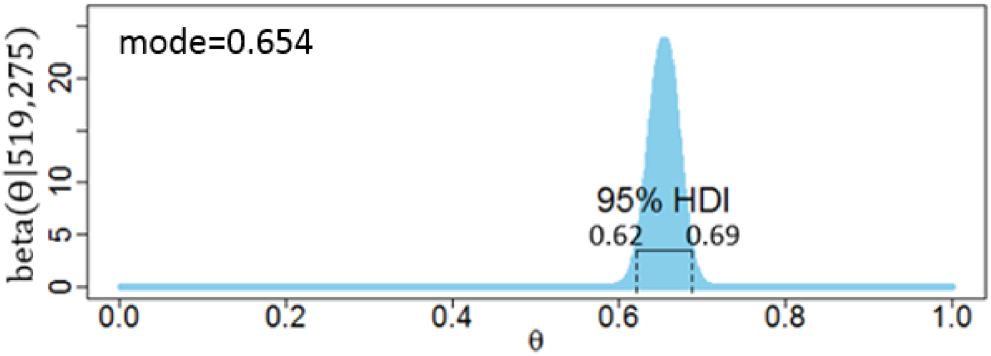


Figure 7.6: Posterior output of TICR = 6 for a CR = 7 bridge in an extremely cold climatic region.

Using this methodology, this procedure was performed for each TICR (Table 7.1, Column 1) in which the mode of the posterior was used as the probability of decrease of CR (Fig. 7.7).

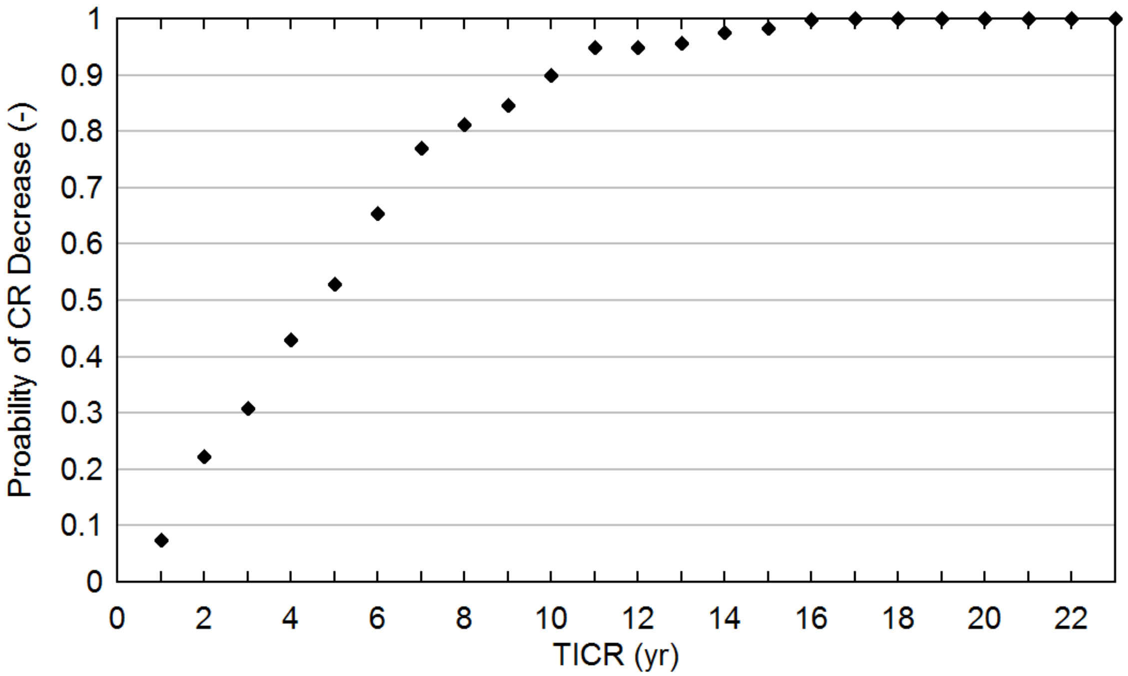


Figure 7.7: Probability of CR decrease in an extremely cold climatic region for a CR 7 bridge.

7.4 Example

Having neither previous prior nor expert data, the authors assumed two hypothetical priors to illustrate the effect of prior data on posterior. Taking again the TICR = 6 for CR = 7 bridge deck example (Table 7.1, highlighted row), we have the following two scenarios:

1. Scenario one: Prior information indicates that TICR = 6 has a probability of CR decrease of 0.2, though it's **not especially confident** i.e., Beta (2, 8)
2. Scenario two: Prior information is **confident** that TICR = 6 has a probability of CR decrease of 0.2, i.e. Beta (200, 800).

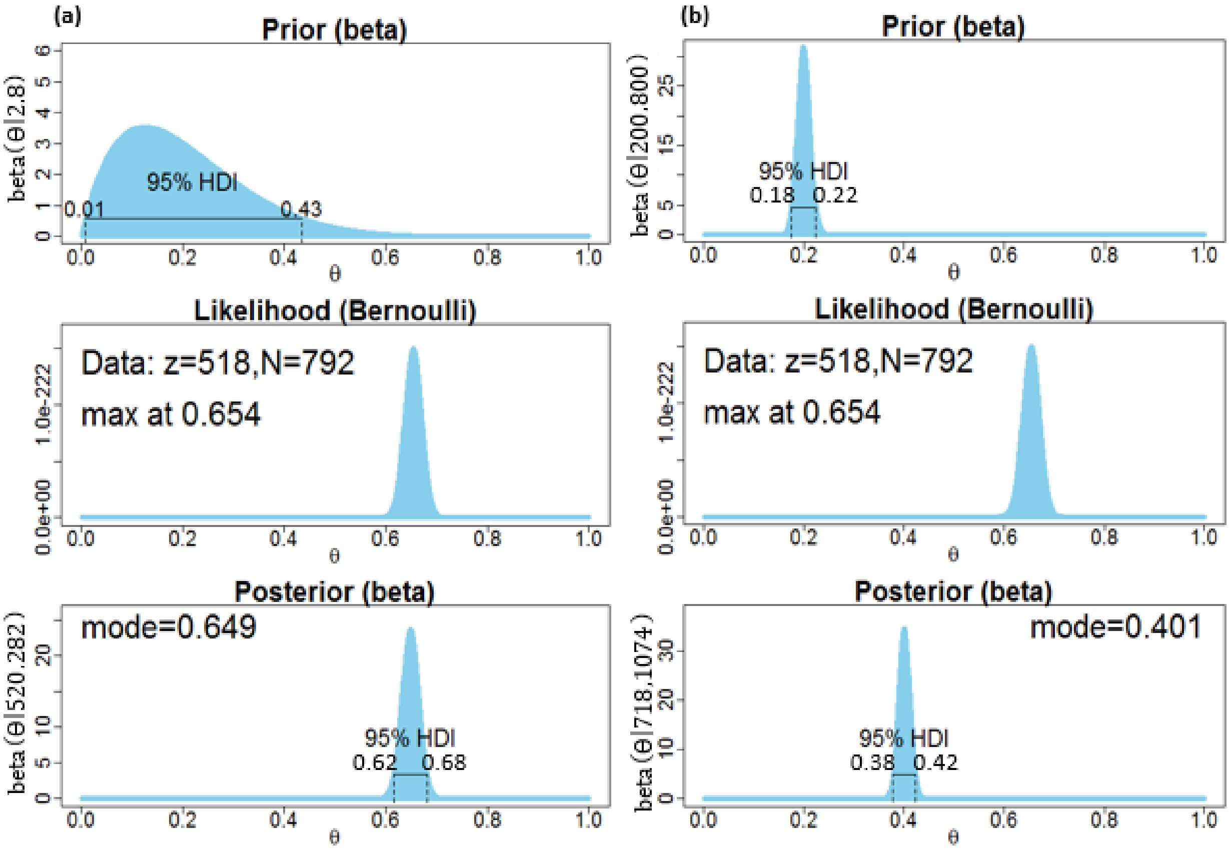


Figure 7.8: Bayesian output of (a) scenario one and (b) scenario two based on TICR = 6 likelihood from Table 7.1.

Because scenario one has a prior that is not confident the prior distribution is spread apart with a high density interval (HDI) varying from 0.01 to 0.43 (Fig 7.8(a) top), as opposed to scenario two where we have a confident prior in which the prior distribution is condensed, having a HDI varying from 0.18 to 0.22 ((Fig 7.8(b) top). Stemming from lack of confidence in scenario one, the posterior distribution does not change relative to the likelihood. Moreover, the mode of the posterior in scenario one at 0.649 (Fig 7.8(a) top) is not that different from when the prior was uniform (Fig. 7.5) and where the posterior mode was 0.654 (Fig. 7.6). Scenario two, however, has a confident prior which resulted in shifting the posterior to the left , in between the likelihood and prior, whose mode of 0.401 was much different than that of scenario one (0.649). We can conclude that confident prior information influences the posterior as opposed to a prior that lacks confidence.

7.5 Results and Discussion

7.5.1 Entire Country

Using a Uniform prior, CR-decrease probability curves for a variety of configurations for TICR and CR were constructed. This procedure was performed for each CR and TICR, and the mode of each posterior output was used as the descriptor for the probability of CR decrease. The advantage of this model is that once we have new data available, such as TICR from future years, we can use the posterior data from the model as the prior and, based on the new data, the Bayesian model can inform new confident posterior outputs. Figure 7.9 shows the results for the entire country.

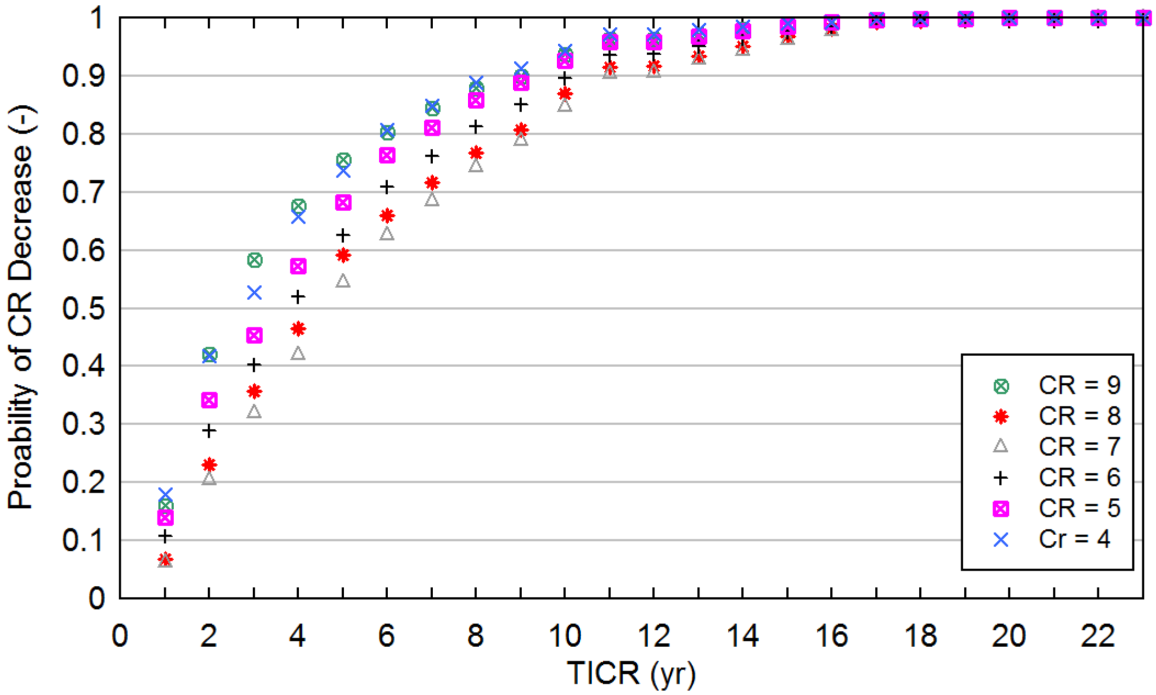


Figure 7.9: Probability of CR decrease for the entire country.

The following key observations can be made from Figure7. 9:

- The curve flattens after 12 years as most CR do not have a TICR > 12. In fact, based on our nationwide dataset, 92% of all bridges rated for all condition have a TICR < 12 years.

- CR = 9 bridges have the highest probabilty for the CR to decrease over time. This makes sense because when the authors spoke with bridge inspectors and other professionals in the field, it became evident that only new bridges are assigned a CR = 9 (see discussion in section 2.9) . Aditionally, they are typically downgraded to a lower CR quickly, e.g. after experiencing minor surface cracks.

- Bridge decks with CR = 8 bridges have a higher probability to decrease than those with CR = 7. This was also found to be consistent with expert opinion.

- CR = 7 has the lowest probability of decrease, or, in other words, shows the longest TICR probabilities .
- CR = 4 exhibits a relatively large jump from TICR = 1 to 2 to 3, from 18% to 42% to 53% respectively. This implies that concrete bridge decks with CR = 4 should be repaired immediately, given that CR = 3 may represent a safety problem.

Finally, a brief example on how to read the probability of CR decrease plots is discussed and illustrated in Figure 7.9. Suppose the following hypothetical question: What is the probability that a bridge deck that has been assigned a CR = 5 will be assigned a lower CR after it has been in that condition for 6 years, i.e. TICR = 6? Answer: 76%.

Based on the logistic regression (chapter 6) ADTT, maintenance responsibility, deck structure type and climatic regions were all parameters that influenced deck deterioration ("lowest DR" vs. "highest DR"). Comparisons and observed differences of those parameters were made based on CR = 8 and 5 using the Bayesian model discussed in this chapter. This selection of CR = 8 and 5 was made because using all CR would lead to crowded figures, whereas using these two provides a comparison between a relatively high vs. a relatively low CR, moreover they were statistically significantly different (Chapter 4) .

7.5.2 ADTT

Recognizing that ADTT plays a big role in deck performance, the Bayesian model was adopted to construct probability of CR decrease curves for ADTT < 100 and ADTT > 8,500, which represent low vs high ADTT, respectively (Fig. 7.10). The ADTT ranges where based on an FHWA study (80).

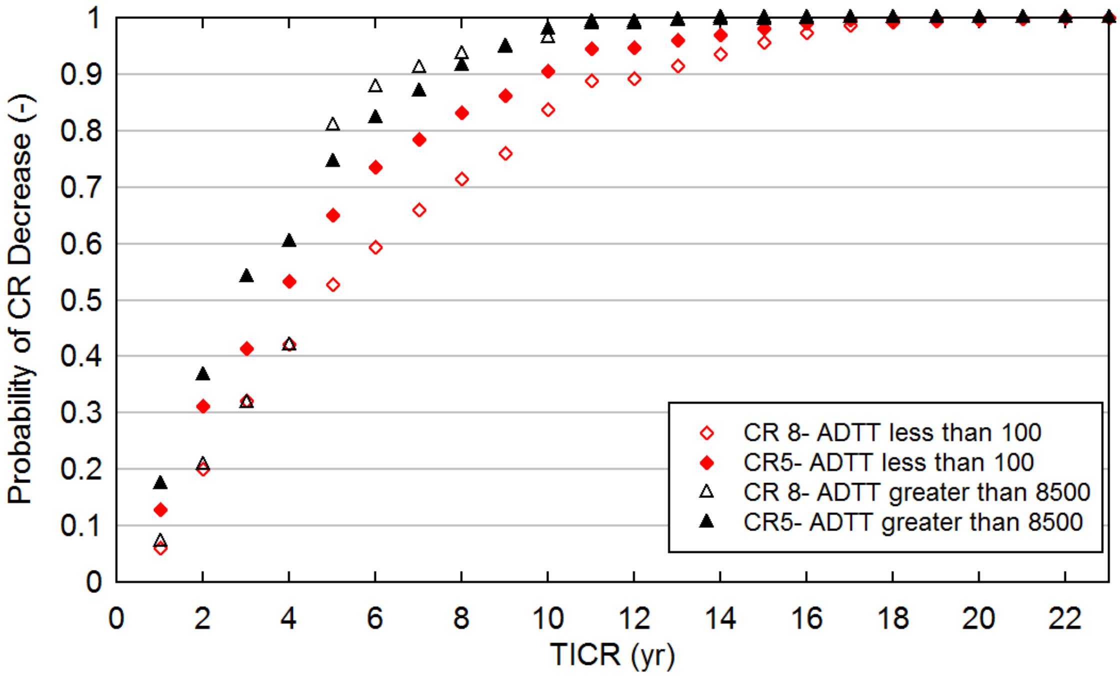


Figure 7.10: Probability of CR decrease for CR = 5 and 8 for ADTT < 100 and ADTT > 8,500.

Some conclusions follow:

- As expected, CR = 5 and 8 probabilities for ADTT < 100 are below those of CR = 5 and 8 for ADTT > 8,500, respectively, as bridge decks having high ADTT are expected to have a higher probability of CR decrease.

- A bridge deck with CR = 8 having ADTT > 8,500 has a lower probability of CR decrease than one with CR = 5 with ADTT > 8,500, up until TICR = 5. Moreover, a deck with CR = 8 having ADTT > 8,500 shows a substantial jump from TICR 4 to 5, a change not observed when the authors considered CR = 9, 7, or 6.

7.5.3 Maintenance Responsibility

Four different maintenance responsibility entities were considered: State Highway Agency, County Highway Agency, Town or Township Highway Agency, City or Municipal Highway Agency, and State Toll Authority. Two sets of curves were plotted, one for CR = 8 (Fig. 7.11) and the other for CR = 5 (Fig. 7.12), to avoid overcrowded plots.

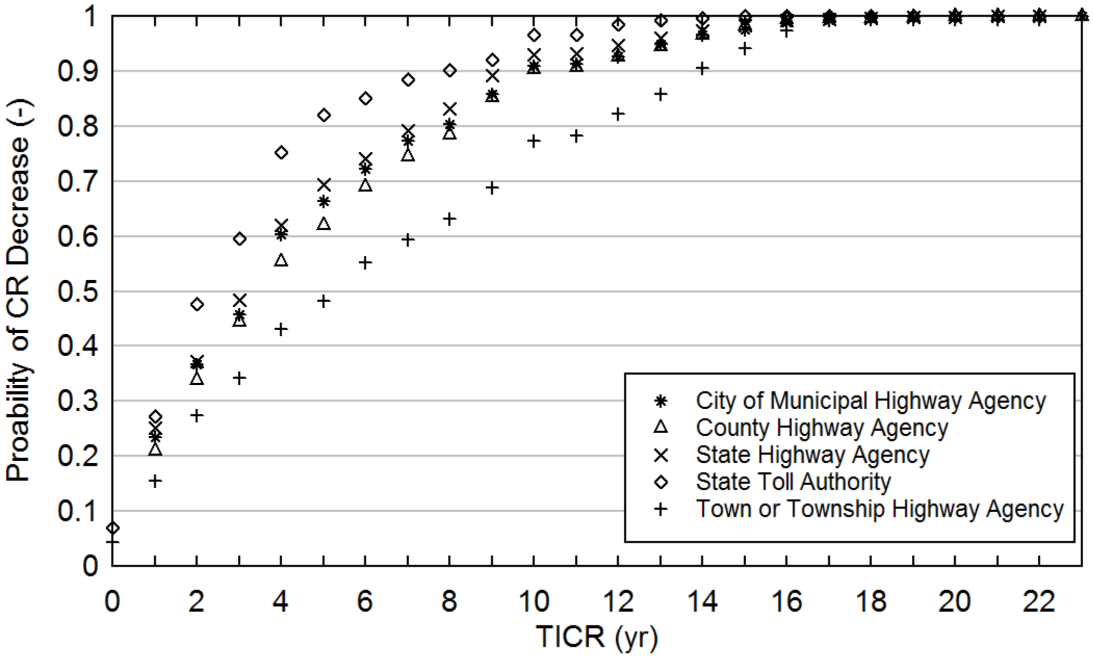


Figure 7.11: Probability of CR decrease for maintenance responsibility (CR = 8).

Based on Figure 7.11, bridge decks associated with Town Highway Agency have the lowest probability of CR decrease, and bridge decks from the State Toll Authority bridges the highest one. Bridge decks under City of Municipal Highway Agencies, County Highway Agencies, and State Highway Agencies have similar probabilities of CR decrease, with those of County Highway Agencies having the lowest one, located in between Town and State Toll. Because this model was used to measure true deck deterioration, we can conclude from these results that the construction practices, deck protection mechanisms, and repair/rehabilitation methods used by different agencies across the US varies, with State Toll Authorities underperforming(has the highest probabilities). This model can be adopted by individual states in order to analyze performance of their agencies.

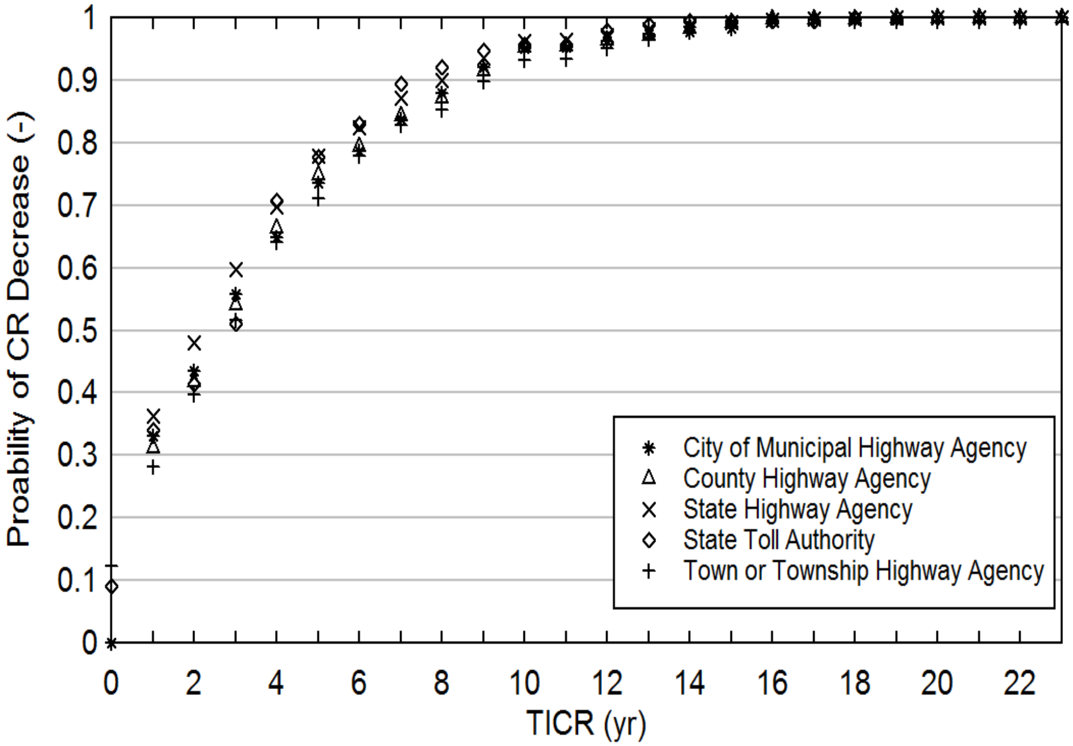


Figure 7.12: Probability of CR decrease for maintenance responsibility (CR = 5).

From Figure 7.12 we can observe close proximity for all probability of CR decrease curves for bridge decks having CR = 5, with town’s having the lowest probabilities. State toll and highway agencies have the highest probabilities (interchangeably throughout the 23 years). Also examined, though not plotted, is a comparison of CR = 8 with CR = 5, those of CR = 8 show a lower probability than those of CR = 5 with the exception that for state toll highway agencies CR = 8 had a higher probability of CR decrease compared to CR = 5. It is uncommon for CR = 8 bridges to have a higher probability of CR decrease than those of CR = 5. This it might have been due to the deterioration mechanisms, construction practices and, design specification associated with those bridge decks.

7.5.4 Deck Structure Type

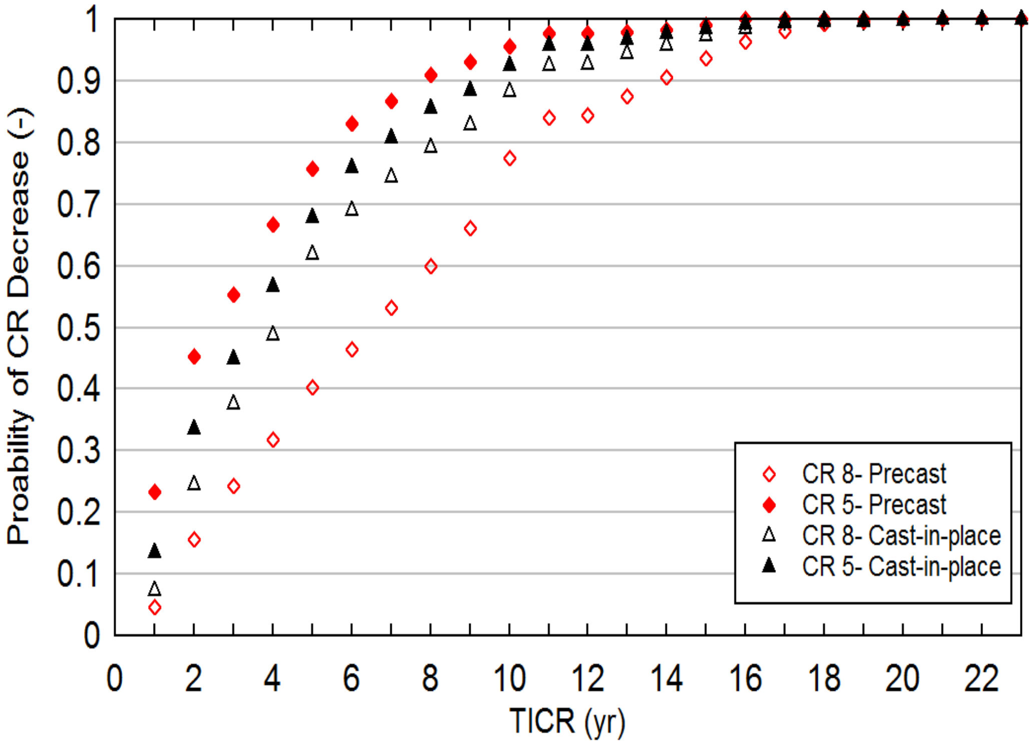


Figure 7.13: Probability of CR decrease for CR 5 and CR 8 for precast and cast-in-place bridge decks.

For both precast and cast-in-place decks, bridge decks with CR = 8 have a lower probability of CR decrease than those with CR = 5, as might be expected. Moreover, a CR = 8 for a precast bridge decks have a much lower probability of CR decrease than those of a cast-in-place bridge decks, also as expected, as precast structures are usually constructed in and controlled environment of a factory. A CR = 5 for a precast deck has a higher probability of CR decrease than a cast-in-place deck.

7.5.5 Climatic Regions

Based on the results from the one-way statistical analysis (chapter 3) and logistic regression (chapter 6) we noticed that climatic region is an important parameter influencing concrete bridge deck performance. “very hot” and “very cold” climatic regions were chosen for comparison in this analysis. Areas of extreme heat and cold were focused on here and since the “very hot” climate zone is mainly in the South (Fig. 7.3), an area that experiences little snow as compared to the “very cold” climatic zone, which experiences significant amounts of snow.

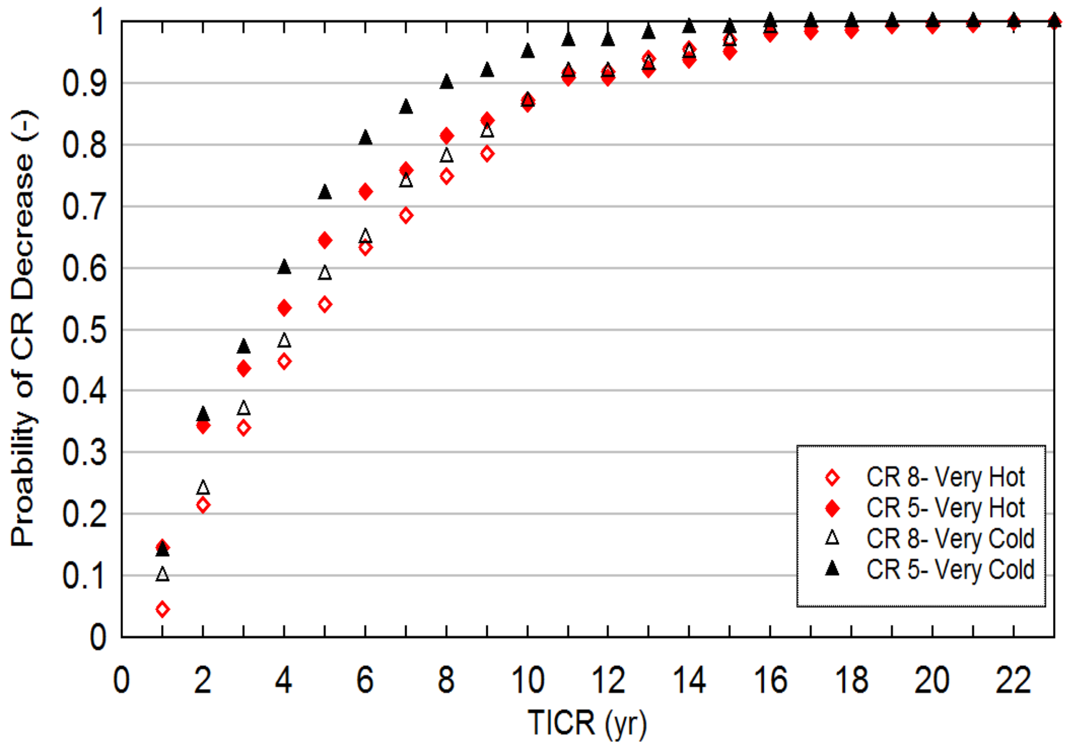


Figure 7.14: Probability of CR decrease for CR =5 and CR = 8 for Very Hot and Very Cold climatic regions.

As can be observed in Figure 7.14, bridges in the “very hot” climatic region having a CR = 8 and 5 have a lower probability of CR decrease than those having a CR = 8 and 5 and in the “very cold” climatic region, respectively. This is reasonable because of the absence of snow in the latter region. Bridge decks with CR = 8 have a noticeably lower probability of decrease than CR 5 bridges irrespectively of the climatic region they are located in.

7.6 Conclusions

This paper introduces a Bayesian methodology to develop probability of CR decrease curves for the concrete highway bridge decks using the nationwide database in Chapter 4. The advantage of this model is that future inspection data can be used to update the probability curves. Furthermore, the results of this study can be used as priors in other Bayesian studies that use different kinds of information to model CR deterioration. In an example, the paper illustrates how prior information could influence a posterior outcome. The conclusion is that confident prior information with narrow HDI (high density intervals at 95%) meaningfully influence the posterior distribution. Moreover, prior information lacking in confidence (i.e., having broad HDI intervals) tends to have no influence on the posterior distribution. The paper further shows the effects of ADTT, maintenance responsibility fulfillment, deck structure type, and climatic region on CR decrease. The objective of this paper was to 1) introduce a Bayesian model to predict probability of CR decrease for concrete bridge decks, and 2) to demonstrate a network-level analysis of concrete bridge deck performance. Results from this model can be compared with other models adopted from bridge management systems such as AASHTOWARE.

Chapter 8

CONCLUSIONS

8.1 Summary and Principal Findings

This research introduced a nationwide database for concrete highway bridge decks for the United States based on the NBI data and additional parameters: deck area, National Centers for Environmental Information (NCEI) Climatic Regions, International Energy Conservation Code (IECC) Climatic Regions, distance to seawater, and bridge age. This nationwide database is based on two performance parameters developed from the NBI concrete bridge deck ratings (CR): time-in-condition rating (TICR) and deterioration rate (DR). A two-step cluster analysis was then introduced to visualize associations between concrete bridge deck design parameters and bridge deck condition ratings. Next, a logistic regression (LR) based on the nationwide database was developed. The aim of the LR was to link environmental and deck design parameters, examine how these parameters affect bridge deck deterioration, and use the logistic model to predict the likelihood of bridge decks being in the highest deterioration group. Lastly, a Bayesian methodology was then developed (based on the nationwide database) for the US to predict how long CR last before deteriorating. The results of this study can be used as priors in future Bayesian studies that employ different kinds of information to model CR. The advantage of this model is that is exclusively accounts for history of CR something that is not achieved by the Markovian model.

The following conclusions can be made from the results of this study:

8.1.1 Chapter 4

Box-and-Whisker plots and means with 95% confidence intervals of 11 parameters (maintenance responsibility, functional classification, structural material/design, type of design and/or construction, deck structure type, type of wearing surface, type of membrane, deck protection, average daily truck traffic (ADTT), international energy conservation code (IECC) climatic regions, and distance to sweater) from the nationwide database were compared for CR 5 and 8. The following conclusions can be made:

1. As CR decreases from (7 to 4) DR increases and TICR decreases. With the exception of CR = 9 where the TICR is significantly lower and DR is significantly higher for any of 6 < CR < 8. Moreover, CR = 8 average TICR was slightly less than CR 7.

2. CR = 8 has a higher TICR than CR = 5 for nearly all categories, which may be interpreted as bridge decks with lower CR deteriorate faster compared to ones with higher CR.

3. Lower ADTT is associated with higher TICR for both CR = 5 and 8.

4. Bridge decks that are further away from seawater have a higher TICR for both CR = 5 and 8.

5. Rural bridge decks show a higher TICR than urban ones for both CR = 5 and 8.

6. Bridge decks on simple span bridges have a higher TICR compared to the ones supported by continuous span bridges for both TICR = 5 and 8.

8.1.2 Chapter 5

A Two-step cluster based on 9,809 concrete highway bridge decks in the Northeast climatic region was developed. Traffic volume and concrete deck design parameters were both taken into consideration. The following conclusions can be made:

7. Cast-in-place bridge decks that have a bituminous wearing surface, a preformed fabric membrane, and epoxy-coated reinforcement protection are strongly associated with high bridge deck condition ratings regardless of the average daily truck traffic (ADTT).
8. Conversely, results show that bridges with cast-in-place bridge decks that have a bituminous wearing surface but have neither a deck membrane nor deck reinforcement protection are strongly associated with low bridge deck CRs regardless of ADTT.

8.1.3 Chapter 6

Logistic regression model was developed based on 3,296 observations extracted from a nationwide database. DR (“lowest DR” and “highest DR”) was used as the dependent variable, while ADTT, climatic region, functional classification of inventory route, and distance from seawater, type of design and construction and maintenance responsibility were used as independent variables. The following conclusions can be made:

9. Based on the odds ratio and elasticities, bridge decks that have higher ADDT or are categorized as “urban” have higher odds/probabilities of being associated with “highest DR”.
10. As a climatic region becomes colder, bridge decks have higher odds of being associated with “highest DR”.
11. Decks further away from seawater have lower probabilities of being of being associated with “highest DR”.
12. Type of construction and maintenance responsibility are additional parameters affecting the model.

8.1.4 Chapter 7

Bayesian methodology was developed to predict the probability of CR decrease for the concrete highway bridge decks using the nationwide database. Based on the Bayesian model the research concluded that confident prior information influences posterior outcome (probability of CR decrease). Moreover, prior information lacking in confidence tends to have no influence on the posterior outcome (probability of CR decrease). The effects of ADTT, maintenance responsibility fulfillment, deck structure type, and climatic region on CR decrease were studied. The following conclusions can be made:

Entire Country

13. The curve flattens after 12 years as most CR do not have a TICR > 12. In fact, based on our nationwide dataset, 92% of all bridges rated for all condition have a TICR < 12 years.

14. CR = 9 bridges have the highest probabilty for the CR to decrease over time. This makes sense because when the authors spoke with bridge inspectors and other professionals in the field, it became evident that only new bridges are assigned a CR = 9 (see discussion in section 2.9) . Aditionally, they are typically downgraded to a lower CR quickly, e.g. after experiencing minor surface cracks.

15. Bridge decks with CR = 8 bridges have a higher probability to decrease than those with CR = 7. This was also found to be consistent with expert opinion.

16. CR = 7 has the lowest probability of decrease, or, in other words, shows the longest TICR probabilities.

17. CR = 4 exhibits a relatively large jump from TICR = 1 to 2 to 3, from 18% to 42% to 53% respectively. This implies that concrete bridge decks with CR = 4 should be repaired immediately, given that CR = 3 may represent a safety problem.

ADTT

18. As expected, CR = 5 and 8 probabilities for ADTT < 100 are below those of CR = 5 and 8 for ADTT > 8,500, respectively, as bridge decks having high ADTT are expected to have a higher probability of CR decrease.

19. A bridge deck with CR = 8 having ADTT > 8,500 has a lower probability of CR decrease than one with CR = 5 with ADTT > 8,500, up until TICR = 5. Moreover, a deck with CR = 8 having ADTT > 8,500 shows a substantial jump from TICR 4 to 5, a change not observed when the authors considered CR = 9, 7, or 6.

Maintenance Responsibility

20. Based on CR 8: Bridge decks associated with Town Highway Agency have the lowest probability of CR decrease, and bridge decks from the State Toll Authority bridges the highest one. Bridge decks under City of Municipal Highway Agencies, County Highway Agencies, and State Highway Agencies have similar probabilities of CR decrease, with those of County Highway Agencies having the lowest one, located in between Town and State Toll. State Toll Authorities is underperforming (has the highest probabilities of CR decrease).

21. Based on CR 5: close proximity for all probability of CR decrease curves, with town's having the lowest probabilities. State toll and highway agencies have the highest probabilities (interchangeably throughout the 23 years).

22. Comparison between CR = 8 with CR = 5, showed, those of CR = 8 show a lower probability than those of CR = 5 with the exception that for state toll highway agencies CR = 8 had a higher probability of CR decrease compared to CR = 5.

Deck Structure Type

23. For both precast and cast-in-place decks, bridge decks with CR = 8 have a lower probability of CR decrease than those with CR = 5.

24. CR = 8 for a precast bridges deck have a much lower probability of CR decrease than those of a cast-in-place bridge decks.

25. CR = 5 for a precast deck has a higher probability of CR decrease than a cast-in-place deck

Climatic Region

26. Bridges in the “very hot” climatic region having a CR = 8 and 5 have a lower probability of CR decrease than those having a CR = 8 and 5 and in the “very cold” climatic region, respectively.
27. Bridge decks with CR = 8 have a noticeably lower probability of decrease than CR 5 bridges irrespectively of the climatic region they are located in.

8.2 Recommendation for Future Work

We believe that the proposed nationwide database can be used in the future to develop other advanced statistical models such as Bayesian hierarchical survival analysis and tensor factorization, deterioration models such as Markovian and stimulation models, and machine learning algorithms such as neural networks to get a better understanding of the effects of various parameters and develop new deterioration models for US concrete bridge decks. Furthermore, this database does not contain certain critical parameters such as structural design characteristics (e.g., minimum deck thickness, reinforcement bar size, bar spacing), construction practices (e.g., concrete temperature, placement procedure, curing practices), specifications (e.g., water-to-cement ratio and minimum cementitious material content), and other notable factors (e.g., application of deicing salts). We would advise future research to try to incorporate such factors into the database in order to get an even better understanding of the factors affecting bridge deck deterioration and to better model concrete bridge deck deterioration.

REFERENCES

[1] ASCE | 2013 Report Card for America's Infrastructure. (n.d.). Retrieved September 23, 2014, from http://www.infrastructurereportcard.org/cat-item/bridges/

[2] Li, Victor C.; Zhang, J.(2000). "Approaches to Enhancing Concrete Bridge Deck Durability" Proceedings of the Durability Workshop: Long Term Durability of Structural Materials, in Proceedings of the Durability Workshop: Long Term Durability of Structural Materials, Berkeley, CA, October, 2000, pp. 11-22.

[3] Williamson, G., Weyers, R. E., Brown, M. C., Sprinkel, M. M., Virginia Transportation Research Council., & Virginia. (2007). *Bridge deck service life prediction and costs*. Charlottesville, Va: Virginia Transportation Research Council.

[4] ACI Committee 365. (2000). *Service life prediction: State-of-the art report*. Farmington Hills, Mich: American Concrete Institute.

[5] Azizinamini, A., National Research Council (U.S.). & Second Strategic Highway Research Program (U.S.). (2014). *Design guide for bridges for service life*.

[6] Stewart, M. G., & Rosowsky, D. V. (January 01, 1998). Time-dependent reliability of deteriorating reinforced concrete bridge decks. *Structural Safety, 20,* 1, 91-109.

[7] Hansen, E. J., & Saouma, V. E. (January 01, 1999). Numerical simulation of reinforced concrete deterioration: part II: steel corros. *Aci Materials Journal May/jun, 96,* 3, 331-338.

[8] Williamson, G. S. (2007). *Service life modeling of Virginia bridge decks*. Blacksburg, Va.: University Libraries, Virginia Polytechnic Institute and State University.

[9] Life-365™ Consortium III (2008). Life-365 Service Life Prediction Model™ and Computer Program for Predicting the Service Life and Life-Cycle Costs of Reinforced Concrete Exposed to Chlorides (Rep.).

[10] Bentz, E. C. (January 01, 2003). Probabilistic Modeling of Service Life for Structures Subjected to Chlorides. *Aci Materials Journal, 100,* 391-397.

[11] Stewart, M. G., & Rosowsky, D. V. (December 01, 1998). Structural Safety and Serviceability of Concrete Bridges Subject to Corrosion. *Journal of Infrastructure Systems, 4,* 4, 146-155.

[12] Alice, Michy. "How to Perform a Logistic Regression in R." DataScience+. N.p., 13 Sept. 2015. Web. 15 Feb. 2017.

[13] Kyle, N. L. (2001). *Subsidence cracking of concrete over steel reinforcement bar in bridge decks*. Blacksburg, Va.: University Libraries, Virginia Polytechnic Institute and State University.

[14] Tonias, D. E. (1995). *Bridge engineering: Design, rehabilitation, and maintenance of modern highway bridges*. New York: McGraw-Hill.

[15] Kirkpatrick, T. J., Weyers, R. E., Anderson-Cook, C. M., & Sprinkel, M. M. (January 01, 2002). Probabilistic model for the chloride-induced corrosion service life of bridge decks. *Cement and Concrete Research, 32,* 12, 1943.

[16] Kassir, M. K., & Ghosn, M. (January 01, 2002). Chloride-induced corrosion of reinforced concrete bridge decks. *Cement and Concrete Research, 32,* 1, 139-143.

[17] Vu, K. A. T., & Stewart, M. G. (January 01, 2000). Structural reliability of concrete bridges including improved chloride-induced corrosion models. *Structural Safety, 22,* 4, 313-333.

[18] Yannis, G., Laiou, A., Vardaki, S., Papadimitriou, E., Dragomanovits, A., & Kanellaidis, G. (January 01, 2011). Parameters affecting seat belt use in Greece. *International Journal of Injury Control and Safety Promotion, 18,* 3, 189-97.

[19] Russell, H. G., National Cooperative Highway Research Program., American Association of State Highway and Transportation Officials., & National Research Council (U.S.). (2004). *Concrete bridge deck performance*. Washington, D.C: Transportation Research Board.

[20] Violetta, B. (December 01, 2002). Life-365 service life prediction model. *Concrete International, 24,* 12, 53-57.

[21] Wu, N.-C. (2010). An exploratory data analysis of national bridge inventory.

[22] Organisation for Economic Co-operation and Development. (1989). *Durability of concrete road bridges: Report*. Paris, France: Organisation for Economic Co-operation and Development.

[23] Xanthakos, P. P. (1996). *Bridge strengthening and rehabilitation*. Upper Saddle River, N.J: Prentice Hall PTR.

[24] Statictical Solutions. (n.d.). Assumptions of Logistic Regression. Retrieved January, 2017, from http://www.statisticssolutions.com/assumptions-of-logistic-regression/

[25] Ehlen, M. A., Thomas, M. D. A., & Bentz, E. C. (January 01, 2009). Life-365 Service Life Prediction Model^{TM} Version 2.0 - Widely used software helps assess uncertainties in concrete service life and life-cycle costs. *Concrete International : Design & Construction, 31*, 5, 41.

[26] N. Sauer. (2014). *Stadium Overview* [Powerpoint slides].

[27] Marchand, J. (May 01, 2001). Modeling the behavior of unsaturated cement systems exposed to aggressive chemical environments. *Materials and Structures : Matériaux Et Construction, 34*, 4, 195-200.

[28] James, G., Witten, D., Hastie, T., & Tibshirani, R. (2015). *An introduction to statistical learning: With applications in R*.

[29] Markow, M. J. (2009). NCHRP Synthesis 397: Bridge Management Systems for Transportation Agency Decision Making. Place of publication not identified: publisher not identified.

[30] FHWA. (1995). *Recording and coding guide for the structure inventory and appraisal of the nation's bridges*. Washington, D.C: U.S. Dept. of Transportation, Federal Highway Administration.

[31] Burkan Isgor, (2014) Current Challenges and Future Direction in the Measurement of Corrosion in Reinforced Concrete Structures.

[32] Wong, C. H. (October 01, 2004). Contractor Performance Prediction Model for the United Kingdom Construction Contractor: Study of Logistic Regression Approach. *Journal of Construction Engineering and Management*, 130, 5, 691-698.

[33] Hatami, A., Morcous, G., University of Nebraska--Lincoln., & Nebraska. (2011).*Developing deterioration models for Nebraska bridges*. Lincoln, Neb: University of Nebraska-Lincoln.

[34] Broach, J. (2012, May). Discrete Choice Modeling: Theoretical Assumptions and Transportation Applications. Retrieved February 28, 2017, from https://drive.google.com/file/d/0B8GGT7br4AVqRWplaEhDbHlGUnM/view

[35] Ulfarsson, G. F., & Mannering, F. L. (January 01, 2004). Differences in male and female injury severities in sport-utility vehicle, minivan, pickup and passenger car accidents. *Accident Analysis and Prevention, 36,* 2, 135-147.

[36] Nasrollahi, M., & Washer, G. (September 01, 2015). Estimating Inspection Intervals for Bridges Based on Statistical Analysis of National Bridge Inventory Data. *Journal of Bridge Engineering, 20,* 9.

[37] Attoh-Okine, N. O., & Bowers, S. (June 01, 2006). A Bayesian belief network model of bridge deterioration. *Proceedings of the Institution of Civil Engineers - Bridge Engineering, 159,* 2, 69-76.

[38] Frangopol, D. M., & Estes, A. C. (January 01, 1999). Optimum Lifetime Planning of Bridge Inspection and Repair Programs. *Structural Engineering International, 9,* 3, 219-224.

[39] Virginia Department of Transportation. (n.d.). Retrieved November 15, 2015, from http://www.virginiadot.org/info/contactus.asp

[40] AASHTOWare Bridge Management -. (n.d.). Retrieved November 15, 2015, from http://aashtowarebridge.com/

[41] Kruschke, J. K. (2011). *Doing Bayesian data analysis: A tutorial with R and BUGS*. Burlington, MA: Academic Press.

[42] Kang, T. H.-K., & Mitra, N. (August 01, 2012). Prediction of performance of exterior beam-column connections with headed bars subject to load reversal. *Engineering Structures, 41*, 209-217.

[43] Hensher, D. A., Rose, J. M., & Greene, W. H. (2015). *Applied choice analysis: A primer*. Cambridge [u.a.: Cambridge Univ. Press.

[44] Agrawal A.K., Kawaguchi A., & Chen Z. (2010). Deterioration rates of typical bridge elements in New York. *Journal Of Bridge Engineering*, *15*(4), 419-429. doi:10.1061/(ASCE)BE.1943-5592.0000123

[45] Bolukbasi, Melik, Mohammadi, Jamshid,Arditi, David,. (2004). Estimating the future condition of highway bridge components using national bridge inventory data. *Periodical on Structural Design and Construction*, 9(1), 16-25.

[46] Dekelbab, W., Al-Wazeer, A., & Harris, B. (May 01, 2008). History lessons from the national bridge inventory. *Public Roads, 71,* 6.

[47] Tae-Hoon, H., Seung-Hyun, C., Seung-Woo, H., & Sang-Youb, L. (July 01, 2006). Service Life Estimation of Concrete Bridge Decks. *Ksce Journal of Civil Engineering, 10,*4, 233-241.

[48] Tabatabai, H., Lee, C.-W., & Tabatabai, M. (January 01, 2011). Reliability of bridge decksin Wisconsin. *Journal of Bridge Engineering, 16,* 1, 53-62.

[49] Karl, T., Koss, W. J., & National Climatic Data Center (U.S.). (1984). *Regional and national monthly, seasonal, and annual temperature weighted by area, 1895-1983*. Asheville, N.C: National Climatic Data Center.

[50] Abed-Al-Rahim, I. J., & Johnston, D. W. (1995). Bridge Element Deterioration Rates. *Transportation Research Record,* (1490), 9.

[51] UCLA. (n.d.). How are the likelihood ratio, Wald, and Lagrange multiplier (score) tests different and/or similar? Retrieved February 20, 2017, from http://www.ats.ucla.edu/stat/mult_pkg/faq/general/nested_tests.htm

[52] Morcous, G., Rivard, H., & Hanna, A. M. (September 01, 2002). Modeling Bridge Deterioration Using Case-based Reasoning. *Journal of Infrastructure Systems, 8,* 3, 86-95.

[53] Koch, G. H., United States., CC Technologies Laboratories., NACE International., & Turner-Fairbank Highway Research Center. (2002). *Corrosion cost and preventive strategies in the United States*. McLean, Va. (6300 Georgetown Pike, McLean 22101-2296: U.S. Dept. of Transportation, Federal Highway Administration, Research, Development, and Technology, Turner-Fairbank Highway Research Center.

[54] FHWA. (2016). Highway Bridges by Deck Structure Type 2016. Retrieved March 19, 2017, from https://www.fhwa.dot.gov/bridge/nbi/no10/deck16.cfm

[55] Krauss, P. D., Rogalla, E. A., National Research Council (U.S.)., American Association of State Highway and Transportation Officials., United States., & National Cooperative Highway Research Program. (1996). *Transverse cracking in newly constructed bridge decks*. Washington, D.C: National Academy Press.

[56] Weyers, R. E., & Strategic Highway Research Program (U.S.). (1993). *Concrete bridge protection, repair, and rehabilitation relative to reinforcement corrosion: A methods application manual*. Washington, DC: Strategic Highway Research Program, National Research Council.

[57] International Code Council. (2009). *IECC international energy conservation code 2009*. Country Club Hills, Ill: International Code Council.

[58] Radovic, M., Ghonima, O., & Schumacher, T. (July 20, 2016). Data Mining of Bridge Concrete Deck Parameters in the National Bridge Inventory by Two-Step Cluster Analysis. *Asce-asme Journal of Risk and Uncertainty in Engineering Systems, Part A: Civil Engineering,* 12.)

[59] Birnbaum, Z. W., & Saunders, S. C. (August 14, 1969). A new family of life distributions. *Journal of Applied Probability, 6,* 2, 319-327.

[60] Mathew, A. (2015, August 17). Evaluating Logistic Regression Models. Retrieved February 20, 2017, from https://www.r-bloggers.com/evaluating-logistic-regression-models/

[61] Alice, M. (2015, September 15). Predicting creditability using logistic regression in R: cross validating the classifier (part 2). Retrieved February 20, 2017, from http://firsttimeprogrammer.blogspot.com/2015/09/predicting-creditability-using-logistic_15.html

[62] Morcous, G. (May 01, 2006). Performance Prediction of Bridge Deck Systems Using Markov Chains. *Journal of Performance of Constructed Facilities, 20,* 2, 146-155.

[63] Cady, P. D. and Weyers, R. E., Chloride Penetration and the Deterioration of Concrete Bridge Decks, *Cement, Concrete, and Aggregates,* CCAGDP, Vol. 5, No. 2, Winter 1983, pp. 81-87.

[64] FHWA. (2004). “NBIS regulations.” Washington, DC.

[65] Henchi, K., Samson, E., Chapdelaine, F., & Marchand, J. (January 01, 2007). Advanced Finite-Element Predictive Model for the Service Life Prediction of Concrete Infrastructures in Support of Asset Management and Decision-Making.

[66] Mitchell, D., & Frohnsdorff, G. (January 01, 2004). Service-Life Modeling and Design of Concrete Structures for Durability. *Concrete International Detroit-, 26,* 12, 57-63.

[67] Tan, P., Steinbach, M., and Kumar, V. (2006). *Introduction to data mining*, Pearson Addison Wesley, Boston.

[68] TRB (Transportation Research Board). (1979). Durability of concrete bridge decks. *Natl. Cooperative Highway Res. Program Rep. Synth. Highway Pract.*, 57(1), 1–57.

[69] Adarkwa, O., Schumacher, T., and Attoh-Okine, N., (October 01, 2014). Multiway Analysis of bridge structural types in the National Bridge Inventory (NBI): A tensor decomposition approach. 1-6.

[70] IBM.(2016).*Two-step cluster analysis*.⟨https://www.ibm.com/support/knowledgecenter/SSLVMB_20.0.0/com.ibm.spss.statistics.help/alg_twostep.htm⟩ (Jun. 29, 2016).

[71] Bacher, J.,Wenzig, K., and Vogler,M. (2004). SPSS *TwoStep cluster-a first evaluation*, Lehrstuhl für Soziologie, Nürnberg, Germany.

[72] FHWA (Federal Highway Administration). (2015). National bridge inventory (NBI) dataset. ⟨http://www.fhwa.dot.gov/bridge/nbi/ascii .cfm⟩ (Feb. 1, 2015).

[73] Kaufman, L., & Rousseeuw, P. J. (1990). *Finding groups in data: An introduction to cluster analysis*. New York: Wiley.

[74] Michigan Department of Transportation . (n.d.). NBI Rating Guidlines. Retrieved January, 2017, from https://www.michigan.gov/documents/mdot/MDOT_BIR_Ratings_Guide_367482_7.pdf

[75] NOAA and NCEI (National Oceanic and Atmospheric Administration and National Centers for Environmental Information). (2015). “U.S. climate regions.” ⟨http://www.ncdc.noaa.gov/monitoring-references/maps/us -climate-regions.php⟩ (Feb. 10, 2015).

[76] Krauss, P.D. and E.A. Rogalla, NCHRP Report 380: *Transverse Cracking in Newly Constructed Bridge Decks*, Transportation Research Board,National Research Council, Washington, D.C., 1996, 126 pp.

[77] Minnesota Department of Transportation. (2016, February 16). Bridge Inspection Field Manual Version 2.0. Retrieved March, 2017, from http://www.dot.state.mn.us/bridge/pdf/insp/bridgeinspectionmanual.pdf

[78] Lu, Y., & Madanat, S. (1994). Bayesian updating of infrastructure deterioration models. *Transportation Research Record*, No. 1442 (1994).

[79] FHWA (Federal Highway Administration). (2015). National bridge inventory (NBI) dataset. ⟨http://www.fhwa.dot.gov/bridge/nbi/ascii .cfm⟩ (Feb. 1, 2015).

[80] FHWA. (2015). Ti:2015 Status of the Nation's Highways, Bridges, and Transit: Conditions & Performance . Retrieved April, 2015, from https://www.fhwa.dot.gov/policy/2015cpr/pdfs/2015cpr.pdf

[81] STATGRAPHICS CENTURION [Computer software]. (n.d.). Retrieved from http://www.statgraphics.com/

[82] RStudio Team (2015). RStudio: Integrated Development for R. RStudio, Inc., Boston, MA URL http://www.rstudio.com/.

[83] FHWA. (n.d.). The Bridge Portal. Retrieved May 01, 2017, from https://fhwaapps.fhwa.dot.gov/ltbpp/

Appendix A

PREPROCESSING ACTIONS PERFORMED ON NATIONWIDE PARAMETERS

Maintenance Responsibility

States the actual names of the agency's responsible for the maintenance of the structures. This parameter consists of 22 groups (as shown in Table A1) with some of them having almost no data. Comment: we show the original and final histogram (Figure A1 and A2) and the groups of each are listed in Table A1.

Table A1: Groups and tabulated frequencies for maintenance responsibility (original dataset).

Code	Item 21 - Maintenance Responsibility	Frequency	Percentage
1	State Highway Agency	137961	57.5
2	County Highway Agency	79235	33.0
3	Town or Township Highway Agency	9053	3.8
4	City or Municipal Highway Agency	8365	3.5
11	State Park, Forest, or Reservation Agency	42	0.0
12	Local Park, Forest, or Reservation Agency	10	0.0
21	Other State Agencies	97	0.0
25	Other Local Agencies	420	0.2
26	Private (other than railroad)	137	0.1
27	Railroad	67	0.0
31	State Toll Authority	4066	1.7
32	Local Toll Authority	139	0.1
60	Other Federal Agencies (not listed below)	3	0.0
61	Indian Tribal Government	0	0.0
62	Bureau of Indian Affairs	112	0.0
63	Bureau of Fish and Wildlife	0	0.0
64	U.S. Forest Service	75	0.0
66	National Park Service	0	0.0
67	Tennessee Valley Authority	0	0.0
68	Bureau of Land Management	0	0.0
69	Bureau of Reclamation	1	0.0
70	Corps of Engineers (Civil)	9	0.0
71	Corps of Engineers (Military)	0	0.0
72	Air Force	0	0.0
73	Navy/Marines	0	0.0
74	Army	0	0.0
75	NASA	0	0.0
76	Metropolitan Washington Airports Service	0	0.0
80	Unknown	2	0.0
	Total	239794	

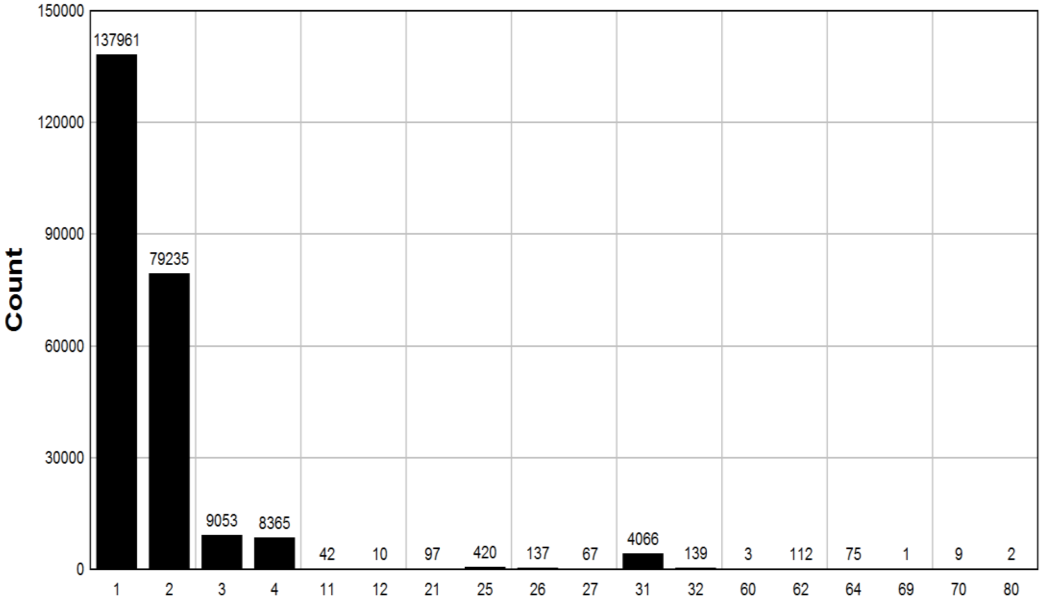


Figure A1: Histogram for maintenance responsibility (original dataset).

After analyzing the histogram, we decided to only consider the following six categories while discarding the others:

- State Highway Agency (Group 1)
- County Highway Agency (Group 2)
- Town or Township Highway Agency (Group 3)
- City of Municipal Highway Agency (Group 4)
- Private (other than railroad) (Group 26)
- State Toll Authority (Group 31)

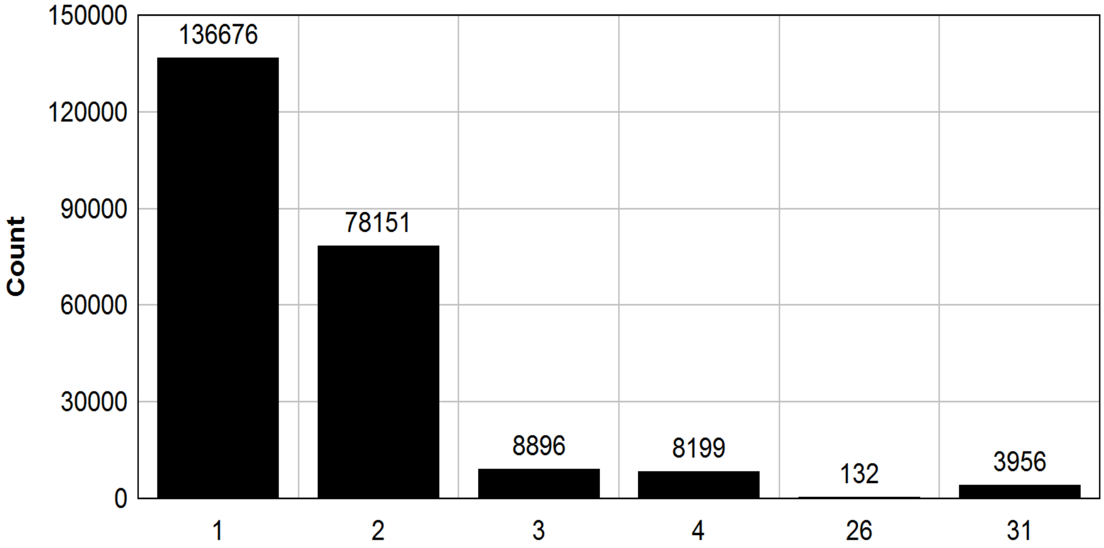


Figure A2: Histogram for maintenance responsibility 1 (final dataset).

Functional Classification of Inventory Route

Table A2: Groups and tabulated frequencies for functional classification of inventory route (original dataset).

Code	Item 26 - Functional Classification of Inventory Route	Frequency	Percentage
	Rural		
1	Principal Arterial - Interstate	19690	8.2
2	Principal Arterial - Other	17477	7.3
6	Minor Arterial	19134	8.0
7	Major Collector	43817	18.3
8	Minor Collector	18923	7.9
9	local	60538	
	Urban		
11	Principal Arterial - Interstate	21031	8.8
12	Principal Arterial – Other Freeways or Expressways	11249	4.7
14	Other Principal Arterial	9123	3.8
16	Minor Arterial	6861	2.9
17	Collector	5308	2.2
19	Local	6643	2.8
	Total	239794	

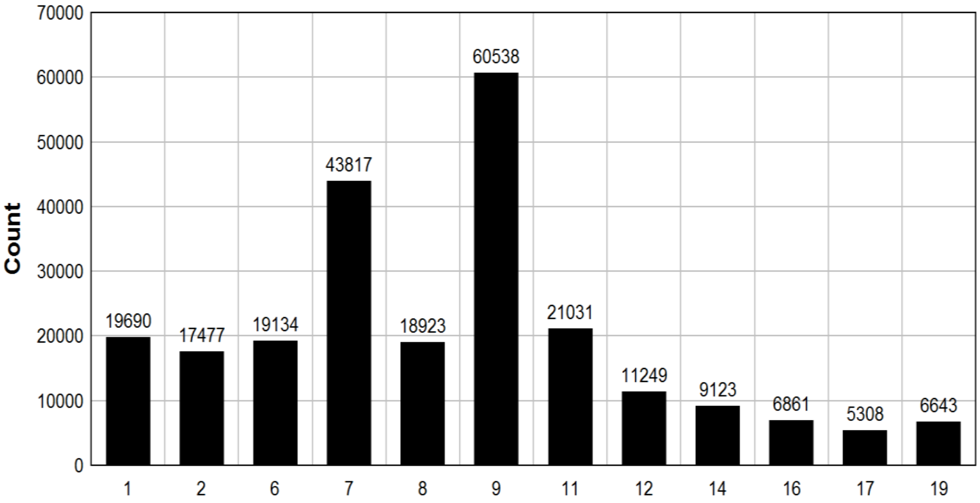


Figure A3: Histogram for functional classification of inventory route (original dataset).

This parameter had 12 groups, some with minor differences. We decided to combine groups 1 to 9 as Rural and groups 11 to 19 as Urban :

1. Rural (Group 1)
2. Urban (Group 2)

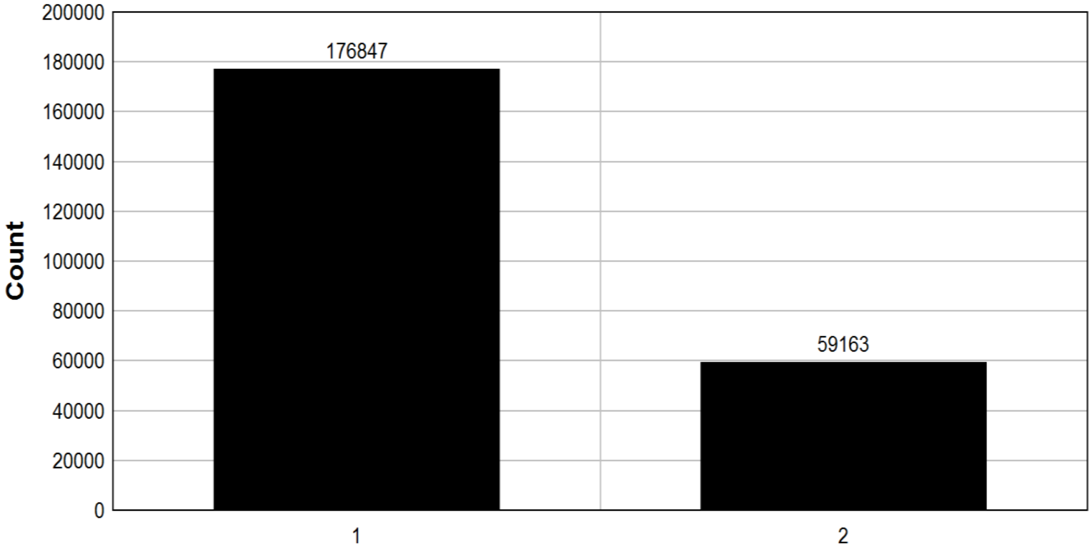
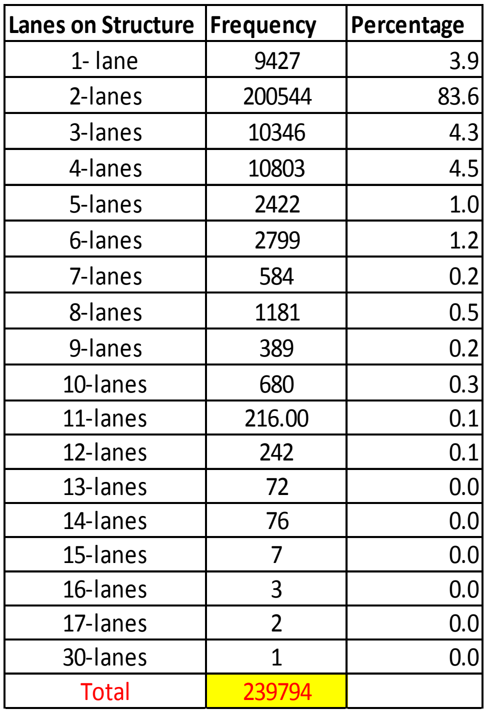


Figure A4: Histogram for functional classification of inventory route (final dataset).

Lanes on Structure

Table A3: Groups and tabulated frequencies for lanes on structure (original dataset).



Lanes on Structure	Frequency	Percentage
1- lane	9427	3.9
2-lanes	200544	83.6
3-lanes	10346	4.3
4-lanes	10803	4.5
5-lanes	2422	1.0
6-lanes	2799	1.2
7-lanes	584	0.2
8-lanes	1181	0.5
9-lanes	389	0.2
10-lanes	680	0.3
11-lanes	216.00	0.1
12-lanes	242	0.1
13-lanes	72	0.0
14-lanes	76	0.0
15-lanes	7	0.0
16-lanes	3	0.0
17-lanes	2	0.0
30-lanes	1	0.0
Total	239794	

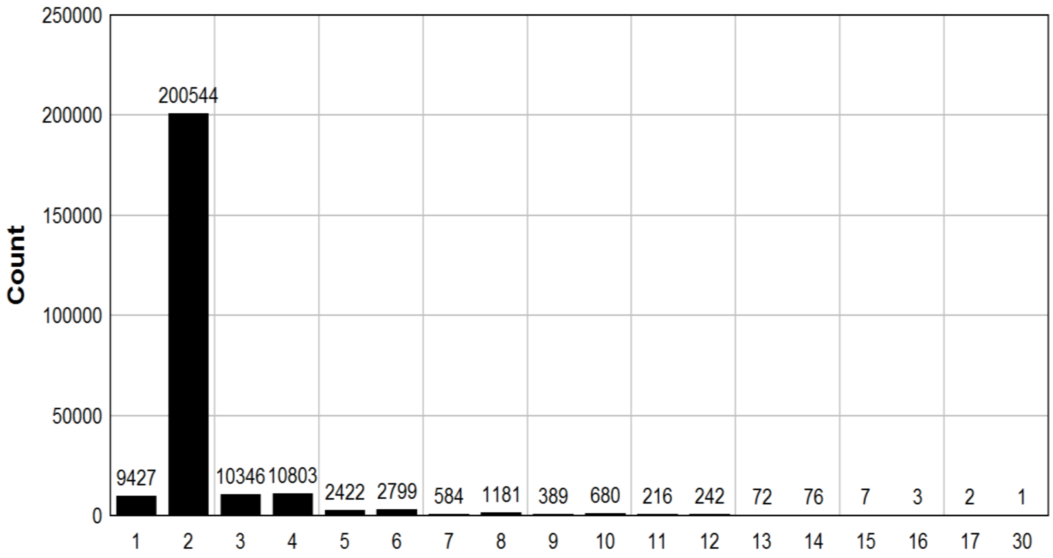


Figure A5: Histogram for lanes on structure (original dataset).

The histogram for this parameter was very strongly skewed with the majority of bridges having 2 lanes. We reduced the number of lane groups (originally there were 18 groups) to 4, combining the number of lanes as follows: 1 and 2, 3 and 4, 5 and 6, and greater than 6 up to 12. Decks with more than 13 lanes were not considered. The groups were as follows:

- 1 and 2 lanes (Group 1)
- 3 and 4 lanes (Group 3)
- 5 and 6 lanes (Group 5)
- 7 and 8 lanes (Group 7)
- 9 and 10 lanes (Group 9)
- 11 and 12 lanes (Group 11)

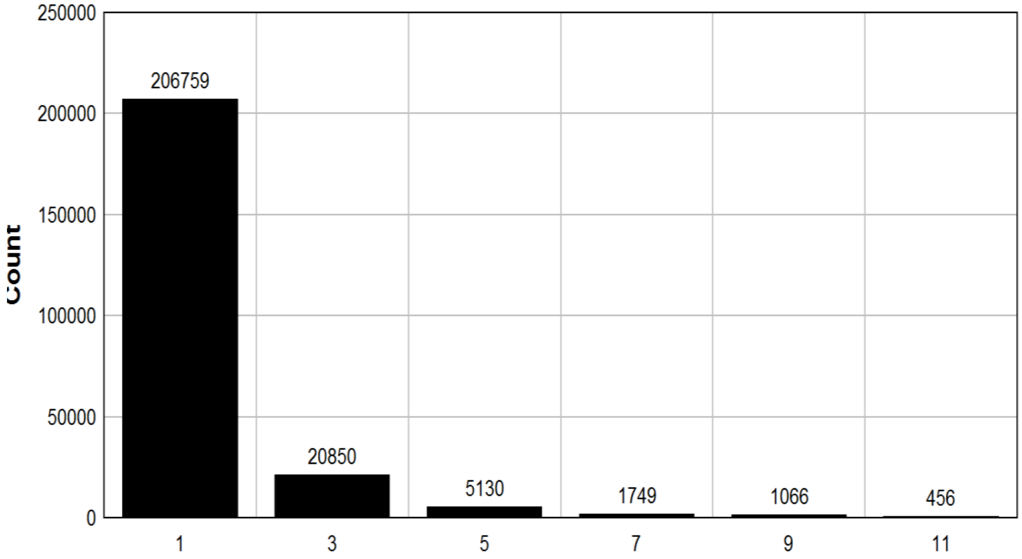


Figure A6: Histogram for lanes on structure (final dataset).

Structural Material/Design

Table A4: Groups and tabulated frequencies for structural material/design (original dataset).

Code	Item 43a Structural Material/design	Frequency	Percentage
0	Other	12	0.01
1	Concrete	49332	20.57
2	Concrete continuous	38849	16.20
3	Steel	54645	22.79
4	Steel continuous	36027	15.02
5	Prestressed concrete	49935	20.82
6	Prestressed concrete continuous	9994	4.17
7	Wood or Timber	964	0.40
8	Masonry	35	0.01
9	Aluminum, Wrought Iron, or Cast Iron	1	0.00
	total	239794	

Some of the groups had very few entries with rare types such as wood/timber, masonry, which were not considered. Only the following configurations are considered:

- 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)

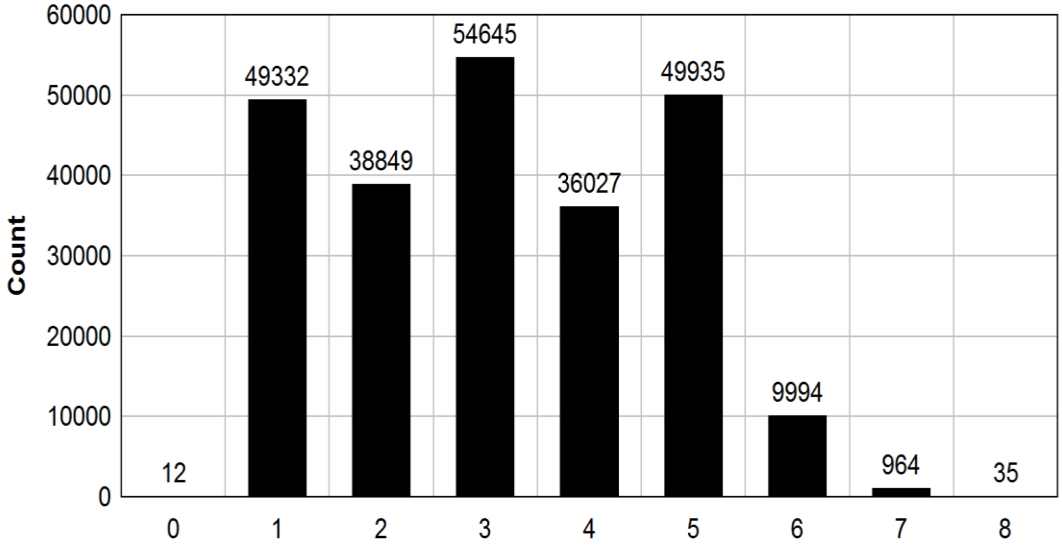


Figure A7: Histogram for structural material/design (original dataset).

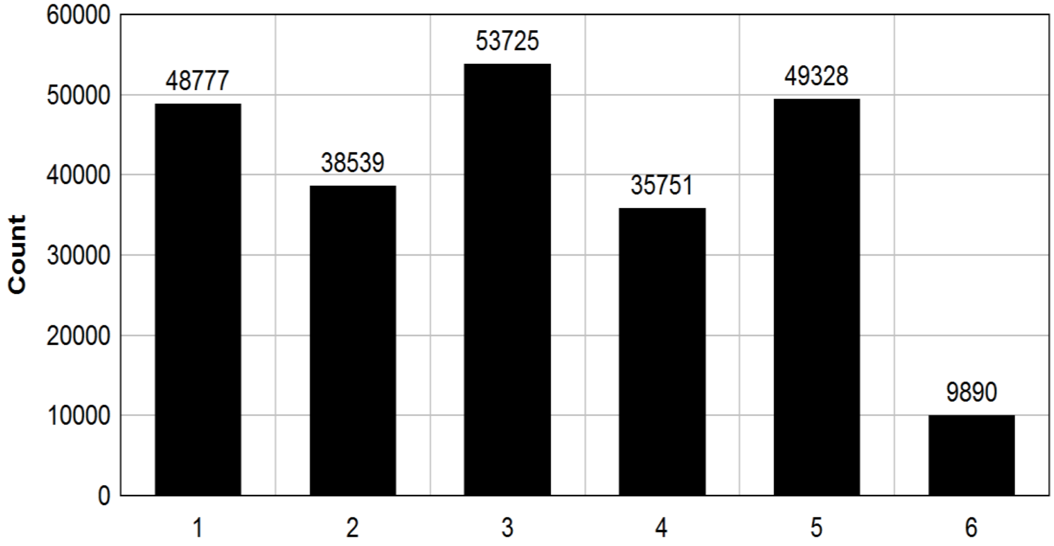


Figure A8: Histogram for structural material/design (final dataset).

Type of Design and/or Construction

Table A5: Groups and tabulated frequencies for type of design and/or construction (original dataset).

Code	Item 43B Type of design and/or construction	Frequency	Percentage
1	Slab	50257	21.0
2	Stringer/Multi-beam or Girder	122478	51.1
3	Girder and Floorbeam System	2905	1.2
4	Tee Beam	21187	8.8
5	Box Beam or Girders – Multiple	27874	11.6
6	Box Beam or Girders - Single or Spread	4219	1.8
7	Frame (except frame culverts)	1550	0.6
8	Orthotropic	12	0.0
9	Truss - Deck	279	0.1
10	Truss – Thru	3017	1.3
11	Arch – Deck	1010	0.4
12	Arch - Thru	150	0.1
13	Suspension	33	0.0
14	Stayed Girder	13	0.0
15	Movable – Lift	13	0.0
16	Movable – Bascule	46	0.0
17	Movable – Swing	39	0.0
18	Tunnel	0	0.0
19	Culvert (includes frame culverts)	4	0.0
20	Mixed types	4	0.0
21	Segmental Box Girder	66	0.0
22	Channel Beam	4405	1.8
0	Other	226	0.1
Nan	Mising Data	7	0.0
	Total	239794	100

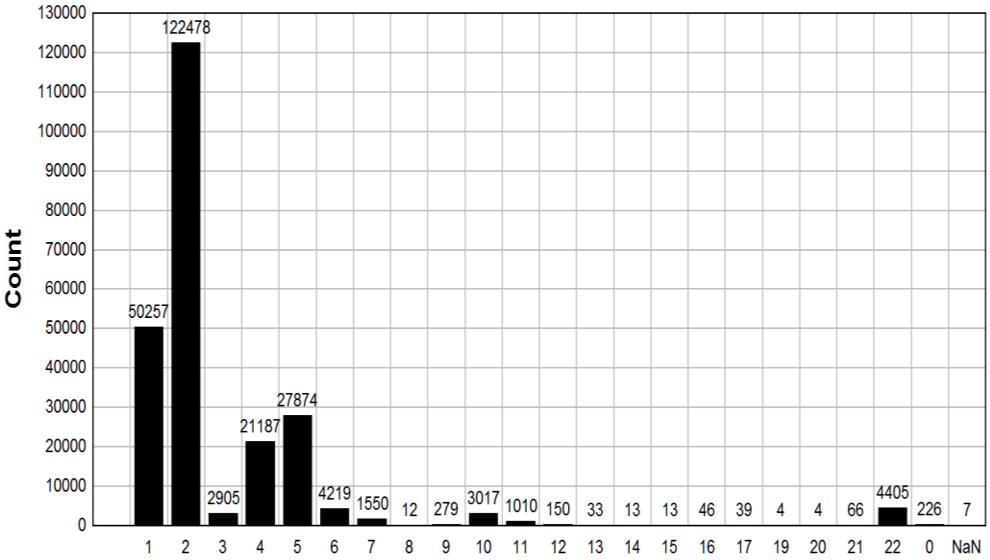


Figure A9: Histogram for type of design and/or construction (original dataset).

This parameter had 24 groups with some of them having very few entries. We decided to disregard any design that has less than 950 data points. The following groups were considered:

- Slab (Group 1)
- Stringer/multi-beam or girder (Group 2)
- Girder and floor beam system (Group 3)
- Tee beam (Group 4)
- Box beam or girders – multiple (Group 5)
- Box beam or girders – single or spread (Group 6)
- Frame (Group 7)
- Truss – through (Group 10)
- Arch – deck (Group 11)

- Channel beam (Group 22)

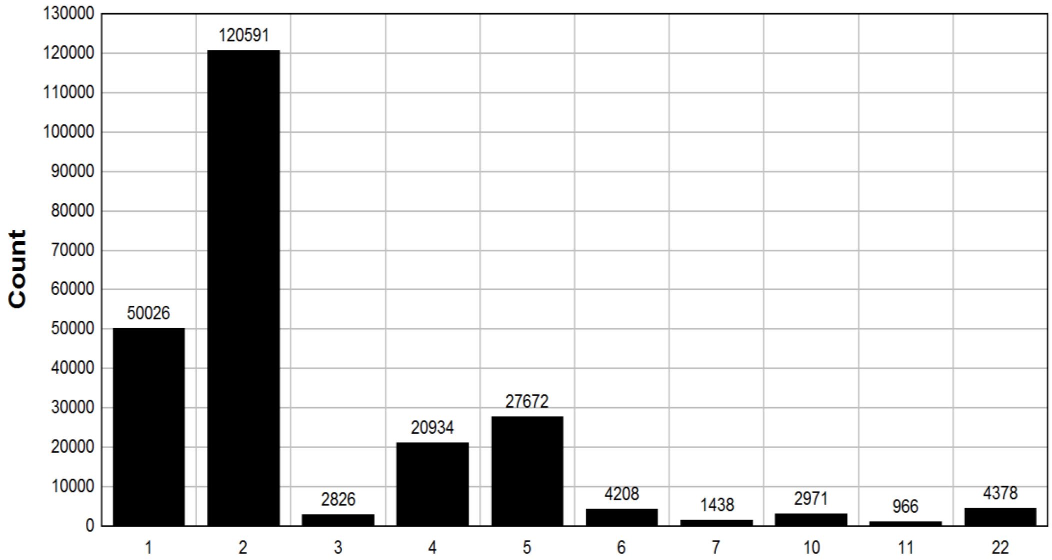


Figure A10: Histogram for type of design and/or construction (final dataset).

Designated Inspection Frequency

Table A6: Groups and tabulated frequencies for designated inspection frequency (original dataset).

Code	Item 91 Designated Inspection Frequency	Frequency	Percentage
1	1 month	15	0.01
2	2 months	0	0.00
3	3 months	101	0.04
4	4 months	14	0.01
5	5 months	5	0.00
6	6 months	302	0.13
7	7 months	2	0.00
8	8 months	13	0.01
9	9 months	11	0.00
10	10 months	9	0.00
11	11 months	12	0.01
12	12 months	29220	12.19
13	13 months	6	0.00
14	14 months	9	0.00
15	15 months	57	0.02
16	16 months	172	0.07
17	17 months	3	0.00
18	18 months	5	0.00
19	19 months	2	0.00
20	20 months	17	0.01
21	21 months	4	0.00
22	22 months	10	0.00
23	23 months	56	0.02
24	24 months	203476	84.85
36	36 months	2	0.00
48	48 months	6271	2.62
	Total	239794	

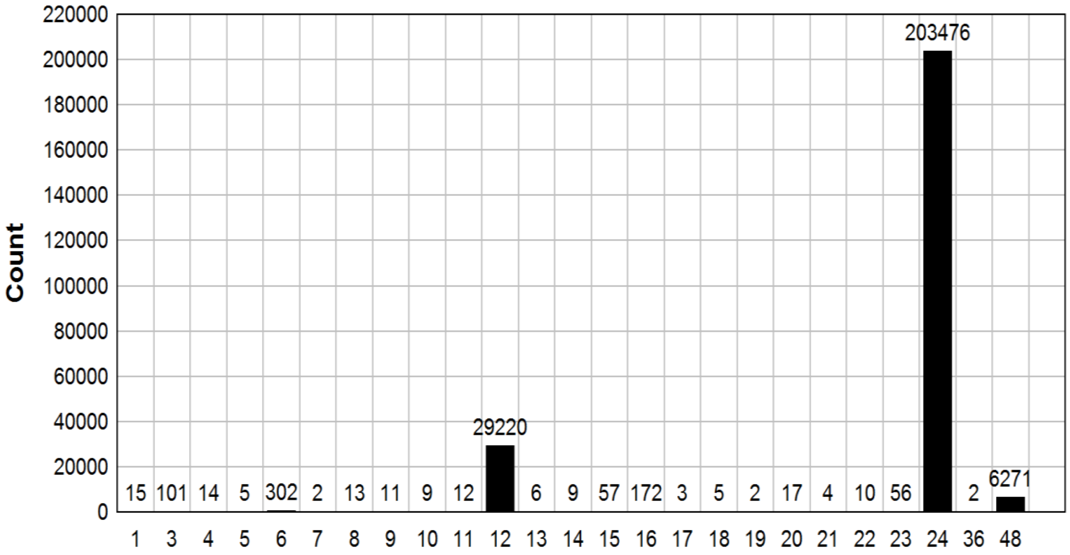


Figure A11: Histogram for designated inspection frequency (original database).

The histogram of this parameter showed that an overwhelming number of bridge with an inspection frequency of 24 months, followed by 12 months. We decided to combine some of the intermediate frequencies and create the following categories: 1 to 4 months were combined with 3, 5 to 7 months were combined with 6, 12 months, 24 months, and 48 months.

Codes for new dataset:

- Inspection frequencies of 1, 3 and 4 months (Group 3)
- Inspection frequencies of 5, 6 and 7 months (Group 6)
- The rest are the same as the group number, i.e. each number represents the time in months between inspection frequencies

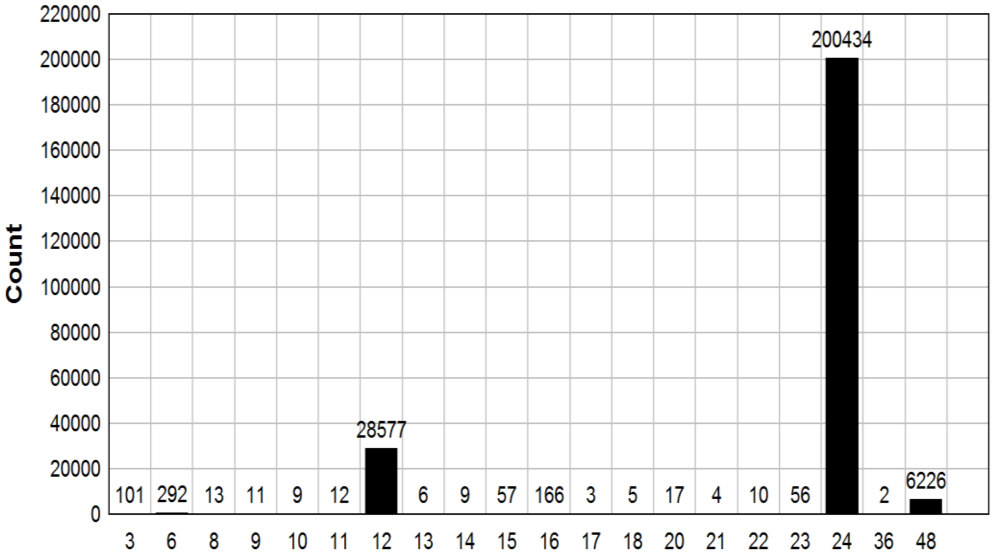


Figure A12: Graph. Histogram for designated inspection frequency (final database).

Deck Structure Type

Table A7: Groups and tabulated frequencies for deck structure type (original database).

Code	Deck Structure Type	Frequency	Percentage
1	cast-in-place	215472	89.9
2	Concrete Precast Panels	24322	10.1
	Total	239794	

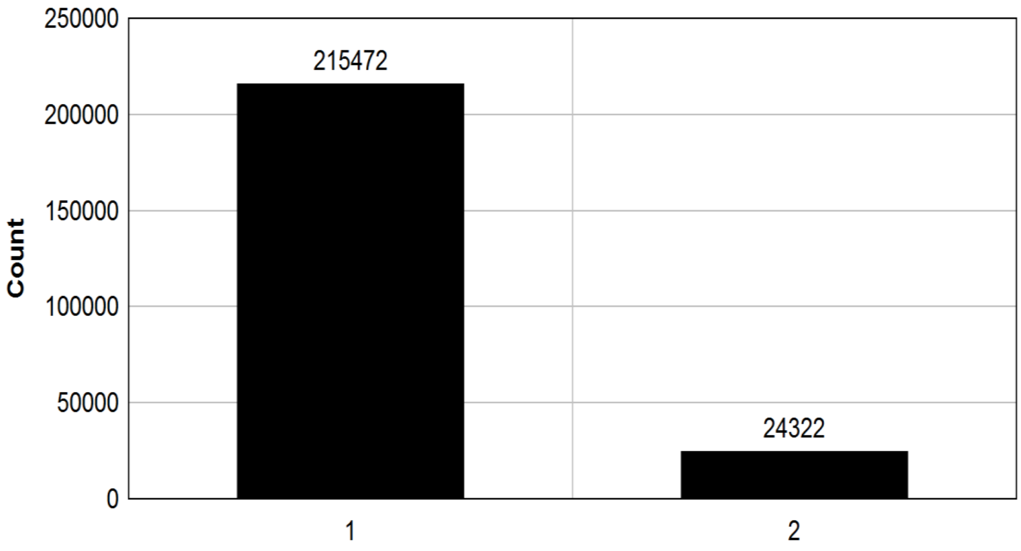


Figure A13: Histogram for deck structure type (original database).

Nothing was changed in this item. The new data based on the changes is

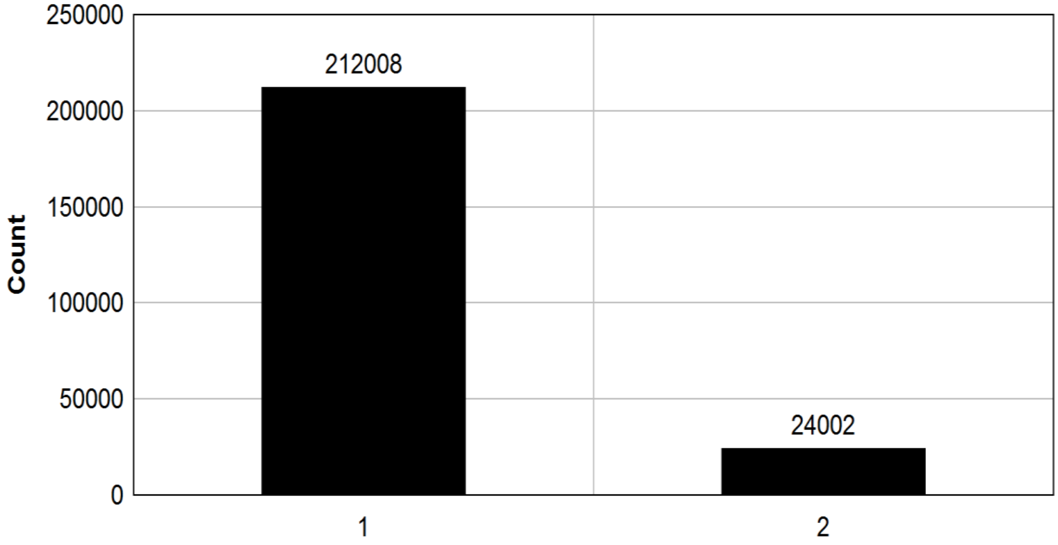


Figure A14: Histogram for deck structure type (final database).

Type of Wearing Surface

Table A8: Groups and tabulated frequencies for type of wearing surface (original database).

code	Type of wearing surface	Frequency	Percentage
1	monolithic concrete	92787	38.69
2	integral concrete	14137	5.90
3	latex concrete or similar additive	10270	4.28
4	low-slump concrete	7041	2.94
5	epoxy overlay	2781	1.16
6	bituminous	74928	31.25
7	gravel	125	0.05
8	timber	6991	2.92
9	other	7090	2.96
0	none	23535	9.81
NaN	Not Applicable	109	0.05
	Total	239794	

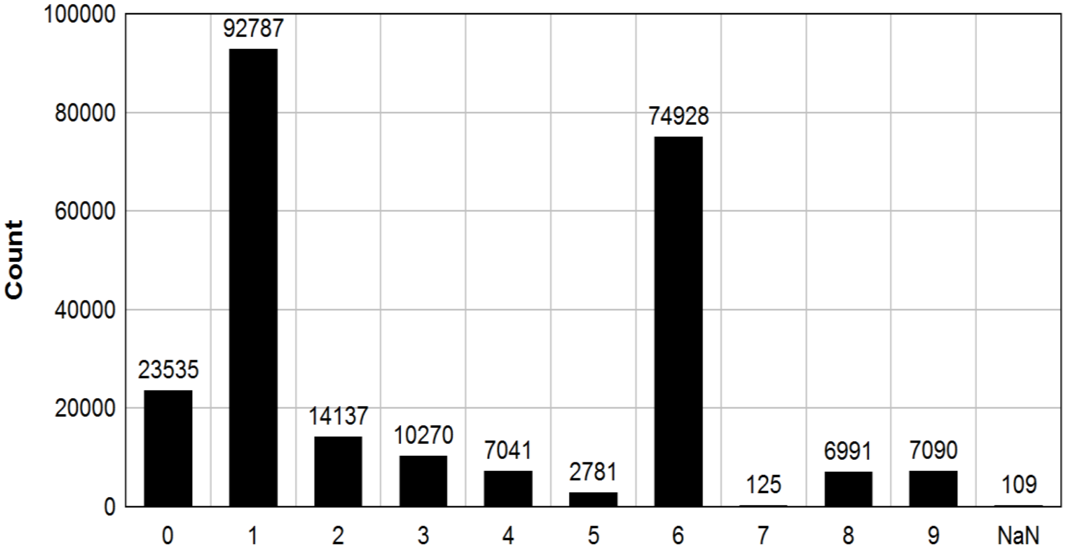


Figure A15: Histogram for type of wearing surface (original database).

All groups except "gravel" and "NaN" are considered, which results in a total of nine groups.

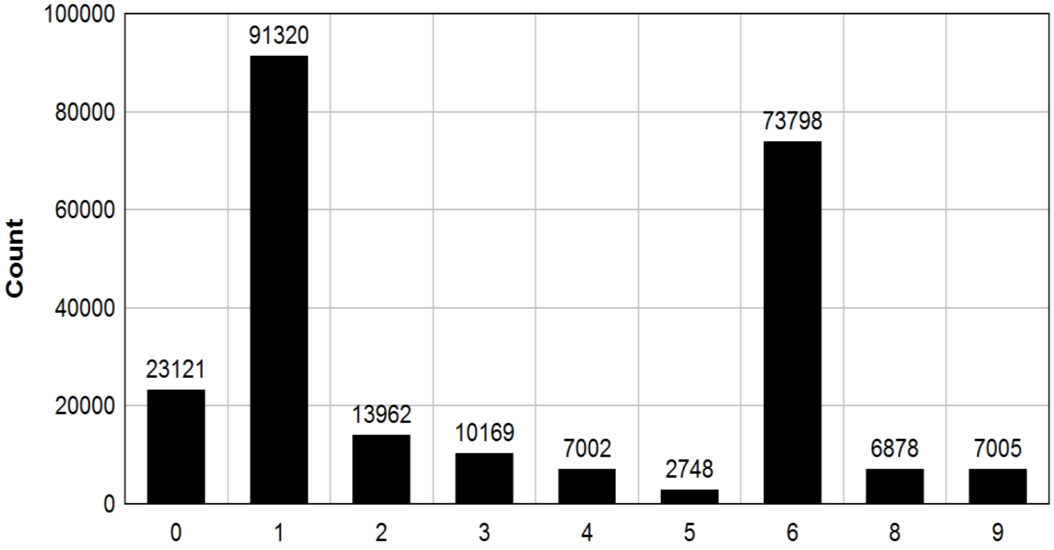


Figure A16: Histogram for type of wearing surface (final database).

Type of Membrane

Table A9: Groups and tabulated frequencies for type of membrane (original database).

Code	Type of Membrane	Frequency	Percentage
1	built-up	5710	2.38
2	preformed fabric	7494	3.13
3	epoxy	2365	0.99
8	unknown	38137	15.90
9	other	4799	2.00
0	none	180986	75.48
NaN	Not Applicable	303	0.13
	Total	239794	

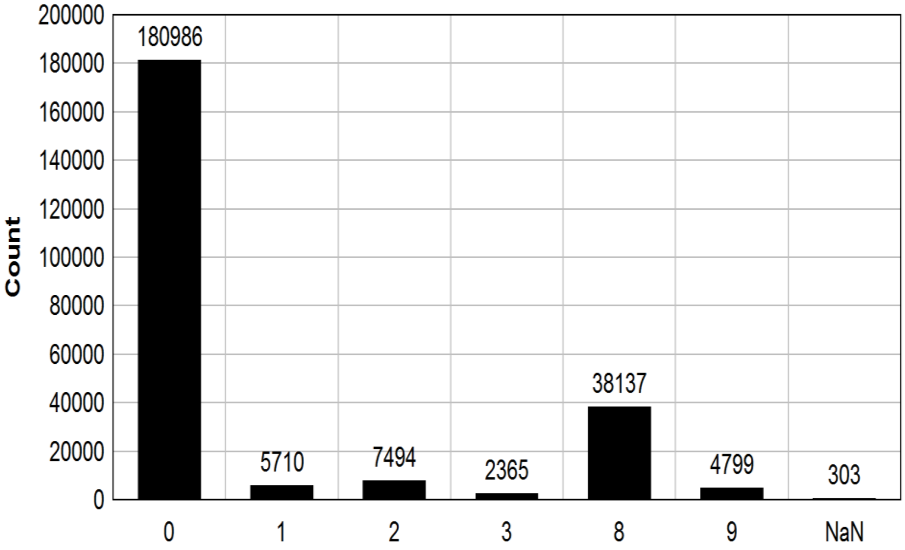


Figure A17: Histogram for type of membrane (original database).

All groups are considered except for “NaN”, which results in a total of six groups.

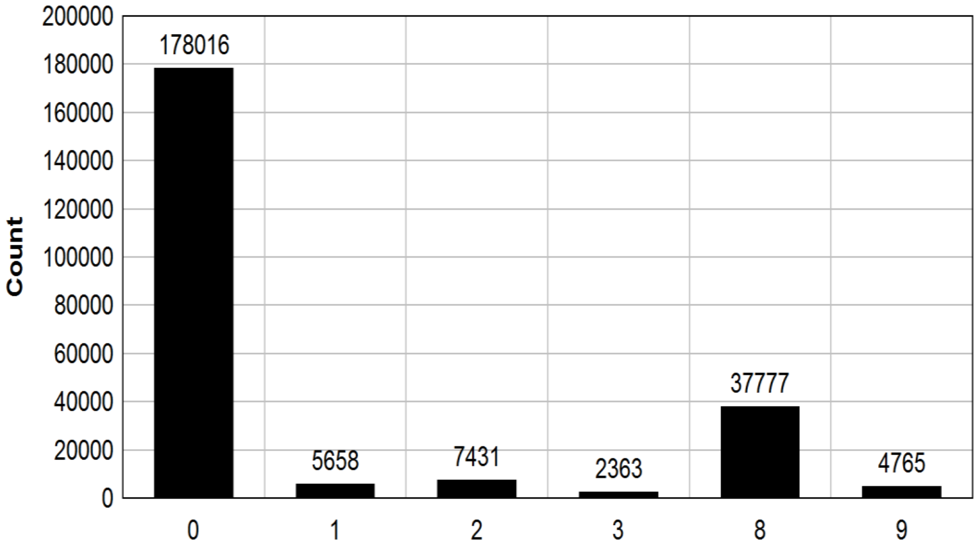


Figure A18: Histogram for type of membrane (final database).

Deck Protection

Table A10: Groups and tabulated frequencies for deck protection (original database).

Code	Deck protection	Frequency	Percentage
1	epoxy-coated reinforcing	39260	16.4
2	galvanized reinforcing	418	160.8
3	other coated reinforcing	118	45.4
4	cathodic protection	242	93.1
6	polymer impregnated	497	191.2
7	internally sealed	44	16.9
8	unknown	33816	13006.2
9	other	1351	519.6
0	none	163788	62995.4
NaN	Not aplicable	260	77044.8
	Total	239794	

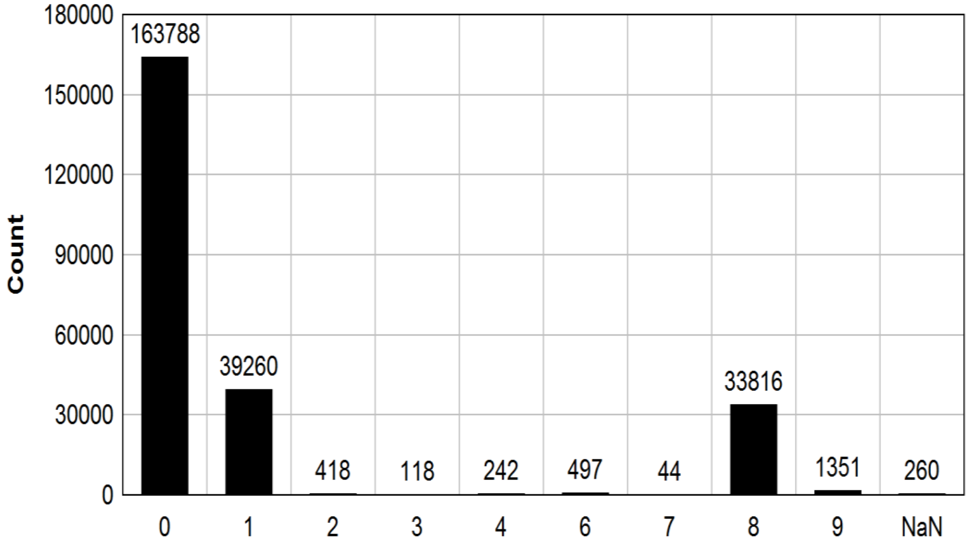


Figure A19: Histogram for deck protection (original database).

All groups are kept except “NaN”, which leads to a total of nine groups.

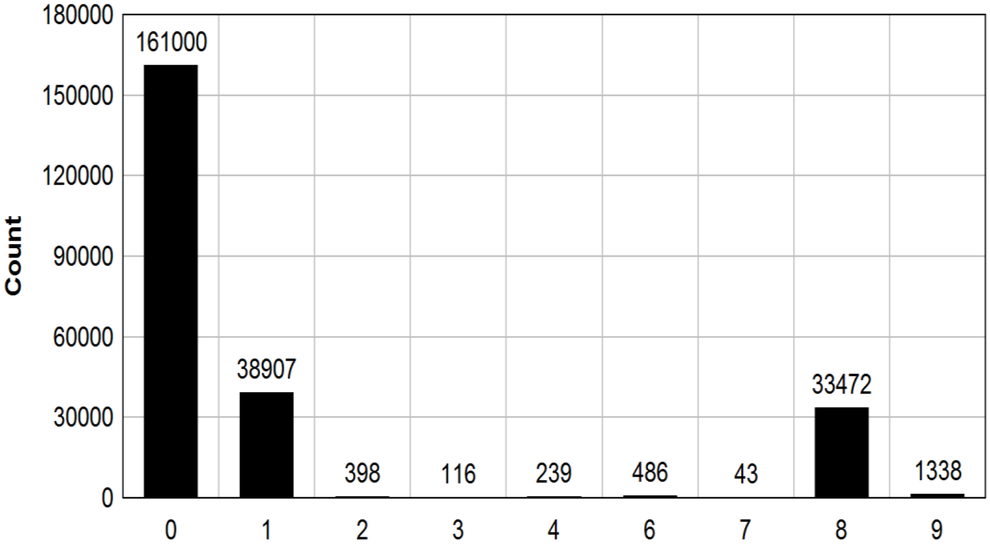


Figure A20: Histogram for deck protection (final database).

Average Daily Truck Traffic (ADTT)

Figure: A21 is based on the new dataset, after data manipulation, with limits based on the FHWA 2015 study (80):

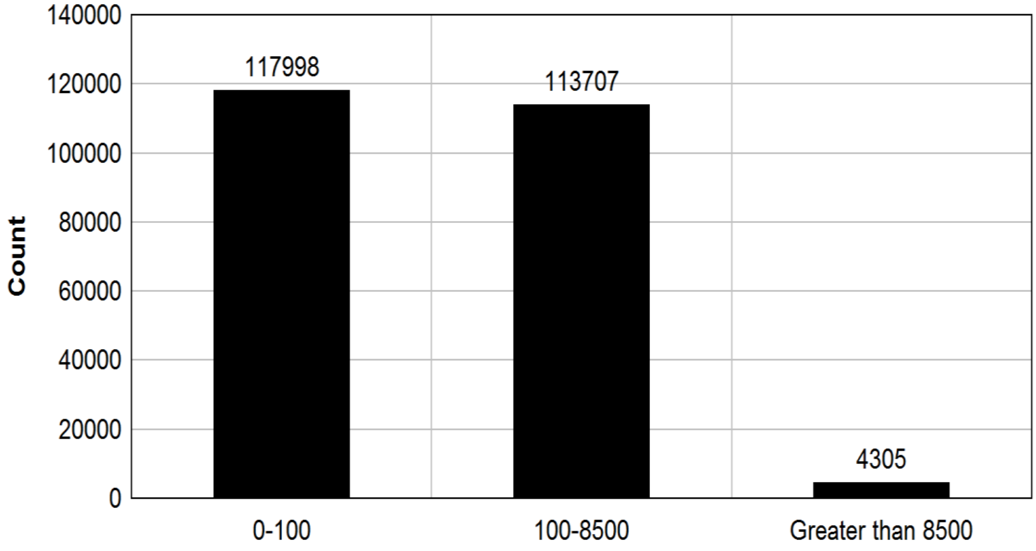


Figure A21: Histogram for ADTT (final database).

National Oceanic and Atmospheric Administration (NOAA) Climatic Regions

Table A11: Groups and tabulated frequencies for NOAA Climatic Regions (initial dataset).

code	Climatic Region	Frequency	Percentage
1	Northwest	7028	2.93
2	West	18098	7.55
3	Northern rockis and plains	16581	6.91
4	Southwest	5756	2.40
5	upper midwest	29877	12.46
6	South	51125	21.32
7	Ohio Valley	57129	23.82
8	Northeast	26968	11.25
9	Southeast	25768	10.75
10	Alaska	414	0.17
11	Hawai and Peurto rico	1050	0.44
	total	239794	

The new data based on the changes done to other parameters is

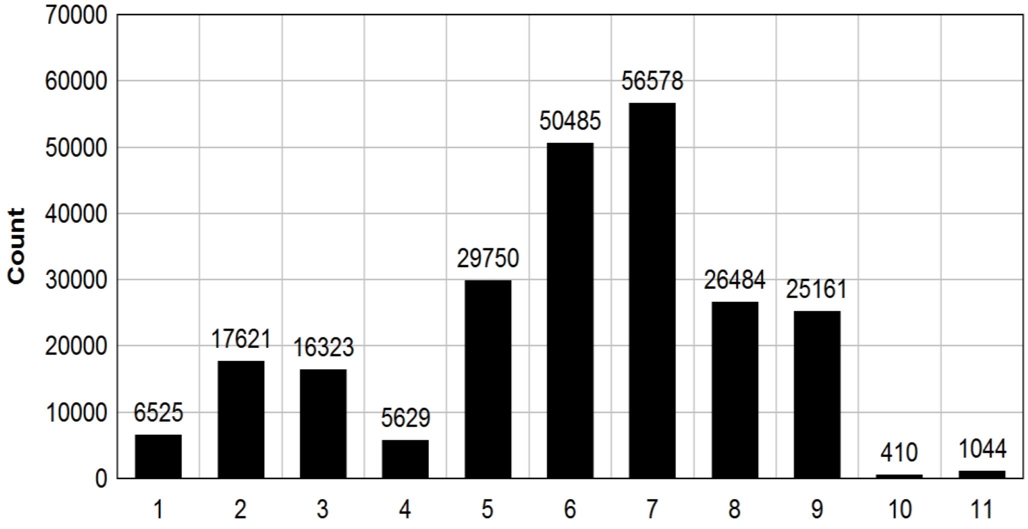


Figure A22: Histogram for NOAA Climatic Regions (final dataset)

International Energy Conservation Code (IECC) Climatic Regions

Table A12: Groups and tabulated frequencies for IECC Climatic Region (initial dataset).

Code	Climatic Region	Frequency	Percentage
2	Very Hot	17667	7.37
3	Hot	54245	22.62
4	Average	42144	17.58
5	Cold	81066	33.81
6	Very cold	35174	14.67
7	Extremly Cold	2520	1.05
8	Subartic	142	0.06
9	Average Marine	3850	1.61
10	Hot Marine	2986	1.25
		239794	

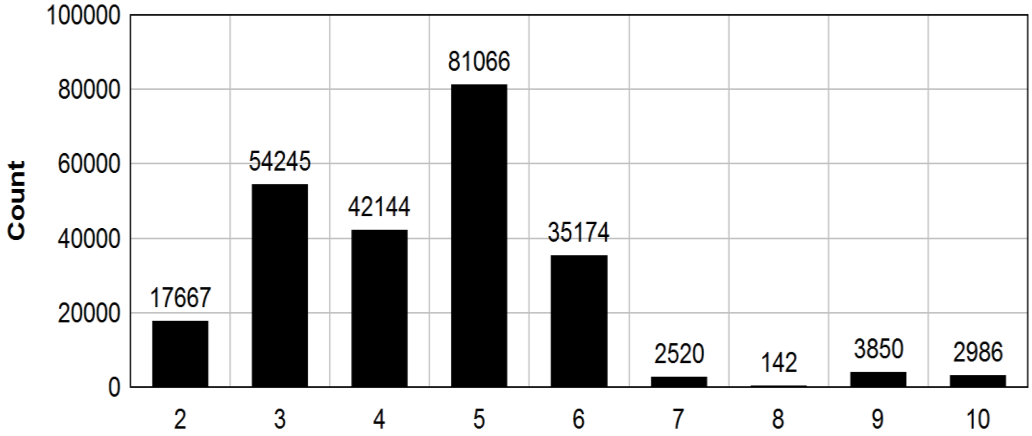


Figure A23: Histogram for IECC Climatic Regions (initial dataset).

The new data based on the changes done to other parameters is

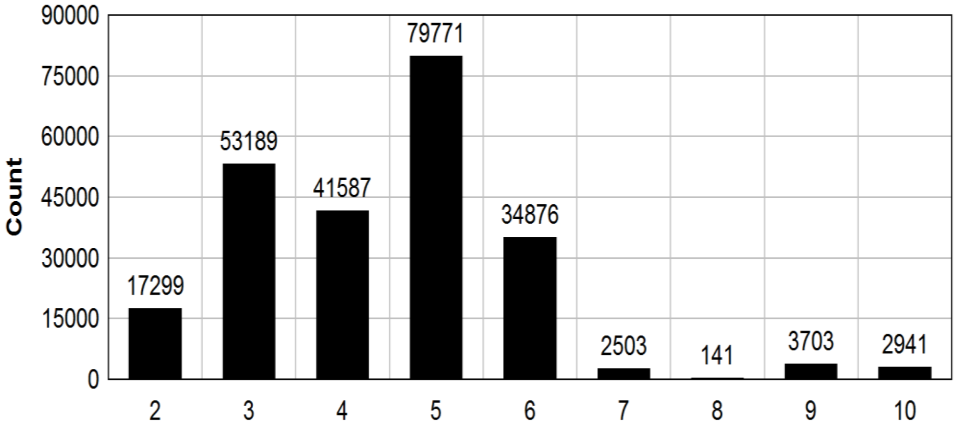


Figure A24: Histogram for IECC Climatic Regions (final dataset).

Distance from Seawater

This parameter looks at the distance of bridge decks from seawater. It does not consider the height of the bridge deck but the location of it relative to seawater. The distance was split into three groups guided by a study performed by McGee on (17):

- Distance from seawater < 1 km (0.62 miles)
- 1 km (0.62 miles) < distance from seawater < 2 km (1.24 miles)
- Distance from seawater > 2 km (1.24 miles)

The histogram shown in Figure A25 is based on the final dataset.

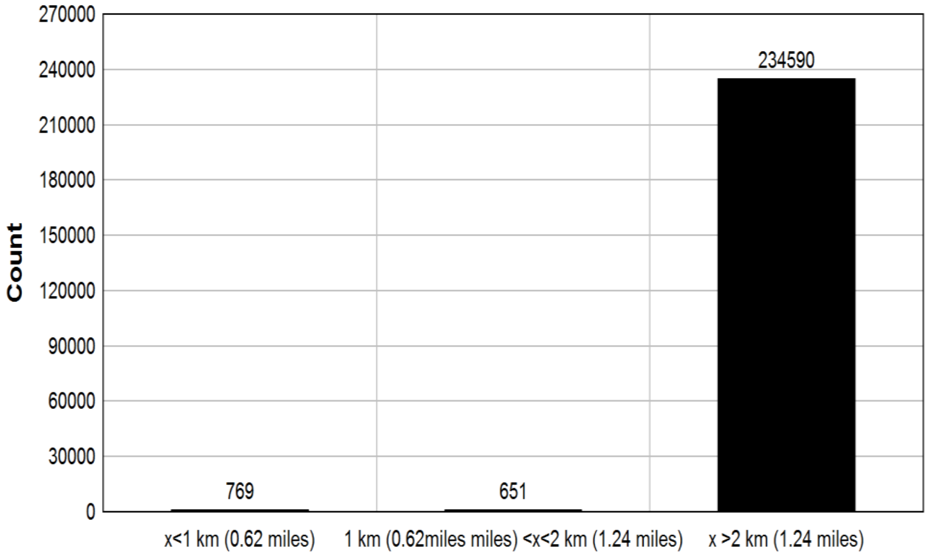


Figure A24: Histogram for distance from seawater (final dataset).

Appendix B

KRUSKAL-WALLIS TEST RESULTS

The results were computed using the commercial program STATGRAPHICS CENTURION (81). The comments following the analysis (tables) were copied verbatim from the program.

Condition Rating

Table B1: Summary statistics for CR

CR	Count	Average	Median	Standard deviation	Coeff. of variation	Minimum	Maximum	Range
3	397	3.13098	2.0	2.5342	80.9396%	1.0	21.0	20.0
4	2694	4.21158	3.0	3.30689	78.519%	1.0	22.0	21.0
5	12780	4.74906	4.0	3.52637	74.254%	1.0	22.0	21.0
6	39649	5.30984	4.0	3.85532	72.6071%	1.0	22.0	21.0
7	84136	6.19252	5.0	4.15663	67.1235%	1.0	22.0	21.0
8	77914	5.84183	5.0	4.05665	69.4414%	1.0	22.0	21.0
9	18404	4.17963	3.0	3.37438	80.7337%	1.0	22.0	21.0
Total	235974	5.66549	5.0	4.02136	70.9799%	1.0	22.0	21.0

The StatAdvisor

This table shows various statistics for each of the 7 columns of data. To test for significant differences amongst the column means, select Analysis of Variance from the list of Tabular Options. Select Means Plot from the list of Graphical Options to display the means graphically.

WARNING: The standardized skewness and/or kurtosis is outside the range of -2 to +2 for 7 columns. This indicates some significant nonnormality in the data, which violates the assumption that the data come from normal distributions. You may wish to transform the data or use the Kruskal-Wallis test to compare the medians instead of the means.

Table B2: Kruskal-wallis test for CR

CR	Sample Size	Average Rank
3	397	-11702.5
4	2694	-14537.7
5	12780	-16937.5
6	39649	-12702.9
7	84136	-5693.73
8	77914	-9539.44
9	18404	-12853.5

Test statistic = -710732. P-Value = 1.0

Table B3: 95.0 percent Bonferroni intervals

Contrast	Sig.	Difference	+/- Limits
3 - 4		2835.29	11125.7
3 - 5		5235.07	10546.8
3 - 6		1000.47	10438.6
3 - 7		-6008.73	10411.2
3 - 8		-2163.01	10413.1
3 - 9		1151.0	10498.1
4 - 5		2399.78	4387.44
4 - 6		-1834.82	4120.5
4 - 7	*	-8844.02	4050.59
4 - 8	*	-4998.3	4055.61
4 - 9		-1684.29	4269.13
5 - 6	*	-4234.6	2105.12
5 - 7	*	-11243.8	1964.78
5 - 8	*	-7398.09	1975.1
5 - 9	*	-4084.07	2382.97
6 - 7	*	-7009.2	1260.67
6 - 8	*	-3163.48	1276.69

6 - 9		150.531	1845.92
7 - 8	*	3845.72	1028.96
7 - 9	*	7159.73	1684.12
8 - 9	*	3314.02	1696.15

The StatAdvisor

The Kruskal-Wallis test tests the null hypothesis that the medians within each of the 7 columns is the same. The data from all the columns is first combined and ranked from smallest to largest. The average rank is then computed for the data in each column. Since the P-value is greater than or equal to 0.05, there is not a statistically significant difference amongst the medians at the 95.0% confidence level.

The second part of the output shows pairwise comparisons between the average ranks of the 7 groups. Using the Bonferroni procedure, 11 of the comparisons are statistically significant at the 95.0% confidence level.

Maintenance Responsibility

Table B4: Maintenance responsibility group definitions

Code	Item 21 - Maintenance Responsibility
1	State Highway Agency
2	County Highway Agency
3	Town or Township Highway Agency
4	City or Municipal Highway Agency
26	Private (other than railroad)
31	State Toll Authority

CR = 5

Table B5: Summary statistics for TICR

Maintenance Responsibility	Count	Average	Median	Standard deviation	Coeff. of variation	Minimum	Maximum	Range	Stnd. skewness	Stnd. kurtosis
1	7379	4.56878	4.0	3.43483	75.1804%	1.0	22.0	21.0	49.2005	36.5576
2	4222	4.97466	4.0	3.595	72.2663%	1.0	22.0	21.0	32.9931	17.9666
3	455	5.24615	4.0	3.78858	72.2164%	1.0	18.0	17.0	9.95375	3.51297
4	526	4.97719	4.0	3.83262	77.0038%	1.0	22.0	21.0	12.9895	10.1927
26	8	8.125	10.5	5.54044	68.19%	1.0	15.0	14.0	-0.452108	-1.11529
31	190	4.77368	4.0	3.39878	71.1982%	1.0	21.0	20.0	9.2534	11.0601
Total	12780	4.74906	4.0	3.52637	74.254%	1.0	22.0	21.0	61.8923	41.3787

The StatAdvisor

This table shows various statistics for each of the 6 columns of data. To test for significant differences amongst the column means, select Analysis of Variance from the list of Tabular Options. Select Means Plot from the list of Graphical Options to display the means graphically.

WARNING: The standardized skewness and/or kurtosis is outside the range of -2 to +2 for 5 columns. This indicates some significant nonnormality in the data, which violates the assumption that the data come from normal distributions. You may wish to transform the data or use the Kruskal-Wallis test to compare the medians instead of the means.

Table B6: Kruskal-wallis test for maintenance responsibility

Maintenance Responsibility	Sample Size	Average Rank
1	7379	6197.25
2	4222	6648.81
3	455	6875.78
4	526	6518.47
26	8	8428.75
31	190	6553.76

Test statistic = 53.117   P-Value = 3.18236E-10

Table B7: 95.0 percent Bonferroni intervals

Contrast	Sig.	Difference	+/- Limits
1 - 2	*	-451.563	208.971
1 - 3	*	-678.534	523.098
1 - 4		-321.226	488.714
1 - 26		-2231.5	3830.77
1 - 31		-356.509	795.682
2 - 3		-226.971	534.336
2 - 4		130.336	500.725
2 - 26		-1779.94	3832.32
2 - 31		95.0536	803.114
3 - 4		357.308	693.317
3 - 26		-1552.97	3862.21

3 - 31		322.025	935.391
4 - 26		-1910.28	3857.7
4 - 31		-35.2828	916.606
26 - 31		1874.99	3908.47

* denotes a statistically significant difference.

The StatAdvisor

The Kruskal-Wallis test tests the null hypothesis that the medians within each of the 6 columns is the same. The data from all the columns is first combined and ranked from smallest to largest. The average rank is then computed for the data in each column. Since the P-value is less than 0.05, there is a statistically significant difference amongst the medians at the 95.0% confidence level.

The second part of the output shows pairwise comparisons between the average ranks of the 6 groups. Using the Bonferroni procedure, 2 of the comparisons are statistically significant at the 95.0% confidence level.

CR = 8

Table B8: Summary statistics for maintenance responsibility

Maintenance Responsibility	Count	Average	Median	Standard deviation	Coeff. of variation	Minimum	Maximum	Range	Stnd. skewness	Stnd. kurtosis
1	44792	5.57073	5.0	3.89391	69.8995%	1.0	22.0	21.0	104.946	53.2709
2	25562	6.10476	5.0	4.12003	67.4888%	1.0	22.0	21.0	61.7797	8.31043
3	3582	7.79676	7.0	4.99204	64.027%	1.0	22.0	21.0	11.4308	-12.2466
4	2655	5.86478	5.0	4.16848	71.0764%	1.0	22.0	21.0	23.9589	8.4705

26	24	5.375	4.5	3.65718	68.0406%	2.0	13.0	11.0	2.07829	-0.142458
31	1299	4.58661	4.0	3.12367	68.1042%	1.0	17.0	16.0	21.4306	13.0843
Total	77914	5.84183	5.0	4.05665	69.4414%	1.0	22.0	21.0	425.624	39.6953

The StatAdvisor

This table shows various statistics for each of the 6 columns of data. To test for significant differences amongst the column means, select Analysis of Variance from the list of Tabular Options. Select Means Plot from the list of Graphical Options to display the means graphically.

WARNING: The standardized skewness and/or kurtosis is outside the range of -2 to +2 for 6 columns. This indicates some significant nonnormality in the data, which violates the assumption that the data come from normal distributions. You may wish to transform the data or use the Kruskal-Wallis test to compare the medians instead of the means.

Table B9: Kruskal-Wallis test for maintenance responsibility

Maintenance Responsibility	Sample Size	Average Rank
1	44792	37602.6
2	25562	40479.4
3	3582	47540.9
4	2655	38834.4
26	24	36734.0
31	1299	32353.7

Test statistic = 923.61   P-Value = 0

Table B10: 95.0 percent Bonferroni intervals

Contrast	*Sig.*	*Difference*	*+/- Limits*
1 - 2	*	-2876.83	517.503
1 - 3	*	-9938.36	1146.33
1 - 4		-1231.84	1318.68
1 - 26		868.57	13479.6
1 - 31	*	5248.89	1858.1
2 - 3	*	-7061.54	1177.82
2 - 4	*	1644.99	1346.14
2 - 26		3745.4	13482.3
2 - 31	*	8125.72	1877.7
3 - 4	*	8706.53	1690.67
3 - 26		10806.9	13521.1
3 - 31	*	15187.3	2138.22
4 - 26		2100.41	13536.8
4 - 31	*	6480.73	2235.36
26 - 31		4380.32	13599.9

* denotes a statistically significant difference.

The StatAdvisor

The Kruskal-Wallis test tests the null hypothesis that the medians within each of the 6 columns is the same. The data from all the columns is first combined and ranked from smallest to largest. The average rank is then computed for the data in each column. Since the P-value is less than 0.05, there is a statistically significant difference amongst the medians at the 95.0% confidence level.

The second part of the output shows pairwise comparisons between the average ranks of the 6 groups. Using the Bonferroni procedure, 9 of the comparisons are statistically significant at the 95.0% confidence level.

Functional Classification

Table B11: Functional classification group definitions

Code	Item 26 - Functional Classification
1	Rural
2	Urban

CR = 5

Table B12: Summary statistics for functional classification

Functional Classification	Count	Average	Median	Standard deviation	Coeff. of variation	Minimum	Maximum	Range	Stnd. skewness	Stnd. kurtosis
1	9408	4.88765	4.0	3.59461	73.5449%	1.0	22.0	21.0	50.5022	28.8076
2	3372	4.3624	4.0	3.29842	75.6104%	1.0	22.0	21.0	36.5561	36.0448
Total	12780	4.74906	4.0	3.52637	74.254%	1.0	22.0	21.0	61.8923	41.3787

The StatAdvisor

This table shows various statistics for each of the 2 columns of data. To test for significant differences amongst the column means, select Analysis of Variance from the list of Tabular Options. Select Means Plot from the list of Graphical Options to display the means graphically.

WARNING: The standardized skewness and/or kurtosis is outside the range of -2 to +2 for 2 columns. This indicates some significant nonnormality in the data, which violates the assumption that the data come from normal distributions. You may

wish to transform the data or use the Kruskal-Wallis test to compare the medians instead of the means.

Table B13: Kruskal-Wallis test for functional classification

Functional Classification	Sample Size	Average Rank
1	9408	6531.97
2	3372	5995.8

Test statistic = 53.2857 P-Value = 0

Table B14: 95.0 percent Bonferroni intervals

Contrast	Sig.	Difference	+/- Limits
1 - 2	*	536.173	145.137

* denotes a statistically significant difference.

The StatAdvisor

The Kruskal-Wallis test tests the null hypothesis that the medians within each of the 2 columns is the same. The data from all the columns is first combined and ranked from smallest to largest. The average rank is then computed for the data in each column. Since the P-value is less than 0.05, there is a statistically significant difference amongst the medians at the 95.0% confidence level.

The second part of the output shows pairwise comparisons between the average ranks of the 2 groups. Using the Bonferroni procedure, 1 of the comparisons are statistically significant at the 95.0% confidence level.

CR = 8

Table B15: Summary statistics for functional classification

Functional Classification	Count	Average	Median	Standard deviation	Coeff. of variation	Minimum	Maximum	Range	Stnd. skewness	Stnd. kurtosis
1	59743	6.01413	5.0	4.13978	68.8342%	1.0	22.0	21.0	-500.234	23.6535
2	18171	5.27533	4.0	3.71462	70.415%	1.0	22.0	21.0	74.4598	46.7389
Total	77914	5.84183	5.0	4.05665	69.4414%	1.0	22.0	21.0	425.624	39.6953

The StatAdvisor

This table shows various statistics for each of the 2 columns of data. To test for significant differences amongst the column means, select Analysis of Variance from the list of Tabular Options. Select Means Plot from the list of Graphical Options to display the means graphically.

WARNING: The standardized skewness and/or kurtosis is outside the range of -2 to +2 for 2 columns. This indicates some significant nonnormality in the data, which violates the assumption that the data come from normal distributions. You may wish to transform the data or use the Kruskal-Wallis test to compare the medians instead of the means.

Table B16: Kruskal-Wallis test for functional classification

Functional Classification	Sample Size	Average Rank

1	59743	39831.0
2	18171	36085.7

Test statistic = 390.598   P-Value = 0

Table B17:   95.0 percent Bonferroni intervals

Contrast	Sig.	Difference	+/- Limits
1 - 2	*	3745.3	373.466

* denotes a statistically significant difference.

The StatAdvisor

The Kruskal-Wallis test tests the null hypothesis that the medians within each of the 2 columns is the same. The data from all the columns is first combined and ranked from smallest to largest. The average rank is then computed for the data in each column. Since the P-value is less than 0.05, there is a statistically significant difference amongst the medians at the 95.0% confidence level.

The second part of the output shows pairwise comparisons between the average ranks of the 2 groups. Using the Bonferroni procedure, 1 of the comparisons are statistically significant at the 95.0% confidence level.

Structural Material/Design

Table B18: Structural material/design group definition.

Code	Structural Material/design
1	Concrete
2	Concrete continuous
3	Steel
4	Steel continuous
5	Prestressed concrete
6	Prestressed concrete continuous

CR = 5

Table B19: Summary statistics for structural material/design

Structural Material/Design	Count	Average	Median	Standard deviation	Coeff. of variation	Minimum	Maximum	Range	Stnd. skewness	Stnd. kurtosis
1	2328	5.38187	4.0	3.95024	73.3991%	1.0	22.0	21.0	23.4667	10.4968
2	1822	4.13063	3.0	3.22375	78.0452%	1.0	22.0	21.0	27.1897	23.2728
3	4857	5.11592	4.0	3.53145	69.0286%	1.0	22.0	21.0	35.4018	23.02
4	2200	4.38409	3.0	3.31535	75.6223%	1.0	19.0	18.0	25.606	15.9776
5	1310	4.05191	3.0	3.1888	78.6986%	1.0	19.0	18.0	22.0887	17.2323
6	263	3.18251	2.0	2.60302	81.7915%	1.0	21.0	20.0	18.0153	38.0843
Total	12780	4.74906	4.0	3.52637	74.254%	1.0	22.0	21.0	61.8923	41.3787

The StatAdvisor

This table shows various statistics for each of the 6 columns of data. To test for significant differences amongst the column means, select Analysis of Variance from the list of Tabular Options. Select Means Plot from the list of Graphical Options to display the means graphically.

WARNING: The standardized skewness and/or kurtosis is outside the range of -2 to +2 for 6 columns. This indicates some significant nonnormality in the data, which violates the assumption that the data come from normal distributions. You may wish to transform the data or use the Kruskal-Wallis test to compare the medians instead of the means.

Table B20: Kruskal-Wallis test for structural material/design

Structural Material/Design	Sample Size	Average Rank
1	2328	6956.55
2	1822	5688.24
3	4857	6881.54
4	2200	5989.89
5	1310	5578.41
6	263	4572.82

Test statistic = 366.0 P-Value = 0

Table B21: 95.0 percent Bonferroni intervals

Contrast	Sig.	Difference	+/- Limits
1 - 2	*	1268.31	338.73
1 - 3		75.0063	272.982
1 - 4	*	966.661	321.993
1 - 5	*	1378.14	374.024
1 - 6	*	2383.73	704.466

2 - 3	*	-1193.31	297.504
2 - 4		-301.651	343.029
2 - 5		109.823	392.28
2 - 6	*	1115.41	714.326
3 - 4	*	891.655	278.298
3 - 5	*	1303.13	337.142
3 - 6	*	2308.72	685.597
4 - 5	*	411.475	377.922
4 - 6	*	1417.06	706.543
5 - 6	*	1005.59	731.723

* denotes a statistically significant difference.

The StatAdvisor

The Kruskal-Wallis test tests the null hypothesis that the medians within each of the 6 columns is the same. The data from all the columns is first combined and ranked from smallest to largest. The average rank is then computed for the data in each column. Since the P-value is less than 0.05, there is a statistically significant difference amongst the medians at the 95.0% confidence level.

The second part of the output shows pairwise comparisons between the average ranks of the 6 groups. Using the Bonferroni procedure, 12 of the comparisons are statistically significant at the 95.0% confidence level.

CR = 8

Table B22: Summary statistics for structural material/design

Structural Material/Design	Count	Average	Median	Standard deviation	Coeff. of variation	Minimum	Maximum	Range	Stnd. skewness	Stnd. kurtosis
1	17950	6.48357	5.0	4.36149	67.2699%	1.0	22.0	21.0	48.9757	7.83227
2	11493	5.32663	5.0	3.52624	66.2002%	1.0	22.0	21.0	57.2089	36.8411

3	13335	5.25819	4.0	3.80843	72.4285%	1.0	22.0	21.0	61.981	33.025
4	9902	4.95233	4.0	3.68132	74.3351%	1.0	22.0	21.0	54.5202	30.7709
5	21259	6.33722	5.0	4.21508	66.5131%	1.0	22.0	21.0	53.7246	2.49924
6	3975	5.95774	5.0	4.02799	67.6094%	1.0	22.0	21.0	29.9857	10.449
Total	77914	5.84183	5.0	4.05665	69.4414%	1.0	22.0	21.0	425.624	39.6953

The StatAdvisor

This table shows various statistics for each of the 6 columns of data. To test for significant differences amongst the column means, select Analysis of Variance from the list of Tabular Options. Select Means Plot from the list of Graphical Options to display the means graphically.

WARNING: The standardized skewness and/or kurtosis is outside the range of -2 to +2 for 6 columns. This indicates some significant nonnormality in the data, which violates the assumption that the data come from normal distributions. You may wish to transform the data or use the Kruskal-Wallis test to compare the medians instead of the means.

Table B23: Kruskal-Wallis test for structural material/design

Structural Material/Design	Sample Size	Average Rank
1	17950	42107.9
2	11493	37102.8
3	13335	35521.7
4	9902	33617.2
5	21259	41735.6
6	3975	40065.0

Test statistic = 1651.67 P-Value = 0

Table B24: 95.0 percent Bonferroni intervals

Contrast	Sig.	Difference	+/- Limits
1 - 2	*	5005.1	788.693
1 - 3	*	6586.16	754.754
1 - 4	*	8490.72	826.42
1 - 5		372.256	669.199
1 - 6	*	2042.87	1157.27
2 - 3	*	1581.07	840.279
2 - 4	*	3485.63	905.199
2 - 5	*	-4632.84	764.358
2 - 6	*	-2962.22	1214.78
3 - 4	*	1904.56	875.786
3 - 5	*	-6213.91	729.287
3 - 6	*	-4543.29	1193.02
4 - 5	*	-8118.47	803.228
4 - 6	*	-6447.85	1239.61
5 - 6	*	1670.62	1140.83

* denotes a statistically significant difference.

The StatAdvisor

The Kruskal-Wallis test tests the null hypothesis that the medians within each of the 6 columns is the same. The data from all the columns is first combined and ranked from smallest to largest. The average rank is then computed for the data in each column. Since the P-value is less than 0.05, there is a statistically significant difference amongst the medians at the 95.0% confidence level.

The second part of the output shows pairwise comparisons between the average ranks of the 6 groups. Using the Bonferroni procedure, 14 of the comparisons are statistically significant at the 95.0% confidence level.

Type of Design and/or Construction

Table B25: Type of design and/or construction group definition.

Code	Type of design and/or construction
1	Slab
2	Stringer/Multi-beam or Girder
3	Girder and Floorbeam System
4	Tee Beam
5	Box Beam or Girders – Multiple
6	Box Beam or Girders - Single or Spread
7	Frame (except frame culverts)
10	Truss – Thru
11	Arch – Deck
22	Channel Beam

CR = 5

Table B26: Summary statistics for type of design and/or construction

Type of Design and/or Construction	Count	Average	Median	Standard deviation	Coeff. of variation	Minimum	Maximum	Range	Stnd. skewness	Stnd. kurtosis
1	1855	4.84528	4.0	3.87901	80.0574%	1.0	22.0	21.0	24.359	13.9434
2	7263	4.77007	4.0	3.45168	72.3612%	1.0	22.0	21.0	45.9375	31.7881
3	309	5.0712	5.0	3.4521	68.0727%	1.0	16.0	15.0	7.08014	1.66978
4	1243	4.99356	4.0	3.62181	72.5296%	1.0	21.0	20.0	18.7273	11.8045
5	1106	3.566	3.0	2.73831	76.7894%	1.0	16.0	15.0	20.8658	17.7568

6	193	4.95855	4.0	3.18825	64.298%	1.0	16.0	15.0	5.2173	1.09579
7	68	5.60294	4.5	4.31637	77.0375%	1.0	17.0	16.0	3.66946	0.657507
10	493	5.62272	5.0	3.90326	69.4194%	1.0	22.0	21.0	9.13898	2.77227
11	94	5.73404	5.0	4.18953	73.0642%	1.0	22.0	21.0	6.36251	5.06892
22	156	4.44231	4.0	3.31417	74.6048%	1.0	16.0	15.0	5.92517	2.82199
Total	12780	4.74906	4.0	3.52637	74.254%	1.0	22.0	21.0	61.8923	41.3787

The StatAdvisor

This table shows various statistics for each of the 10 columns of data. To test for significant differences amongst the column means, select Analysis of Variance from the list of Tabular Options. Select Means Plot from the list of Graphical Options to display the means graphically.

WARNING: The standardized skewness and/or kurtosis is outside the range of -2 to +2 for 10 columns. This indicates some significant nonnormality in the data, which violates the assumption that the data come from normal distributions. You may wish to transform the data or use the Kruskal-Wallis test to compare the medians instead of the means.

Table B27: Kruskal-Wallis test for type of design and/or construction

Type of Design and/or Construction	Sample Size	Average Rank
1	1855	6305.1
2	7263	6465.1
3	309	6834.73
4	1243	6670.35

5	1106	5068.93
6	193	6840.64
7	68	6983.01
10	493	7252.92
11	94	7380.95
22	156	6055.42

Test statistic = 200.365   P-Value = 0

Table B28:   95.0 percent Bonferroni intervals

Contrast	Sig.	Difference	+/- Limits
1 - 2		-159.994	312.966
1 - 3		-529.625	739.189
1 - 4		-365.247	440.972
1 - 5	*	1236.17	457.033
1 - 6		-535.539	909.897
1 - 7		-677.906	1485.39
1 - 10	*	-947.818	609.581
1 - 11		-1075.85	1271.89
1 - 22		249.681	1002.88
2 - 3		-369.631	698.789
2 - 4		-205.253	369.272
2 - 5	*	1396.17	388.31
2 - 6		-375.545	877.393
2 - 7		-517.912	1465.71
2 - 10	*	-787.824	559.906
2 - 11		-915.857	1248.84
2 - 22		409.675	973.487
3 - 4		164.379	764.731
3 - 5	*	1765.8	774.104
3 - 6		-5.91336	1103.75
3 - 7		-148.281	1611.44
3 - 10		-418.192	872.896
3 - 11		-546.226	1417.06
3 - 22		779.307	1181.58
4 - 5	*	1601.42	497.286
4 - 6		-170.292	930.767
4 - 7		-312.659	1498.27
4 - 10		-582.571	640.315
4 - 11		-710.604	1286.9

4 - 22		614.928	1021.85
5 - 6	*	-1771.71	938.483
5 - 7	*	-1914.08	1503.07
5 - 10	*	-2183.99	651.48
5 - 11	*	-2312.02	1292.49
5 - 22		-986.491	1028.89
6 - 7		-142.367	1696.54
6 - 10		-412.279	1021.5
6 - 11		-540.312	1513.13
6 - 22		785.22	1295.24
7 - 10		-269.912	1556.26
7 - 11		-397.945	1915.21
7 - 22		927.587	1748.18
10 - 11		-128.033	1353.97
10 - 22	*	1197.5	1105.13
11 - 22		1325.53	1570.8

* denotes a statistically significant difference.

The StatAdvisor

The Kruskal-Wallis test tests the null hypothesis that the medians within each of the 10 columns is the same. The data from all the columns is first combined and ranked from smallest to largest. The average rank is then computed for the data in each column. Since the P-value is less than 0.05, there is a statistically significant difference amongst the medians at the 95.0% confidence level.

The second part of the output shows pairwise comparisons between the average ranks of the 10 groups. Using the Bonferroni procedure, 11 of the comparisons are statistically significant at the 95.0% confidence level.

CR = 8

Table B29: Summary statistics for type of design and/or construction

Type of Design and/or Construction	Count	Average	Median	Standard deviation	Coeff. of variation	Minimum	Maximum	Range	Stnd. skewness	Stnd. kurtosis
1	18286	6.14634	5.0	4.06748	66.1773%	1.0	22.0	21.0	55.0318	17.9972
2	39327	5.50011	4.0	3.92678	71.3944%	1.0	22.0	21.0	95.4912	36.9348
3	539	5.77551	4.0	4.28532	74.1982%	1.0	17.0	16.0	9.16339	-0.532283
4	5812	5.62939	5.0	3.69709	65.6749%	1.0	22.0	21.0	32.2154	12.7714
5	9670	6.29586	5.0	4.22484	67.105%	1.0	22.0	21.0	41.145	6.23584
6	1590	5.93774	5.0	4.01091	67.5494%	1.0	21.0	20.0	16.7267	2.98822
7	470	5.4766	4.0	3.90867	71.3704%	1.0	21.0	20.0	9.76938	2.6828
10	400	5.5125	4.0	4.30769	78.1441%	1.0	18.0	17.0	9.18208	1.12356
11	139	4.70504	4.0	3.24697	69.0105%	1.0	18.0	17.0	6.68833	4.72783
22	1681	8.85128	8.0	5.21632	58.933%	1.0	22.0	21.0	6.62846	-6.82039
Total	77914	5.84183	5.0	4.05665	69.4414%	1.0	22.0	21.0	425.624	39.6953

The StatAdvisor

This table shows various statistics for each of the 10 columns of data. To test for significant differences amongst the column means, select Analysis of Variance from the list of Tabular Options. Select Means Plot from the list of Graphical Options to display the means graphically.

WARNING: The standardized skewness and/or kurtosis is outside the range of -2 to +2 for 10 columns. This indicates some significant nonnormality in the data, which violates the assumption that the data come from normal distributions. You may wish to transform the data or use the Kruskal-Wallis test to compare the medians instead of the means.

Table B30: Kruskal-Wallis test for type of design and/or construction

Type of Design and/or Construction	Sample Size	Average Rank
1	18286	41012.8
2	39327	36899.9
3	539	37575.8
4	5812	38514.6
5	9670	41664.5
6	1590	39740.8
7	470	36758.2
10	400	35644.1
11	139	32971.0
22	1681	52297.0

Test statistic = 1256.1 P-Value = 0

Table B31: 95.0 percent Bonferroni intervals

Contrast	Sig.	Difference	+/- Limits
1 - 2	*	4112.94	656.453
1 - 3	*	3436.99	3205.25
1 - 4	*	2498.26	1104.38
1 - 5		-651.655	922.175
1 - 6		1272.05	1917.59
1 - 7	*	4254.6	3426.18
1 - 10	*	5368.72	3706.95

1 - 11	*	8041.87	6244.32
1 - 22	*	-11284.2	1869.22
2 - 3		-675.949	3180.61
2 - 4	*	-1614.68	1030.66
2 - 5	*	-4764.6	832.481
2 - 6	*	-2840.89	1876.1
2 - 7		141.66	3403.13
2 - 10		1255.78	3685.66
2 - 11		3928.93	6231.71
2 - 22	*	-15397.1	1826.64
3 - 4		-938.735	3302.27
3 - 5	*	-4088.65	3245.88
3 - 6		-2164.94	3655.47
3 - 7		817.609	4628.61
3 - 10		1931.73	4840.13
3 - 11		4604.87	6976.88
3 - 22	*	-14721.2	3630.33
4 - 5	*	-3149.91	1217.27
4 - 6		-1226.2	2075.69
4 - 7		1756.34	3517.11
4 - 10		2870.46	3791.15
4 - 11		5543.61	6294.67
4 - 22	*	-13782.5	2031.09
5 - 6		1923.71	1984.75
5 - 7	*	4906.26	3464.22
5 - 10	*	6020.38	3742.14
5 - 11	*	8693.52	6265.27
5 - 22	*	-10632.5	1938.06
6 - 7		2982.55	3850.65
6 - 10		4096.67	4102.48
6 - 11	*	6769.81	6486.94
6 - 22	*	-12556.3	2565.7
7 - 10		1114.12	4989.18
7 - 11		3787.27	7081.1
7 - 22	*	-15538.8	3826.8
10 - 11		2673.15	7221.13
10 - 22	*	-16652.9	4080.1
11 - 22	*	-19326.1	6472.81

* denotes a statistically significant difference.

The StatAdvisor

The Kruskal-Wallis test tests the null hypothesis that the medians within each of the 10 columns is the same. The data from all the columns is first combined and ranked from smallest to largest. The average rank is then computed for the data in each column. Since the P-value is less than 0.05, there is a statistically significant difference amongst the medians at the 95.0% confidence level.

The second part of the output shows pairwise comparisons between the average ranks of the 10 groups. Using the Bonferroni procedure, 24 of the comparisons are statistically significant at the 95.0% confidence level.

Deck Structure Type

Table B32: Deck structure type group definition.

Code	Deck Structure Type
1	cast-in-place
2	Concrete Precast Panels

CR = 5

Table B33: Summary statistics for deck structure type

Deck Structure Type	Count	Average	Median	Standard deviation	Coeff. of variation	Minimum	Maximum	Range	Stnd. skewness	Stnd. kurtosis
1	12057	4.79589	4.0	3.53993	73.8117%	1.0	22.0	21.0	59.6834	39.4965
2	723	3.96819	3.0	3.19458	80.5048%	1.0	17.0	16.0	16.7661	13.3306
Total	12780	4.74906	4.0	3.52637	74.254%	1.0	22.0	21.0	61.8923	41.3787

The StatAdvisor

This table shows various statistics for each of the 2 columns of data. To test for significant differences amongst the column means, select Analysis of Variance from the list of Tabular Options. Select Means Plot from the list of Graphical Options to display the means graphically.

WARNING: The standardized skewness and/or kurtosis is outside the range of -2 to +2 for 2 columns. This indicates some significant nonnormality in the data, which violates the assumption that the data come from normal distributions. You may

wish to transform the data or use the Kruskal-Wallis test to compare the medians instead of the means.

Table B34: Kruskal-Wallis test for deck structure type

Deck Structure Type	*Sample Size*	*Average Rank*
1	12057	6447.14
2	723	5445.88

Test statistic = 51.061   P-Value = 0

Table B35: 95.0 percent Bonferroni intervals

Contrast	Sig.	Difference	+/- Limits
1 - 2	*	1001.26	276.874

* denotes a statistically significant difference.

The StatAdvisor

The Kruskal-Wallis test tests the null hypothesis that the medians within each of the 2 columns is the same. The data from all the columns is first combined and ranked from smallest to largest. The average rank is then computed for the data in each column. Since the P-value is less than 0.05, there is a statistically significant difference amongst the medians at the 95.0% confidence level.

The second part of the output shows pairwise comparisons between the average ranks of the 2 groups. Using the Bonferroni procedure, 1 of the comparisons are statistically significant at the 95.0% confidence level.

CR = 8

Table B36: Summary statistics for deck structure type

Deck Structure Type	*Count*	*Average*	*Median*	*Standard deviation*	*Coeff. of variation*	*Minimum*	*Maximum*	*Range*	*Stnd. skewness*	*Stnd. kurtosis*
1	68203	5.60462	5.0	3.92639	70.0563%	1.0	22.0	21.0	1652.05	55.1056
2	9711	7.50777	7.0	4.53771	60.4402%	1.0	22.0	21.0	21.4768	-10.1052
Total	77914	5.84183	5.0	4.05665	69.4414%	1.0	22.0	21.0	425.624	39.6953

The StatAdvisor

This table shows various statistics for each of the 2 columns of data. To test for significant differences amongst the column means, select Analysis of Variance from the list of Tabular Options. Select Means Plot from the list of Graphical Options to display the means graphically.

WARNING: The standardized skewness and/or kurtosis is outside the range of -2 to +2 for 2 columns. This indicates some significant nonnormality in the data, which violates the assumption that the data come from normal distributions. You may wish to transform the data or use the Kruskal-Wallis test to compare the medians instead of the means.

Table B37: Kruskal-Wallis test for deck structure type

Deck Structure Type	Sample Size	Average Rank
1	68203	37735.7
2	9711	47538.3

Test statistic = 1632.43 P-Value = 0

Table B38: 95.0 percent Bonferroni intervals

Contrast	Sig.	Difference	+/- Limits
1 - 2	*	-9802.54	478.135

* denotes a statistically significant difference.

The StatAdvisor

The Kruskal-Wallis test tests the null hypothesis that the medians within each of the 2 columns is the same. The data from all the columns is first combined and ranked from smallest to largest. The average rank is then computed for the data in each column. Since the P-value is less than 0.05, there is a statistically significant difference amongst the medians at the 95.0% confidence level.

The second part of the output shows pairwise comparisons between the average ranks of the 2 groups. Using the Bonferroni procedure, 1 of the comparisons are statistically significant at the 95.0% confidence level.

Type of Wearing Surface

Table B39: Type of wearing surface group definition.

Code	Type of wearing surface
0	none
1	monolithic concrete
2	integral concrete
3	latex concrete or similar additive
4	low-slump concrete
5	epoxy overlay
6	bituminous
8	timber
9	other

CR = 5

Table B40: Summary statistics for type of wearing surface

Type of Wearing Surface	Count	Average	Median	Standard deviation	Coeff. of variation	Minimum	Maximum	Range	Stnd. skewness	Stnd. kurtosis
0	1060	4.05094	3.0	3.31808	81.9089%	1.0	21.0	20.0	22.632	20.0173
1	4012	4.7834	4.0	3.4893	72.946%	1.0	22.0	21.0	32.9943	21.9399
2	954	3.75891	3.0	2.73306	72.7089%	1.0	20.0	19.0	19.8275	22.3489
3	577	4.06412	3.0	3.10539	76.4098%	1.0	17.0	16.0	14.5408	11.7508
4	247	3.69231	3.0	2.69493	72.9878%	1.0	17.0	16.0	11.9089	15.8953
5	85	3.78824	3.0	2.28397	60.2912%	1.0	12.0	11.0	5.78943	4.95019

6	5063	5.16018	4.0	3.68143	71.3431%	1.0	22.0	21.0	35.0919	18.3587
8	477	5.42977	5.0	3.8846	71.5426%	1.0	20.0	19.0	10.2032	4.54413
9	305	4.35082	3.0	3.85744	88.66%	1.0	22.0	21.0	12.9565	11.7546
Total	12780	4.74906	4.0	3.52637	74.254%	1.0	22.0	21.0	61.8923	41.3787

The StatAdvisor

This table shows various statistics for each of the 9 columns of data. To test for significant differences amongst the column means, select Analysis of Variance from the list of Tabular Options. Select Means Plot from the list of Graphical Options to display the means graphically.

WARNING: The standardized skewness and/or kurtosis is outside the range of -2 to +2 for 9 columns. This indicates some significant nonnormality in the data, which violates the assumption that the data come from normal distributions. You may wish to transform the data or use the Kruskal-Wallis test to compare the medians instead of the means.

Table B41: Kruskal-Wallis test for type of wearing surface

Type of Wearing Surface	Sample Size	Average Rank
0	1060	5522.4
1	4012	6450.55
2	954	5402.72
3	577	5646.79
4	247	5338.73
5	85	5705.81
6	5063	6839.19
8	477	7052.9
9	305	5672.54

Test statistic = 280.921   P-Value = 0

Table B42:   95.0 percent Bonferroni intervals

Contrast	*Sig.*	*Difference*	*+/- Limits*
0 - 1	*	-928.157	407.333
0 - 2		119.677	526.376
0 - 3		-124.395	610.207
0 - 4		183.669	833.355
0 - 5		-183.416	1329.64
0 - 6	*	-1316.8	398.4
0 - 8	*	-1530.5	650.307
0 - 9		-150.145	766.403
1 - 2	*	1047.83	424.857
1 - 3	*	803.762	525.151
1 - 4	*	1111.83	773.248
1 - 5		744.741	1292.82
1 - 6	*	-388.638	249.306
1 - 8	*	-602.344	571.254
1 - 9	*	778.012	700.575
2 - 3		-244.072	622.042
2 - 4		63.9924	842.059
2 - 5		-303.093	1335.11
2 - 6	*	-1436.47	416.299
2 - 8	*	-1650.18	661.425
2 - 9		-269.822	775.859
3 - 4		308.064	896.853
3 - 5		-59.0206	1370.33
3 - 6	*	-1192.4	518.253
3 - 8	*	-1406.11	729.906
3 - 9		-25.7498	835.007
4 - 5		-367.085	1483.22
4 - 6	*	-1500.46	768.579
4 - 8	*	-1714.17	924.603
4 - 9		-333.814	1009.64
5 - 6		-1133.38	1290.03
5 - 8		-1347.09	1388.65
5 - 9		33.2708	1446.66
6 - 8		-213.706	564.918
6 - 9	*	1166.65	695.419
8 - 9	*	1380.36	864.745

* denotes a statistically significant difference.

The StatAdvisor

The Kruskal-Wallis test tests the null hypothesis that the medians within each of the 9 columns is the same. The data from all the columns is first combined and ranked from smallest to largest. The average rank is then computed for the data in each column. Since the P-value is less than 0.05, there is a statistically significant difference amongst the medians at the 95.0% confidence level.

The second part of the output shows pairwise comparisons between the average ranks of the 9 groups. Using the Bonferroni procedure, 17 of the comparisons are statistically significant at the 95.0% confidence level.

CR = 8

Table B43: Summary statistics for type of wearing surface

Type of Wearing Surface	Count	Average	Median	Standard deviation	Coeff. of variation	Minimum	Maximum	Range	Stnd. skewness	Stnd. kurtosis
0	8072	6.02639	5.0	4.03588	66.9702%	1.0	22.0	21.0	47.1312	15.8863
1	32565	6.04087	5.0	4.12538	68.2911%	1.0	22.0	21.0	73.9602	16.8054
2	4359	4.60656	3.0	3.40161	73.8428%	1.0	22.0	21.0	41.4202	35.1202
3	2265	4.25519	4.0	2.9509	69.3483%	1.0	17.0	16.0	27.8034	21.7937
4	2210	4.48688	4.0	3.26415	72.7487%	1.0	17.0	16.0	27.4277	20.536
5	690	4.83623	4.0	3.20931	66.3598%	1.0	17.0	16.0	13.7015	8.66951
6	24207	6.02144	5.0	4.12933	68.5772%	1.0	22.0	21.0	64.7312	18.6986
8	1785	6.47675	6.0	4.14421	63.986%	1.0	21.0	20.0	13.3921	-0.892318
9	1759	5.39682	4.0	4.25422	78.8284%	1.0	21.0	20.0	20.6215	5.89053

Total	77912	5.84187	5.0	4.05669	69.4416%	1.0	22.0	21.0	425.657	39.6886

The StatAdvisor

This table shows various statistics for each of the 9 columns of data. To test for significant differences amongst the column means, select Analysis of Variance from the list of Tabular Options. Select Means Plot from the list of Graphical Options to display the means graphically.

WARNING: The standardized skewness and/or kurtosis is outside the range of -2 to +2 for 9 columns. This indicates some significant nonnormality in the data, which violates the assumption that the data come from normal distributions. You may wish to transform the data or use the Kruskal-Wallis test to compare the medians instead of the means.

Table B44: Kruskal-Wallis test for type of wearing surface

Type of Wearing Surface	Sample Size	Average Rank
0	8072	40640.4
1	32565	40058.4
2	4359	31801.9
3	2265	30022.0
4	2210	31238.6
5	690	34102.7
6	24207	39872.0
8	1785	42775.0
9	1759	35190.3

Test statistic = 1370.09 P-Value = 0

Table B45: 95.0 percent Bonferroni intervals

Contrast	*Sig.*	*Difference*	*+/- Limits*
0 - 1		582.014	894.021
0 - 2	*	8838.52	1351.52
0 - 3	*	10618.4	1709.72

0 - 4	*	9401.77	1726.26
0 - 5	*	6537.68	2851.94
0 - 6		768.38	924.171
0 - 8	*	-2134.57	1880.68
0 - 9	*	5450.09	1892.03
1 - 2	*	8256.51	1159.68
1 - 3	*	10036.4	1562.5
1 - 4	*	8819.75	1580.57
1 - 5	*	5955.67	2766.19
1 - 6		186.367	610.203
1 - 8	*	-2716.58	1747.92
1 - 9	*	4868.07	1760.13
2 - 3		1779.86	1862.46
2 - 4		563.245	1877.64
2 - 5		-2300.84	2946.03
2 - 6	*	-8070.14	1183.08
2 - 8	*	-10973.1	2020.53
2 - 9	*	-3388.43	2031.1
3 - 4		-1216.62	2149.91
3 - 5	*	-4080.71	3126.61
3 - 6	*	-9850.01	1579.94
3 - 8	*	-12753.0	2275.77
3 - 9	*	-5168.3	2285.15
4 - 5		-2864.09	3135.68
4 - 6	*	-8633.39	1597.82
4 - 8	*	-11536.3	2288.21
4 - 9	*	-3951.68	2297.55
5 - 6	*	-5769.3	2776.08
5 - 8	*	-8672.25	3223.27
5 - 9		-1087.59	3229.91
6 - 8	*	-2902.95	1763.53
6 - 9	*	4681.71	1775.63
8 - 9	*	7584.66	2415.73

* denotes a statistically significant difference.

The StatAdvisor

The Kruskal-Wallis test tests the null hypothesis that the medians within each of the 9 columns is the same. The data from all the columns is first combined and ranked from smallest to largest. The average rank is then computed for the data in each column. Since the P-value is less than 0.05, there is a statistically significant difference amongst the medians at the 95.0% confidence level.

The second part of the output shows pairwise comparisons between the average ranks of the 9 groups. Using the Bonferroni procedure, 27 of the comparisons are statistically significant at the 95.0% confidence level.

Type of Membrane

Table B46: Type of membrane group definition.

Code	Type of Membrane
0	none
1	built-up
2	preformed fabric
3	epoxy
8	unknown
9	other

CR = 5

Table B47: Summary statistics for type of membrane

Type of Membrane	Count	Average	Median	Standard deviation	Coeff. of variation	Minimum	Maximum	Range	Stnd. skewness	Stnd. kurtosis
0	10299	4.80251	4.0	3.58373	74.6221%	1.0	22.0	21.0	55.5386	35.7735
1	333	3.86186	3.0	3.31737	85.9008%	1.0	18.0	17.0	12.9256	12.3042
2	470	4.47872	4.0	2.94487	65.7524%	1.0	18.0	17.0	10.5941	7.7674
3	92	4.18478	3.0	2.91615	69.6847%	1.0	14.0	13.0	4.88744	2.63696
8	1293	4.67517	4.0	3.27217	69.9903%	1.0	21.0	20.0	16.924	10.6529
9	293	4.8157	4.0	3.68264	76.4715%	1.0	21.0	20.0	10.4916	8.52223
Total	12780	4.74906	4.0	3.52637	74.254%	1.0	22.0	21.0	61.8923	41.3787

The StatAdvisor

This table shows various statistics for each of the 6 columns of data. To test for significant differences amongst the column means, select Analysis of Variance from the list of Tabular Options. Select Means Plot from the list of Graphical Options to display the means graphically.

WARNING: The standardized skewness and/or kurtosis is outside the range of -2 to +2 for 6 columns. This indicates some significant nonnormality in the data, which violates the assumption that the data come from normal distributions. You may wish to transform the data or use the Kruskal-Wallis test to compare the medians instead of the means.

Table B48: Kruskal-Wallis test for type of membrane

Type of Membrane	Sample Size	Average Rank
0	10299	6429.56
1	333	5224.66
2	470	6351.9
3	92	5944.16
8	1293	6419.11
9	293	6418.37

Test statistic = 36.4862 P-Value = 7.59163E-7

Table B49: 95.0 percent Bonferroni intervals

Contrast	Sig.	Difference	+/- Limits
0 - 1	*	1204.89	602.953
0 - 2		77.6555	510.783
0 - 3		485.401	1134.05
0 - 8		10.4465	319.505
0 - 9		11.1849	641.584
1 - 2	*	-1127.24	775.68
1 - 3		-719.494	1275.48

1 - 8	*	-1194.45	665.479
1 - 9	*	-1193.71	867.415
2 - 3		407.746	1234.58
2 - 8		-67.209	583.275
2 - 9		-66.4705	806.074
3 - 8		-474.955	1168.5
3 - 9		-474.216	1294.19
8 - 9		0.738422	700.671

* denotes a statistically significant difference.

The StatAdvisor

The Kruskal-Wallis test tests the null hypothesis that the medians within each of the 6 columns is the same. The data from all the columns is first combined and ranked from smallest to largest. The average rank is then computed for the data in each column. Since the P-value is less than 0.05, there is a statistically significant difference amongst the medians at the 95.0% confidence level.

The second part of the output shows pairwise comparisons between the average ranks of the 6 groups. Using the Bonferroni procedure, 4 of the comparisons are statistically significant at the 95.0% confidence level.

CR = 8

Table B50: Summary statistics for type of membrane

Type of Membrane	Count	Average	Median	Standard deviation	Coeff. of variation	Minimum	Maximum	Range	Stnd. skewness	Stnd. kurtosis
0	53670	5.87928	5.0	4.15221	70.6244%	1.0	22.0	21.0	-219.137	33.9456
1	1824	5.98684	5.0	4.19921	70.1407%	1.0	22.0	21.0	15.3636	-0.194485

2	2297	5.38311	5.0	3.64166	67.6498%	1.0	21.0	20.0	23.4634	9.9589
3	678	4.57522	4.0	3.01147	65.8212%	1.0	16.0	15.0	14.3362	8.26174
8	17833	5.88061	5.0	3.82985	65.1266%	1.0	22.0	21.0	46.9126	10.5254
9	1612	5.18797	4.0	3.87403	74.6734%	1.0	22.0	21.0	24.0934	17.083
Total	77914	5.84183	5.0	4.05665	69.4414%	1.0	22.0	21.0	425.624	39.6953

The StatAdvisor

This table shows various statistics for each of the 6 columns of data. To test for significant differences amongst the column means, select Analysis of Variance from the list of Tabular Options. Select Means Plot from the list of Graphical Options to display the means graphically.

WARNING: The standardized skewness and/or kurtosis is outside the range of -2 to +2 for 6 columns. This indicates some significant nonnormality in the data, which violates the assumption that the data come from normal distributions. You may wish to transform the data or use the Kruskal-Wallis test to compare the medians instead of the means.

Table B51: Kruskal-Wallis test for type of membrane

Type of Membrane	Sample Size	Average Rank
0	53670	38991.1
1	1824	39334.3
2	2297	36981.0
3	678	32491.8
8	17833	39674.5
9	1612	35016.2

Test statistic = 143.584   P-Value = 0

Table B52: 95.0 percent Bonferroni intervals

Contrast	Sig.	Difference	+/- Limits
0 - 1		-343.212	1571.85
0 - 2	*	2010.1	1406.65
0 - 3	*	6499.29	2551.39
0 - 8	*	-683.421	570.624
0 - 9	*	3974.9	1668.82
1 - 2	*	2353.31	2070.5
1 - 3	*	6842.5	2969.49
1 - 8		-340.209	1622.93
1 - 9	*	4318.11	2256.82
2 - 3	*	4489.19	2885.45
2 - 8	*	-2693.52	1463.51
2 - 9		1964.8	2145.04
3 - 8	*	-7182.71	2583.18
3 - 9		-2524.38	3021.94
8 - 9	*	4658.32	1717.02

* denotes a statistically significant difference.

The StatAdvisor

The Kruskal-Wallis test tests the null hypothesis that the medians within each of the 6 columns is the same. The data from all the columns is first combined and ranked from smallest to largest. The average rank is then computed for the data in each column. Since the P-value is less than 0.05, there is a statistically significant difference amongst the medians at the 95.0% confidence level.

The second part of the output shows pairwise comparisons between the average ranks of the 6 groups. Using the Bonferroni procedure, 11 of the comparisons are statistically significant at the 95.0% confidence level.

Deck Protection

Table B53: Deck protection group definition.

Code	Deck protection
0	none
1	epoxy-coated reinforcing
2	galvanized reinforcing
3	other coated reinforcing
4	cathodic protection
6	polymer impregnated
7	internally sealed
8	unknown
9	other

CR = 5

Table B54: Summary statistics for deck protection

Deck Protection	Count	Average	Median	Standard deviation	Coeff. of variation	Minimum	Maximum	Range	Stnd. skewness	Stnd. kurtosis
0	9858	4.84753	4.0	3.64844	75.2639%	1.0	22.0	21.0	54.1471	33.7747
1	1686	3.9917	3.0	2.71624	68.0473%	1.0	16.0	15.0	19.2738	9.05371
2	20	4.1	2.5	3.89196	94.9259%	1.0	15.0	14.0	2.94416	1.85078
3	6	6.5	5.5	3.72827	57.358%	2.0	11.0	9.0	0.416804	-0.816469
4	10	4.9	5.0	2.18327	44.5565%	2.0	8.0	6.0	-0.105444	-1.00299
6	45	3.37778	3.0	2.34801	69.5133%	1.0	11.0	10.0	2.79594	1.33356

7	2	5.0	5.0	5.65685	113.137%	1.0	9.0	8.0		
8	1063	5.13264	4.0	3.45925	67.397%	1.0	21.0	20.0	14.4628	8.47014
9	90	4.31111	4.0	2.46159	57.0987%	1.0	12.0	11.0	2.4048	-0.123204
Total	12780	4.74906	4.0	3.52637	74.254%	1.0	22.0	21.0	61.8923	41.3787

The StatAdvisor

This table shows various statistics for each of the 9 columns of data. To test for significant differences amongst the column means, select Analysis of Variance from the list of Tabular Options. Select Means Plot from the list of Graphical Options to display the means graphically.

WARNING: The standardized skewness and/or kurtosis is outside the range of -2 to +2 for 6 columns. This indicates some significant nonnormality in the data, which violates the assumption that the data come from normal distributions. You may wish to transform the data or use the Kruskal-Wallis test to compare the medians instead of the means.

Table B55: Kruskal-Wallis test for deck protection

Deck Protection	Sample Size	Average Rank
0	9858	6450.41
1	1686	5747.38
2	20	5230.4
3	6	8464.17
4	10	7361.1
6	45	4978.97
7	2	6028.0
8	1063	6919.39
9	90	6354.59

Test statistic = 88.2778   P-Value = 0

Table B56:   95.0 percent Bonferroni intervals

Contrast	*Sig.*	*Difference*	*+/- Limits*
0 - 1	*	703.027	310.849
0 - 2		1220.01	2640.09
0 - 3		-2013.76	4816.71
0 - 4		-910.688	3731.76
0 - 6		1471.44	1762.29
0 - 7		422.412	8341.09
0 - 8	*	-468.983	380.771
0 - 9		95.8227	1248.95
1 - 2		516.985	2653.01
1 - 3		-2716.78	4823.8
1 - 4		-1613.72	3740.92
1 - 6		768.418	1781.59
1 - 7		-280.615	8345.19
1 - 8	*	-1172.01	461.94
1 - 9		-607.204	1276.04
2 - 3		-3233.77	5490.22
2 - 4		-2130.7	4568.14
2 - 6		251.433	3169.78
2 - 7		-797.6	8747.32
2 - 8		-1688.99	2662.11
2 - 9		-1124.19	2915.77
3 - 4		1103.07	6090.85
3 - 6		3485.2	5126.22
3 - 7		2436.17	9630.49
3 - 8		1544.77	4828.81
3 - 9		2109.58	4973.16
4 - 6		2382.13	4123.53
4 - 7		1333.1	9136.28
4 - 8		441.706	3747.37
4 - 9		1006.51	3931.63
6 - 7		-1049.03	8523.57
6 - 8	*	-1940.43	1795.11
6 - 9		-1375.62	2153.44
7 - 8		-891.394	8348.09
7 - 9		-326.589	8432.41
8 - 9		564.805	1294.85

* denotes a statistically significant difference.

The StatAdvisor

The Kruskal-Wallis test tests the null hypothesis that the medians within each of the 9 columns is the same. The data from all the columns is first combined and ranked from smallest to largest. The average rank is then computed for the data in each column. Since the P-value is less than 0.05, there is a statistically significant difference amongst the medians at the 95.0% confidence level.

The second part of the output shows pairwise comparisons between the average ranks of the 9 groups. Using the Bonferroni procedure, 4 of the comparisons are statistically significant at the 95.0% confidence level.

CR = 8

Table B57: Summary statistics for deck protection

Deck Protection	Count	Average	Median	Standard deviation	Coeff. of variation	Minimum	Maximum	Range	Stnd. skewness	Stnd. kurtosis
0	46126	5.94407	5.0	4.21503	70.9116%	1.0	22.0	21.0	99.5145	30.1918
1	15139	5.40201	4.0	3.77202	69.8262%	1.0	22.0	21.0	57.4257	19.0441
2	103	4.41748	3.0	3.23439	73.218%	1.0	16.0	15.0	6.14971	4.44461
3	42	4.71429	3.5	3.24064	68.7408%	1.0	13.0	12.0	2.14634	-0.320902
4	45	4.06667	3.0	2.80746	69.0358%	1.0	15.0	14.0	5.20912	6.39202
6	73	5.9863	5.0	3.42172	57.1591%	1.0	17.0	16.0	4.08513	2.14642
7	18	8.38889	8.5	5.18072	61.7569%	1.0	17.0	16.0	0.129926	-0.991427
8	15908	5.99283	5.0	3.80947	63.5671%	1.0	22.0	21.0	41.469	8.43303
9	458	5.32969	4.0	4.40489	82.6482%	1.0	22.0	21.0	13.6803	9.16465

Total	77912	5.84192	5.0	4.05665	69.4403%	1.0	22.0	21.0	425.664	39.692

The StatAdvisor

This table shows various statistics for each of the 9 columns of data. To test for significant differences amongst the column means, select Analysis of Variance from the list of Tabular Options. Select Means Plot from the list of Graphical Options to display the means graphically.

WARNING: The standardized skewness and/or kurtosis is outside the range of -2 to +2 for 8 columns. This indicates some significant nonnormality in the data, which violates the assumption that the data come from normal distributions. You may wish to transform the data or use the Kruskal-Wallis test to compare the medians instead of the means.

Table B58: Kruskal-Wallis test for deck protection

Deck Protection	Sample Size	Average Rank
0	46126	39256.7
1	15139	36671.8
2	103	30613.1
3	42	33009.8
4	45	28898.3
6	73	42280.4
7	18	50041.8
8	15908	40458.2
9	458	34525.0

Test statistic = 288.344 P-Value = 0

Table B59: 95.0 percent Bonferroni intervals

Contrast	Sig.	Difference	+/- Limits
0 - 1	*	2584.86	673.5
0 - 2	*	8643.57	7092.82
0 - 3		6246.89	11100.1
0 - 4		10358.4	10724.0
0 - 6		-3023.69	8422.39
0 - 7		-10785.1	16951.2
0 - 8	*	-1201.49	661.131
0 - 9	*	4731.74	3376.49
1 - 2		6058.71	7108.97
1 - 3		3662.02	11110.4
1 - 4		7773.57	10734.7
1 - 6		-5608.55	8435.99
1 - 7		-13370.0	16958.0
1 - 8	*	-3786.36	816.407
1 - 9		2146.88	3410.3
2 - 3		-2396.69	13164.2
2 - 4		1714.86	12848.7
2 - 6	*	-11667.3	11000.9
2 - 7	*	-19428.7	18369.2
2 - 8	*	-9845.07	7107.81
2 - 9		-3911.83	7841.21
3 - 4		4111.54	15427.0
3 - 6		-9270.58	13925.7
3 - 7		-17032.0	20256.7
3 - 8		-7448.38	11109.7
3 - 9		-1515.14	11592.6
4 - 6		-13382.1	13627.8
4 - 7	*	-21143.5	20053.1
4 - 8	*	-11559.9	10734.0
4 - 9		-5626.69	11233.1
6 - 7		-7761.41	18922.4
6 - 8		1822.19	8435.02
6 - 9		7755.43	9061.63
7 - 8		9583.6	16957.5
7 - 9		15516.8	17277.8
8 - 9	*	5933.24	3407.88

* denotes a statistically significant difference.

The StatAdvisor

The Kruskal-Wallis test tests the null hypothesis that the medians within each of the 9 columns is the same. The data from all the columns is first combined and ranked from smallest to largest. The average rank is then computed for the data in each column. Since the P-value is less than 0.05, there is a statistically significant difference amongst the medians at the 95.0% confidence level.

The second part of the output shows pairwise comparisons between the average ranks of the 9 groups. Using the Bonferroni procedure, 11 of the comparisons are statistically significant at the 95.0% confidence level.

Average Daily Truck Traffic (ADTT)

Table B60: Average Daily Truck Traffic (ADTT) group definition.

Code	Average Daily Truck Traffic (ADTT)
1	ADTT< 100
2	100 < ADTT < 8500
3	ADTT > 8500

CR = 5

Table B61: Summary statistics for ADTT

ADTT	Count	Average	Median	Standard deviation	Coeff. of variation	Minimum	Maximum	Range	Stnd. skewness	Stnd. kurtosis
1	6257	5.07895	4.0	3.71247	73.0952%	1.0	22.0	21.0	39.7933	21.1823
2	6216	4.44949	4.0	3.32881	74.8133%	1.0	22.0	21.0	46.4284	37.3915
3	307	4.09121	3.0	2.82811	69.1265%	1.0	17.0	16.0	8.21989	4.97173
Total	12780	4.74906	4.0	3.52637	74.254%	1.0	22.0	21.0	61.8923	41.3787

The StatAdvisor

This table shows various statistics for each of the 3 columns of data. To test for significant differences amongst the column means, select Analysis of Variance from the list of Tabular Options. Select Means Plot from the list of Graphical Options to display the means graphically.

WARNING: The standardized skewness and/or kurtosis is outside the range of -2 to +2 for 3 columns. This indicates some significant nonnormality in the data, which violates the assumption that the data come from normal distributions. You may wish to transform the data or use the Kruskal-Wallis test to compare the medians instead of the means.

Table B62: Kruskal-Wallis test for ADTT

ADTT	Sample Size	Average Rank
1	6257	6711.62
2	6216	6094.29
3	307	5843.16

Test statistic = 95.7706 P-Value = 0

Table B63: 95.0 percent Bonferroni intervals

Contrast	Sig.	Difference	+/- Limits
1 - 2	*	617.331	158.17
1 - 3	*	868.463	516.31
2 - 3		251.132	516.39

* denotes a statistically significant difference.

The StatAdvisor

The Kruskal-Wallis test tests the null hypothesis that the medians within each of the 3 columns is the same. The data from all the columns is first combined and ranked from smallest to largest. The average rank is then computed for the data in each column. Since the P-value is less than 0.05, there is a statistically significant difference amongst the medians at the 95.0% confidence level.

The second part of the output shows pairwise comparisons between the average ranks of the 3 groups. Using the Bonferroni procedure, 2 of the comparisons are statistically significant at the 95.0% confidence level.

CR = 8

Table B64: Summary statistics for ADTT

ADTT	Count	Average	Median	Standard deviation	Coeff. of variation	Minimum	Maximum	Range	Stnd. skewness	Stnd. kurtosis
1	40821	6.39377	5.0	4.31071	67.4205%	1.0	22.0	21.0	75.7873	8.92354
2	36143	5.25131	4.0	3.68774	70.2252%	1.0	22.0	21.0	98.3566	51.0735
3	950	4.59158	5.0	2.43039	52.9314%	1.0	17.0	16.0	17.3924	24.3468
Total	77914	5.84183	5.0	4.05665	69.4414%	1.0	22.0	21.0	425.624	39.6953

The StatAdvisor

This table shows various statistics for each of the 3 columns of data. To test for significant differences amongst the column means, select Analysis of Variance from the list of Tabular Options. Select Means Plot from the list of Graphical Options to display the means graphically.

WARNING: The standardized skewness and/or kurtosis is outside the range of -2 to +2 for 3 columns. This indicates some significant nonnormality in the data, which violates the assumption that the data come from normal distributions. You may wish to transform the data or use the Kruskal-Wallis test to compare the medians instead of the means.

Table B65: Kruskal-Wallis test for ADTT

ADTT	Sample Size	Average Rank
1	40821	41778.2
2	36143	35888.8

3	950	34502.8

Test statistic = 1367.0   P-Value = 0

Table B66:   95.0 percent Bonferroni intervals

Contrast	Sig.	Difference	+/- Limits
1 - 2	*	5889.47	388.901
1 - 3	*	7275.48	1767.19
2 - 3		1386.01	1769.79

* denotes a statistically significant difference.

The StatAdvisor

The Kruskal-Wallis test tests the null hypothesis that the medians within each of the 3 columns is the same. The data from all the columns is first combined and ranked from smallest to largest. The average rank is then computed for the data in each column. Since the P-value is less than 0.05, there is a statistically significant difference amongst the medians at the 95.0% confidence level.

The second part of the output shows pairwise comparisons between the average ranks of the 3 groups. Using the Bonferroni procedure, 2 of the comparisons are statistically significant at the 95.0% confidence level.

International Energy Conservation Code (IECC) Climatic Regions

Table B67: IECC group definition.

Code	Climatic Region
2	Very Hot
3	Hot
4	Average
5	Cold
6	Very cold
7	Extremly Cold
8	Subartic
9	Average Marine
10	Hot Marine

CR = 5

Table B68: Summary statistics for *IECC*

IECC	Count	Average	Median	Standard deviation	Coeff. of variation	Minimum	Maximum	Range	Stnd. skewness	Stnd. kurtosis
2	303	5.39274	4.0	4.42385	82.0334%	1.0	22.0	21.0	10.1289	6.28564
3	2446	4.44563	4.0	3.22708	72.5899%	1.0	21.0	20.0	28.3575	24.626
4	2075	5.1947	4.0	3.83453	73.8163%	1.0	22.0	21.0	23.6164	13.3101
5	5064	4.9293	4.0	3.63815	73.8066%	1.0	22.0	21.0	35.0056	16.7053
6	2432	4.39844	4.0	3.13359	71.2432%	1.0	22.0	21.0	28.3492	23.0988
7	147	5.02041	4.0	3.95604	78.7992%	1.0	17.0	16.0	5.25994	0.920993
8	4	3.5	3.0	1.0	28.5714%	3.0	5.0	2.0	1.63299	1.63299

9	94	3.64894	3.0	2.89125	79.2353%	1.0	15.0	14.0	7.95237	9.51262
10	215	3.03256	2.0	2.26799	74.7881%	1.0	17.0	16.0	12.6809	20.9566
Total	12780	4.74906	4.0	3.52637	74.254%	1.0	22.0	21.0	61.8923	41.3787

The StatAdvisor

This table shows various statistics for each of the 9 columns of data. To test for significant differences amongst the column means, select Analysis of Variance from the list of Tabular Options. Select Means Plot from the list of Graphical Options to display the means graphically.

WARNING: There is more than a 3 to 1 difference between the smallest standard deviation and the largest. This may cause problems since the analysis of variance assumes that the standard deviations at all levels are equal. Select Variance Check from the list of Tabular Options to run a formal statistical test for differences among the sigmas. You may want to consider transforming the data to remove any dependence of the standard deviation on the mean.

WARNING: The standardized skewness and/or kurtosis is outside the range of -2 to +2 for 8 columns. This indicates some significant nonnormality in the data, which violates the assumption that the data come from normal distributions. You may wish to transform the data or use the Kruskal-Wallis test to compare the medians instead of the means.

Table B69: Kruskal-Wallis test for IECC

IECC	Sample Size	Average Rank
2	303	6707.24
3	2446	6148.01
4	2075	6797.22

5	5064	6547.51
6	2432	6140.17
7	147	6434.14
8	4	5814.38
9	94	5167.41
10	215	4426.79

Test statistic = 131.868   P-Value = 0

Table B70:   95.0 percent Bonferroni intervals

Contrast	Sig.	Difference	+/- Limits
2 - 3		559.228	718.343
2 - 4		-89.9795	725.386
2 - 5		159.734	697.576
2 - 6		567.068	718.571
2 - 7		273.1	1185.55
2 - 8		892.864	5936.24
2 - 9	*	1539.83	1392.53
2 - 10	*	2280.45	1051.76
3 - 4	*	-649.208	352.025
3 - 5	*	-399.494	290.428
3 - 6		7.83999	337.757
3 - 7		-286.129	1001.63
3 - 8		333.636	5902.26
3 - 9		980.601	1239.71
3 - 10	*	1721.22	839.013
4 - 5		249.714	307.437
4 - 6	*	657.048	352.49
4 - 7		363.079	1006.7
4 - 8		982.844	5903.13
4 - 9	*	1629.81	1243.8
4 - 10	*	2370.43	845.052
5 - 6	*	407.334	290.991
5 - 7		113.366	986.845
5 - 8		733.13	5899.77
5 - 9	*	1380.1	1227.79
5 - 10	*	2120.72	821.303
6 - 7		-293.969	1001.8
6 - 8		325.796	5902.29
6 - 9		972.761	1239.84

6 - 10	*	1713.38	839.208
7 - 8		619.764	5977.14
7 - 9		1266.73	1557.69
7 - 10	*	2007.35	1262.32
8 - 9		646.965	6021.62
8 - 10		1387.59	5952.05
9 - 10		740.621	1458.44

* denotes a statistically significant difference.

The StatAdvisor

The Kruskal-Wallis test tests the null hypothesis that the medians within each of the 9 columns is the same. The data from all the columns is first combined and ranked from smallest to largest. The average rank is then computed for the data in each column. Since the P-value is less than 0.05, there is a statistically significant difference amongst the medians at the 95.0% confidence level.

The second part of the output shows pairwise comparisons between the average ranks of the 9 groups. Using the Bonferroni procedure, 13 of the comparisons are statistically significant at the 95.0% confidence level.

CR = 8

Table B71: Summary statistics for *IECC*

IECC	Count	Average	Median	Standard deviation	Coeff. of variation	Minimum	Maximum	Range	Stnd. skewness	Stnd. kurtosis
2	9089	6.04049	5.0	4.02366	66.6115%	1.0	22.0	21.0	39.6297	12.4853
3	18876	6.33953	5.0	4.19307	66.1416%	1.0	22.0	21.0	63.2831	25.202
4	13144	5.48486	4.0	3.9662	72.3118%	1.0	22.0	21.0	59.1505	27.8156
5	23298	5.72354	5.0	4.06215	70.9726%	1.0	22.0	21.0	62.0706	7.85705

6	11106	5.74248	5.0	4.00811	69.7976%	1.0	22.0	21.0	43.2712	7.27971
7	823	6.06075	5.0	3.93391	64.9079%	1.0	17.0	16.0	9.06919	-0.10143
8	36	4.75	5.0	2.94109	61.9176%	1.0	15.0	14.0	3.43307	3.59814
9	1122	3.7656	3.0	2.61836	69.5337%	1.0	17.0	16.0	25.661	30.2739
10	420	4.74524	5.0	0.879005	18.5239%	1.0	9.0	8.0	-19.0432	32.5253
Total	77914	5.84183	5.0	4.05665	69.4414%	1.0	22.0	21.0	425.624	39.6953

The StatAdvisor

This table shows various statistics for each of the 9 columns of data. To test for significant differences amongst the column means, select Analysis of Variance from the list of Tabular Options. Select Means Plot from the list of Graphical Options to display the means graphically.

WARNING: There is more than a 3 to 1 difference between the smallest standard deviation and the largest. This may cause problems since the analysis of variance assumes that the standard deviations at all levels are equal. Select Variance Check from the list of Tabular Options to run a formal statistical test for differences among the sigmas. You may want to consider transforming the data to remove any dependence of the standard deviation on the mean.

WARNING: The standardized skewness and/or kurtosis is outside the range of -2 to +2 for 9 columns. This indicates some significant nonnormality in the data, which violates the assumption that the data come from normal distributions. You may

wish to transform the data or use the Kruskal-Wallis test to compare the medians instead of the means.

Table B72: Kruskal-Wallis test for IECC

IECC	Sample Size	Average Rank
2	9089	40362.8
3	18876	42017.6
4	13144	36758.8
5	23298	37999.0
6	11106	38373.9
7	823	40709.6
8	36	34256.9
9	1122	26535.8
10	420	38582.4

Test statistic = 919.191 P-Value = 0

Table B73: 95.0 percent Bonferroni intervals

Contrast	Sig.	Difference	+/- Limits
2 - 3	*	-1654.74	918.034
2 - 4	*	3604.06	980.938
2 - 5	*	2363.82	889.267
2 - 6	*	1988.89	1017.07
2 - 7		-346.74	2617.5
2 - 8		6105.92	12008.0
2 - 9	*	13827.0	2275.33
2 - 10		1780.46	3588.8
3 - 4	*	5258.8	816.876
3 - 5	*	4018.56	704.162
3 - 6	*	3643.63	859.925
3 - 7		1308.0	2560.54
3 - 8		7760.65	11995.7
3 - 9	*	15481.8	2209.56
3 - 10		3435.2	3547.47
4 - 5	*	-1240.24	784.409
4 - 6	*	-1615.17	926.782

4 - 7	*	-3950.8	2583.76
4 - 8		2501.86	12000.7
4 - 9	*	10223.0	2236.43
4 - 10		-1823.6	3564.26
5 - 6		-374.932	829.145
5 - 7	*	-2710.56	2550.37
5 - 8		3742.09	11993.6
5 - 9	*	11463.2	2197.77
5 - 10		-583.363	3540.13
6 - 7		-2335.63	2597.69
6 - 8		4117.03	12003.7
6 - 9	*	11838.2	2252.51
6 - 10		-208.431	3574.38
7 - 8		6452.66	12243.6
7 - 9	*	14173.8	3300.11
7 - 10		2127.2	4311.97
8 - 9		7721.13	12175.1
8 - 10		-4325.46	12487.4
9 - 10	*	-12046.6	4113.25

* denotes a statistically significant difference.

The StatAdvisor

The Kruskal-Wallis test tests the null hypothesis that the medians within each of the 9 columns is the same. The data from all the columns is first combined and ranked from smallest to largest. The average rank is then computed for the data in each column. Since the P-value is less than 0.05, there is a statistically significant difference amongst the medians at the 95.0% confidence level.

Distance from seawater

Table B74: Distance from seawater group definition

Code	Distance from seawater
1	d< 1 km (0.62miles)
2	1 km (0.62miles)< d < 2 km (1.2miles)
3	d > 2 km (1.2miles)

CR = 5

Table B75: Summary Statistics for distance from seawater

Distance from seawater	Count	Average	Median	Standard deviation	Coeff. of variation	Minimum	Maximum	Range	Stnd. skewness	Stnd. kurtosis
1	39	4.07692	3.0	2.91443	71.4861%	1.0	13.0	12.0	3.06958	1.47019
2	55	4.12727	3.0	3.65683	88.6016%	1.0	17.0	16.0	5.3128	4.35288
3	12686	4.75382	4.0	3.52732	74.1996%	1.0	22.0	21.0	61.5944	41.158
Total	12780	4.74906	4.0	3.52637	74.254%	1.0	22.0	21.0	61.8923	41.3787

The StatAdvisor

This table shows various statistics for each of the 3 columns of data. To test for significant differences amongst the column means, select Analysis of Variance from the list of Tabular Options. Select Means Plot from the list of Graphical Options to display the means graphically.

WARNING: The standardized skewness and/or kurtosis is outside the range of -2 to +2 for 3 columns. This indicates some significant nonnormality in the data, which violates the assumption that the data come from normal distributions. You may wish to transform the data or use the Kruskal-Wallis test to compare the medians instead of the means.

Table B76: Kruskal-Wallis test for distance from seawater

Distance from seawater	Sample Size	Average Rank
1	39	5787.55
2	55	5439.85
3	12686	6396.48

Test statistic = 4.80407   P-Value = 0.0905336

Table B77: 95.0 percent Bonferroni intervals

Contrast	Sig.	Difference	+/- Limits
1 - 2		347.706	1848.97
1 - 3		-608.924	1416.49
2 - 3		-956.63	1193.54

* denotes a statistically significant difference.

The StatAdvisor

The Kruskal-Wallis test tests the null hypothesis that the medians within each of the 3 columns is the same. The data from all the columns is first combined and ranked from smallest to largest. The average rank is then computed for the data in each column. Since the P-value is greater than or equal to 0.05, there is not a statistically significant difference amongst the medians at the 95.0% confidence level.

The second part of the output shows pairwise comparisons between the average ranks of the 3 groups. Using the Bonferroni procedure, 0 of the comparisons are statistically significant at the 95.0% confidence level.

CR = 8

Table B78: Summary statistics for distance from seawater

Distance from seawater	Count	Average	Median	Standard deviation	Coeff. of variation	Minimum	Maximum	Range	Stnd. skewness	Stnd. kurtosis
1	195	5.48205	5.0	3.02284	55.1407%	1.0	15.0	14.0	5.0355	1.01995
2	181	5.1989	5.0	3.09196	59.4734%	1.0	15.0	14.0	5.48386	1.46916
3	77538	5.84423	5.0	4.06077	69.4834%	1.0	22.0	21.0	434.539	39.3568
Total	77914	5.84183	5.0	4.05665	69.4414%	1.0	22.0	21.0	425.624	39.6953

The StatAdvisor

This table shows various statistics for each of the 3 columns of data. To test for significant differences amongst the column means, select Analysis of Variance from the list of Tabular Options. Select Means Plot from the list of Graphical Options to display the means graphically.

WARNING: The standardized skewness and/or kurtosis is outside the range of -2 to +2 for 3 columns. This indicates some significant nonnormality in the data, which violates the assumption that the data come from normal distributions. You may wish to transform the data or use the Kruskal-Wallis test to compare the medians instead of the means.

Table B79: Kruskal-Wallis test for distance from seawater

Distance from seawater	Sample Size	Average Rank
1	195	39580.0
2	181	37163.6
3	77538	38960.1

Test statistic = 1.3161 P-Value = 0.517859

Table B80: 95.0 percent Bonferroni intervals

Contrast	Sig.	Difference	+/- Limits
1 - 2		2416.38	5557.59
1 - 3		619.904	3860.8
2 - 3		-1796.48	4006.97

* denotes a statistically significant difference.

The StatAdvisor

The Kruskal-Wallis test tests the null hypothesis that the medians within each of the 3 columns is the same. The data from all the columns is first combined and ranked from smallest to largest. The average rank is then computed for the data in each column. Since the P-value is greater than or equal to 0.05, there is not a statistically significant difference amongst the medians at the 95.0% confidence level.

The second part of the output shows pairwise comparisons between the average ranks of the 3 groups. Using the Bonferroni procedure, 0 of the comparisons are statistically significant at the 95.0% confidence level.