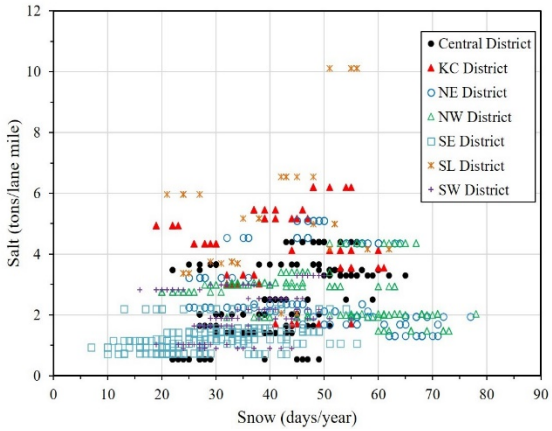
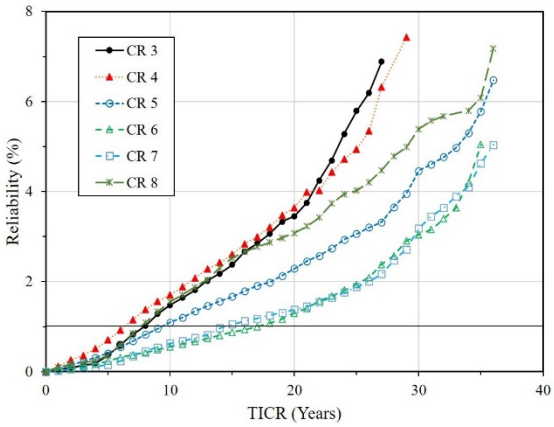
Evaluation of Missouri's NBI Data to Predict the Deterioration of Bridges





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16. Abstract

The objectives of this study were to develop deterioration curves for state-owned bridges in Missouri, study certain parameters that affect structure deterioration, and develop recommendations for cost effective designs. The study used inspection history data stored in the National Bridge Inventory (NBI). NBI data from 1983 through 2019 was used to determine the inspection histories and Condition Ratings (CR) for bridge components and culverts. Two different deterioration models were used to analyze these data. The Kaplan-Meir survival methodology was used to determine the Time in Condition Rating (TICR) and hazard functions for primary bridge components and culverts. Cox regression analysis was used to study parameters that affect structure deterioration. Parameters studied included the rate of salt application, span length, traffic volume, and environmental conditions. The performance of cast-in-place (CIP) bridge decks in different districts in the state was also studied.

The results showed that the deterioration patterns for structures generally had an inflection point at CR 5, where deterioration rates increased as compared with CR 6,7, and 8. The results also demonstrated that the application of salt to the roadway to prevent icing had a significant impact on the deterioration of all structures, and its impact was commonly at least twice that of any other parameter studied. It was also found that increasing span length increased the rate of deterioration. Traffic volume as measured by Average Daily Traffic (ADT) and Average Daily Truck Traffic (ADTT) did not have a statistically significant effect on the deterioration of bridges. It was also found that the deterioration of bridge decks was different in different districts, and reliability curves were developed for each district to aid engineers in decision-making regarding maintenance and repair.

Recommendations from the research included increasing the use of preservation strategies to maintain bridges in CR 6,7, and 8, where deterioration rates are lower as compared with CR 5, 4, and 3. Actions to prevent exposure to deicing chemicals, many of which are already applied in some cases, were described. Looking forward, research results should be considered as one factor in the selection of materials and geometry for new bridges.

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Evaluation of Missouri's NBI Data to Predict the Deterioration of Bridges
TR202012

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ACKNOWLEDGMENTS

We would like to thank the Missouri Department of Transportation (MoDOT) for sponsoring this research. We would like to acknowledge the assistance provided by David Koenig and other MoDOT personnel with several aspects of the research, such as data analysis objectives and needs, providing guidance and methods to resolve bridge number changes, providing data on salt usage is different districts across the state, and providing review and comment throughout the research.

DISCLAIMER

The opinions, findings, and conclusions expressed in this document are those of the investigators. They are not necessarily those of the Missouri Department of Transportation, U.S. Department of Transportation, or Federal Highway Administration. This information does not constitute a standard or specification.

EXECUTIVE SUMMARY

This report documents research conducted under research project TR202012, "*Evaluation of Missouri's NBI Data to Predict the Deterioration of Bridges.*" The objectives of this research were to develop deterioration curves for different bridge components and culverts, identify trends in deterioration patterns affected by parameters such as the structure type, age, span length, and other relevant parameters, and develop recommendations on cost-effective bridge types. To conduct this analysis, records from the Federal Highway Administration's (FHWA) National Bridge Inventory (NBI) were obtained for the years of 1983 through 2019. These data include the Condition Ratings (CRs) for primary bridge components (deck, superstructure, and substructure) and culverts as submitted each year by Missouri, as well as myriad other data regarding the location, route, and design of individual structures. The project includes the analysis of primary bridge components and culverts. The combined group of bridge components and culverts is referred to in the report generically as "structures."

Deterioration curves were developed based on Kaplan-Meir (K-M) method of survival analysis. This methodology applies the NBI CR data collected over a time interval of 37 years to calculate the probability of likelihood of a structure to transition to the next lower CR. These data were then analyzed and median service life estimates were provided for the deck, superstructure, and substructure of bridges formed from the materials of steel, reinforced concrete (RCC), and prestressed concrete (PSC). Similar curves and service life estimates were produced for concrete culverts.

Cox regression analysis was used to identify and quantify trends in the deterioration of different types of bridges MoDOT has built over the years. These data were analyzed to determine the influence of covariates, generally parameters that are believed to affect the deterioration patterns for bridges. The methodology for Cox regression analysis involved first determining if a given covariate or parameter has a statistically significant influence on the model. The report illustrated this procedure for CIP decks and provided raw data on the beta factors for the different covariates. For other components and culverts, the raw data is available in the appendix. Hazard ratios were used to explore the influence of the statistically significant covariates on the deterioration patterns for bridges.

The results of the research showed the following:

- *The quantity of salt application had greater impact on the deterioration of structures than any other parameter studied.*
- *CIP decks formed on steel continuous superstructures had longer median service life estimate (54 years) as compared with steel simple girders (50 years) and PSC continuous superstructures (44 years). PSC box beams provided the shortest service life for CIP decks (38 years), while RCC slabs (59 years) provided the longest service life.*

- *The primary modern superstructure types, including steel simple girder, steel continuous girders, and PSC continuous bridge types, had very similar deterioration patterns between CR 8 and CR 4. PSC box beam bridges had the shortest median service life, while RCC slab bridges had the longest service life.*
- *The age of a component or culvert has a statistically significant effect on its reliability, resulting in increased likelihood of transition to the next lower CR or between 3 and 10% per 10 years of age.*
- *Span length has a small but measurable (statistically significant) effect on the deterioration of structures.*
- *In almost all cases, the deterioration rate of structures as measured by median service life graphs had an increase in slope at CR 5, meaning that once a bridge is rated in CR 5, the deterioration rate is increased.*
- *The research showed that structures formed from RCC, such as slabs, RCC beam bridge, and culverts had the longest median service life estimates. PSC box girder bridges had the shortest estimated median service life.*
- *The data showed that ADT and ADTT did not have a statistically significant effect on the reliability of structures.*

The report also included a section on how to implement the results of the research for asset management such as forecasting future bridge conditions based on the results of the research.

Based on the results of the research, four recommendations were made:

Recommendation 1: Implement preservation strategies to maintain bridges in good condition.

Recommendation 2: Perform a best-practices survey for PSC box beam bridges.

Recommendation 3: Consider impact of parameters studied for bridge type and geometry selection during preliminary design.

Recommendation 4: Improve monitoring of salt application.

INTRODUCTION

This report documents research conducted under research project TR202012, "*Evaluation of Missouri's NBI Data to Predict the Deterioration of Bridges.*" The objectives of this research were to develop deterioration curves for different bridge components and culverts, identify trends in deterioration patterns affected by parameters such as the structure type and age, span length, and other relevant parameters that influence deterioration patterns, and develop recommendations for cost-effective bridge types. To conduct this analysis, records from the Federal Highway Administration's (FHWA) National Bridge Inventory (NBI) were obtained for the years of 1983 through 2019. These data include the CRs for primary bridge components (deck, superstructure, and substructure) and culverts as submitted each year by Missouri, as well as myriad other data regarding the location, route, and design of individual structures. The project includes the analysis of primary bridge components and culverts. The combined group of bridge components and culverts is referred to in the report generically as "structures."

The NBI data were analyzed using two different analytical models to capture both the overall performance of structures based on historical inspection records stored in the NBI and to assess the influence of different parameters that affect deterioration. These data have been analyzed and this report and its appendices provide the results of that analysis. During the course of the research, the research team (RT) met several times with MoDOT personnel to update them on progress and receive input on how to best meet the agency needs through the research. This report and the analysis contained within it have been improved and focused through this collaboration, and specific data presentations have been included to meet some identified needs.

Historically, bridge inspection in the US began shortly after the collapse of the Silver Bridge on December 15, 1967. Following the collapse, requirements for the inspection and reporting of bridge conditions to the FHWA were established in 1971, with the first round of inspection on National Highway System bridges due in 1973. Inspections were completed on a component level basis that rated three primary components of a bridge (deck, superstructure, and substructure). Additional data on the characteristics and location of the structure were also recorded. In conventional component-level bridge inspection, bridge managers use inspection results to identify maintenance needs from the safety perspective to help make decisions. A subjective CR scale ranging from 0-9 is used to characterize the condition of bridge components relative to the as-built condition. Culverts receive a single CR to describe the general condition of the culvert. The CRs are recorded on a 0-9 scale where 0 is a structure in "failed condition – out of service" and 9 is a structure in "excellent condition." Structures in "good" condition have CRs of 7 or greater, structures in "poor" condition have ratings of 4 or less. Structures with CRs of 5 or 6 are considered in "fair" condition. The results of the inspection along with other data describing a structure are submitted annually by bridge

owners to the FHWA. These data are stored in the NBI. Although this data collection has been ongoing since the early 1970s, the available data from the FHWA begins in 1983.

Currently, bridge owners like MoDOT are working to effectively implement asset management strategies to achieve an overall state of good repair and balance limited funding resources with the continuous aging and deterioration of the asset inventory. Recent requirements such as the Moving Ahead for Progress in the 21st Century Act (MAP-21) and the Fixing America's Surface Transportation Act (FAST ACT) require transportation agencies to develop and implement a data-driven, risk-based transportation asset management approach for all National Highway System pavements and bridges, regardless of ownership. In response, agencies were obligated to submit documentation to FHWA outlining Transportation Asset Management Plans (TAMPs). TAMPs generally provide a summary listing of an agency's pavement and bridge assets including their condition, asset management objectives and measures, performance gap analyses, lifecycle cost and risk management processes, and investment strategies to achieve and sustain a state of good repair for all assets. Information on the anticipated deterioration rates and future performance estimates for assets are key data for asset management plans, to identify future funding needs and drive maintenance and repair decisions.

This research is targeted to provide key data on the past and projected future performance of structures in the state of Missouri, based on the NBI data. The focus of the analysis is the CRs for primary bridge components and culverts. These data represent the results of routine bridge inspection conducted every 24 months for most bridges. These data have been analyzed for the purpose of identifying deterioration trends, identifying key parameters that affect bridge deterioration, and providing data-driven analysis of the performance of different bridge types.

The following section provides an overview of the objectives of the research deterioration models used in the research. The Background section also describes how NBI data was acquired and corrected to fix bridge numbering changes that had occurred historically, as noted in the Request for Proposals (RFP) for this project. The parameters or covariates studied in the research are also described, including the statistical data describing the distribution and statistical characteristics of the parameters.

The chapter entitled "RESULTS" includes the results of deterioration modeling and analysis. The section begins with analysis of cast-in-place (CIP) reinforced concrete (RC) bridge decks, followed by an analysis of the effect of different superstructure types on the performance of CIP decks. This section includes a description of the process and results from Cox regression analysis. The results of modeling for superstructure, substructure, and culverts are also shown. Finally, the chapter entitled "CONCLUSIONS" includes a brief summary of the effort and the key findings and conclusions, as well as recommendations related to the results of the research.

A series of appendices are provided that include more detailed descriptions of the statistical methods used, comprehensive listings of the superstructure types included in the NBI, and additional data analysis including detailed data from the Cox regression analysis. The appendices also include reliability and service life plots for CIP decks in different districts, for use by engineers in the district offices to aid in decision-making regarding the preservation and maintenance of bridge decks in their district. Reliability and service life plots for CIP decks on different superstructures types and plots for different superstructure types are also included in the appendices. Verification studies related to the modeling can also be found in the appendices.

BACKGROUND

There are approximately 7,200 state-owned bridges and 3,200 state-owned culverts in the state of Missouri. These structures are deteriorating over time due to evolving damage, much of which results from corrosion of steel, either steel bridge components or the reinforcing steel embedded in concrete components. Over the service life of a structure, this deterioration is monitored through routine inspections that assign a CR to the primary bridge components and culverts. Over time, the deterioration of the components can be tracked through the inspection results represented by the CRs. The rate of deterioration of structures can be affected by a number of variable parameters such as the primary material of construction (e.g., steel, reinforced concrete (RC), or prestressed concrete (PSC)). Structures may have different configurations of span, overall length, and continuity, with some bridges constructed as simple span and others as continuous spans over an interior support. Structures are exposed to different traffic volumes, generally expressed as the Average Daily Traffic (ADT) and Average Daily Truck Traffic (ADTT). The surrounding environmental conditions, freeze/thaw cycles, or the rate of deicing chemical application can have an impact on the deterioration patterns for bridges. Each of these parameters were studied in the research to assess their influence on the deterioration of structures in Missouri.

In order to better understand the performance and deterioration of structures in Missouri, this research had the following specific objectives:

1. Develop deterioration curves for the different parts of a bridge broken out by the different types of materials used on bridges. The different parts would be the deck, superstructure, and substructure and the primary materials would be steel, reinforced concrete, and prestressed concrete.
2. Develop a deterioration curve for reinforced concrete box culverts.
3. Identify and quantify trends in the deterioration of different types of bridges MoDOT has built over the years. Some of the ways to analyze the data could include but are not limited to:
    - Structure type,
    - Age of the structure,
    - Era of construction,
    - Span length,
    - Condition assessment,
    - Material type,
    - Traffic volume, and
    - Location and environmental exposure.
4. Provide recommendations of cost-effective bridge types identified in the previous objective.

To meet the objectives of the research, deterioration modeling and analysis have been completed using two different methodologies. The Kaplan-Meier (K-M) approach has been used to characterize the past performance of different structure types. This approach is a survival analysis that assesses the likelihood of transitioning from one CR to the next CR based on the past performance as represented in the historical inspection records of the NBI. The second method used was Cox regression analysis, which is used to assess the impact of different parameters, such as span length, ADT, ADTT, and salt application rates. The Cox regression analysis is useful for multi-variate analysis such as required to determine the influence of these parameters on the deterioration of bridges. The following section provides a summary of these analysis methodologies. A more complete explanation including modeling assumption used can be found in Appendix A.

Description of the Statistical Methods

The deterioration modeling for the project was conducted using two separate methodologies as noted above. The K-M method of survival analysis was used to determine the overall characteristics of deterioration in terms of the Time in Condition Rating (TICR) for culverts and bridge components of deck, superstructure, and substructure. This analysis was used to characterize the reliability of structures in terms of how rapidly components' CR decreased over time based on historical inspection records that were obtained for the project. The K-M approach to modeling the deterioration patterns for bridges has the advantage of being based specifically on historical data in the form of the inspection results (CRs) that represents the past performance of structures. In this way, the results are closely tied to actual quantitative data in the form of CRs assigned by inspectors. However, the K-M modeling approach is not well-suited for analysis of specific factors or parameters that might affect the deterioration of structures, e.g., the span length, or environmental parameters such as the number of snowy days or application salt, etc. For observing trends in deterioration resulting from these other parameters, Cox regression analysis was used.

Cox regression or Cox proportional hazard analysis was used to assess the effect of independent variables such as span length, application of deicing chemicals (i.e., salt), etc. on bridge component and culvert deterioration. This methodology is optimum for assessing multiple independent variables (i.e., parameters or *covariates*) that might influence the deterioration of structures, how these variables interact, and which variables have a significant influence on bridge deterioration.

It should be mentioned that other deterioration modeling approaches exist that were not used in this research. For example, the Markov modeling approach is a prospective deterioration modeling approach that assesses future performance based on transition probabilities. This model has been in use for many years in various asset management and bridge management software. However, the power-law aspects of the Markov model do not represent the actual deterioration pattern of bridges, because its results represent

more rapid deterioration at the initiation of deterioration. Deterioration rates generally increase with evolving damage over the service life of a structure, so Markov models generally yield inaccurate results when compared with experience. The advantage of Markov models is their mathematical simplicity that allows large data sets to be processed and deterioration patterns projected into the future efficiently, if not accurately. Another popular deterioration modeling approach is Weibull analysis, which is a suitable survival analysis methodology for continuous data. The Weibull approach is best suited for natural systems yielding continuous results, such as tension test data or survival times for components that fail at random time intervals. Bridge inspection results are not continuous since the results are required to be represented in categories on a 0 to 9 scale. As a result, Weibull analysis is theoretically poorly suited to bridge inspection results.

The RT has developed extensive experience with each of these modeling approaches over recent years, and more information on these alternatives can be found in various references [1, 2]. However, for the current research, the K-M methodology is most appropriate and was selected as the backbone of the analysis. The Cox regression approach was also used for multi-variate analysis, as previously mentioned.

The following sections provide a summary of the two different data analysis approaches used in the research. A more detailed review of the methodologies, along with the assumption applied and methodologies used to resolve issues within the modeling approaches are shown in Appendix A.

Kaplan-Meier Survival Analysis

Before introducing the statistical methods used in this research in detail, providing the definition of the terms that are used in subsequent sections of the report would be helpful. The first term is "dependent variable," also called an "outcome variable," which is defined as "any outcome variable associated with some measure" such as the CR of bridge components or culverts recorded at some inspection interval [3]. The dependent variable in this research is the time or duration a structure stayed in a CR. For example, a bridge superstructure is rated in CR 7 for 15 years, therefore this superstructure has a TICR of 15 in CR 7. Say this superstructure then transitioned to CR 6 and stayed in CR 6 for nine years, then the superstructure has a TICR of 9 in CR 6 and so on. The duration that a bridge component or culvert is in service is called survival time or reliability of that structure. This survival time can be subdivided into survival time for each CR, because each CR has distinct definition. A component "survives" in one CR until it either transitions to the next lower CR or is improved by repair to transition to a higher CR.

The second term is "covariate," also called an explanatory variable, defined as "any variable that is measurable and considered to have a statistical relationship with the dependent variable" [3]. Examples of the covariates considered in this project and speculated to have a relationship with the dependent variable

are snow days, freeze/thaw cycles, ADT, ADTT, and so on. Covariates are divided into continuous and categorical families. Continuous covariates are those that can take any numeric values such as ADT or number of snow days in a given year. Categorical covariates are those that are qualitative without any numeric value such as the location of a bridge in any of seven districts of Missouri, or the subdivision of bridge superstructures into prestressed concrete girders and steel girders. Categorical covariates have two or more levels or categories.

The approach of the research was to perform survival analysis, known in engineering as reliability analysis or time to failure analysis, employing statistical methods to study the incidence and time of events [4]. One of the methods for time to failure analysis is the K-M estimator or the product-limit method. Kaplan-Meier (K-M) method is a nonparametric maximum likelihood estimator of time to event data (i.e., component transitioning to a different CR) and is a common method for treating discontinuous reliability data [4, 5].

Reliability data can be calculated using the K-M estimator by equation **(1)**.

$$\hat{S}(t) = \prod_{j:t_j \leq t} (1 - \frac{d_j}{n_j}) \text{ for } t_1 \leq t \leq t_k \qquad \textbf{(1)}$$

In equation **(1)**, $\hat{S}(t)$ is the K-M estimator, d_j is the number of bridge components for which the event occurred (transitioned to the lower CR) at time t_j, n_j is the number of bridge components at risk of event at time t_j, and t_1 and t_k are the boundary for k distinct event times. The K-M estimator is accompanied by statistics such as the mean, median, confidence interval for the median, standard error of the mean, and hazard rate that can be used to analyze results.

The hazard or failure rate is the number of bridge components per unit of time (year) to transition from one CR to the lower one (assuming the rate is constant during the year). The hazard rate can be computed instantaneously, cumulatively, or averaged within a certain time interval [6]. The instantaneous hazard rate is the number of bridge components transitioning to lower CR in a unit of time (year) and this quantity varies from one year to the next. This estimate can be computed for $t_j \leq t \leq t_{j+1}$ using equation **(2)** in which $\tau_j = t_{j+1} - t_j$ [7].

$$\hat{h}(t) = \frac{d_j}{n_j \cdot \tau_j} \qquad \textbf{(2)}$$

The cumulative failure rate is the integral of the instantaneous hazard rate within the interval of 0 to t, and this quantity could be computed as $H(t) = -\ln(\hat{S}(t))$. Similarly, average failure rate (AFR) could be

computed within any two time-intervals. Since instantaneous failure rate is variable and changes in each unit of time, the AFR could be used to give a single number to indicate the average number of bridge components in a given CR per year to transition to the lower CR during the years the data are available for analysis.

Finally, the K-M estimator can be used to study the effect of time-invariant covariates (explanatory variables) on bridge performance such as bridge families with different ADT, span length, location and environmental conditions, and so on. Or bridges can be grouped based on construction era (1980 – 2000 vs. 2000 – 2017) by time-blocking to study the effect of higher standards and improved construction material on bridge performance with those of the old standards and lower quality material. Certain other parameters described in Objective 3 can also be studied in this way. However, the analysis of these covariates using time-blocking with the K-M methodology has the significant disadvantage that the quantity of data available for analysis is reduced when time-blocking is used. For example, if one wished to study the effect of construction era, then the data would be divided according to the era of construction of the structure. Therefore, far fewer structures would be in each group and the analysis would be for a smaller sample set and may not be statistically significant. Additionally, the K-M method cannot study the interaction among covariates, for example, the interaction between snow days and salt application. For this reason, alternative methods for analysis that better fit the situation were explored and the Cox regression approach was selected as described below.

In this research, the K-M method has been used to study certain covariates, such as the material of construction for superstructure components (e.g., steel, PSC, etc.) and deterioration patterns among districts. However, the K-M estimator is not effective for analyzing the potential interactions between multiple covariates, such as the effect of deicing chemical application, snowy days, and ADT in combination. For this reason, Cox regression analysis has been used to study these covariates, as will be described in further sections of the report.

Figure 1 shows the K-M deterioration model for steel superstructures in Missouri. It should be noted that the K-M model produces a step-wise deterioration curve that is a series of steps that extend horizontally from each data point, then drop vertically to the next data point, at one-year intervals. In reading the figure, starting on the left at time 0, each data point maintains that value until the data point for the next year, at which point it drops vertically to the new value. Presentation of data in that format is difficult to read. To make the figures easier to read and more readily interpreted, these data have been smoothed by simply running the line through each data point. Given that it is unlikely that a value in-between the 1-year interval data points would be required, there is very little lost in smoothing this curve. If a value was required for a time interval of less than one year, the reader should round to the higher value. This is practical since it is

known the data is only recorded on a yearly basis, so the previous year's result would be unchanged during the subsequent year.

The data in Figure 1 indicates the TICR in years for bridges with different CRs ranging from 8 to 3. Figure 1A shows the reliability (probability) of a component transitioning from one CR to another. The red line in the figure illustrates the median transition time. For example, for CR 5 (+), 50% of the components will transition to CR 4 after about 7 years in CR 5. Figure 1B illustrates the deterioration rate of the component which is the compliment of the reliability. As shown in the figure, the rate of deterioration is initially slow and increases as damage accumulates. It is also notable that the deterioration rate slows near the end of the 37-year time interval. Several factors may contribute to the apparent slowing of deterioration as the TICR increases. The K-M method is a survival analysis and as a result, those structures that have not transitioned from one CR to another after ~15 years may have survived because they have superior durability characteristics or are located in an unaggressive environment where ADT is low, and the application of deicing chemicals is limited. As a result, these structures are more resistant to transitioning to the next lower CR (i.e., deteriorating) than a typical structure of similar design characteristics in a more typical environment.

Additionally, the NBI CR scale does not have uniform damage quantities between different CRs. For example, very little damage has typically occurred when a component transitions from CR 8 to CR 7 (very good to good), whereas a significant amount of damage occurs to transition from a CR 5 to CR 4 (fair to poor). The CRs assigned by inspectors are also subjective, so different inspectors can assign different CR for the same condition. Regardless, these CR data stem directly from the inspection results, and therefore represent the deterioration patterns according to the NBIS CR definitions and implementation of bridge inspection in Missouri. As a result, the deterioration models and results presented are empirical and based on actual inspection results collected over the time interval of inspections studied in the research (1983-2019).

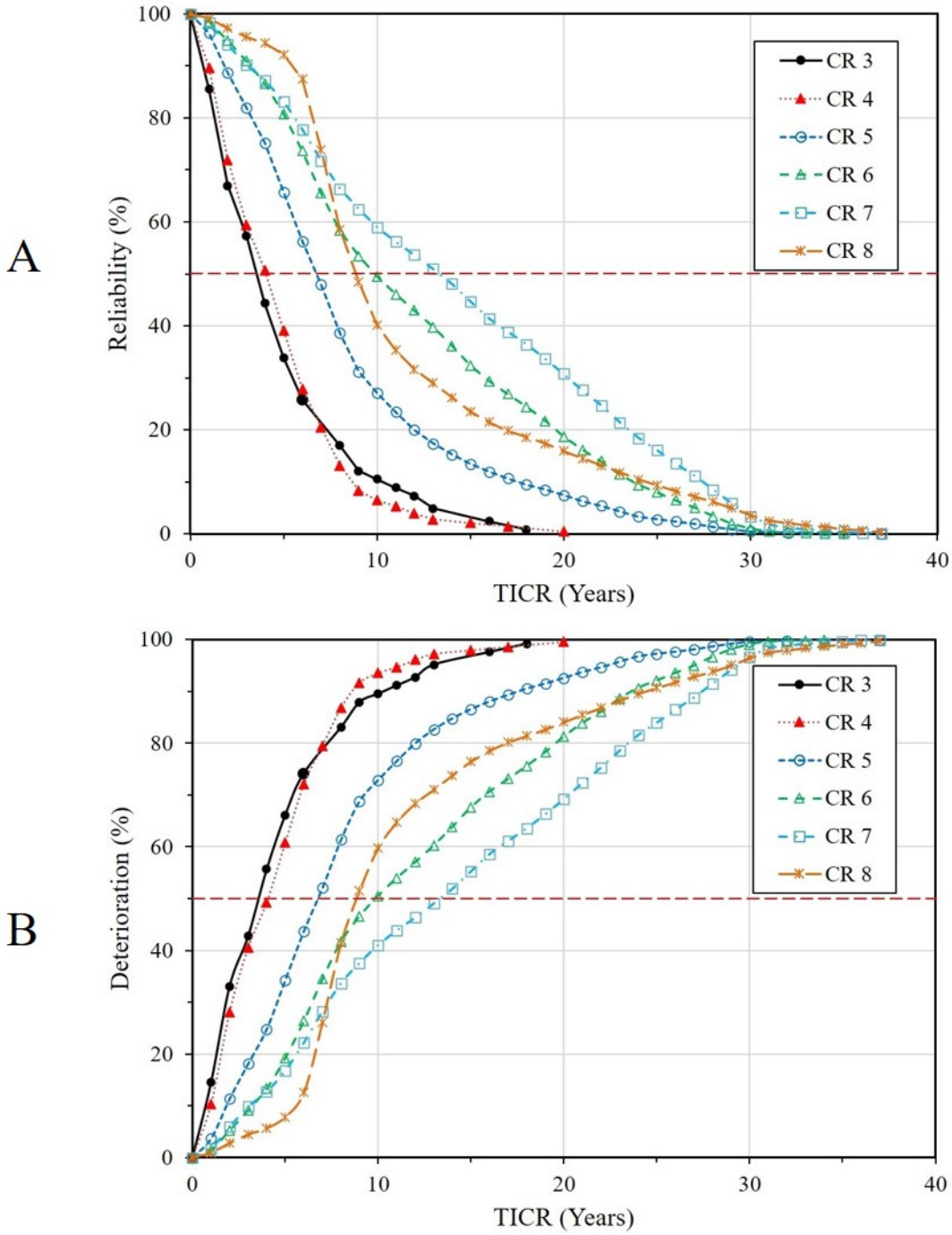

Figure 1. K-M deterioration models for steel superstructures in Missouri.

The K-M deterioration curves are produced within the report for CIP decks, superstructures of various materials, substructures, and culverts.

The K-M method is only capable of analyzing survival data or the dependent variable alone to describe the reliability and deterioration patterns for bridge components and culverts. To investigate the effect of

covariates on the reliability or deterioration of the bridge components or culverts another statistical method called *Cox proportional hazard* method or *Cox regression* is used.

Cox Regression Analysis

Cox proportional hazard or Cox regression is semi-parametric method used for analyzing the effect of explanatory variable on the survival data [8]. This method is called semi-parametric as it has "a fully parametric regression structure but leaves their dependence on time unspecified" [9]. The equation for the Cox regression model is shown in equation **(3)**.

$$h(t, X, \beta) = \lambda_0(\mathrm{t}) \times \exp(\beta_1 X_1 + \beta_2 X_2 + \cdots) \qquad \textbf{(3)}$$

In equation **(3)**, h(t, X, β) is the dependent variable as a function of time and covariates (X, β). The dependent variable corresponds to the NBI condition rating assigned by inspectors to each one of the bridge components (deck, superstructure, and substructure) and culverts. The CR changes as structures deteriorate, typically dropping to the next lower CR. Deterioration of the structures and changes in CR are affected by factors such as salt used for deicing purposes, ADT, snow days, freeze/thaw cycles, and so on. The parameters that are believed to affect the deterioration patterns for bridge components and culverts are called *covariates*. The dependent variable is the product of the hazard function $\lambda_0(\mathrm{t})$ that "characterizes how the hazard function changes as a function of time" and the exponentiated linear function of the covariates, $\exp(\beta_1 X_1 + \beta_2 X_2 + \cdots)$ [9]. As shown, the hazard is a function of time, but the covariates are time independent – the covariates do not change with respect to time. β's are unknown parameters computed based on the available data for each covariate, X_n. No assumption is made about the shape of the hazard function $\lambda_0(\mathrm{t})$, and that is why Cox regression is called semi-parametric. If all covariates are equal to zero, then exp(0) equals a value of 1, leaving only the baseline hazard function, $\lambda_0(\mathrm{t})$. The baseline hazard function is analogous to the intercept or the constant term in ordinary regression [9].

The parameter estimate for each covariate, β, is calculated using the method of partial maximum likelihood for each covariate. One of the properties of the Cox regression is that it can be stratified across variables not considered as a covariate such as the CR 3 - 8. In the case of stratified Cox regression, a single parameter is estimated by pooling the information from all strata – one parameter is estimated for CRs 3 – 8 of bridge components or culverts. Hence, as will be shown later, sample size in a given CR can negatively affect the parameter estimate. In other words, there must be a sufficient number of data points within each CR in order to perform meaningful analysis. It is for this reason that care must be taken regarding how data is divided and characterized in order to ensure sufficient data points for analysis.

The hazard ratio for two subjects (bridges or culverts) with covariate x_0 and x_1 using equation **(3)** only depends on (X,β) because the hazard functions cancel out each other as shown in equation **(4)**:

$$HR(t, x, \beta) = \frac{\exp(\beta_1 X_1)}{\exp(\beta_0 X_0)} \quad \textbf{(4)}$$

In this way, the hazard ratio can be used to compare the effect of one covariate to another. For example, this could be used to compare bridge performance in one district as compared to another, or one superstructure type to another.

Further technical details on the development and testing of the Cox regression analysis are available in the Appendix A.

Model Assumptions

There are two assumptions for the Cox regression model shown in equation **(3)**. 1) the proportional hazard assumption – the hazards are not changing with time and 2) the explanatory variables are modeled with the correct functional form – x, x^2, log(x), or $\sqrt{x}$. Tests are available to verify the assumptions and to take corrective actions in case of any violation. These tests are discussed in Appendix A, along with other details of the K-M and Cox methodologies. Appendix G contains results from validation testing of the Cox regression models. These appendices are intended for other researchers and students wishing to repeat the analysis or conduct similar analysis, and to document the research activities in this project. Data in these appendices is not necessary for understanding the results of the research.

Data Preparation

The data stored in the NBI consists of bridge records formatted according to the Recording and Coding Guide for the Structure Inventory and Appraisal (SI&A) of the Nation's Bridges[10]. This document, commonly referred to as the Coding Guide, defines a uniform system for data reporting.

The data stored in the NBI commonly has various inconsistencies and errors due to random input errors, changes in business practices of the state submitting data, inconsistent or changing numbering practices, and other sources. As a result, analysis of these data must begin with an effort to prepare the data for analysis. This preparation includes identifying and correcting random errors and systematic inconsistencies to ensure the fidelity of the data and organizing these data for analysis.

Inspection data (records) for state-owned bridges and culverts in Missouri were acquired from two different sources within the FHWA. Records from the years of 1992 - 2019 were obtained from the Long-Term Bridge Performance Program (LTBP) web resource called InfoBridge. These data are commonly available

for all states and territories of the US. In addition to these data, NBI records were acquired from 1983 – 1991 from the FHWA Office of Bridges and Structures. Records from these years were not available on the InfoBridge at the time of the research due to typically high number of errors and inconsistency in submissions from all the states and territories from this time period. It should be noted that at the time of this research, the data provided by both the InfoBridge website and the FHWA bridge office contained all numbering errors present in the raw NBI datafiles. Corrections in these data that have been made on the InfoBridge website as of November 30, 2021. In total, 37 years of inspection data were obtained for analysis.

Data recorded in the NBI for the years of 1983 - 2019 for structures in Missouri were affected by various changes in the numbering system used for state bridges. As a result, data preparation included resolving numbering inconsistency in the records such that the historical performance of each bridge could be tracked over time. This step involved making the structure identification (ID) consistent, completing missing data (such as missing characters in the bridge ID number), and defining parameters based on the available data in the NBI files and other sources for Missouri state-owned structures. The following subsections provide detailed information about the data preparation steps taken to prepare the Missouri data for analysis.

Structure Number Consistency

During the time interval for which data was collected for analysis, state-owned structures underwent several changes in the identification (ID) sequence captured by Item 8, Structure Number, of the coding guide. These changes caused the inspection data for a given structure to be attributed to two or three different structure IDs that were assigned for the same structure, resulting in discontinuous records. In order to make the inspection data continuous, the correlation between the IDs was established and a single ID was used for all the inspection data available for each individual structure.

State-owned structures in Missouri were corrected for three changes that had occurred to the structures' ID over the aforementioned timeframe. These changes included changes to the federal ID number, revision numbers that had been added to the ID following certain inspection cycles, and using an alphanumeric ID for some structures at certain times in the past. To make the inspection data continuous, each of these changes were corrected: old federal IDs were correlated to the current federal IDs, the revision numbers were removed, and alphanumeric IDs were correlated to the federal IDs. These three corrections made the inspection data continuous and consistent.

To illustrate the number of corrections required to prepare the data for analysis, Figure 2 depicts the result of the corrections made to the structure IDs. This figure shows the number of years of inspection records available for structures before and after ID correction. As shown in the figure, the 'as received' data – solid

black bar – had at most 20 years of inspection data for any given bridge. Because the structure ID numbers had changed during the 37-year time interval, many bridges were counted two or more times. The most dramatic change occurred when the data was corrected for ID changes that had occurred. Corrections implemented to remove revision numbers in the ID field and removing alphanumeric entries also affected the data, though to a smaller extent as illustrated in the figure.

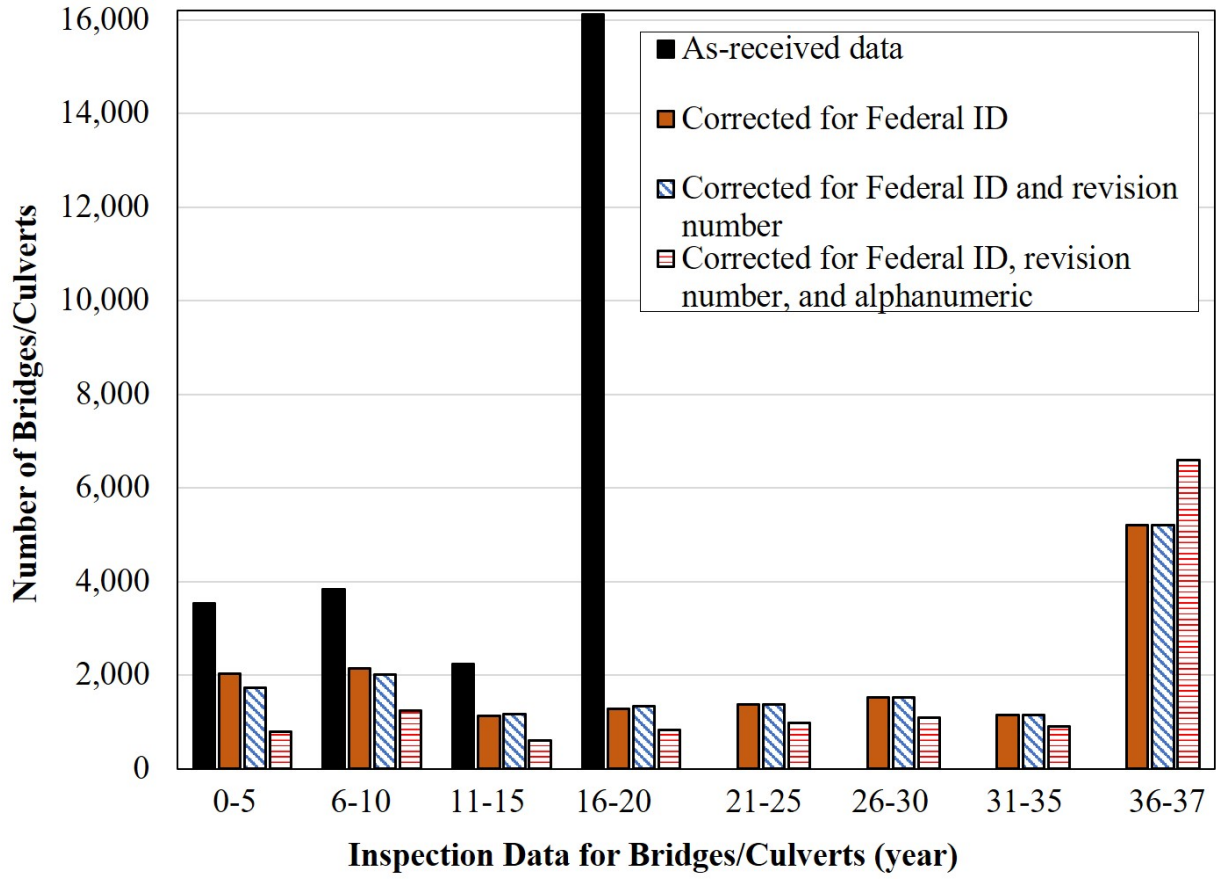

Figure 2. Bar graph showing the results of correcting NBI data for bridges and culverts in Missouri.

As the corrections and correlations were made, the number of structures for the 'as received' data declined, and data become more consistent – increasing the number of years of inspection data for a given structure with ID modifications. Table 1 contains the number of different IDs used for the state-owned structures. In reality, until the data was corrected for the changes, the data did not show the correct number of state-owned structures because several different IDs were assigned to the same structure in a number of cases.

As shown in Table 1, by correlating the old federal ID to the current federal ID, the number of structures declined from 25,732 to 15,871 – a reduction of almost 10,000 structures. When the revision numbers were removed, numbers declined by 400 from 15,871 to 15,491. Finally, removing the alphanumeric IDs and

correlating with the federal ID, the number of structures was further reduced to 13,047. This value is believed to be an accurate account of the number of state-owned bridges and culverts over the 37-year time period. It should be noted that there are currently about 10,400 state structures in Missouri that are on the NBI. The difference between the current number of structures and the number of research datasets results from structures that have been replaced. When a structure is replaced, a new unique structure record is created in the NBI so that all structures can be accounted for over time.

Table 1. Number of bridges/culverts.

Inspection data	Number of bridges/culverts	Comment
As received data	25,732	The 'as received' data includes many structures that are listed more than once due to the variations in the numbering scheme as described in this section.
Data corrected for old federal ID to federal ID	15,871	
Data corrected for old federal ID, and revision numbers	15,491	
Data corrected for old federal ID, revision number, and alphanumeric ID	13,047	The number 13,047 is the current and most accurate number of state-owned bridges and culverts after correction.

To understand the extent of data available for analysis following the preparation of data and including all 37 years of records examined, Figure 3 shows the number of years of inspection records available for this bridge population. As shown, over 50% of the structures (6,586 out of 13,047) have 36 or 37 years of inspection data. Only 793 structures in the data set have one to five years of inspection data.

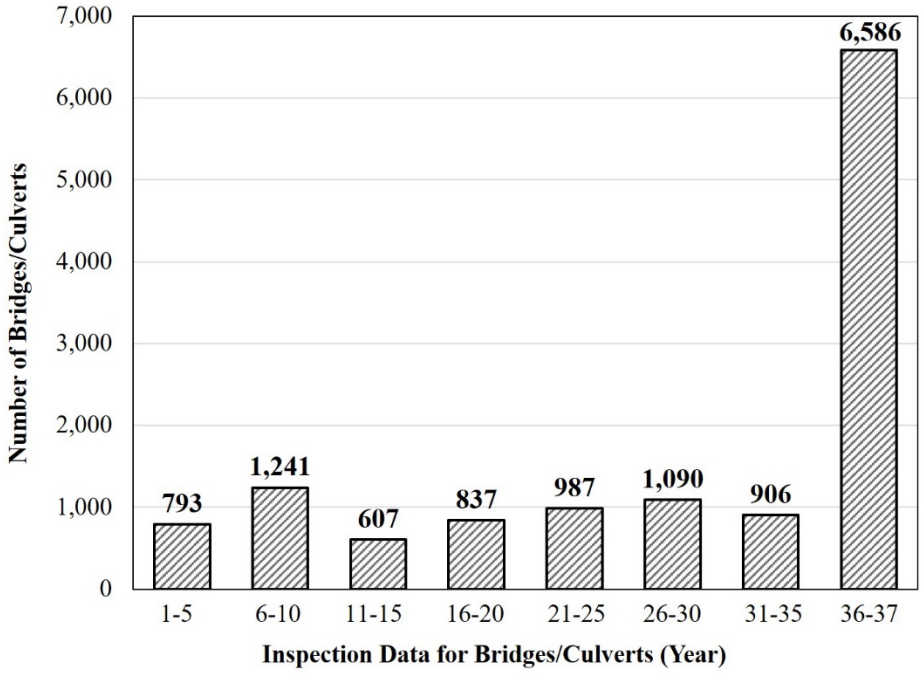

Figure 3. Bar graph showing the years of inspection data for bridges in Missouri.

Figure 3 shows the number of years of available inspection records for the 13,047 state-owned structures broken down by year and shows that many structures have 36 or 37 years of available inspection records. The structures include bridges and culverts formed with many different design and material characteristics. These data were further reduced to form families or groups of bridges and culverts with similar design and materials characteristics to support the analysis.

Data for Analysis

This section describes the data utilized for deterioration modeling of the state-owned structures. To meet the objectives of the research, the trends or deterioration patterns for structures in Missouri were analyzed based on the CRs assigned to structures during periodic inspections. These data were considered dependent variables. The parameters that might affect the deterioration of structures were considered as independent variables which have the potential to influence the dependent variables, (i.e., the CRs). The independent variables (i.e., parameters) used for analysis included the type of material used for construction, the type of structure, the age of the structure, and its era of construction. Maximum span length and overall length were also considered as independent variables. The environment surrounding a given structures was described through several different variables such as the annual number of snow events (i.e., snow days), freeze/thaw cycles, and application of deicing chemicals (salt). The district or region of the state where the structure was located was also considered, as well as the traffic loading on a structure as described through the ADT and ADTT.

These data were obtained from several different sources, including data stored in the NBI, data obtained from MoDOT, and data obtained from the LTBP program InfoBridge website. This section of the report describes the data collected for the analysis, the source of the data, and key statistical parameters listed to provide an illustration of the distribution of values for the different variables/parameters. Table 2 provides a listing of the NBI data items utilized in the research, including the name of the item and the item number from the coding guide. The dependent variables are the CR recorded for the three bridge components (deck, superstructure, and substructure) and culverts (SI&A items 58, 59, 60, and 62) marked as “D” in Table 2. Most of the other items listed are independent variables and are marked as “I” in Table 2. For the purpose of the deterioration analysis, it is assumed that the dependent variables are affected by the independent variables. For example, the ADT or ADTT may be expected to have an effect on the condition of the bridge deck. Certain items from the NBI are simply identifiers that don’t affect the condition of the structure, such as the structure number and the owner, and these items are marked as “N” in Table 2.

In order to summarize the range and typical values for the independent variables used in the research, the distributions and extreme (high and low) values are shown in different tables in this section. This includes

the quartiles of these data that show, for example, the 100% that shows maximum value (100% of the values are equal to or less than this value), the 75%, 50%, and 25% quartile, and the 99% percentile. The five highest and lowest values for each independent variable are also shown. These data provide an overview of the magnitude and distribution of the data for each variable/parameter.

Table 2. Bridges and culverts information used for data analysis.

SI&A item	ID	SI&A item	ID
Structure_number_008	N	Deck_cond_058	D
Owner_022	N	Superstructure_cond_059	D
Year_built_027	I	Substructure_cond_060	D
ADT_029	I	Channel and channel protection_061	I
Structure_kind_043A	I	Culvert_cond_062	D
Structure_type_043B	I	Year_reconstructed_106	I
Structure_len_mt_049	I	Deck_structure_type_107	I
Max_span_len_mt_048	I	Percent_ADT_truck_109	I

Age and Era of Construction

The independent variables from the SI&A data included the age of the structure, which was derived from the Year Built (027) and Year Reconstructed (106). Since some structures are renovated during their service life, the Year Built and Year Reconstructed variables were combined to calculate the age of a structure at any given point in time. For those structures with a reconstruction date, the CR before and after the reconstruction date was examined to determine if the CR increased for any of the components of the structure. The age of the structure is calculated as the inspection year minus the year built if there was no improvement due to reconstruction. If there was improvement or increase in CR at the time of reconstruction, then the age for the improved component was calculated as the inspection year minus the reconstructed year. Mathematically, the age is calculated using the following equation.

$$Age_{bridge\ or\ culvert} = (Inspection\ year) - (reconstruction\ year)\ \boldsymbol{if}\ (reconstuction\ effective)$$

$$\boldsymbol{else}\ (Inspection\ year - year\ built)$$

In this research, the age and era of construction were analyzed primarily through the age a structure was when it transitioned into a given CR, as previously described. The era of construction was not a specific covariate analyzed in the research because separating data into different eras of construction resulted in insufficient data for analysis, and such a covariate correlates with age. As a result, the age of the structure was studied, and the resulting trends are reported herein.

Materials and Type of Construction

Structure Kind and Structure Type

Structure kind (043A) and structure type (043B) variables describe the materials of construction (e.g., steel, reinforced concrete, prestressed concrete, etc.) and construction type (e.g., simply supported, continuous, truss, girder, etc.). The combination of these two items was used to identify families of bridges with similar material and construction type for analysis. There were 56 different combinations of structure type and kind found in the inventory, and a detailed listing of these combinations can be found in Appendix B, Table B-1. The listing in Appendix B also includes the number of structures for each of the materials/construction type combinations.

The most common structure overall was found to be a continuous concrete culvert with 3,310 structures. The most common bridge types were bridges with steel superstructures, either continuous (2,645) or simple span (1,602), followed by prestressed concrete continuous structures (1,262).

The three most common materials for bridge superstructure construction were steel, reinforced concrete (RC), and prestressed concrete (PSC). Considering all structure types for each of these materials, there were 4,836 steel, 5,558 RC structures (including 3,310 culverts), and 2,601 PSC structures.

In order to have sufficient data on which to base statistical analysis, the different superstructure types and materials were grouped into families of related bridge design parameters. As previously mentioned, there are 56 different combinations of superstructure materials and designs, including 51 different bridge combinations and five culvert combinations. In order to have sufficient data for meaningful statistical analysis, these 51 bridge combinations were grouped into six superstructures types. The superstructure types were selected based on the following two rationale:

1. From an engineering perspective, the superstructure types should be those which are currently designed and constructed.
2. From a statistical point of view, each superstructure type should include a sufficient number of bridges to produce accurate results from the models.

From a statistical point of view, it is shown that for a categorical covariate with only two levels to estimate the hazard ratio at $\alpha = 0.05$ (i.e., 95% confidence) and a multiplicative margin of error of 1.2 "requires a total number of 462 events." [13] There are 51 different combinations of superstructures with CIP decks and the NBI records do not provide a sufficient number of bridges in each of the 51 different combinations. Moreover, a sample size of 184 is required for estimating the reliability or deterioration probabilities with a 95% confidence interval for the simplest case of no covariates, which corresponds to the K-M estimates according to the Dvoretzky-Kiefer-Wolfowitz inequality [13]. This value of 184 is for a case where there is no censoring and all structures transition to a lower CR at the end of their available data. The "no

censoring" criteria are addressed in this research by trimming the data at the beginning or the end of the available dataset to eliminate components where the available data may not be representative. Details of the trimming process used in this research are discussed in the section entitled *Condition Rating for Decks, Superstructures, Substructures, and Culverts*.

Therefore, not all superstructure types were included in the analysis. The superstructure types with sufficient counts (i.e., number of bridges) are shown in Table 3. The table shows the SI&A values and the description for superstructure and materials included in the study. The NBI listings were combined into "analysis datasets" to ensure sufficient data was present in each analysis set for meaningful analysis, as shown in Table 9. As shown, some superstructure types are combined together to make a single analysis data set with consideration of the construction material or superstructure type. Some superstructures that are less common or not frequently constructed were also omitted from the analysis, such as truss bridges. Although major bridges are often trusses, the number of those bridges is relatively small as compared with "bread and butter"- type bridges. There were 423 bridges listed as "steel truss," but these were not included in the analysis because their characteristics vary widely (e.g., short pony trusses or small-span rural bridges vs. major river crossings), not all have CIP decks, and when considering the range of CRs, there was insufficient data for meaningful analysis. For these reasons, trusses were not considered in the analysis. There were also some bridge superstructure combinations that were very rare. For example, there are 10 combinations for which only a single bridge is listed in the NBI data (see Appendix B, Table B-1). These were not included in the analysis.

Structure Length and Maximum Span Length

The maximum span length (048) and structure length (049) were used to analyze and study their effects on bridge deterioration. Structure length is the overall length of the structure, e.g., from one abutment backwall to the other, while the maximum span length defines the longest of all of the spans in a given bridge. For a single span bridge, these values should match.

In order to summarize these parameters in terms of the overall inventory of bridges in Missouri, statistical measures of the quantile distribution and the high and low values are presented in Table 4. The quantile data includes the 100% quantile that describes those in the top 1% in terms of length. The 50% value describes the median length for which ½ the structures are longer and ½ the structures are shorter. Data on the five longest and five shortest bridges is also presented. These data characterize the population distribution and are repeated for different items from the NBI data used in the analysis in the following sections.

Table 3. Combinations of superstructures types and materials used to from six bridge families for analysis.

SI&A items		SI&A description	Count	Analysis data set	Combined count
43A	43B				
4	2	Steel continuous stringer/multi beam girder	2,645	Steel cont. girders	2,645
3	2	Steel stringer/multi beam girder	1,602	Steel simple girders	1,602
5	2	Prestressed concrete stringer/multiple-beam or girder	174	PSC cont. girders	1,436
6	2	Prestressed concrete continuous stringer/multi beam girder	1,262		
1	1	Concrete slab	247	RCC slabs	1,014
2	1	Concrete continuous slab	767		
1	4	Concrete tee beam	790	RCC girders	1,022
2	4	Concrete continuous tee beam	20		
1	6	Concrete box beam or girders - single or spread	5		
1	5	Concrete box beam or girders - multiple	2		
2	6	Concrete continuous box beam or girders - single or spread	193		
2	5	Concrete continuous box beam or girder - multiple	12		
5	4	Prestressed concrete tee beam	169	PSC box beams	1,140
6	4	Prestressed concrete continuous tee beam	344		
5	5	Prestressed concrete box beam or girder - multiple	384		
5	6	Prestressed concrete box beam or girder – single	201		
6	5	Prestressed concrete continuous box beam or girder – multiple	16		
6	6	Prestressed concrete continuous box beam or girder – single	26		
Total number					**8,859**

The analysis result for the structure length and maximum span length are also shown in Table 4. The top portion of Table 4 lists the quantiles and percentiles. For example, the lower 25% of the bridges (first quartile) are less than or equal to 43 ft. in length, and the 25% span length is 15 ft. The median or 50% (second quartile) of the bridges are less than or equal to 128 ft. in length, and the median span length is 49 ft. In other words, 25% of the bridges are greater than 43 ft., but less than and equal to 128 ft. in length, and 25% of the maximum span lengths are greater than 15 ft. and less than 49 ft. in length. The bottom portion of Table 4 lists the smallest and largest five values for each variable.

Table 4. Statistical measures for structure length and maximum span length.

Level (%)	Quantile (structure length (ft.))		Quantile (max. span length (ft.))	
100	7,847		1,500	
99	1,649		200	
75	222		78	
50 (median)	128		49	
25	43		15	
Five lowest and five highest statistical measures				
Structure length (ft.)			**Max. span length (ft.)**	
Five lowest values	**Five highest values**		**Five lowest values**	**Five highest values**
15	7,847		3.9	1,500
14	7,847		3.6	1,150
14	7,102		3.0	963
13	6,826		2.6	920
13	6,659		2.0	910

Deck Structure Type (107)

The most common type of deck on a bridge in Missouri is a concrete cast-in-place (CIP) deck. Table 5 lists the available deck types for the state-owned bridges. The letter "N" from the SI&A code indicates that these structures are culverts [10]. Deck structure type can be used to analyze each deck type individually. For example, concrete cast-in-place decks are analyzed as a single family to determine their reliability and deterioration characteristics. However, the number of bridge decks other than CIP decks was too limited for meaningful statistical analysis, and as a result only the 9,341 CIP decks were considered.

Table 5. List of different deck types for state-owned bridges.

SI&A item 107	SI&A in words	No. of decks
1	Concrete cast-in-place	9,341
2	Concrete precast panels	407
3	Open grating	14
4	Closed grating	14
5	Steel plate (includes orthotropic)	3
8	Wood or timber	50
9	Other	21
N	Not Applicable	3,197

Traffic Volume

Average Daily Traffic (ADT) and Average Daily Truck Traffic (ADTT)

The level of service of a bridge in terms of the traffic carried on the bridge is described by the ADT, and the portion of that traffic that are trucks is described by the ADTT. These two covariates were expected to correlate in some way with deterioration of bridge components. The ADTT is recorded as a percentage of the ADT, therefore, ADTT is calculated by multiplying the percentage recorded under ADTT to the number of vehicles recorded under ADT. Table 6 contains the statistical measures for ADT. As shown, 50% of the bridges have less than 1,500 vehicles per day and 25% of the bridges (75% - 50%) have over 1,473 to 6,100

vehicles per day. Five bridges with lowest number of ADT and five bridges with the highest number of ADT are also listed in the lower part of Table 6.

ADTT statistical measures are also shown in Table 6. As shown, 50% of the bridges have less than or equal to 158 ADTT and 75% of the bridges have less than or equal to 779 ADTT. Only 1% of the bridges have over 9,547 to 51,738 ADTT. Five bridges with the lowest ADTT and five bridges with the highest ADTT are listed in the bottom part of Table 6.

Table 6. Table showing statistical measures for ADT and ADTT.

Level (%)	Quantile (ADT)	Quantile (ADTT)
100	287,435	51,738
99	70,348	9,547
75	6,100	779
50 (median)	1,473	158
25	408	43

Five bridges with lowest and five bridges with highest ADT and ADTT			
ADT		ADTT	
Five lowest values	Five highest values	Five lowest values	Five highest values
6	287,435	5	51,738
5	286,696	4	51,065
4	236,045	3	39,971
2	231,513	2	39,971
1	224,573	1	38,297

Condition Rating for Decks, Superstructures, Substructures, and Culverts

The CR for decks, superstructures, substructures, and culverts are the main dependent variables used to determine the reliability of structures in the MoDOT inventory. The TICR was calculated from the CR history of a structure contained within the NBI data. The TICR is calculated by counting the number of years a bridge component or culvert stayed in each of the CR for CR 8 through CR 3. TICR is the only variable used for K-M analysis to determine the reliability and deterioration of the bridge components or culverts. In this way, the K-M analysis is formed directly from the available inspection data, and therefore represents an empirical description of the accurate historical performance of structures.

Similarly, TICR is the dependent variable for Cox regression analysis to study the effect of the independent variables (i.e., salt usage, snow days, ADT, etc.) to check if the TICR is affected by these independent variables. If the TICR was affected by the independent variable, Cox regression was used to analyze how large of an effect each independent variable had on the reliability and deterioration of the bridge components or culverts. Later in this report greater discussion regarding the differences between the K-M and Cox regression models will be presented.

In order to utilize the NBI data for the deterioration analysis used in this research, some treatment of the raw NBI data files (beyond error corrections noted above) was needed. The NBI CRs history for structures

based on data from the years 1983 – 2019 were included in this study. The data are for a fixed time interval and these data may be incomplete relative to the entire service life of a bridge. Bridges built before 1983 or bridges remaining in service after 2019 do not have complete information on the TICR for each bridge component. For example, a bridge deck may be in CR 6 in 1983, when the record starts, and then transition to CR 5 after just one or two inspection cycles, indicating the TICR value for that bridge deck may be just 2 or 4 years. However, it is not known how long that deck may have been in CR 6 prior to 1983, so assuming the TICR was only two or four years would not represent the actual TICR. The same is true for CRs for 2019, the end of the data available for analysis – a bridge may be rated CR 6 in 2019, and it would not be possible to know how long that deck may remain in CR 6 in the future. Therefore, some "trimming" of the data was needed to minimize the effects of the censored data at either end of the time interval considered.

A methodology for "trimming" the NBI datafiles to minimize the impact of the censored data was previously developed and published by the RT, and is now widely used for the analysis of NBI data to determine TICR values [11]. In summary, any bridge component with less than five years of similar CRs in the beginning or the end of the available data for a bridge component had that CR deleted from the data set for that component. In this way, the impact of the fixed time interval on the TICR values calculated for the bridge component is reduced. Any interval of greater than five years at the beginning or end of the time interval is assumed to be representative of the actual deterioration behavior of that component and therefore left unchanged.

Besides the variables extracted from the NBI data files, the RT acquired other data such as the annual number of freeze/thaw cycles, number of snow days, and the amount of salt used by the counties to use in the analysis. These variables are described in the subheadings below.

Location and Environmental Exposure

Annual Freeze/Thaw Cycles and Snow Days

The aggressiveness of the environment surrounding a structure can have an impact on deterioration patterns. The application of deicing chemicals is well-known as a driving force for corrosion damage in structures. Damage as a result of freeze/thaw cycles can also increase the rate of deterioration because the expansion of water when its phase changes to ice can induce additional stress in the concrete and cause cracking and deterioration of the material. In order to characterize the aggressiveness of the environment and correlate the environment with deterioration, data on the number of freeze/thaw cycles, number of snow days, and level of salt application to the roadway were gathered.

The data for freeze/thaw cycles for bridges were downloaded from the FHWA LTBP InfoBridge website and used to study the effect of freeze/thaw cycles on bridge deterioration. Table 7 contains the statistical

measures for the number of freeze/thaw cycles. As shown in the lower part of Table 7, the minimum number of freeze/thaw cycles is 45 days per year and the maximum number of freeze/thaw cycles is 125 days per year. Similarly, 50% of the bridges have at least 85 cycles per year, and 99% of the bridges have less than or equal to 113 cycles of freeze/thaw per year.

The number of snow days per year was also downloaded from the InfoBridge website and used in the analysis to determine how the number of snow days affects bridge deterioration. Table 7 contains the statistical measures for the number of snow days per year for the state-owned bridges. As shown, the smallest number of snow days recorded for the state-owned bridges is five days per year and the maximum number of snow days recorded is 100 days per year. Similarly, 50% of the bridges have at least 39 snow days per year and 75% of the bridges have at least 48 snow days per year.

Table 7. Table showing statistical measures for freeze/thaw cycles and snow days.

Level (%)	Quantile (freeze/thaw cycles (days/year))	Quantile (snow days (days/year))
100	125	100
99	113	76
75	95	48
50 (median)	85	39
25	74	30

Five bridges with the lowest and the highest number of freeze/thaw cycles			
Freeze/thaw cycles (days/year)		(Snow days (days/year))	
Five lowest values	Five highest values	Five lowest values	Five highest values
45	125	5	100
45	125	5	100
45	125	5	100
45	125	5	100
45	125	5	100

Salt Use by Counties

The application of deicing chemicals (i.e., salt) to bridge decks is well known as a driving force for corrosion on steel members and reinforcing embedded in concrete components. However, specific data on the rate or quantity of salt applied to a particular bridge is generally unavailable. Data was provided by MoDOT that recorded the quantity of salt used based on data from salt storage facilities across the state. The data provided indicated the salt usage from different storage facilities on an annual basis. Based on the provided datasheet, salt was stored in several different storage locations in each county. A total quantity of salt was calculated for each county by summing the amount of salt in each storage location in the county. The data provided by MoDOT recorded the salt usage over the time interval from 2001 - 2010. However, the raw data included only total quantities of salt used on an annual basis during that time frame. Factors that might affect the distribution of the salt used, such as how large of an area was serviced by a certain salt storage facility, were not included in the data provided.

These data were reduced by summing the amount of salt used in a particular county, and dividing that value by the miles of state-owned routes in the county. This provided a value of salt used per mile in each county over the time interval of 2001 - 2010, which normalized the data somewhat based on the number of miles of roadway on which the salt is deposited. The county data was summed in order to have district-level salt use statistics. These data were then applied over the entire 37 years of records available on bridge condition. In this way, an estimate of the relative level of salt usage in different areas of the state was calculated and used as a covariate for the analysis.

The statistical measures for salt used by counties from 2001-2010 is shown in Table 8. As shown, 50% of the counties used 1,197 tons of salt per year or less from 2001 – 2010. The five lowest and five highest quantities of salt used by the counties are listed in the bottom part of Table 8.

Table 8. Table showing statistical measures for salt used by counties from 2001-2010.

Level (%)	Quantile (salt used (tons/year))		Quantile (salt per mile (tons/year))	
100	32,949		10.11	
99	10,805		5.66	
75	2,137		4.08	
50 (median)	1,197		2.70	
25	656		2.11	
Five counties with the lowest and the highest salt usage				
Salt used (tons/year)			**Salt per mile (tons/lane miles)**	
Five lowest values	**Five highest values**		**Five lowest values**	**Five highest values**
38	32,949		0.54	10.12
28	17,796		0.54	10.12
27	17,637		0.72	10.12
25	16,364		0.72	10.12
24	15,944		0.72	10.12

There are three issues that should be noted regarding the salt data used in the study.

1. The 'as received' data for salt used by counties contained negative quantities for some of the counties for the time period 2001-2010. The negative quantities were replaced with the average of the available positive quantities for the county, based on the assumption that the negative value was a data error.
2. Compared to the 37 years of bridge inspection data (1983 – 2019), salt data is limited to a very short period of time. To remedy the unavailability of salt data for the remaining number of years, the data for 2001 – 2010 was populated for the rest of the inspection period as well. This assumes that the reported salt data was representative of salt usage in that area of the state during the time interval under consideration (1982-2019).
3. Salt data was converted to salt per lane miles by dividing the salt used in each district by the total lane miles of roadways in that district. The assumption here was that all the roadways in a district are treated with an equal amount of salt, which may not be the case. Roadways with different number of lanes were all treated equally. Similarly, if there were any prioritization among roadways in terms of salt treatment, it was not taken in to account. For example, a certain district may treat interstates more aggressively than lettered state routes, but information on this type of prioritization was not available. Overall, the RT sought conservative assumptions in the absence of more detailed data about salt usage by counties and districts.

The quantity of salt distributed in each district and the number of snow days in the district was compared to assess the correlation between the number of snow days and the application of salt. The data on the quantities of salt applied was provided for the years 2001 – 2010, and the number of snow days in those years was determined from the LTBP InfoBridge website. Figure 4 shows the relationship between the estimated quantity of salt usage and the number of days of snow reported in the county where the storage facility was located. Data is reported according to the district in which the county was located, with each district indicated by a different marker and color. These data illustrate a trend of increased snow days generally correlating with increased salt usage, although the data have a lot of scatter. The data also show some outliers, such as the three points from the St. Louis District that suggest more than 10 tons of salt per lane mile. Overall, the data shows some correlation between the number of snow days and the salt application, but with considerable scatter as shown in the figure.

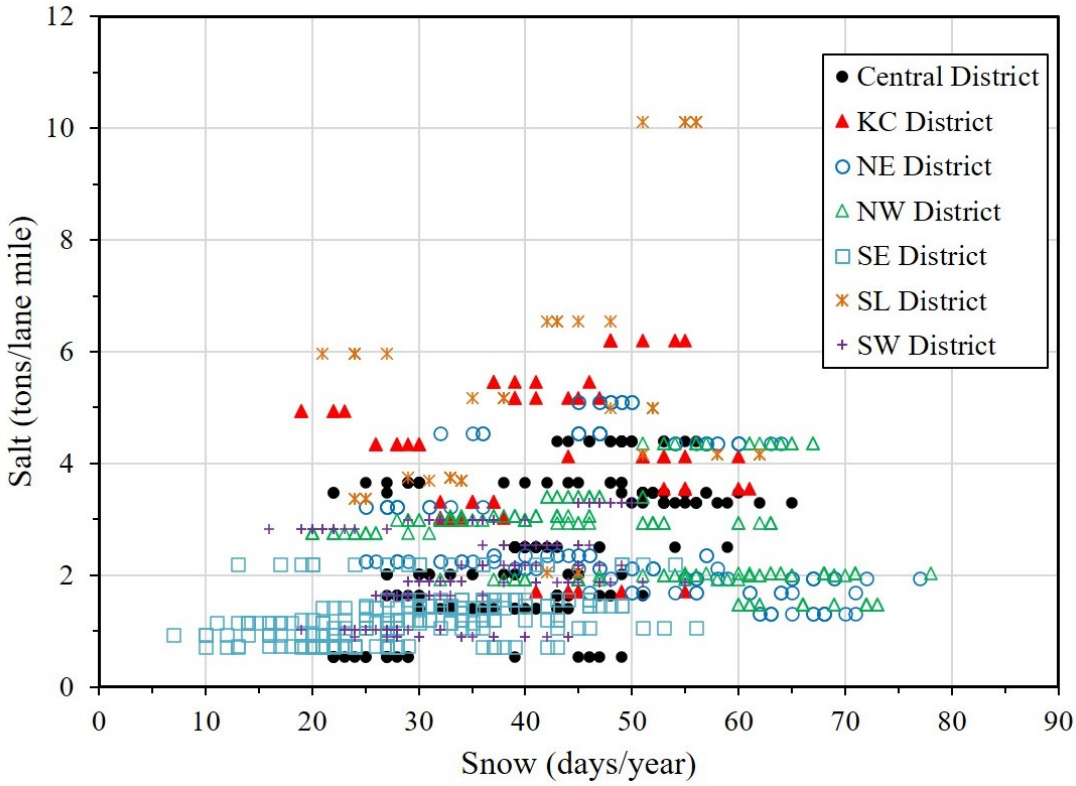

Figure 4. Scatter plot showing snow against salt for 2001-2010.

Districts

Another qualitative (or categorical) covariate included in the analysis were the seven MoDOT districts. The MoDOT districts are the Northwest (NW), Northeast (NE), Kansas City (KC), Central (CD), St. Louis (SL),

Southwest (SW), and Southeast (SE). A map showing the districts is shown in Figure 5. The analysis reported herein examines the trends in deterioration among the different MoDOT districts.

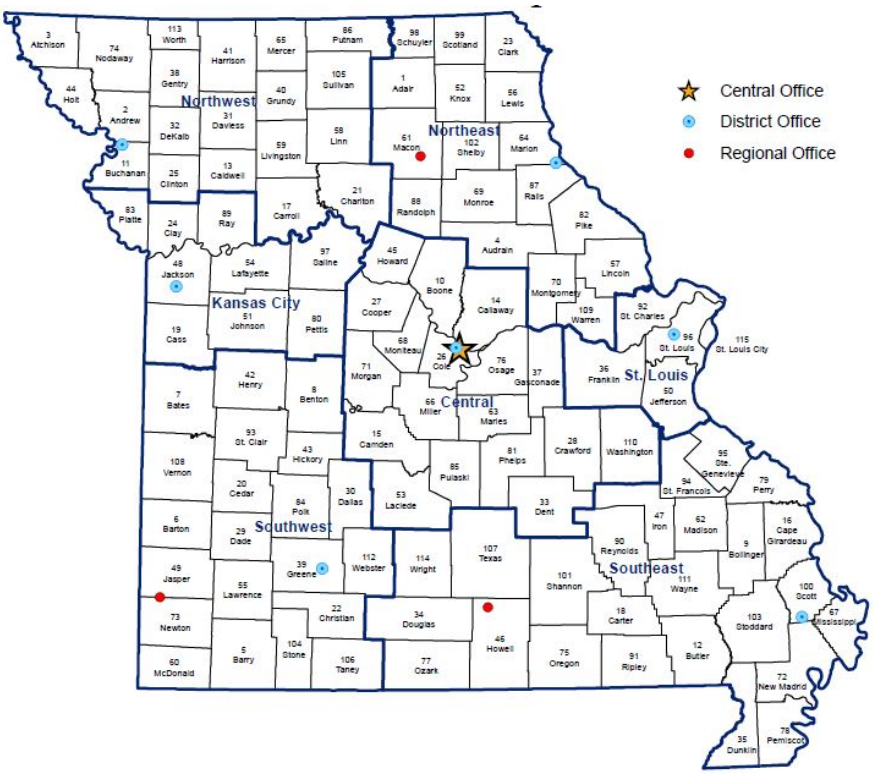

Figure 5. Figure showing MoDOT's seven districts.

The district covariates were analyzed to check if the deterioration of a bridge component or culverts are different from one district to another. Data analysis using the covariates discussed in this section is presented in the following pages.

RESULTS

This section provides the results from data analysis used to calculate deterioration curves for MoDOT structures and to evaluate the effect of the explanatory variables on the deterioration of the structures. For clarity purposes, this section is divided into subsections by bridge component. First, the reliability analysis for CIP bridge decks is provided. This includes analysis of the relationship between CIP deck deterioration on different types of superstructures. The reliability analysis of different types of superstructures is also presented. Substructure and culvert analysis are also included in this section.

Reliability Analysis for CIP Decks

As mentioned before, 9,341 out of 13,047 (71.6%) state-owned structures have cast-in-place (CIP) bridge decks recorded in the NBI data. The section reports the analysis results for the CIP decks. The K-M curves showing the deterioration trends and the TICR based on the NBI condition ratings are presented first, followed by the development of the Cox regression analysis to assess the effect of the covariates on the deterioration of the CIP decks.

The K-M curve for all CIP decks regardless of their location or their superstructure type is shown in Figure 6. The vertical axis is the reliability or survival percentage, and the horizontal axis is the CIP deck TICR. For example, the probability that the CIP decks in CR 6 stay in this CR for more than 14 years is 50% and the probability to stay in this CR for more than 20 years is only ~30%. The graph for other CRs could be read in a similar manner. As shown in the figure, the TICRs for CR 6 and CR 7 are greater than the TICRs for other CRs, while TICR for CR 8 is actually similar to the TICR for CR 3 and CR 4. It is common for this and other analysis results that the TICR for CR 8 is relatively short because not much damage has to accumulate for an inspector to assign a CR of 7.

Similar reliability graphs were produced for CIP decks located in each of the seven districts and CIP decks on different superstructure types. These graphs are presented later and could be read and interpreted similar to Figure 6, but are specific to district or a superstructure type.

The reliability graph shown in Figure 6 can be used to construct service life estimates for CIP decks based on the percentage of the CIP decks still surviving at the median value from the reliability plot. The median value is illustrated on the plot with a horizontal line at 50% reliability.

These data can also be used to plot the hazard function or cumulative hazard graph, a statistical measure of the cumulative likelihood of a component transitioning to the next lower CR. Both the median service life and the cumulative hazard function graphs are produced and discussed in the following section.

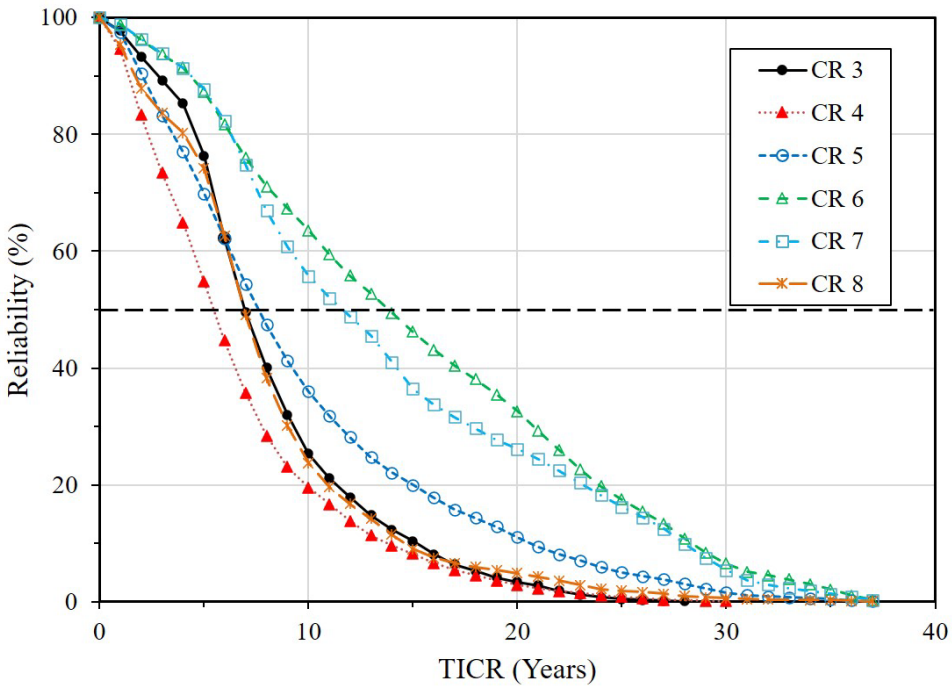

Figure 6. K-M curve showing the reliability of CIP decks for CR 3-8.

Service Life and Hazard for CIP Decks

Service life plots for CIP decks and other components were produced based on the median TICR values from K-M analysis. The median value represents the value which 50% of the decks would transition from a given CR to the next lower CR. The median value is used rather than a mean transition value because the mean (average) tends to be higher than the median due to the fact that some bridge components remain a very long time in a given CR. As a result, the average TICR is commonly larger than the median TICR. The median value provides a more conservative value and better represents the likelihood of transitioning for any given structure.

Using Figure 6, the time span that the median (50%) of CIP decks stay in CR 8-3 is determined by selecting the time (years) for 50% of the decks to transition in each of CRs shown on the plot. These data are plotted in Figure 7A and Figure 7B. Figure 7A shows the median service life along with the 25th and 75th percentiles that represent the distribution of the results. The 25th and 75th percent value are shown to illustrate the distribution of expected service life for the decks for each CR. These data can be interpreted to show the central tendency for service life and the range over which 50% of the bridges will transition. About 1 in 4 decks are expected to have a service life longer than 75th percentile, and 1 in 4 bridges are expected to have a service life shorter than the 25th percentile, based on the K-M analysis of historical records.

Figure 7B shows the median service life with the confidence intervals represented from the original analysis. The error bars shown for each point estimate in the service life plot are based on the 95% confidence interval calculated for median TICR for each CR. Error bars on only the positive or negative sides of the point estimate indicate that the point estimate itself is the positive or negative CI, respectively. Data is provided in this format to illustrate the relative precision of the median values in the plot, i.e., the range of potential error in the median value. As shown in the figure, the 95% confidence interval is very close to the point estimate for each CR.

Based on the median reliability for each CR, typically CIP decks would have 52 years of service life before transitioning from CR 3, by repair, replacement, or deterioration to CR 2. As shown, about 40 years would be the time span between CR 8-5 and 12 years for CR 4-3. These data indicate that the rate of deterioration (in terms of assigned NBI ratings) increases as the condition of the deck decreases with a notable increase in rate for CR 5 and lower. This effect was found to be ubiquitous in the research.

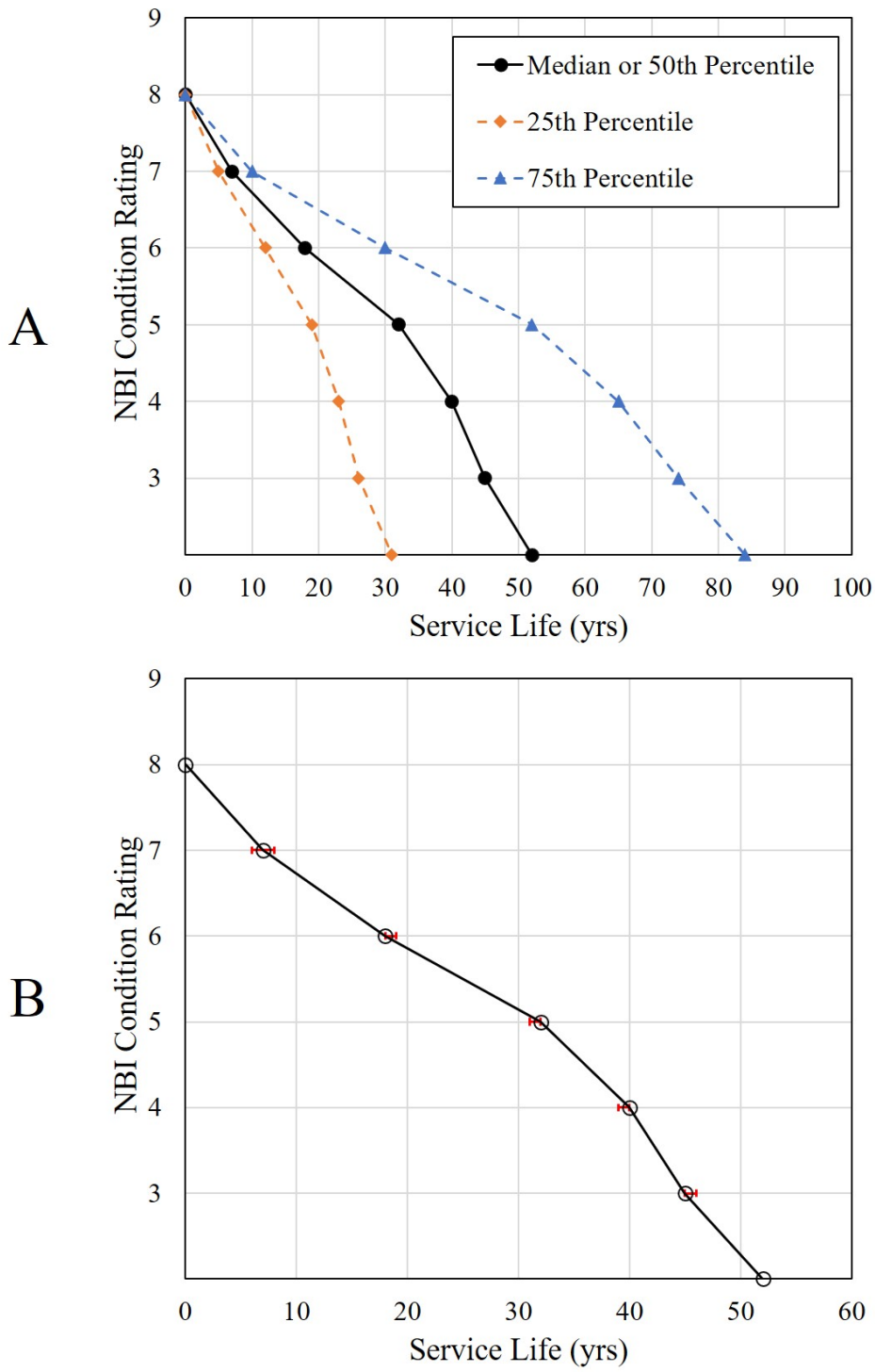

Figure 7. Graph showing the service life for CIP decks statewide based on median reliability in CR 3 – 8, showing A) quartiles and B) confidence intervals.

The cumulative hazard plot for CIP decks is shown in Figure 8. The vertical axis is the cumulative hazard and the horizontal axis is the TICR for CIP decks. This graph provides another way of looking at CIP decks

performance. Contrary to the K-M curve where the reliability for each percentage point is a point estimate, the cumulative hazard is the integration of the hazard from the beginning of the reliability curve to a selected TICR. On the vertical axis, each digit represents 100% damage necessary to move the deck to the next lower CR. For example, for CIP decks in CR 7, it takes about 15 years to accumulate damages fully (100% or for the first time) to qualify for dropping to CR 6. If at this time, the deck is renovated (actually or conceptually) and put back in service in CR 7, it will take about 10 years to accumulate damage fully one more time and again drop to CR 6. In other words, older bridges accumulate damage more rapidly than newer bridges and consequently the rate (slope) of the curves are increasing with time.

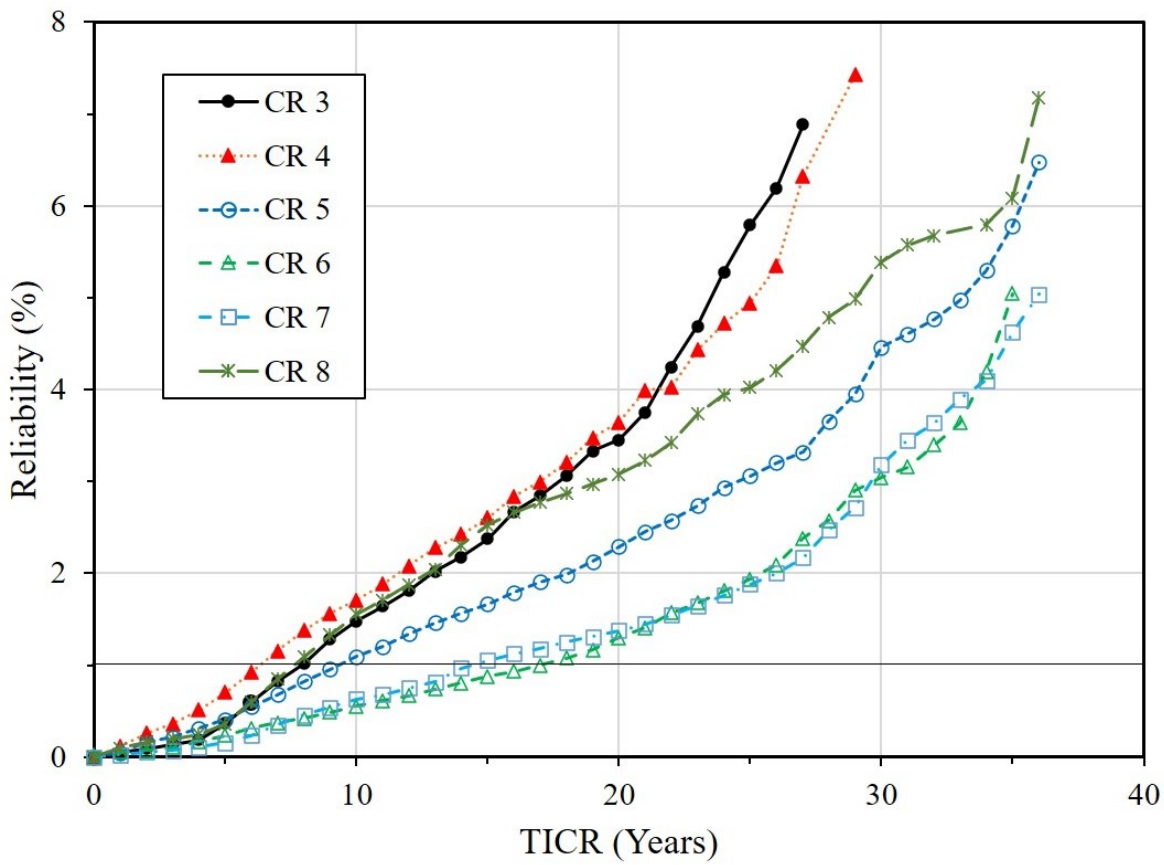

Figure 8. Plot showing cumulative hazard for CIP decks in CR 3-8.

Based on the available data, during the 37 years, the CIP decks in CR 7 would accumulate damage five times – the CIP decks would be on the verge of dropping to CR 6 if the process were repeatable. As shown, CIP decks in CR 3 accumulate damage at a faster rate compared to other CRs, followed by CR 4 and CR 8. Similarly, CR 5, 6, and 7 accumulate damage at a slower rate as demonstrated by the flatter slopes for the curves of these CRs. This type of cumulative hazard interpretation is defined as count-data [12].

If the TICR is divided by the number of times the cumulative hazard is reached for each CR, it provides an average TICR for each CR. Summing the TICR values would provide a service life estimate for CIP decks to deteriorate from CR 8 to CR 3 without any intervention. To perform this calculation, the coordinates of the ultimate point for each CR in Figure 8 were used. Dividing the TICR value (x-axis) for that point by the hazard value (y-axis) yielded the average TICR for that CR. This calculation was repeated for each CR and the resulting values summed. Based on this calculation, it would take 32.5 years for a deck currently in CR 8 to deteriorate to CR 2. This result is different than the service life calculated based on the median TICR because the median TICR value of 52 years of service life is based on the point estimate as compared to the cumulative hazard utilized to determine the service life of 32.5 years.

Generally, the hazard plot is more difficult to interpret and more dependent on statistical measures than the median service life plot based on the results from the K-M analysis. For this reason, median service life plots are generally used in this report to illustrate the deterioration behavior of bridge components. The hazard function can also be used to statistically compare the effect of one covariate, for example, bridge span length or number of snow days, to another covariate to characterize the relative effect of that covariate on bridge deterioration. In this way, trends in the deterioration patterns of structures can be assessed and the relative impact of different parameters can be analyzed. In the following section, the effect of the covariates is investigated to determine how much of the deterioration for CIP decks could be explained by the covariates selected for the analysis.

CIP Decks on Different Superstructures

One of the key factors to be investigated in the research was the effect of the superstructure type on the deterioration behavior of bridges. This section discusses the effect of different types of superstructure designs and materials on the performance of bridge decks. The purpose of this analysis is to determine if, for example, CIP decks on steel structures, which tend to be more flexible as compared with PSC or RC structures, deteriorate at different rates than decks on PSC or RC superstructures. These data could be useful to decision-makers estimating life-cycle costs or planning lifetime maintenance for structures, or selecting superstructure materials for future bridges.

Table 9 shows the count of different superstructure types with CIP decks. The column labelled “Analysis dataset” shows that there are six different superstructure types or families investigated for the performance of the CIP decks. The superstructure type is a categorical covariate with six levels (six different superstructure types). Before presenting the Cox regression result, the K-M analysis was completed for CIP decks on each of the six superstructure types individually and reliability and service life graphs were generated for CIP decks on each superstructure type.

Table 9. Table showing counts of different superstructure types with CIP decks.

SI&A items		SI&A description	Count	Analysis dataset	Combined count
43A	43B				
4	2	Steel continuous stringer/multi beam girder	2,626	CIP decks on steel cont. girders	2,626
3	2	Steel stringer/multi beam girder	1,564	CIP decks on steel simple girders	1,564
5	2	Prestressed concrete stringer/multiple-beam or girder	147	CIP decks on PSC cont. girders	1,385
6	2	Prestressed concrete continuous stringer/multi beam girder	1,238		
1	1	Concrete slab	237	RCC slabs	989
2	1	Concrete continuous slab	752		
1	4	Concrete tee beam	789	CIP decks on RCC beams	1,019
2	4	Concrete continuous tee beam	20		
1	6	Concrete box beam or girders – single or spread	5		
1	5	Concrete box beam or girders – multiple	0		
2	6	Concrete continuous box beam or girders – single or spread	193		
2	5	Concrete continuous box beam or girder – multiple	12		
5	4	Prestressed concrete tee beam	112	CIP decks on PSC box beams	649
6	4	Prestressed concrete continuous Tee beam	319		
5	5	Prestressed concrete box beam or girder – multiple	29		
5	6	Prestressed concrete box beam or girder – single	155		
6	5	Prestressed concrete continuous box beam or girder – multiple	13		
6	6	Prestressed concrete continuous box beam or girder – single	21		
Total number of CIP decks on all six different superstructure types					**8,232**

Table 10 lists the number of events for each of the superstructure types selected in each of the CRs. Of note in these data is that the data for PSC continuous superstructures is heavily weighted toward CR 7 and 8. There is limited data for CR 3, 4, and 5, as noted by bold text in the table. Because the construction of PSC bridges is more recent historically than other types of bridges, the bulk of the population remains in good condition. This should be considered in the interpretation of the results – those PSC bridges in CR 5-3 may be examples of bridges with quality of construction or other issues causing early-life deterioration. PSC box beam bridges also have limited data available in the CR of 5, 4, and 3, as shown in Table 10.

Table 10. Count of CIP decks with different CR for each superstructure family.

Count of CIP decks on different superstructure types						
Superstructure data set name	**CR 3**	**CR 4**	**CR 5**	**CR 6**	**CR 7**	**CR 8**
CIP deck on steel cont. girders	324	528	856	1,629	2,039	1,072
CIP deck on steel simple girders	390	629	883	1,047	700	235
CIP deck on PSC cont. girders	**9**	**7**	**19**	154	959	710
RCC slabs	69	143	289	657	599	587
CIP decks on RCC beams	182	351	530	631	374	95
CIP decks on PSC box beams	**4**	**18**	**16**	59	402	228

A summary of the TICR for the median in each CR for all CIP decks regardless of the superstructure type and the service life for CIP decks on each superstructure type is presented in Table 11. As shown, the service life of the CIP decks on each superstructure type is different. The reason for the difference in the service life of the CIP decks on different superstructure types may not be the superstructure type alone. Other factors may affect the service life of decks on different superstructures (e.g., span length), but K-M modeling cannot account for these factors. As shown in Table 11, the analysis showed that RCC slabs showed the longest service life estimate, 59 years, and CIP decks on PSC box beams had the shortest estimated service life at 38 years. It was also found that CIP decks on continuous steel superstructures had a longer service life (54 years) as compared with the average service life estimate of 52 years, and CIP decks on continuous PSC girders had a shorter than average service life estimate of only 44 years. As mentioned previously, the PSC continuous superstructure data is skewed toward bridges in good condition, with relatively few examples of CIP decks in the fair to poor condition. Consequently, although these data are accurate according to the statistical modeling, these may not be fully representative of the performance of these decks looking toward the future.

Table 11. Table showing TICR and service life for CIP decks on different superstructure types.

Superstructure type	Median TICR (year) for CR 8-3						Service life
	8	7	6	5	4	3	
All CIP decks regardless of the superstructure type	7	11	14	8	5	7	52
RCC slabs	7	14	17	8	6	7	59
CIP decks on steel cont. girders	7	13	16	7	5	6	54
CIP decks on steel simple girders	7	9	14	8	5	7	50
CIP decks on RCC girders	2	9	14	10	6	8	49
CIP decks on PSC cont. girders	8	14	9	5	3[1]	5[1]	44
CIP decks on PSC box beams	5	9	7	8	7[1]	2[1]	38

[1] Data in this CR is very limited.

Median service life graphs and reliability plots for CIP decks on each of the different superstructure types are shown in Appendix E to the report, but the combination of all the service life graphs is shown in Figure 9. This figure can be used to compare the behavior of CIP decks on different superstructure types over the course of their service lives. The figure illustrates the surprisingly rapid deterioration of CIP decks on PSC box girders, which has an almost constant rate of deterioration that is greater than any other CIP/structure type combination. It is also notable that in the area of CR 8-6, CIP decks on PSC continuous girders actually have a lower rate of deterioration than any other bridge type. However, that rate is increasing for CR 5 and lower, where the data is much more sparse. Again, these data are accurate according to the model, but only time will tell if these data are representative looking forward. One interpretation of these data is that deck preservation activities to maintain decks in good condition would be advantageous to prevent the rapid onset of deterioration for CR 5 and lower. This is an important finding in the research and will be discussed more later in the report.

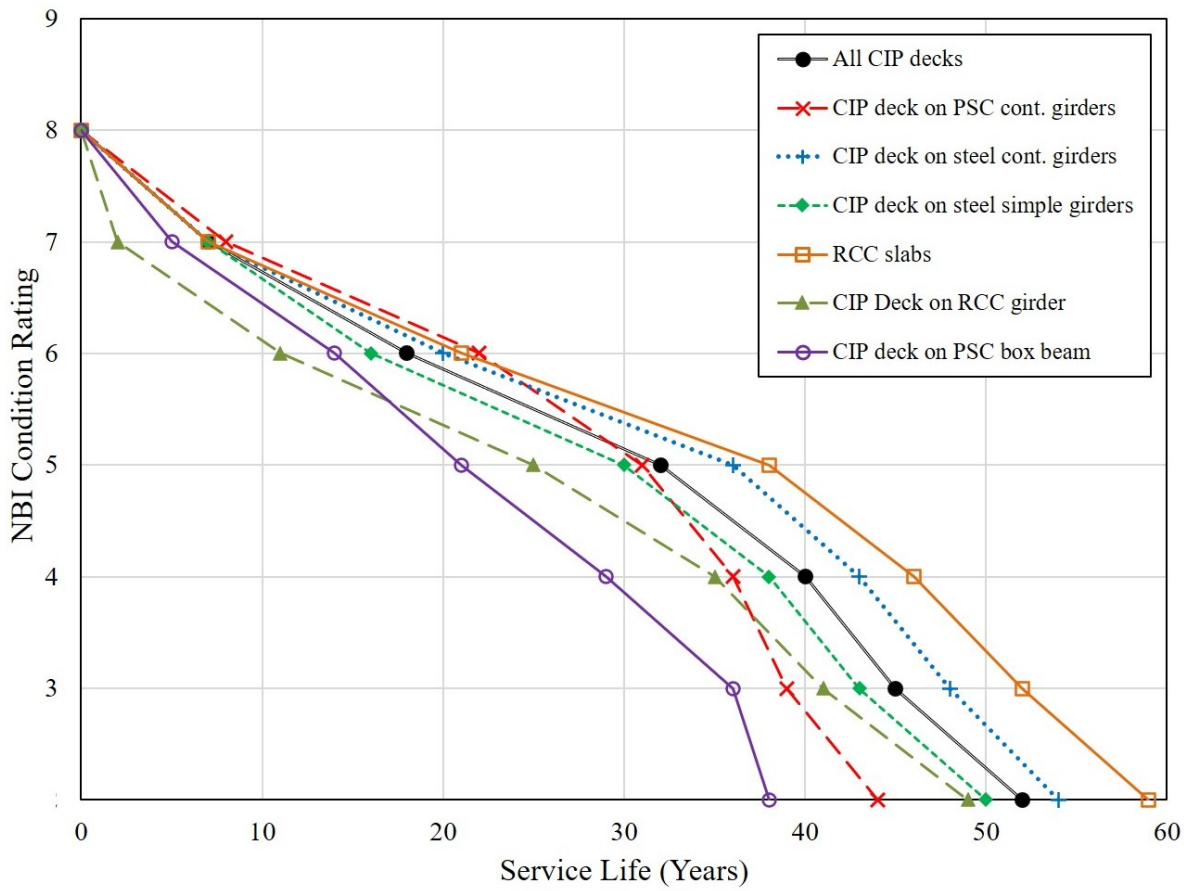

Figure 9. Estimated service life graph for CIP decks on different superstructure types.

Cox Regression Analysis for CIP Decks

This section describes the Cox regression analysis for CIP decks. The Cox regression is used to study the effects of particular parameters on the overall deterioration of CIP decks. The covariates available to consider are superstructure type, maximum span length, structure length, amount of salt used for deicing purposes (tons/lane miles), freeze/thaw cycle (days/year), snow (days/year), ADT, ADTT, and the spatial division – division of the state to districts or a combination of districts to divide the state into regions. Based on discussions with the technical committee for the research project, the variation in deterioration patterns between districts was most practical for implementation of the results of the research. Therefore, the covariate of districts was focused on for the analysis.

Table 12 contains the output for Cox regression for each of the covariates applied separately. The table indicates the -2log L value and the likelihood ratio. These statistical values are used to determine the significance of the different covariates when applied to the deterioration model. More complete descriptions of these parameters can be found in the appendices, including tables showing the general statistics such as

the median values for covariates for each different deck/superstructure combination. The significance of these data shown in Table 12 is to determine which of the covariates have a statistically significant effect on the deterioration of bridges. The data in Table 12 show that most of the covariates assumed in the model are statistically significant when examined individually, with the exception of ADT and ADTT. It was found that ADT and ADTT did not have a statistically significant effect on the deterioration of CIP decks, even when combined with other covariates.

Table 12. Table showing maximum likelihood estimate for CIP deck covariates.

Var. no.	Variables in model	-2log $\hat{L}$	Likelihood ratio	Result
0	None	242,492.64		Null model
1	Age in TICR	242,446.15	46.49	Significant
2	Structure length (ft.)	242,479.71	13.99	Significant
3	Maximum span length (ft.)	24,2435.75	56.89	Significant
4	Freeze/thaw (days/year)	242,455.34	37.30	Significant
5	Snow (days/year)	242,463.27	29.36	Significant
7	Salt (tons/lane miles)	242,419.31	73.33	Significant
8	ADT	242,492.25	0.39	Not significant
9	ADTT	242,492.41	0.23	Not significant
10	District	242,398.57	94.07	Significant
11	Region	242,442.91	49.73	Significant
12	Superstructure type	242,228.75	263.89	Significant

Table 13 lists the effect of covariates on the performance of the CIP decks. This table presents the final results after all modeling steps are completed and all assumptions and diagnosis were met. The table includes details of the results from the Cox regression in raw form. These data are provided for illustration for CIP bridge decks. For other components these data are available in Appendix C but will not be shown in the primary text because it is somewhat difficult to interpret and not particularly useful to practitioners. These data are shown here to illustrate the process of Cox regression modeling and demonstrate the research process. To apply these data to assess trends in deterioration or the impact of specific parameters, these data must be applied as a hazard ratio to compare one specific set of parameters to another, which is shown in the following sections. Regardless, the following section describes these results in detail, followed by practical applications of these data in the form of hazard ratios, which are used to demonstrate the trends in the data.

The first column lists the name of the covariate, the second column shows the number of degrees of freedom, the third column lists the parameter estimate ($\hat{\beta}$) for each covariate, the fourth column contains the standard error for the parameter estimate, the fifth column contains the chi-square value, and the last column contains the probability value (p-value) comparing the chi-square from the fifth column to the critical value of theoretical chi-square for the given degree of freedom.

In Table 13, the first five rows contain the five levels of the categorical covariate superstructure type. The CIP decks on superstructure type steel continuous girders is not listed because it was selected as the

reference to which other combinations are compared, which is necessary for analysis of categorical covariates. In this analysis, CIP decks on steel continuous girders were selected as the reference. Each of the five superstructure types have a parameter estimates and associated standard error that was used to construct the confidence interval for the parameter estimate. The last column for the first five rows shows that the performance of the CIP decks on different superstructure types is different as indicated by the p-value less than 0.05 or 5%. This p-value is a measure of the likelihood that the performance is NOT different, so a p-value of 5% or less means there is at least a 95% likelihood the performance IS different.

Row 6 lists the parameter of the age in TICR and row 7-11 contains the interaction of age in TICR with superstructure types. The interaction of age in TICR with superstructure types demonstrate that age affects the performance of the CIP decks on different superstructure types differently, with the exception of CIP decks on the PSC continuous girders where the p-value is greater than 0.05. This shows that the performance of the CIP deck on PSC continuous girders is not different than CIP deck on the reference superstructure type – steel continuous girders. These data indicate that there is a statistical difference between the effect of age on deterioration of bridge decks *(other than for PSC)*. The effect is relatively small, and the negative value indicates that the performance is better when compared to CIP decks on continuous steel superstructures.

Table 13. Table showing Cox regression model output for CIP decks showing superstructure type, age, and district covariates results.

No.	Parameter	DF	Parameter estimate ($\hat{\beta}$)	Standard error	Chi-square	Pr > chi-square
1	RCC slabs	1	0.197	0.049	15.83	<.0001
2	CIP deck on RCC beams	1	0.336	0.061	30.40	<.0001
3	CIP deck on steel simple girders	1	0.252	0.057	19.61	<.0001
4	CIP deck on PSC cont. girders	1	0.110	0.046	5.592	0.018
5	CIP deck on PSC box beams	1	0.900	0.058	239.2	<.0001
6	Age in TICR	1	0.022	0.001	391.7	<.0001
7	Age in TICR*RCC slabs	1	-0.015	0.001	101.1	<.0001
8	Age in TICR*CIP deck on RCC beams	1	-0.021	0.002	194.3	<.0001
9	Age in TICR*CIP deck on steel simple girders	1	-0.013	0.001	87.79	<.0001
10	Age in TICR*CIP deck on PSC cont. girders	1	-0.002	0.003	0.403	0.525
11	Age in TICR*CIP deck on PSC box beams	1	-0.028	0.004	44.34	<.0001
12	NW	1	-1.388	0.538	6.643	0.010
13	KC	1	-1.078	0.572	3.558	0.059
14	CD	1	-2.567	0.475	29.17	<.0001
15	SL	1	-1.188	0.454	6.844	0.008
16	SW	1	-2.365	0.475	24.78	<.0001
17	SE	1	1.320	0.621	4.511	0.033

Rows 12 -17 show the effect of district on the performance of the CIP decks. The Northeast (NE) district is not listed in the table because this categorical covariate was selected as the reference. From the p-value

column, it is evident that CIP decks located in different districts perform differently, except for the KC district which has a p-value greater than 0.05.

Table 14 shows the results of the Cox regression analysis for the covariates of salt application, freeze/thaw, and snow. Row 1 shows the effect of salt on the performance of the CIP decks and rows 2-7 show the interaction of salt with each of the six districts. The overall value for salt application was negative and not statistically significant when considering all bridges, but when examined at the district level, the effect of salt application was statistically significant in some cases. The p-value column for rows 2-7 indicates that the effect of salt in NW, CD, and SW is different than the effect of salt in NE, as demonstrated by the smaller p-values. In contrast, the effect of salt in KC, SL, and SE is not statistically different than the effect of salt in NE as shown by the p-values greater than 0.05.

Table 14. Table showing Cox regression model output for CIP decks showing salt application, freeze/thaw, and snow covariate results.

No.	Parameter	DF	Parameter estimate ($\hat{\beta}$)	Standard error	Chi-square	Pr > chi-square
1	Salt (tons/lane miles)	1	-0.108	0.132	0.667	0.414
2	Salt*NW	1	0.546	0.193	8.000	0.005
3	Salt*KC	1	0.212	0.161	1.732	0.188
4	Salt*CD	1	1.028	0.171	35.93	<.0001
5	Salt*SL	1	0.193	0.134	2.072	0.150
6	Salt*SW	1	1.240	0.191	42.16	<.0001
7	Salt*SE	1	-0.547	0.426	1.646	0.199
8	Freeze/thaw (days/year)	1	-0.062	0.004	198.0	<.0001
9	Salt * freeze/thaw	1	0.010	0.001	50.12	<.0001
10	Snow (days/year)	1	0.070	0.006	130.9	<.0001
11	Salt*snow	1	-0.012	0.002	31.50	<.0001

Row 8 contains the effect of freeze/thaw cycles on the performance of the CIP decks. As shown, the parameter estimate for this covariate is negative, which indicates that increasing the number of freeze/thaw cycles reduces the hazard of deterioration. In other words, in the CIP decks data set, there are bridges with long TICRs and more freeze/thaw cycles, which causes the negative parameter estimate. Freeze/thaw cycles would be expected to contribute to accelerated deterioration based on experience and previous research, but these data indicate the opposite when considering only the freeze/thaw cycles without other covariates [14]. Row 9 contains the interaction effect of salt and freeze/thaw cycles, and as shown this effect is statistically significant. Row 10 contains the effect of snow on the performance of the CIP decks and row 11 shows the statistically significant interaction effect of snow and salt. The snow and salt interaction is also negative, but also quite small at only about 1%.

The parameter estimates listed in Table 13 and Table 14 are difficult to interpret in raw form, in part because some are compared to a reference. Additionally, these data are for covariates applied individually or with one other covariate with which there is interaction. However, these values can be used to calculate the

hazard ratios for the desired covariate for the purpose of analyzing deterioration trends and the effect of covariate on the deterioration pattern, including the interaction of covariates. The calculation of the hazard ratios is provided here and the hazard ratios for all the covariates are shown in Table 15 and Table 17.

For example, the hazard ratio of deterioration for RCC slabs compared to CIP decks on steel continuous girders can be calculated as follows. The numerator is the parameter estimates for the RCC slab and the denominator is the parameter estimates for the referenced level – CIP deck on steel continuous girders. As shown in Table 13, the parameter estimate for superstructure type RCC slab is listed in row 1 and the parameter estimate for the referenced superstructure type (CIP deck on steel continuous girders) is zero. Also, there is interaction effect for superstructure type and age in TICR. The parameter estimate 0.022 listed in row 6 is the parameter estimate for age effect for CIP decks on steel continuous girders, and the parameter estimate -0.015 in row 7 is the relative age effect for RCC slabs, and the absolute age effect for RCC slabs equal 0.022-0.015=0.007. The mean age in TICR value, which is the average age of a deck in a particular CR, is 29.92 yrs. Since the hazard ratio for effect of superstructure type is calculated, the age in TICR in the interaction term is kept equal for both types.

$$\frac{h(SS = RCC\ slab)}{h(SS = 42)} = \frac{e^{0.197\times(RCC\ slab)+(0.022-0.015)*29.92}}{e^{0\times(CIP\ deck\ on\ steel\ cont.girders)+0.022*29.92}} = \frac{1.501}{1.931} = 0.78 \qquad \textbf{(5)}$$

The hazard ratio indicates that RCC slabs has 78% hazard of deterioration compared to CIP decks on steel continuous girders, or in other words, the hazard of deterioration for RCC slabs is 22% less than the hazard of deterioration for CIP decks on steel continuous girders. This output is shown in Table 17 where RCC slab is compared with CIP decks on steel continuous girders. The inverse of the ratio would provide the hazard ratio of CIP decks on steel continuous girders compared with RCC slabs and that is equal to 1.29, or CIP decks on steel continuous girders has 29% more hazard of deterioration than RCC slabs. In other words, CIP decks on steel continuous girders deteriorate more rapidly than RCC slabs. The confidence interval (CI) for the hazard ratio is calculated by equation (6) where ($\hat{\beta}$) is the parameter estimate and *se* is the standard error of each parameter estimate listed in Table 13.

$$95\%\ CI = e^{[\hat{\beta}\pm 1.96\times se]} \qquad \textbf{(6)}$$

Similar calculations were completed for all the covariates considered for CIP decks and the result is shown in Table 15 thru Table 17. These tables contain the hazard ratios for all the covariates considered for the CIP decks. Table 15 contains the hazard ratios for each covariate and the CI for the hazard ratio. Statistically nonsignificant hazard ratios are those with confidence intervals containing one (1), and these are shaded in the table. For example, the effect of salt on the performance of CIP decks in NE shows that for each extra ton of salt the hazard is increased by 24%, but since the CI for this point estimate contains one (1), this

effect is not statistically significant. In other words, the performance of CIP decks might be 24%, but the CI includes the value of 1.0, which indicates that the performance might not be different (i.e., 0% different) within the overall confidence interval. Consequently, this cannot be viewed as a statistically significant result.

For the effect of covariates investigated on the district level an average effect is also provided as shown in the last column of Table 15. For example, on average, increasing the amount of salt by one ton per lane mile would increase the hazard of deterioration by 2.13, or the hazard would be doubled, on average. These data can also be examined on a district-by-district level, for example, for each increase in one ton of salt in the KC district, the increased hazard is 54%, while for the central district the value is ~350% or 3.5 times higher. Given that the rate of salt application was derived from some limited historical data, and is not that precise, the average value is probably more indicative of the overall trend.

The effect of other covariates and their interactions are also shown in the table. For example, a 10-year increase in age of CIP decks results in the hazard ratio increasing by 10%, holding all other covariates constant. So, if two decks were in CR 6, and one was on a bridge that was 20 years old, and the second was 30 years old, the 30-year-old bridge decks has 10% more hazard, or risk of transitioning to the next lower CR as compared with the 20-year-old bridge.

The effect of structure length is provided as well in Table 15. This effect is calculated using a separate model where maximum span length is replaced by the structure length and the Cox regression model is fitted to the data. The reason for doing so is that maximum span length and structure length are correlated to each other because longer bridges also tend have longer spans. One remedy for the effect of correlated covariates is to build separate models using each correlated covariate. As shown, for every 100 ft. increase in structure length of a CIP deck, the deterioration hazard is increased by one percent (1%). In terms of span length, the hazard is increased 3% for each additional 10 ft. of span length. These data can be interpreted broadly that the overall structure length has only a small or no effect on the deterioration, but increases in the maximum span length have a larger impact on deterioration, increasing 3% for every 10 additional ft. of maximum span length.

Table 15. Table showing the effect of covariates on cast-in-place bridge decks.

Covariate name		Point estimate	95% confidence interval		Average point estimate
Salt (one tons/lane miles) at mean snow =39 days/year and mean freeze/thaw cycle = 83 days/year	NE	1.24	0.98	1.58	2.13
	NW	2.15	1.59	2.90	
	KC	1.54	1.25	1.90	
	CD	3.48	2.74	4.41	
	SL	1.51	1.35	1.68	
	SE	0.72	0.32	1.60	
	SW	4.30	3.23	5.73	
Age in TICR (10 years)	CIP deck on PSC cont. girders	1.22	1.16	1.29	1.10
	CIP deck on PSC box beams	0.95	0.87	1.02	
	RCC slab	1.07	1.05	1.10	
	CIP deck on RCC beams	1.01	0.99	1.04	
	CIP deck on steel cont. girders	1.25	1.22	1.27	
	CIP deck on steel simple girders	1.10	1.07	1.12	
Maximum span length (10 ft.)		1.03	1.02	1.04	1.03
Structure length (100 ft.)		1.01	1.01	1.02	1.01
Snow (10 days, at salt mean =2.93)		1.39	1.32	1.46	1.39
Freeze/thaw cycle (days/year)		0.72	0.69	0.74	0.72

Table 16 shows the hazard ratio of CIP deck performance compared between districts. The covariate district contains factors other than those explicitly included in the analysis. In other words, the covariate district or region contains "everything else" information not captured by other covariates in the model. The effect of district might encompass anything, such as different inspection practices among districts, different quality of construction materials, or any other factors that are not captured explicitly by other covariates in the model. If the covariate district or region was not statistically significant in the presence of other covariates, it could be described that the other covariates define all the variability in the model and district or region is not significant and could be dropped out of the model. But if the covariate district or region is significant in the presence of other covariates, which it is in this case, it indicates that there is information in the covariate district or region that is not captured by other covariates [15]. The hazard ratio was computed at one ton of salt per lane mile for each district since there is an interaction effect of salt and district. All other covariates were kept equal – same superstructure type, equal number of snow days, equal maximum span length or structure length, and equal age in TICR. In this way, the data is normalized to illustrate the trends based on salt application. Some of the hazard ratios are not significant and these cells are shaded. For example, the hazard ratio of deterioration for a CIP deck located in Central (CD) district compared to a CIP deck located in Kansas City (KC) for all other covariates being equal is 51%, but the CI shows that this hazard ratio is not statistically significant – the performance might be the same, because the confidence interval includes 1.0. On the other hand, the hazard ratio of a CIP deck located in CD compared to a CIP deck located in NE (with all other covariates being equal) is 22% and this comparison is statistically significant. This means that the decks in NE have deteriorated more rapidly than decks in CD.

Table 16. Comparison of the effect of 1 ton of salt per mile in different districts.

Comparison of districts at salt = one tons/lane miles				
Comparison		Point estimate	95% confidence interval	
CD	KC	0.51	0.23	1.11
CD	NE	0.22	0.12	0.39
CD	NW	0.50	0.26	0.95
CD	SE	0.10	0.06	0.16
CD	SL	0.58	0.32	1.06
CD	SW	0.66	0.40	1.11
KC	NE	0.42	0.19	0.95
KC	NW	0.98	0.42	2.28
KC	SE	0.19	0.10	0.40
KC	SL	1.14	0.51	2.57
KC	SW	1.30	0.61	2.75
NE	NW	2.14	1.18	4.57
NE	SE	0.46	0.28	0.76
NE	SL	2.71	1.43	5.14
NE	SW	3.08	1.75	5.42
NW	SE	0.20	0.11	0.35
NW	SL	1.17	0.59	2.32
NW	SW	1.33	0.72	2.46
SE	SL	5.86	3.56	9.65
SE	SW	6.67	4.51	9.86
SL	SW	1.14	0.65	2.00

Similar to Table 16, Table 17 presents the hazard ratio for the effect of the superstructure type on the performance of the CIP decks. In this model, the mean age in TICR is kept constant because there is an interaction effect of age in TICR with the superstructure type. For example, assuming that the mean age in TICR was the same for a steel simple girder bridge deck and an RCC slab, the point estimate for the hazard ratio is 0.89, meaning that the RCC slab has a smaller hazard (i.e., deteriorates slower) as compared to the CIP deck on a steel simple girder.

The hazard ratios for CIP decks on different superstructures listed in Table 17 could be used to rank the performance of the CIP decks qualitatively from the best performing CIP decks to the worst performing CIP deck while keeping all other covariates equal. In the analysis, the mean age in TICR is kept constant. The hazard ratios compared one superstructure type to a reference superstructure type to produce the hazard ratio of one compared with the other. For example, comparing CIP deck performance for an RCC slab as compared with a CIP deck on a steel girder bridge, the RCC slab has only 89% of the hazard as compared with the steel girder, or a CIP deck hazard is 1/0.89 = 1.12 or about 12% more risk. Such a ranking is shown in the bottom part of Table 17, where the hazard ratios were used to form a ranking of hazard for CIP decks on different types of superstructures.

Table 17. Table showing the effect of covariates on cast-in-place bridge decks.

Comparison of CIP deck performance at mean age in TICR				
Comparison		**Point estimate**	**95% confidence interval**	
RCC slab	RCC girders	1.04	0.97	1.12
RCC slab	Steel simple girder	0.89	0.84	0.95
RCC slab	Steel cont. girder	0.78	0.74	0.82
RCC slab	PSC cont. girder	0.74	0.65	0.83
RCC slab	PSC box beam	0.72	0.60	0.87
RCC girder	Steel simple girder	0.86	0.80	0.92
RCC girder	Steel cont. girder	0.75	0.70	0.80
RCC girder	PSC cont. girder	0.71	0.62	0.80
RCC girder	PSC box beam	0.69	0.57	0.84
Steel simple girder	Steel cont. girder	0.87	0.82	0.92
Steel simple girder	PSC cont. girder	0.83	0.73	0.93
Steel girder	PSC box beam	0.81	0.67	0.98
Steel cont. girder	PSC cont. girder	0.94	0.84	1.06
Steel cont. girder	PSC box beam	0.93	0.77	1.12
PSC cont. girder	PSC box beam	0.98	0.79	1.21

Ranking CIP decks performance on different superstructures					
Best -1	**2**	**3**	**4**	**5**	**Worst - 6**
CIP deck on RCC girders	RCC slab	CIP deck on steel simple girders	CIP deck on steel cont. girders	CIP deck on PSC cont. girder	CIP deck on box beams

The ranking of the decks using the hazard ratio in Table 17 produces a different ranking than the service life rankings listed in Table 11, which lists the estimated service life based on historical data (K-M model). In Table 11, the data is based on the actual historical performance of the different deck and superstructure combinations, regardless of how other covariates, such as span length, age, etc. may differ for the different deck/superstructure combinations. In Table 17, these other covariates are held constant between the different deck/superstructure types, so these data are in effect normalized to a uniform set of covariates. In the real world, these covariates are different. For example, long-span RCC slabs are not typically constructed and therefore are not found in the inventory.

One interpretation of these data is that for maintenance and preservation decision-making, Table 11 illustrates how the bridges in Missouri have actually performed historically and is most relevant for managing the existing structures. For design of new structures, to compare the use of one material to another, for example, Table 17 provides relevant data because other covariates like span length and age would be the same at the design stage for one particular structure. Therefore, these normalized data in Table 17 show relevant data for design decisions when comparing two different options for the same span. In a similar way, Table 15 shows relative effects of design parameters like the span or structure length, and the effect of certain environmental factors like salt application or number of snow days.

Effect of Salt on Bridge Decks

The Cox regression analysis showed that salt had the highest effect on the deterioration of the CIP decks. This relationship was examined considering the amount of salt and the service life of the CIP decks in each MoDOT district. Table 18 lists the average amount of salt (tons/lane miles) for each district over ten years of the available salt data from 2001-2010 vs. the service life of the CIP decks (based on median values from the K-M model) located in each district. It was found that reduced service life corresponded with increased use of salt for most districts except for the KC District. The lower the amount of salt used, the longer the service life of the CIP decks and vice versa. As shown, the average amount of salt used by the Southeast district is the lowest, and the service life of the CIP decks located in this district is the longest. This relationship ignores other factors that may affect the service life of the CIP decks, but it is another way of looking at the effect of salt on the performance of the CIP decks.

Table 18. Table showing the relationship between the amount of salt used by districts vs. the CIP decks service life.

District name	Highway length	Number of CIP deck	Mean salt (tons/lane miles)	CIP deck service life
SE	16,206	1,671	1.24	57
KC	7,931	1,464	4.23	54
SW	14,697	1,395	2.16	53
NW	11,385	1,239	2.72	51
NE	9,810	830	2.89	51
CD	11,568	1,025	2.65	51
SL	5,951	1,223	5.10	50

Figure 10 depicts the relation between the service life of the CIP decks and the amount of salt used by districts in a scatter plot. As shown in the figure, there appears to be a consistent trend of increasing salt use leading to shorter service life, except for the KC District. The KC District appears to be an outlier as compared with other districts. Given that the quality of the salt use data may have some imperfections, this outlier may be a result of the data quality and not a real affect.

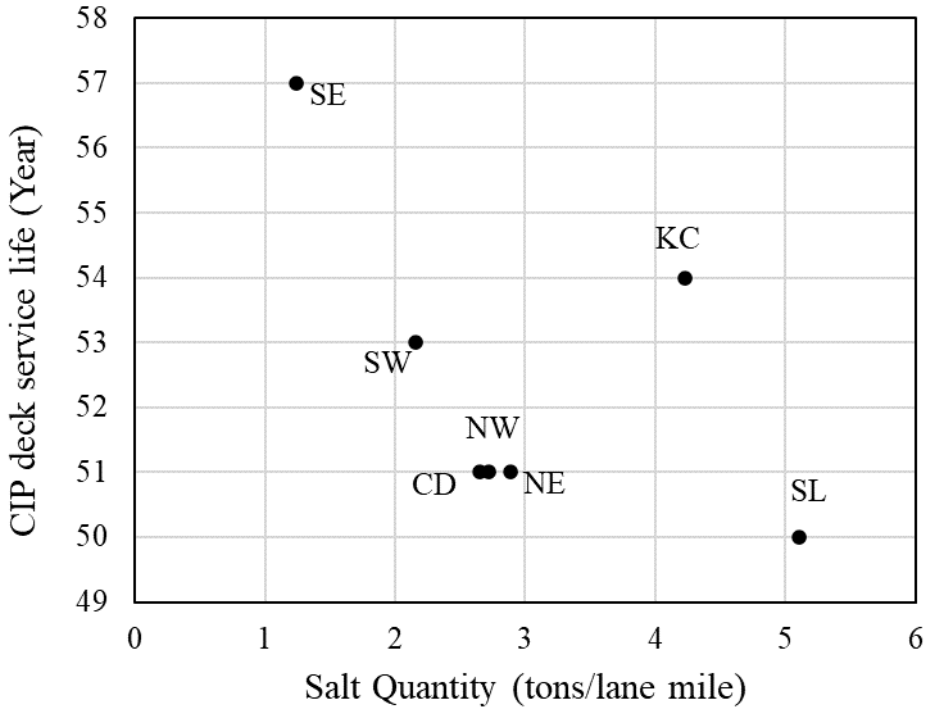

Figure 10. Plot showing the relationship between the service life of the CIP decks vs. the quantity of salt used by districts.

An analysis was developed to provide a graphical illustration of the effect of increased salt use on the deterioration pattern of a CIP deck on a PSC superstructure. Figure 11 shows the reliability model results. This combination of a CIP deck on a PSC superstructure was selected for illustration because of the prevalence of PSC structures in new construction. The hazard ratio was determined holding other covariates equal and calculating the hazard ratio for salt application of 2.85 tons/mile vs. 3.85 tons/mile, and these data were used to generate the plot from the existing deterioration data. As shown in the figure, the likelihood of transitioning to the next lower CR is increased with the additional application of one additional ton of salt per mile. Consequently, the likelihood of failure (transition) is increased and the overall service life it decreased. For example, in these data, if the service life was estimated based on the median (50%) transition, the service life is reduced from ~64 years to ~50 years, or about a 22% decrease in service life.

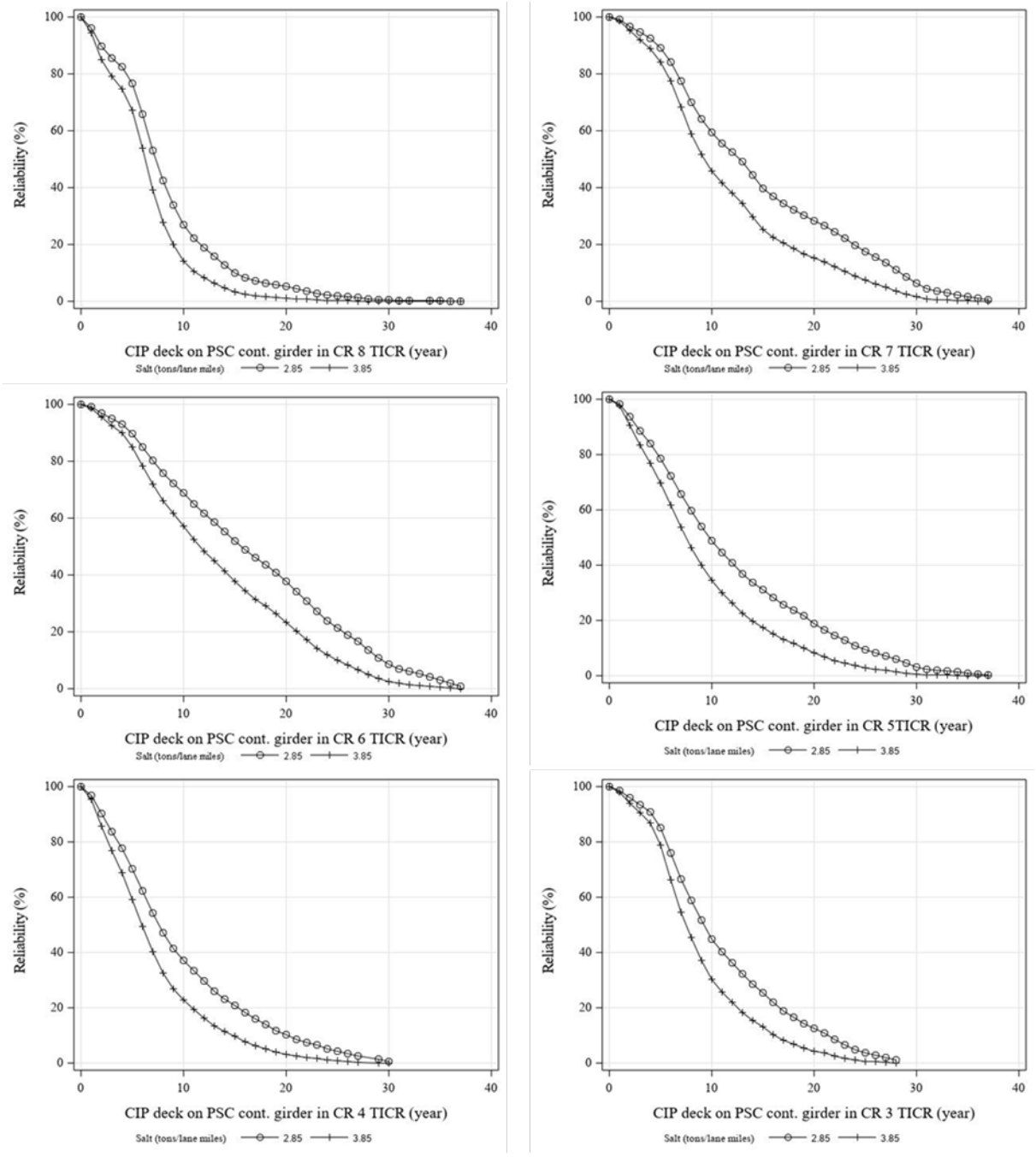

Figure 11. Graphs showing the effect of salt use increasing from 2.85 to 3.85 tons/mile for a CIP deck on PSC continuous girder.

Reliability Analysis for Superstructures

This section presents the reliability analysis for superstructures. The reliability and the service life graph are produced for each superstructure type separately to show the trend and capture any difference in TICR among the superstructure types. Later, the superstructure type is used along with other covariates to see if

there are any differences between the performance of the superstructure types using the Cox regression and measure the effect of each covariate on the performance of superstructures.

Table 19 lists the superstructure types available for analysis. As shown, the 8,859 bridges with superstructures that are available for reliability analysis fall in one of the six superstructure types in terms of construction material or construction type. The superstructures are grouped either due to their construction material or construction type in order to have sufficient number of observations for each group, as previously discussed. The column labelled "Analysis data set" lists the name of the six different superstructure types that are included in building the K-M analysis and the Cox regression.

Table 19. Table showing different types of superstructures, their count, and their combination for analysis.

SI&A items		SI&A description	Count	Analysis data set	Combined count
43A	43B				
4	2	Steel continuous stringer/multi beam girder	2,645	Steel cont. girders	2,645
3	2	Steel stringer/multi beam girder	1,602	Steel simple girders	1,602
5	2	Prestressed concrete stringer/multiple-beam or girder	174	PSC cont. girders	1,436
6	2	Prestressed concrete continuous stringer/multi beam girder	1,262		
1	1	Concrete slab	247	RCC slabs	1,014
2	1	Concrete continuous slab	767		
1	4	Concrete tee beam	790	RCC girders	1,022
2	4	Concrete continuous tee beam	20		
1	6	Concrete box beam or girders - single or spread	5		
1	5	Concrete box beam or girders - multiple	2		
2	6	Concrete continuous box beam or girders - single or spread	193		
2	5	Concrete continuous box beam or girder - multiple	12		
5	4	Prestressed concrete tee beam	169	PSC box beams	1,140
6	4	Prestressed concrete continuous tee beam	344		
5	5	Prestressed concrete box beam or girder - multiple	384		
5	6	Prestressed concrete box beam or girder – single	201		
6	5	Prestressed concrete continuous box beam or girder – multiple	16		
6	6	Prestressed concrete continuous box beam or girder – single	26		
Total number					**8,859**

The reliability graph using the K-M method for steel continuous girders is shown in Figure 12. The vertical axis shows the reliability in percentage of the superstructures and the horizonal axis show the TICR. This graph could be used to understand the performance of steel continuous girders based on the NBI CR without taking into account the effect of any covariate that would be included in building the Cox regression model later. For example, the probability for steel continuous girders to stay longer than 15 years in CR 7 is over 50%. Or the probability for steel continuous girders in CR 4 to stay for more than 10 years in this CR is

less than about 5%. Also as shown, generally steel continuous girders stay longer in CR 7 followed by CR 8, 6, and 5. The performance in CR 7 is notable, being somewhat dramatically slower rate of transition to CR 6 as compared with other CRs. Also notable is that the deterioration in CR 8, 7 and 6 is markedly slower than for CR 5, 4 or 3. This means that once damage begins to accumulate, presuming that the CR falls from "good" condition to "fair" condition as a result of the accumulating damage, the rate of deterioration increases significantly.

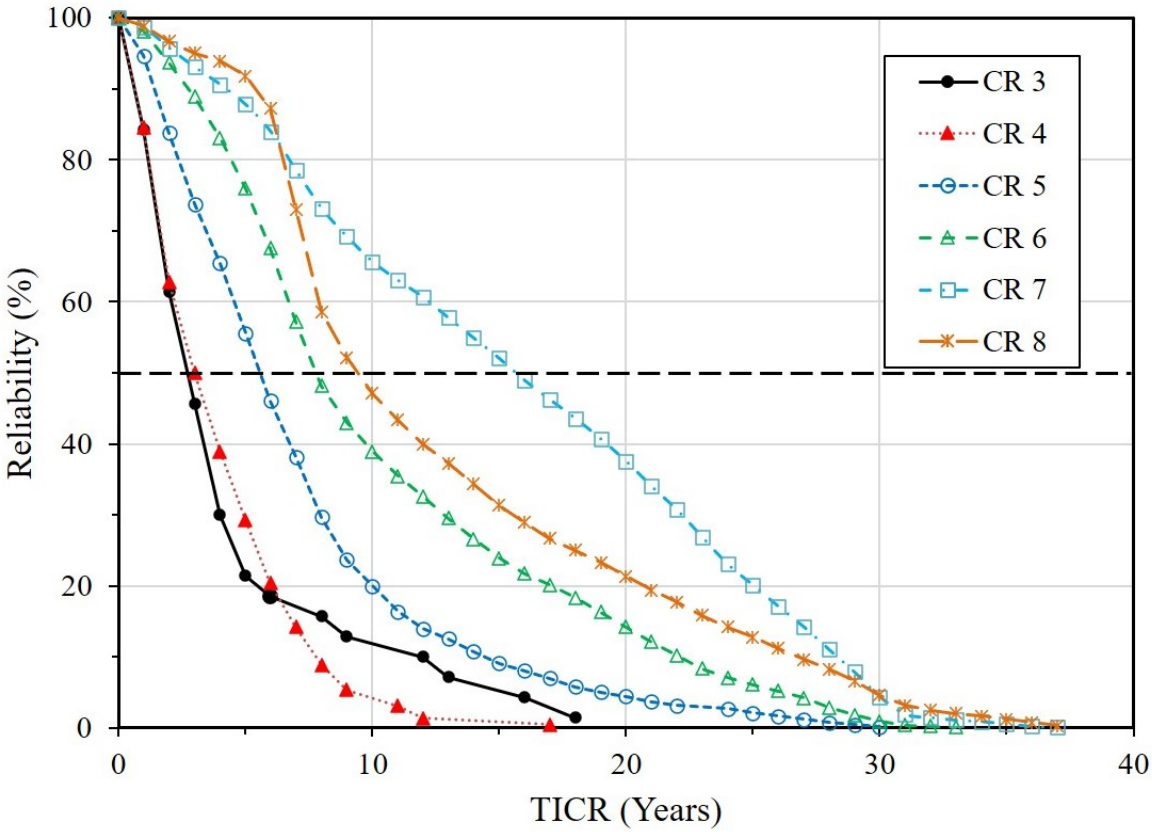

Figure 12. K-M graphs showing the reliability curves for steel continuous girders in CR 3 – 8.

These data could be interpreted to provide rationale for investments in maintenance and preservation activities. Although not specifically studied within this research project, other research conducted with MoDOT and other states, combined with practical experience, indicates that the primary damage mode affecting steel bridges is corrosion damage [16, 17]. The corrosion damage most commonly occurs in the area below joints that are leaking, causing coatings to fail and initiating corrosion damage. As a result, the CR drops over time as corrosion damage becomes more advanced. Preservation strategies such as maintaining leak-free joints and spot or zone painting to repair deteriorating coatings would help maintain structures in the fair to good condition and avoid the rapid deterioration that is shown in the figure above. Previous research also illustrated the zone maintenance painting with Calcium Sulphonate, a maintenance

coating that can be easily applied in the field, was effective in preventing corrosion damage if the joint was also repaired to prevent water and deicing chemicals from coming in repeated contact with the superstructure [17].

The reliability graph could be used to construct the service life graph for steel continuous girders at any percentage point desired. Such a graph is shown in Figure 13 for the median reliability. As shown, the service life for steel continuous girders in CR 8 – 3 calculated at median TICR is 44 years. The service life graph is shown with the 25th, 50th, and 75th percentiles to illustrate the distribution of results. As shown in the figure, the results are somewhat right skewed, showing that some steel continuous girders have much longer service lives than shown with the median values. This is consistent with experience; steel bridges that are 60 or 80 years old are not uncommon. Steel superstructures that deteriorate to CR 3 in less than 20 or 30 years, on the other hand, are very uncommon. Reliability and service life graphs for other superstructure types listed in Table 19 are shown in Appendix F.

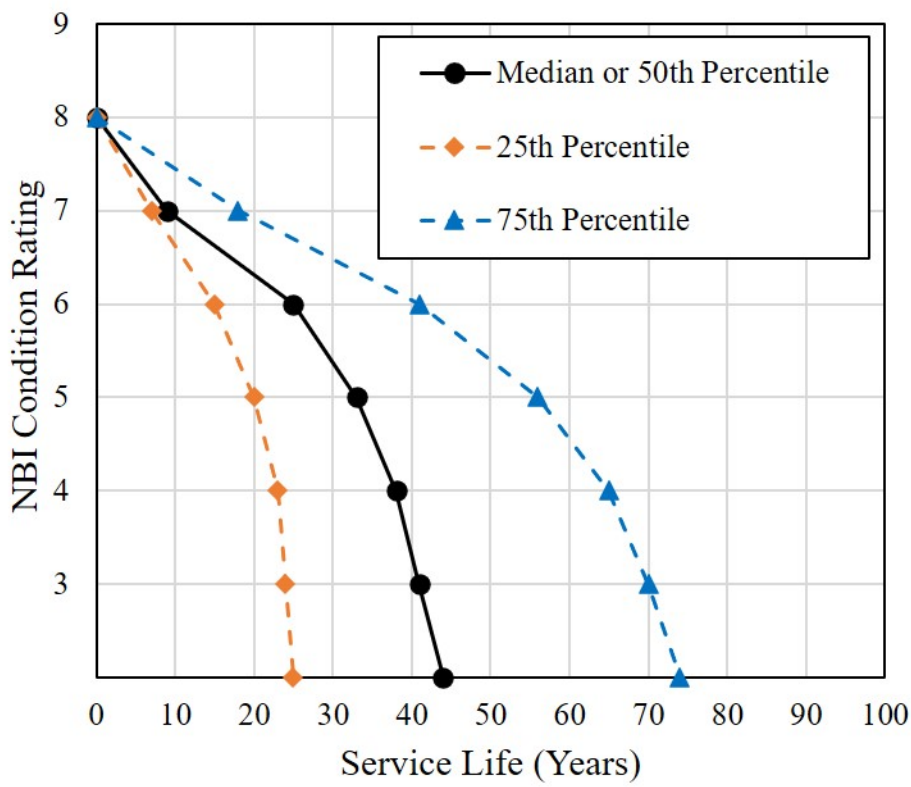

Figure 13. Graph showing the service life based on median reliability for steel continuous girders in CR 3 – 8.

The overall performance of different bridge types in terms of median service life are shown in Figure 14. The figure illustrates the service life for different types of superstructures as determined from the median TICR for each CR. Each of the curves shown in this graph can be found individually in Appendix G. The

data showed that the shortest service life was for PSC box beams, which showed the trend of deteriorating more rapidly than any other bridge type through the primary service life of the bridge, when the CR is between 8 and 4. It is also notable the steel continuous steel girder bridges performed relatively better early in their service life, with CR 8-7, but deterioration accelerated relative to other bridge types for CR 6-3. It is also notable that for CR 4, most bridge types had very similar service lives up to reaching CR 4, poor condition. If one defined the service life as when the superstructure moves from satisfactory to poor condition, then RCC slabs clearly outperform the other bridge types, and PSC box beams clearly perform poorly, but other bridge types all have approximately the same median times, about 40 years.

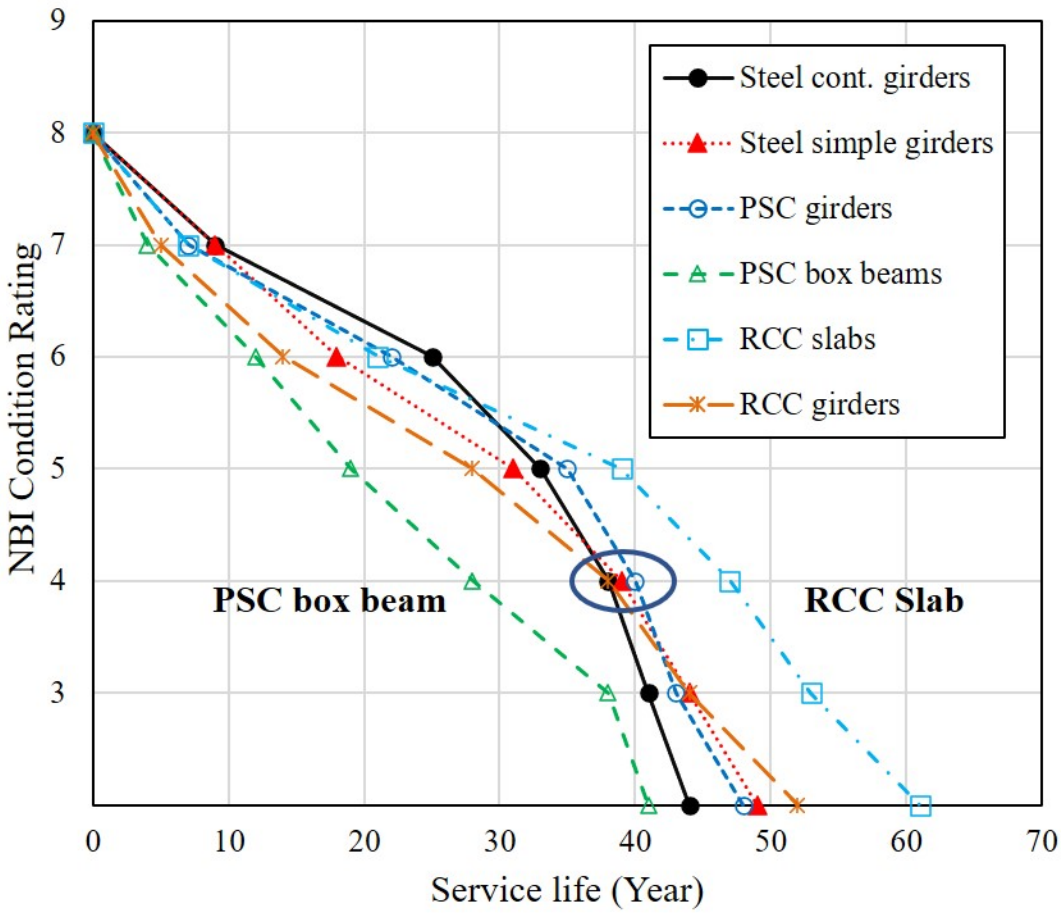

Figure 14. Service life plot for different types of superstructures.

The rank order of the superstructure types is shown in Table 20, which shows the 25th, 50th (median), and 75th percentiles for service life based on the median value of TICRs in each CR. The table also shows the ratio of the median service life for each bridge type as compared to the average of the median service life. As shown, RCC slabs and RCC beam bridges have a greater than average median estimated service life, while steel simple, steel continuous, and PSC continuous bridges showed an estimated median service life

near the overall average, and PSC box beams have the shortest median service life. Also shown in the table is the average service life, which is consistently longer than the median service life due to the fact that some bridge superstructures having much longer service lives than the median value. This is the same effect illustrated in Figure 13 for steel continuous girders showing the 75th percentile skewed to the right.

Table 20. Ranking of SS types showing 25, 50, and 75 percentiles and average service life based on TICR.

SS type	25th% years	Median years	75th% years	Avg. years	Median ratio
RCC slab	31	61	95	62	125%
RCC beam	29	52	91	57	106%
Steel simple	27	49	74	50	100%
PSC cont.	23	48	79	50	98%
Steel cont.	25	44	74	48	90%
PSC box	23	41	71	45	84%
Average service life	26	49	81	52	

Cox Regression Analysis for Superstructures

The Cox regression model output to investigate the effect of covariates on the performance of the superstructure types is presented next. The initial step of the Cox regression model building was to determine the statistically significant covariates. It was found that the number of snow days and the ADT/ADTT covariates were not significant for the Cox regression analysis of superstructure types when applied individually. Data on the significance measures are included in Appendix C. In the next step, these covariates were combined as outlined in the model development section to investigate the effect of covariates on the performance of superstructures. In the combined model, some of the covariates may become insignificant, or some insignificant covariates may become significant in the presence of other covariates. These data are also available in Appendix C.

Table 21 shows the effect of statistically significant covariates on superstructure types in table format. The first covariate listed in this table is the effect of salt on the performance of bridge superstructure TICR. The effect of salt on superstructure performance is subdivided by the amount of salt used in each of the seven districts. As noted in the first column, the effect of salt is provided for increasing one ton of salt, that is from no salt to one ton of salt or from two tons of salt to three tons of salt per lane mile. The effect of salt on the performance of the superstructures is analyzed for the case where every other covariate included in the model is set equally. That is, the bridge is located in the same district, has the same maximum span length, has the same age in TICR, and is of the same superstructure type. With these two things in place, the effect of salt on the performance of the superstructures is provided by the point estimate and the 95% confidence interval. The 95% confidence interval means that if 100 bridges are selected to find the effect of salt on their performance for the case where every other covariate being equal, we are confident that 95 of the responses will fall within the provided range.

Table 21. Table showing the effect of covariates on superstructures in terms of hazard ratios.

Covariate name		Point estimate	95% confidence interval		Average point estimate
Salt (one tons/lane miles)	NE	1.88	1.43	2.48	2.58
	NW	0.55	0.36	0.86	
	KC	1.78	1.41	2.24	
	CD	4.15	3.20	5.38	
	SL	1.34	1.20	1.51	
	SE	0.48	0.23	0.98	
	SW	7.91	6.04	10.36	
Maximum span length (10 ft.)	Steel continuous girders	1.03	1.03	1.04	1.05
	Steel simple girders	1.00	0.98	1.02	
	PSC cont. girders	1.06	1.03	1.09	
	PSC box beams	1.15	1.12	1.17	
	RCC slabs	1.03	1.03	1.06	
	RCC beams*	0.98	0.95	0.99	
Age in TICR (10 year)	Steel continuous girders	1.23	1.20	1.26	1.11
	Steel simple girders	1.11	1.08	1.13	
	PSC cont. girders	1.24	1.17	1.30	
	PSC box beams	1.03	0.96	1.11	
	RCC slabs	1.05	1.02	1.08	
	RCC beams	0.98	0.95	1.01	

Salt has the detrimental effect of increased deterioration on bridge superstructures with different amounts for each district. For example, the mean effect of increasing one ton of salt on a bridge superstructure in NE would increase the hazard of a superstructure type to transition to the lower CR 1.88 times, or approximately doubles the hazard of transitioning to the lower CR. This effect is as low as 1.43 for some of the superstructures, or as high as 2.48 for others in that district, as shown by the confidence interval. Similarly, the mean effect of salt on superstructures in KC is 1.78 or as before, it approximately doubles the hazard of transitioning to the lower CR. This effect is as low as 1.41 for some superstructures or as high as 2.24 for that district. As a last demonstration, the mean effect of increasing the application of salt on a roadway by one ton per mile in SW results in the hazard of a superstructure transitioning to a lower CR would increase by almost eight times (7.91). One point to remember is that the base hazard or no hazard is 1, as $e^0=1$. This effect is as low as 6.04 for some superstructures and as high as 10.36 for others in that district.

The effect of salt on superstructures in NW and SE is nondetrimental as the point estimate and the confidence interval are less than one, which correspond to the negative parameter estimate for these two districts. For example, the mean effect of salt on superstructures in NW reduces the hazard of transitioning to lower CR by 0.45 (1-0.55). This estimate is as low for some superstructures as 0.64 (1-0.36) and as high as 0.14 (1-0.86). Similarly, the mean effect of salt on superstructures located in SE reduces the hazard by 0.52 (1-0.48). This effect is as low as 0.77 (1-0.23) for some superstructures and as high as 0.02 (1-0.98). The reason for the effect of salt on superstructures in NW and SE is that superstructures have stayed longer

in a CR in these two districts, or have longer TICR even though the roadway is treated with more salts. This result is the opposite of what would be assumed since application of additional salt on the roadway would be assumed to result in increased rates of deterioration. As noted in the section titled "Location and Environmental Exposure," the salt data had some limitations and conservative assumptions were made when the salt data was reduced for use in the analysis. These assumptions may have resulted in some inaccuracies when examined on a district-by-district basis. Hence, the average effect of salt which is calculated as the average of the mean effect of salt for the seven districts to provide a general value that could be used instead to represent effect of salt on superstructure components.

The second covariate listed in Table 21 is the maximum span length. The effect of this covariate is listed for 10 ft. increase for the maximum span length and all other covariates being equal i.e., located in the same districts, being the same superstructure type, and having identical age in TICR. For example, for each 10 ft. increase in maximum span length for PSC continuous girders, the mean effect is increased by 1.06, or 6%, and this effect is as low as 3% for some of the PSC superstructures and as high as 9% for others. Similarly, the mean effect of maximum span length on steel continuous girders is 1.03, or the hazard is increased by 3%. The confidence interval for this point estimate is 3% - 4%. The effect of maximum span length on RCC beams is not statistically significant as the confidence interval of 0.95 – 1.01 contains the value of 1. In other words, based on the available data for RCC superstructures' TICR, the maximum span length is not a predictor of their performance.

The third covariate listed in Table 21 is age in TICR. That is the age of superstructure recorded when the superstructure first transitioned to a new CR. Similar to the effect of maximum span length, the effect of age in TICR is calculated for 10 years of increase in this covariate for all other covariates being equal. The effect of this covariate could be interpreted in a similar manner as that for the maximum span length provided above.

Table 22 shows the results of Cox regression analysis for superstructure types with the bridge age and maximum span length taken at mean values for the entire data set. These data can be used to compare the relative hazard of the different superstructure families without the influence of age or span length. As shown, if steel simple girders are compared to PSC continuous girders, the mean hazard for steel simple girders is 72% of the hazard for PSC continuous girders. The confidence interval for this estimate is as low as 64% for some superstructures and as high as 81% for others. These data can be used to rank the hazard for different types of superstructures relative to other types. From this analysis, ranking the different superstructure types from least hazard (best performing) to greatest hazard as follows: RCC beams, RCC slabs, steel continuous girders, steel simple girders, PSC continuous girders, and finally PSC box beams. These data could also be interpreted for making a design choice - for example, for a single-span bridge,

where a PSC box girder might be selected, and steel girder bridge would have significantly better performance with only 66% of the hazard as compared with a PSC box girder. If PSC continuous were selected, the hazard would be 94% as compared with the box beam solution. (Note: simple span PSC girders are included in the PSC continuous group, because the number of simple spans was too small to analyze separately). The PSC superstructure type has limited data available for CR 5, 4, and 3. Since the Cox regression is fitted across all possible CRs, the sparsity of data in the lower CR may influence these results.

Table 22. Comparison of superstructure type at mean age in TICR and mean maximum span length.

Superstructure types comparison		Point estimate	95% confidence interval	
RCC slabs	RCC beams	1.08	0.99	1.18
RCC slabs	Steel simple girders	0.82	0.75	0.91
RCC slabs	Steel cont. girders	0.87	0.80	0.95
RCC slabs	PSC cont. girders	0.59	0.52	0.67
RCC slabs	PSC box beams	0.54	0.46	0.65
RCC beams	Steel simple girders	0.76	0.70	0.83
RCC beams	Steel cont. girders	0.80	0.75	0.86
RCC beams	PSC cont. girders	0.55	0.48	0.62
RCC beams	PSC box beams	0.50	0.43	0.59
Steel simple girders	Steel cont. girders	1.05	0.98	1.12
Steel simple girders	PSC cont. girders	0.72	0.64	0.81
Steel simple girders	PSC box beams	0.66	0.56	0.78
Steel cont. girders	PSC cont. girders	0.68	0.61	0.76
Steel cont. girders	PSC box beams	0.63	0.53	0.73
PSC cont. girders	PSC box beams	0.94	0.78	1.14

The effect of span length on the deterioration of a structure is of interest for design engineers, so to illustrate how the increase in hazard manifests for actual span lengths, a model is provided looking at two different materials that are common for modern construction in Missouri and how the span length effect would impact deterioration. Figure 15 shows the deterioration pattern for PSC and steel continuous superstructures in CR 6. The horizontal axis is the TICR, and the vertical axis is the reliability, or the likelihood that the superstructure would not transition in the next time interval. The effect of different span length ranging from 80 to 120 ft. is shown. As illustrated in the figure, the increase in hazard results in a decrease in the time to transition from CR 6 to CR 5. For example, just looking at the median value, for a steel continuous girder with a span length of 80 ft., the median (50%) value is about 15 years, but if the span length was 120 ft., the median value would be about 13 years before transitioning.

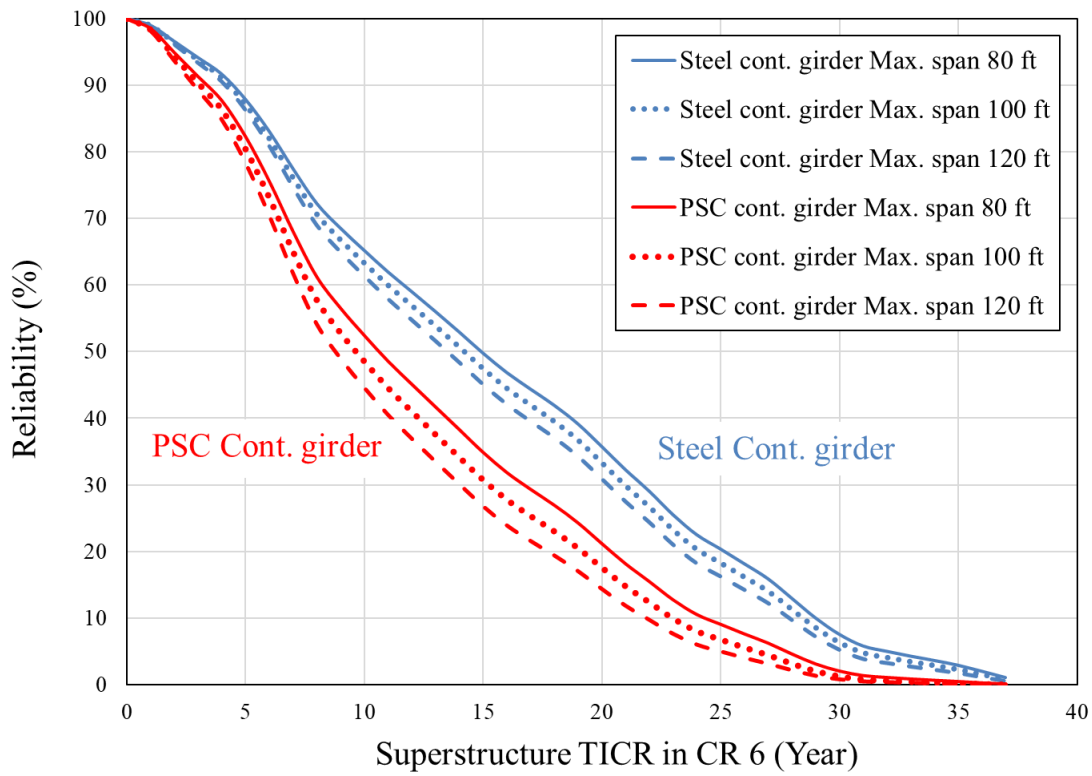

Figure 15. Effect of span length on deterioration of steel and PSC continuous superstructures.

Reliability Analysis for Substructures

This section contains the deterioration curves and the investigation of the covariates affecting the deterioration of substructures. The substructures data set encompasses substructures for all bridges with any type of superstructure. Table 23 shows the number of substructures in each CR and total number of substructures included in the analysis. For substructure components, the NBI data does not include the materials that the substructure is formed from, so the analysis of substructures includes all materials and designs in one population.

Table 23. Table showing counts of substructures for each CR and as a total.

Bridge component	Numbers of substructures in each CR					
	3	4	5	6	7	8
Substructures	238	955	2579	5217	5411	6125
Total number of substructures	8872					

Before investigating the effect of the covariates on the deterioration of the substructures, the data set is analyzed using the K-M method to determine the reliability and deterioration pattern for substructures using the NBI CR. The smoothed reliability graph based on the K-M method is shown in Figure 16. As shown, substructures in CR 6 and 7 have the highest reliability and therefore remain longer in these CRs and

substructures in CR 3 and 4 have the lowest reliability and hence remain in a given CR for a shorter amount of time.

The reliability graph could be used to understand the performance of the substructures based on the NBI CR data. For example, the probability for substructures to stay more than 12 years in CR 7 is 50%. Similarly, the probability for substructures in CR 3 to stay in CR 3 more than five years is only about 30%, or a 1 in 3 chance of staying in CR 3 more than five years. Similar readings could made for other CRs.

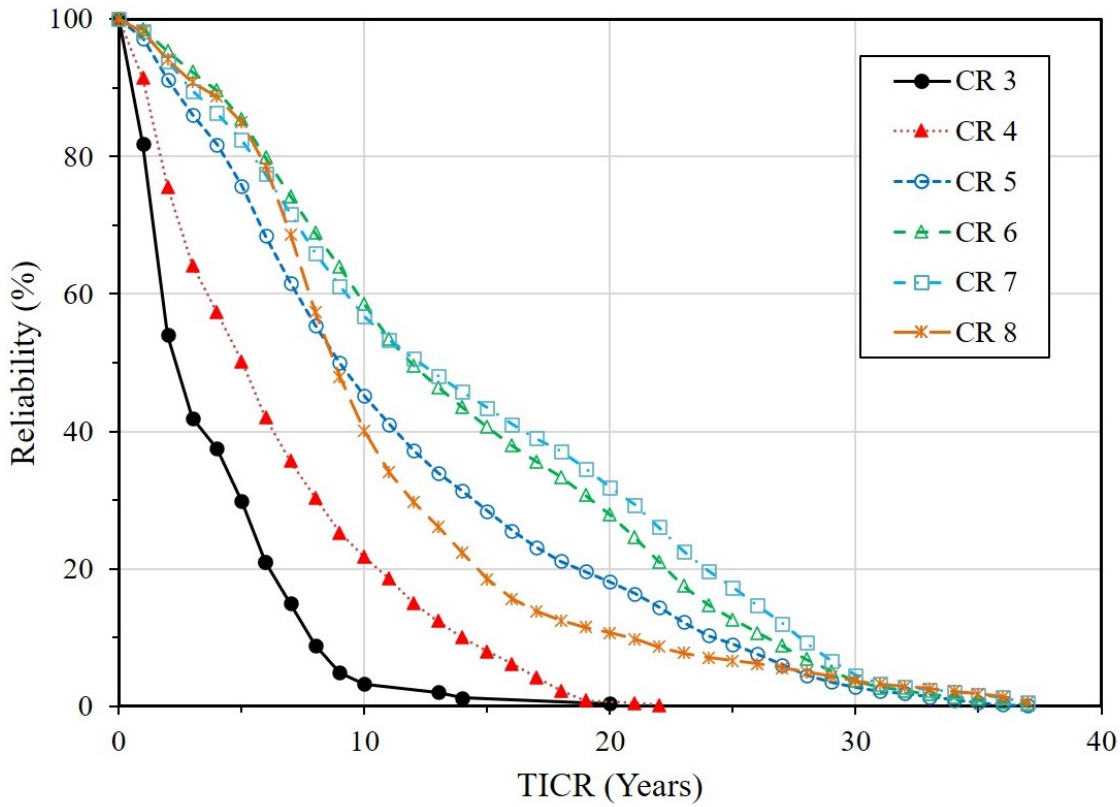

Figure 16. K-M graphs showing the reliability curves for substructures.

The reliability graph was used to construct the service life graph for substructures based on median TICR value, or the 50% reliability. Such a graph for substructures based on the median TICR is shown in Figure 17. As shown, the service life of substructures based on median reliability is 49 years. The service life graph is supplemented with the 25th and 75th percentile data to illustrate the range of results.

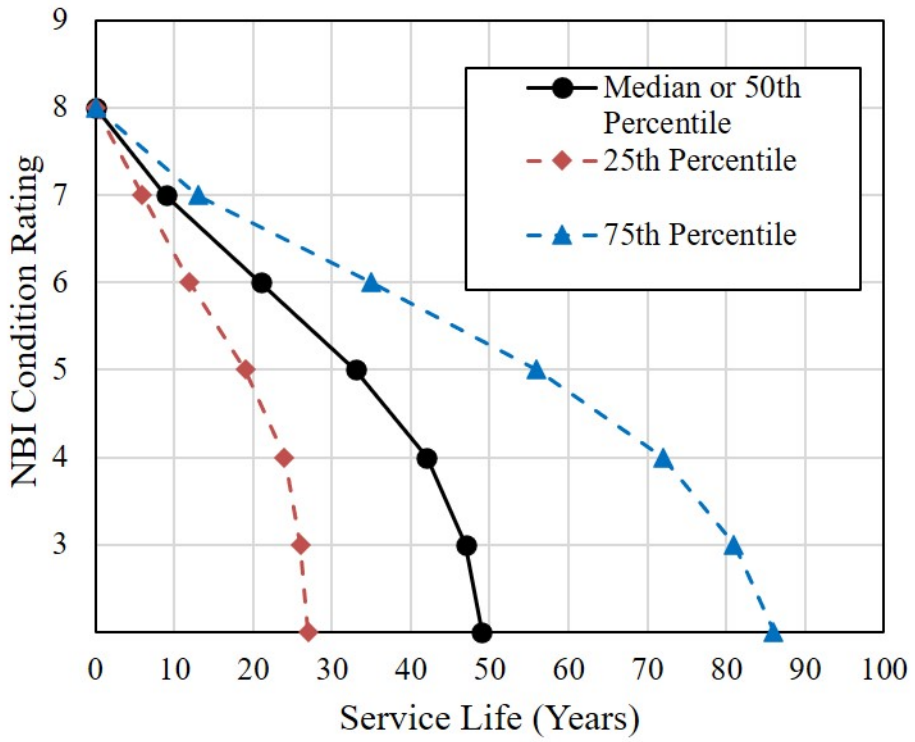

Figure 17. Graph showing the service life based on median reliability for substructures in CR 3 – 8.

The reliability graph could be used to construct the cumulative hazard as well. The cumulative hazard, the integral of the hazard substructures are exposed to from the TICR zero (putting the bridge into service) to any selected TICR is a "counting process" way of looking at hazard for substructures [12]. The cumulative hazard for substructures is shown in Figure 18. The graph for substructures in CR 3 has the steepest slope compared to all other CRs, and hence substructures in CR 3 experiences about five times the hazard in 15 years (TICR=15). Similarly, substructures in CR 6 and 7 have the shallowest slope, and for example, substructures in CR 7 accumulate hazard over four times during the whole-time span of data available for analysis (TICR =37). The cumulative hazard graphs provide another way of looking at the performance of the substructure in each CR.

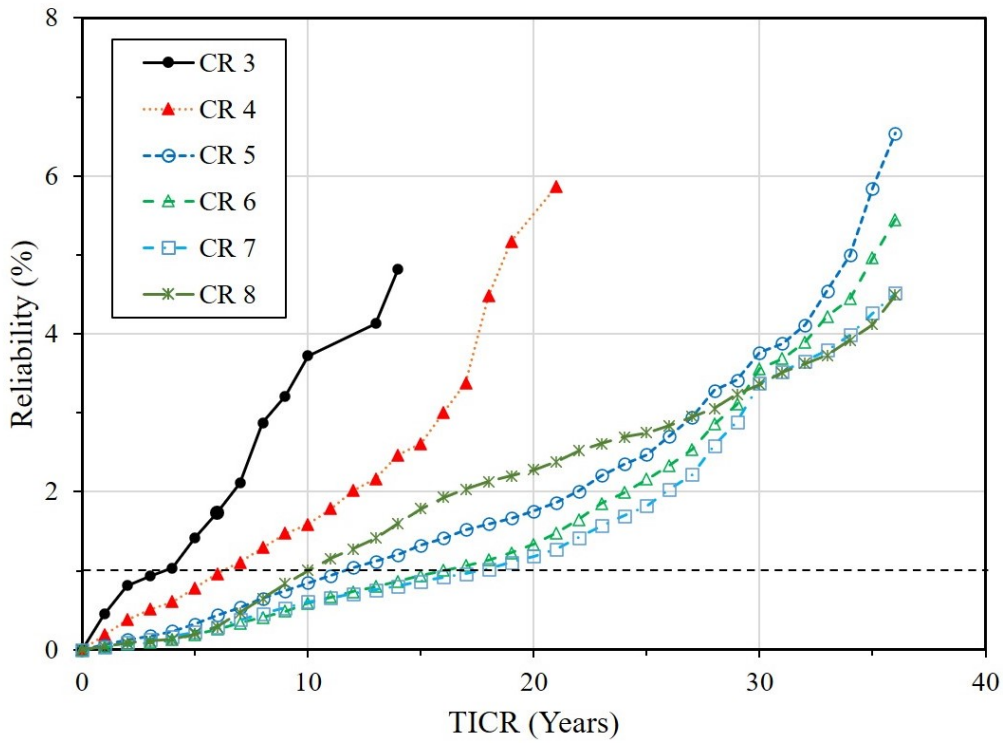

Figure 18. Graph showing the cumulative hazard for substructures.

Cox Regression Analysis for Substructures

The effect of covariates on the performance of substructures was investigated using the Cox regression and is presented in the following paragraphs. For building the Cox regression models the procedures described in the modeling section were followed.

The final Cox regression model for substructures after investigating the influential observations and outliers are shown in Appendix A. The statistically significant covariates are age in TICR, salt, district, structure length, whether a bridge is located on waterway or not, and interaction of district with salt.

The effect of salt on the deterioration of substructure components was very pronounced, as shown in Table 24. The average point estimate was 6.52, indicating a very significant effect of salt application. The effect of salt in each district is also listed in the table. As shown, the effect of salt in the Southwest District appeared to be an anomaly, calculated at a value of 22.5. Considering that this may be an anomaly, or there may be other factors not considered in the model, the average point estimate calculated without the Southwest data is also shown, only 3.85. This value is still relatively large as compared with hazard ratios for other covariates. Regardless, the trend of the data shows that substructures are significantly impacted by the salt applied to the roadway, and this effect appears to be more pronounced for the substructure (say ~3.85) as compared with the deck or superstructure (2.13 and 2.58, respectively).

It was found that the length of the superstructure on the given substructure has a statistically significant effect on the hazard for substructure, although the effect is small. The data indicated the increase in hazard was between 0.7% and 1.3% per 100 ft. of additional span length. The age of the substructure also had a statistically significant effect, about 6% increase in hazard for every 10 years of age.

It was also found that substructures for bridges over waterways had greater hazard than substructures for bridges not over waterways. In Table C-14 in the appendix, the covariate waterway is shown as a categorical covariate comparing the reliability of substructure for a bridge located on a waterway to those that are not located on a waterway. The reference level is substructures not located on a waterway and the parameter estimate for substructures located on a waterway is 0.105 relative to substructures not located on a waterway. The hazard ratio for these two categories of substructures is $e^{0.105}$=1.11, or substructures located on a waterway has 11% more hazard of deteriorating to lower CRs than those not located on a waterway. Inverting the hazard ratio shows that substructures not located on a waterway has 90% of the hazard of substructures located on a waterway.

Table 24. Table showing the effect of covariates on substructures.

Covariate name		Point estimate	95% confidence interval		Average point estimate
Salt (one tons/lane miles)	NE	2.48	2.06	3.00	6.52 / 3.85
	NW	7.40	5.31	10.32	
	KC	2.21	1.75	2.80	
	CD	6.68	5.14	8.68	
	SL	1.82	1.67	1.98	
	SE	2.48	1.27	4.85	
	SW	22.6	17.55	29.12	
Structure length (100 ft.)		1.01	1.007	1.013	1.01
Age in TICR (10 years)		1.06	1.05	1.07	1.06
Bridges not on a waterway vs. on a waterway		0.90	0.87	0.94	0.90

Table 25 shows the results of the Cox regression analysis comparing the performance of substructures in different districts assuming a salt distribution of 1 ton per lane mile. In some cases, the results from the Cox regression analysis show very significant differences, such as the ratio for the SE district as compared with the SW district, which show almost 25 times the hazard. Several of the comparisons resulted in hazard ratios that were not significant.

Table 25. Cox regression results showing hazard ratios for substructures in different districts.

Comparison of districts at salt = 1 tons/lane miles				
Comparison		**Point estimate**	**95% confidence interval**	
CD	KC	0.65	0.27	1.54
CD	NE	0.28	0.16	0.50
CD	NW	1.65	0.80	3.37
CD	SE	0.07	0.04	0.11
CD	SL	0.41	0.24	0.72
CD	SW	1.76	1.05	2.95
KC	NE	0.44	0.19	1.02
KC	NW	2.54	0.98	6.58
KC	SE	0.11	0.05	0.24
KC	SL	0.64	0.28	1.48
KC	SW	2.72	1.21	6.13
NE	NW	5.79	2.94	11.4
NE	SE	0.25	0.17	0.37
NE	SL	1.46	0.88	2.41
NE	SW	6.20	3.89	9.88
NW	SE	0.04	0.02	0.08
NW	SL	0.25	0.13	0.49
NW	SW	1.07	0.56	2.04
SE	SL	5.82	3.93	8.63
SE	SW	24.79	17.63	34.86
SL	SW	4.26	2.69	6.74

Reliability Analysis for Culverts

This section of the report describes the reliability analysis for reinforced concrete culverts. There are more than 3,300 culverts in the NBI inventory for Missouri, as shown in Table 26. The vast majority of these culverts (~98%) were constructed of reinforced concrete and fit the coding guide descriptions for concrete continues culverts. Other culvert types were too small in number to support a statistical analysis of their deterioration patterns. As a result, analysis was only completed for concrete continuous culverts.

Table 26. Table showing the number of different types of culverts in the inventory.

SI&A items		SI&A in words	Number of culverts
43A	**43B**		
2	19	Concrete continuous culvert	3,288
3	19	Steel culverts	33
4	19	Steel continuous culvert	4
8	19	Masonry culvert	9
0	19	Other culvert	1
Total number of culverts			3,335

Count of concrete continuous culverts after data preparation (trimming)						
	Count of culverts in each CR					
CR	**3**	**4**	**5**	**6**	**7**	**8**
Concrete continuous culvert	19	132	705	2,387	2,590	1,854
Total count of culverts after trimming	3,262					

The count of concrete continuous culverts for each CR, and as a whole, is provided in the bottom part of Table 26. Twenty-six concrete culverts were eliminated during the data trimming process because these culverts had inadequate data for analysis, either because the culvert was relatively new, there was a

numbering error that couldn't be resolved, or the trimming of the data resulted in the culvert not providing adequate historical data for analysis. From the total count of 3,262 culverts, 3,067 are filled culverts and 195 culverts do not have fill, meaning the top flange of the culvert is directly exposed to traffic loading and the application of deicing chemicals. These 195 culverts have a deck type indicated for the NBI database coding item for deck structure type (Item 107), whereas the vast majority of culverts are filled, and item 107 is entered as "N" or "not applicable." Due to a small number of culverts without fill, comparison between these two types of culverts was not possible and all reinforced concrete culverts were treated as one uniform group.

This section of the report provided the analysis for reinforced continuous concrete culverts. First, the reliability or survival is shown using the K-M analysis based on the NBI CR data, and then the effect of covariates is shown for the reliability of culverts.

The survival, or reliability curve, for concrete continuous culverts constructed using the K-M method is shown in Figure 19 for CR 3 - 8. As shown, culverts stay the longest in CR 6 and stay the shortest in CR 3. Also, it should be noted that the number of culverts in CR 3 is 19 as shown in Table 26 and the reliability curve may not be as accurate as those plotted for other CRs. The plot for CR 8 shows that initially culverts in CR 8 remain longer than all other CRs, but as the TICR is getting longer, culverts drop from CR 8 at a faster pace as demonstrated by the steep reliability curve for this CR. This graph could be used to assess the performance of the culverts in each CR. For example, the probability for culverts in CR 6 to stay in this CR more than 20 years is over 50%. Similarly, the probability for culverts in CR 3 to stay in this CR for more than 10 years is less than 10%. Similar reading could be made for other CRs.

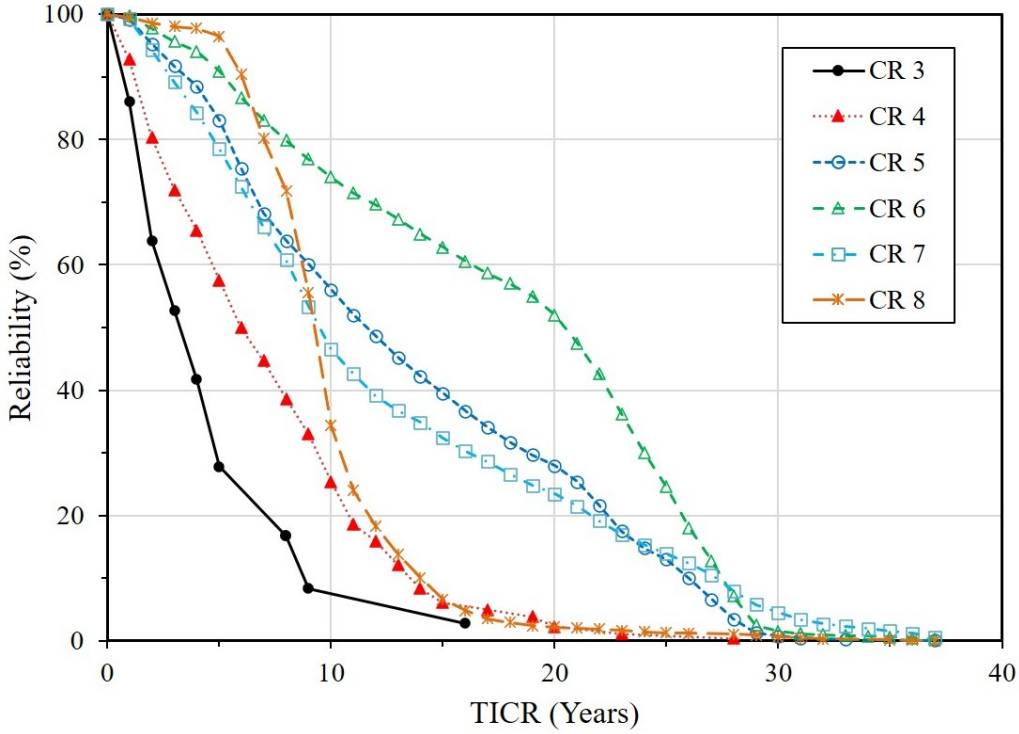

Figure 19. Graph showing the reliability curve for culverts using the K_M method.

The reliability curve in Figure 19 can be used to calculate the service life for culverts, the time frame it takes culverts to deteriorate from CR 8 to CR 3. For example, the service life for median or 50% of the culverts is shown in Figure 20. As shown, this graph indicates that the service life for culverts is 59 years, seven years longer than the service life of CIP decks. The service life graph is supplemented with the 25th and 75th percentile curves to illustrate the distribution of the results.

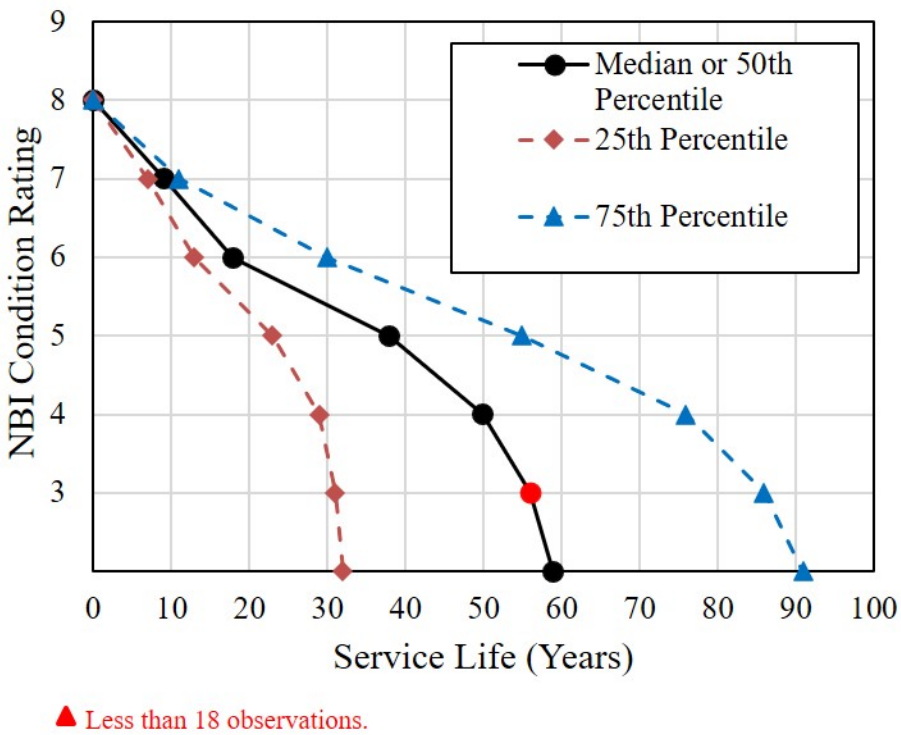

Figure 20. Graph showing the time span (service life) for culverts stay in CR 3 – 8 based on median reliability.

Cox Regression Analysis for Culverts

The effect of the covariates on the reliability or survival of the culverts are investigated using the Cox regression and presented in the following paragraphs. Before beginning the statistical analysis of the effect of covariates on deterioration of the culverts, general information about the covariates is provided in the upper part of Table C-17 of the appendix, and the distribution of the concrete continuous culverts within each district is shown in the lower part of Table C-17. The covariates considered for data analysis of concrete continuous culverts are structure length (ft.), maximum span length (ft.), amount of salt used for deicing purposes (tons/lane miles), freeze-thaw cycles (days/year), snow (days/year), ADT, ADTT, and district.

Table C-18 in the appendix shows the result of the Cox regression analysis for concrete continuous culverts for each of the covariates individually, and the result is compared with the null model, no covariates in the model. This initial analysis shows whether a covariate is statistically significant individually. A non-significant covariate may become significant in the presence of other covariates when all covariates are included in the model, and this was also assessed. The model building procedure described in the model development section is followed to build the Cox regression model for concrete continuous culverts.

The final output for Cox regression model for concrete continuous culverts is shown in Table 27. The parameter estimates were used to calculate the hazard ratios for all covariates listed in this table, as shown. Table 27 indicates the effect of the application of an additional 1 ton of salt per lane mile of roadway with results presented for each district and the average point estimate across all districts. These data indicate the significant effect of increasing the amount of salt applied to the roadway on the deterioration of culverts along that roadway. The increased hazard for culverts is somewhat surprising given that the vast majority of culverts are filled culverts and therefore separated from the roadway by some depth of soil. The increased hazard of 76% is smaller than other components such as the deck (2.13), superstructure (2.58), and substructure (3.85), but still larger than other covariates expected to affect the deterioration pattern.

Other covariate effects on the hazard ratios reported in Table 27 include increasing the structure length by 10 ft., the age of the structure, and the effect of 10 additional days of snow. Of these, the effect of 10 additional snow days had the largest effect of a 13% increase in the hazard.

The comparison of hazard ratios between different districts at a mean value of salt application of 2.54 tons per lane mile is also shown in the table. These data indicate the relative increase in hazard between different districts. For example, the hazard for transitioning to the next lower CR for a culvert in the NE District as compared to the Central District is about 2, or twice the hazard based on the Cox regression analysis. Many of the district comparisons were found to not be statistically significant, and these are shaded in the table. For these district comparisons, the 95% confidence interval include 1.0, indicating that statistically the hazard could be the same between the two districts.

Table 27. Table showing the hazard ratios for covariates investigated for culverts.

Covariate name		Point estimate	95% confidence interval		Average point estimate
Salt (one ton/lane miles)	NE	3.93	2.85	5.41	1.76
	NW	2.38	0.97	5.85	
	KC	1.91	0.92	3.97	
	CD	1.79	1.07	3.01	
	SL	1.55	1.19	2.04	
	SE	0.26	0.07	0.91	
	SW	0.51	0.32	0.80	
Structure length (10 ft.)		1.08	1.06	1.11	1.08
Age in TICR (10 years)		1.03	1.02	1.04	1.03
Snow (10 days) at mean salt		1.13	1.08	1.18	1.13

Table 28. Hazard ratios for culverts in different districts with 2.54 ton/lane mile of salt.

Comparison		Point estimate	95% confidence interval	
CD	KC	2.88	0.83	10.04
CD	NE	2.02	1.73	2.35
CD	NW	1.40	1.15	1.70
CD	SE	5.78	1.10	30.19
CD	SL	2.89	1.44	5.82
CD	SW	1.12	0.90	1.40
KC	NE	0.70	0.20	2.45
KC	NW	0.48	0.14	1.71
KC	SE	2.00	0.25	15.8
KC	SL	1.04	0.24	4.17
KC	SW	0.39	0.11	1.38
NE	NW	0.69	0.56	0.87
NE	SE	2.86	0.54	15.05
NE	SL	1.43	0.71	2.92
NE	SW	0.56	0.43	0.72
NW	SE	4.13	0.78	21.8
NW	SL	2.06	1.00	4.25
NW	SW	0.80	0.61	1.06
SE	SL	0.50	0.08	3.01
SE	SW	0.19	0.04	1.02
SL	SW	0.39	0.19	0.80

CONCLUSIONS

Summary/Review

Deterioration curves were developed based on K-M method of survival analysis. This methodology applies the NBI CR data collected over a time interval of 37 years to calculate the probability or likelihood of a bridge component or culvert to transition to the next lower CR. These data were then analyzed and median service life estimates were provided for the deck, superstructure, and substructure and the primary materials of steel, reinforced concrete, and prestressed concrete. Similar curves and service life estimates were produced for concrete culverts.

Cox regression analysis was used to identify and quantify trends in the deterioration of different types of bridges MoDOT has built over the years. These data were analyzed to determine the influence of covariates, generally parameters that are believed to affect the deterioration patterns for bridges. The methodology for Cox regression analysis involved first determining if a given covariate or parameter has a statistically significant influence on the model. Covariates that showed a statistically significant influence on the model individually were used for further analyses that include the interaction of the covariates. Covariates that were not statistically significant when considered individually or in combination with other covariates were not considered in further analysis. The report illustrated this procedure for CIP decks, and provided raw data on the beta factors for the different covariates. For other components and culverts, the raw data was provided in the appendix. Hazard ratios were used to explore the influence of the statistically significant covariates on the deterioration patterns for bridges.

The research illustrates trends and provides measures of the influence of different parameters for the deterioration of structures in Missouri. Based on the analysis, the following conclusion are made with respect to the initial objectives of the research.

The quantity of salt application had the greatest impact on the deterioration of structures of any parameter studied.

Working with MoDOT, the RT was able to assemble some quantitative data that described the rate of application of deicing chemical (salt) in different counties across the state. These data were limited such that assumptions based on the salt usage reported from individual sheds were made in the analysis. For example, these data were normalized to show the rate of salt application in tons/lane mile in each county, and subsequently in each MoDOT district. The assumption is that the normalized data provide a relative measure of the quantity of salt applied in a district. Although this is not a direct quantitative measure of the quantity of salt applied, it was still more information that has traditionally been available for this type of

deterioration modeling. It was found in the modeling that the rate of salt application affected all of the structures in the study, with increases in rate of salt application resulting in increased risk or likelihood of deterioration by a factor of 2 or more for bridge components. It would be expected that an increased rate in salt application would have a negative impact on the deterioration of bridge components, but quantifying the results in this way illuminated some interesting results. For example, the increase in hazard was slightly more for superstructures (2.58) than for decks (2.13), and largest among bridge components for substructures (3.85). Although an indirect measure, these results would suggest that the condition of bridge joints was critical since this is the primary source for water and deicing chemicals to come in contact with the superstructure and substructure of a bridge. Jointless bridges and deck drainage with scuppers that release drainage away from the superstructure, and the maintenance of drainage, would appear to be important factors for increasing the durability of bridges. Again, this is generally known, but quantitative analysis illustrating this effect based on the NBI data has not been previously available.

The effect was that salt application was pronounced and significantly larger than any other factor. To the knowledge of the RT, this is the first time the rate of salt application has been quantitatively tied to the deterioration models and patterns in bridges, although many current projects in other states are working toward this goal.

Effect of Structure Type

- *CIP decks formed on steel continuous superstructures had longer median service life estimate (54 years) as compared with steel simple girders (50 years) and PSC continuous superstructures (44 years). PSC box beams provided the shortest service life for CIP decks (38 years), while RCC slabs (59 years) provided the longest service life.*
- *The primary modern superstructure types, including steel simple, steel continuous, and PSC continuous bridge types, had very similar deterioration patterns between CR 8 and CR 4. PSC box beam bridges had the shortest median service life, while RCC slab bridges had the longest service life.*

The structure type was studied in two different contexts. First, the effect of the structure type on the deterioration patterns for CIP bridge decks was studied to determine if the type of superstructure affected the service life or deterioration pattern for the deck. Second, the differences in the performance of different structure types in terms of service life and deterioration patterns was studied in an effort to determine which superstructure types provided the best durability.

In terms of the interaction between the superstructure design and CIP deck deterioration, the analysis showed that RCC slabs showed the longest service life estimate, 59 years, and CIP decks on PSC box beams

had the shortest estimated service life at 38 years. It was also found that CIP decks on steel continuous superstructures had a longer service life (54 years) as compared with the average service life estimate of 52 years, and CIP decks on continuous PSC girders had a shorter than average service life estimate of only 44 years. As mentioned previously, the PSC continuous superstructure data is skewed toward bridges in good condition, with relatively few examples of CIP decks on PSC continuous superstructures in the fair to poor condition. Consequently, although these data are accurate according to the statistical modeling, these may not be fully representative of the performance of these decks looking toward the future.

In terms of superstructure type, it was found that the primary modern-day bridges being constructed, including steel simple girders, steel continuous girders, and PSC continuous girders, all had very similar median service life estimates between CR 8 and CR 4. It was notable that most superstructure types showed a noticeable change in slope at CR 5, indicating an increase in deterioration rate once a superstructure was rated CR 5. The exception was PSC box beam superstructures, which had a high and constant deterioration rate from CR 7 through CR 3. See Figure 14.

Age of the Structure and Era of Construction

- *The age of a component or culvert has a statistically significant effect on its reliability, resulting in increased likelihood of transition to the next lower CR of between 3 and 10% per 10 years of age.*

The age and era of construction for a given bridge component was studied through the use of Cox regression analysis. The age and the era of construction are actually correlated variables since a bridge from a given era of construction would also have age characteristics from that time interval. Therefore, it was beneficial to utilize the age in TICR values to assess the effects of age and through that there is some insight into the era of construction, even though the era itself was not identified.

It was found that the age at which a bridge component enters a given CR has a statistically significant effect on the deterioration pattern for that component as measured by the increase in the hazard or hazard ratio. Table 29 shows the average point estimate for the covariate of age in TICR analyzed using Cox regression analysis. The results show the relative increase in hazard, or likelihood of transitioning to next lower CR, taken as the average hazard ratio. For this analysis, other covariates such as span length, salt application, etc. are held constant and just the effect of the age of the component when it transitioned to a given CR is considered. These data indicate the trend of the age of a bridge component (or culvert) increase of 10 years results in about a 10% increase in relative hazard, as compared to the same component with 10 fewer years in service. In summary, the older the component is, the shorter the TICRs interval will be, i.e., the faster

the component will deteriorate. It was found that this effect was less but still statistically significant for substructures and culverts.

Table 29. Summary of hazard ratios for age in TICR for bridge components and culverts.

Component	Average hazard ratio (point estimate)
Age in TICR	
CIP decks on different types of superstructures	1.10
Superstructures	1.11
Substructures	1.06
Culverts	1.03

Span Length

- *Span length has a small but measurable (statistically significant) effect on the deterioration of structures.*

Two correlated covariates were considered to assess the effect of span length – the overall structure length and the span length. The span length was studied for CIP decks and superstructures of different materials, and the overall structure length was studied for substructures and culverts. It was shown that there is a small but statistically significant increase in the hazard ratio as span or structure length increased. This effect was most pronounced for the superstructure designs of different materials and design types. As shown in Table 30, there was approximately a 5% increase in hazard for each additional 10 ft. of maximum span length for superstructures.

Table 30. Summary of hazard ratios for different components and culverts for the covariate of span or structure length increase.

Component	Covariate (ft.)	Average hazard ratio (point estimate)
CIP decks on different types of superstructures	Span, 10 ft.	1.03
Superstructures	Span, 10 ft.	1.05
Substructures	Length, 100 ft.	1.01
Culverts	Length, 10 ft.	1.03

These data can be interpreted that the deterioration of a bridge or culvert increases as the length (either maximum span length for superstructures or deck, or overall structure length for substructures and culverts) increases.

Among superstructures of different design types, it was found that slab bridges and RCC superstructures were least affected by the span length covariate, although these types of bridges have other design limitations on maximum span length, and therefore are typically shorter bridges. For longer spans, it was found span length had a smaller influence on both steel continuous and simple bridges as compared with PSC bridges, and PSC box beams were found to be most affected by increasing span length.

Condition Assessment

- *In almost all cases, the deterioration rate of structures as measured by median service life graphs had an increase in slope at CR 5, meaning that once a bridge is rated in CR 5, the deterioration rate is increased.*

Most of the data and results described in this report are associated with the condition assessment of structures through the CRs that were analyzed. The CRs were analyzed to calculate the TICR values and overall median life estimates for different components of a bridge and for culverts. These data are summarized in Table 31, Table 32, and Table 33 that show the TICR and median service life for the different bridge components and culverts studied through the research. It was found that RCC slabs and RCC beam bridges showed longer median service life estimates as compared with other bridge types. This may be due in part to the applications for bridges of this design – the RCC components would generally be of shorter span and likely on relatively lower ADT and ADTT routes. Among the most common contemporary bridge types, it was found that steel simple superstructure bridges had slightly longer overall estimated service lives as compared with PSC superstructures. It was found that PSC box girder bridges had poor deterioration characteristics – not only shorter estimated service life for PSC box superstructures, but also poor performance of decks formed on PSC box beams. A caveat is that both PSC continuous superstructures and PSC box girder bridges are relatively modern bridges and the data on the deterioration in the poor condition (i.e., CR 4 and 3) is more limited as compared with more traditional bridge types. As a result, although these data and the analysis of the data showed a statistically significant difference in the age and TICR behavior, this result may be influenced by the lack of uniform data across all bridge types and CR values. Regardless, these data are accurate representations from the available data on the performance of bridges and culverts and passed statistical tests.

It should be noted that the values for TICR for CR 4 and CR 3 are generally smaller than for CR 5, 6, or 7. These data illustrate the increasing rate of deterioration once a structure has dropped to the CR 5 level. A caveat for this conclusion is that repairs may occur when bridges are in CR 4 and CR 3, and that may result in an apparently shorter TICR, but transitioning due to repair rather than further deterioration.

Table 31. Summary of TICRs, median estimated service life, and good repair life for CIP bridge decks.

Component	Median TICR (year) for CR 8-3						Service life	Good repair life[1]
	8	7	6	5	4	3		
All CIP decks regardless of the superstructure	7	11	14	8	5	7	**52**	*32*
CIP decks on different superstructure types								
RCC slabs	7	14	17	8	6	7	**59**	*38*
CIP decks on steel cont. girders	7	13	16	7	5	6	**54**	*36*
CIP decks on steel simple girders	7	9	14	8	5	7	**50**	*30*
CIP decks on RCC girders	2	9	14	10	6	8	**49**	*25*
CIP decks on PSC cont. girders	8	14	9	5	3[2]	5[2]	**44**	*31*
CIP decks on PSC box beams	5	9	7	8	7[2]	2[2]	**38**	*21*

[1] "Good repair life" shows time interval for CR 8, 7, and 6
[2] Data in this CR is very limited.

Table 32. Summary of TICRs, median estimated service life, and good repair life for different types of superstructures.

Superstructure type	Median TICR (year) for CR 8-3						Service life	Good repair life[1]
	8	7	6	5	4	3		
RCC slab	7	14	18	8	6	8	**61**	*39*
RCC beam	5	9	14	10	6	8	**52**	*28*
Steel simple	9	9	13	8	5	5	**49**	*31*
PSC continuous	7	15	13	5	3[2]	5[2]	**48**	*35*
Steel continuous girder	9	16	8	5	3	3	**44**	*33*
PSC box	4	8	7	9	10[2]	3[2]	**41**	*19*

[1] "Good repair life" shows time interval for CR 8, 7, and 6
[2] Data in this CR is very limited.

Table 33. Summary of TICRs, median estimated service life, and good repair life for different substructures and culverts.

Component	Median TICR (year) for CR 8-3						Service life	Good repair life[1]
	8	7	6	5	4	3		
Substructure	9	12	12	9	5	2	**49**	*33*
Culvert	9	9	20	12	6	3[2]	**59**	*38*

[1] "Good repair life" shows time interval for CR 8, 7, and 6
[2] Data in this CR is very limited.

Table 31, Table 32, and Table 33 also have a column labeled "good repair life." This column represents the sum of the median TICR values for CR 8, 7, and 6. In this range of CR, the components are in the satisfactory to good condition ranges, and it is in this time interval where maintenance and preservation would be most effective to delay the increase in deterioration commonly found for bridges once CR 5 is assigned. This effect can be observed in the various service life plots provided in the report (e.g., Figure 9), which shows a change in the slope of the service life graph once the components have been assigned the CR of 5. The rate of deterioration tends to increase as damage accumulates and the CR of 5 is assigned, with TICR values in CR 5, 4, and 3 generally being shorter than for CR 8, 7, and 6. Therefore, preserving a bridge in CR 8, 7, or 6 will have the benefit of extending TICR values and avoiding the accumulation of

damage that leads to CR 5, 4, or 3. In other words, "good repair life" can be used to target preservation and maintenance activities as part of an effective bridge management strategy.

Material Type

- *The research showed that structures formed from RCC, such as slab, RCC beam bridge, and culverts had the longest median service life estimates. PSC box girder bridges had the shortest estimated median service life.*

The type of materials from which the bridge component or culvert was formed was studied as part of the research. For culverts, the vast majority of culverts in Missouri are formed from reinforced concrete, and there was not sufficient data available to study other materials for culverts. For superstructure types, the materials and design types were grouped into six superstructure types with sufficient data for meaningful statistical analysis.

As mentioned previously, it was found that components formed from RCC generally had longer median service lives as compared with other superstructure types. For superstructure components, RCC slabs and RCC beam bridges had the longest median service lives. PSC box beam bridges had the shortest median service life. For CIP decks, RCC slab bridges had the longest median service life for their decks, and PSC box beam bridges had the shortest CIP service life among any of the different types.

Traffic Volume

- *The data showed that ADT and ADTT did not have a statistically significant effect on the reliability of structures.*

The study showed that the ADT and the ADTT were not statistically significant factors in the deterioration patterns for bridges. This result was unexpected, because experience would indicate that the volume of truck traffic (ADTT) would have a significant effect. It should be noted that not having a statistically significant effect is not the same as not having <u>any</u> effect, it only means that the data did not support a conclusive statistical measure of the effect. It may be that the effect is more pronounced as damage accumulates and CR is reduced to a 5 or a 4. The statistical measures that were used assess the influence or correlation with damage across all of the CRs, not just 5 and 4, and it may be that this results in the outcome that the effect is not statistically significant when considered across all CRs between 8 and 3. Additionally, bridges on higher volume routes may experience additional maintenance and preservation as compared with lower volume routes, mitigating the effect of the increased volume, or may have more durable design or higher quality of construction. These potential factors in the outcome of effect of ADT/ADTT are only conjecture. Additional analysis focused on this topic specifically may be needed to recognize the reason that the statistical modeling does not agree with common experience in this case.

Location and Environmental Exposure

- *The rate of application of deicing chemical had the largest influence on the deterioration patterns for structures as compared with other parameters studied, roughly twice the impact of any other factor.*
- *Bridge decks perform differently in different districts.*

The location and environmental exposure parameters were studied in the research in the form of the effect of the district where a structure was located, and the environmental factors that included the number of days of snow per year at the location of the structure, the number of freeze/thaw cycles, and an estimate of the amount of salt applied to the roadway in the district where the structure is located.

It was found that the quantity of salt applied to the roadway had the most significant effect on the deterioration of structures. This was true for any material and any structure type. The average hazard ratios considering the covariate of salt application (1 ton/lane mile) are summarized in Table 34. As shown in the table, it was found that salt application had the greatest effect of any covariate on the deterioration of structures.

Table 34. Summary of hazard ratios for the covariate of salt application for different structure types.

Component	Average hazard ratio (point estimate)
Salt application (1 ton/lane mile)	
CIP decks on different types of superstructures	2.13
Superstructures	2.58
Substructures	6.52/3.85
Culverts	1.76

It was also found the number of freeze/thaw cycles a structure experienced did not correlate with increased deterioration rates. In fact, the analysis indicated that as the number of freeze/thaw cycles increased, the hazard decreased. This is contrary to experience and expected behavior, and may indicate that there were other factors not considered in the analysis that affected the correlation of increased freeze/thaw cycles with increased deterioration rates.

Data was also analyzed to assess performance of bridge decks in different districts across the state. Data showed the correlation between increased salt application in different districts and a corresponding increase in bridge deterioration (see Table 18). In most cases, it was found that increased levels of salt application between districts correlated with decreased median service life estimates. It was also found that the deterioration of bridge decks was affected by the district where the deck is located, when the salt application level was normalized to 1 ton/lane mile.

It was also found that the deterioration patterns for CIP bridge decks differed by district across the state. Reliability curves based on the K-M methods have been provided for each district for future use in Appendix E. These curves can be used to estimate the likelihood of transition to the next lower CR based on the years a component has been in its current CR, as described below.

Methods for Implementing Research Results

This section of the report discusses how the results of the research can be used for bridge management and decision-making. The overall results from the research provide data on the deterioration of different structures including bridge components of superstructure, substructure and deck, and culverts. These results can be used for the development of asset management plans in terms of identifying future repair and replacement needs on the overall bridge population or for specific sectors of the bridge population. This section of the report describes three ways in which the K-M modeling results can be used. First, a method of using linear deterioration curves for simple calculations and predictions is discussed, followed by ways in which an engineer could use the reliability curves and service life curves for decision-making. Third, using the results of the research for prospective deterioration modeling with a Markov model is shown. Finally, use of the results from the Cox regression analysis is described.

The rate of deterioration can be expressed simply by examining the typical median service life graphs. These data were developed from the actual inspection records as the K-M methodology provides the likelihood of survival within a given CR on a per year basis based on those results. To characterize the deterioration of structures in a general sense, the K-M service life plots were used to calculate a single rate of deterioration between CR 7 to CR 5 and from CR 5 to CR 3. In this way, the general deterioration trend is expressed in a simple number. For this analysis, the service life plots based on median TICR were used to determine a single slope from CR 7 to CR 5 using linear regression, and a second slope was determined for CR 5 to CR 3, also using linear regression. The correlation coefficients for the regressed lines (R^2) were typically 0.98 or greater, with the exception being for RCC culverts at a little over 0.95. The results of this analysis are shown in Table 35, Table 36, and Table 37, which tabulate the slope values for the bifurcated line. This provides a simple "rule of thumb" value for the median rate of deterioration that can be used for decision-making and is simple to apply to large spreadsheets or other data analysis scenarios. Generally, the rule of thumb for structures in CR 7-5 is deterioration occurs at ~8% per year, except for PSC box beams, which deteriorate at ~13% per year. A deterioration rate of ~8% per year corresponds to a TICR value of ~12.5 years. Once CR 5 is reached, deterioration accelerates to ~15% per year, or a TICR of about 6.6 years.

Table 35. Deterioration rates for different superstructure types.

Structure type	Deterioration rate (%/year)	
	CR 7-5	CR 5-3
Steel cont. girder	8.0	24.5
Steel simple girder	9.0	15.1
PSC cont. girder	7.1	24.5
RCC slabs	6.2	14.2
RCC girders	8.6	12.2
PSC box beam	13.3	10.5

Table 36. Deterioration rates for CIP decks on different superstructure types.

Structure type	Deterioration rate (%/year)	
	CR 7-5	CR 5-3
CIP decks	8.0	15.1
CIP deck on steel cont. girders	6.9	16.5
CIP deck on steel simple girders	8.6	15.1
CIP deck on PSC cont. girders	8.6	24.5
RCC slabs	6.4	14.2
CIP decks on RCC girders	8.6	12.2
CIP decks on PSC box beams	12.4	13.3

Table 37. Deterioration rates for substructures and culverts.

Structure type	Deterioration rate (%/year)	
	CR 7-5	CR 5-3
Substructures	8.3	13.9
Culverts	6.6	10.7

These data can be visualized as shown in Figure 21, which shows the regressed slopes determined from the service life plots for typical superstructures (Figure 21A) and for CIP decks, substructures, and culverts (Figure 21B). These plots present a visualization of the values presented in the tables that make it easier to compare the results between different components. The linearized curves, each with one slope for CR 7 to CR 5 and a second slope for CR 5 to CR 3, can be used for generalized data analysis and planning for future funding needs.

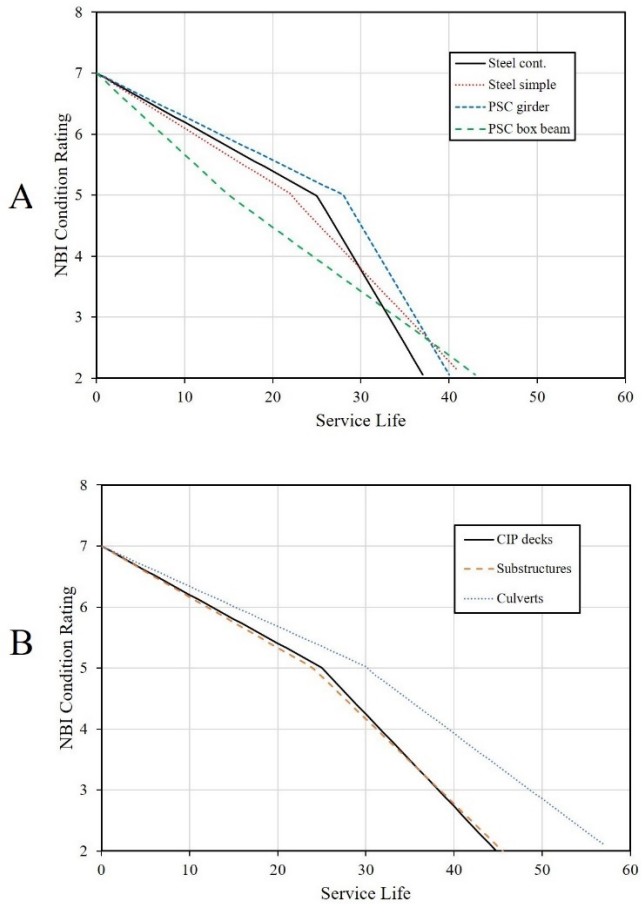

Figure 21. Linear deterioration curves for structures in Missouri showing A) typical superstructure types and B) CIP decks, substructures, and culverts.

The service life and reliability plots can also be used for predictions for specific bridges or families of bridges, based on the K-M analysis. For example, the following section illustrates how the reliability curves can be used to forecast future performance for a component. These could be used by district engineers to predict future funding and repair needs across the inventory of bridges in their districts.

Consider Figure 22A, which shows the reliability plot for CIP decks in the St. Louis District. The vertical axis is the reliability, or the likelihood that a component would NOT transition in a given year. For example, suppose an engineer had a CIP deck that had been in CR 7 for 10 years and wanted to know the likelihood of that deck transitioning to CR 6 in the next inspection cycle. On Figure 22A, extend a line from 10 years on the horizontal axis until it intersects with the reliability curve for CR 7. Then extend a line to the vertical axis – the data shows ~60% chance that the deck would not transition in the next year. In other words, there is approximately a 2/5 chance of the deck transitioning in the next year. Projecting for the next five years, extending a line from 15 years on the horizontal axis, shows that there is about a 40% chance that the deck

has not transitioned to the CR 6 based on the historic performance. In other words, there is a 3/5 chance that a deck in CR 7 will transition to CR 6 after 15 years.

For Figure 22 B, showing the median service life estimate, consider the following example. An engineer has a deck that has just transitioned to CR 6, and they want to know how long it will be before the deck transitions to CR 4, poor condition. Extending a line from the vertical axis at CR 6, and intersecting with the median service life plot, extend a vertical line to the horizontal axis, where the median life estimate in just less than 20 years. Extending a second horizontal line from the vertical axis but now at CR 4, the median life estimate is about 38 years. Therefore, the median life expectancy from the current CR of 6 to CR 4 would take about 18 years. That is a median value, meaning that 50% of the CIP decks would transition in a shorter time and 50% would transition in a longer period of time. These data are useful for estimating and planning future work.

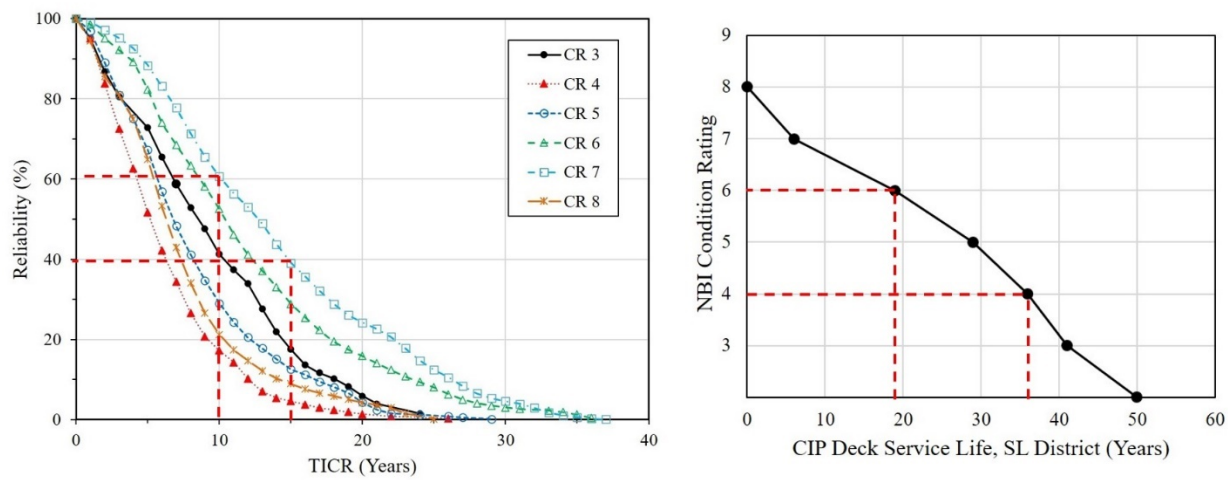

Figure 22. Plot showing CIP deck reliability (A) and estimated median service life (B).

The results of the research could also be used to build prospective deterioration models like those used in the AASHTO bridge management software. This software, and many other bridge management software packages, utilize Markov deterioration curves to predict future performance of bridge components. A significant difference between Markov deterioration curves and the K-M methodology used in this research is that Markov models are predictive (prospective), whereas the K-M survival analysis is retrospective. However, these two approaches can be used in a complimentary fashion. The Markov chain deterioration model is built using bridges' initial condition vector (CV) and the transition probability matrix (TPM) as shown below.

$$CV_{Future} = CV_{Initial} \cdot TPM^{n} \quad \textbf{(7)}$$

The $CV_{initial}$ is the current proportion of the bridge components in each CR as shown in equation 8:

$$CV_{Initial} = (\%_8 \quad \%_7 \quad \%_6 \quad \%_5 \quad \%_4 \quad \%_3) \tag{8}$$

And the TPM is an *n x n* (square) matrix in which each element is either the probability of staying in a CR or the probability of transitioning to other CRs as shown in the matrix shown below:

$$TPM = \begin{pmatrix} P_{8,8} & P_{8,7} & P_{8,6} & P_{8,5} & P_{8,4} & P_{8,3} \\ P_{7,8} & P_{7,7} & P_{7,6} & P_{7,5} & P_{7,4} & P_{7,3} \\ P_{6,8} & P_{6,7} & P_{6,6} & P_{6,5} & P_{6,4} & P_{6,3} \\ P_{5,8} & P_{5,7} & P_{5,6} & P_{5,5} & P_{5,4} & P_{5,3} \\ P_{4,8} & P_{4,7} & P_{4,6} & P_{4,5} & P_{4,4} & P_{4,3} \\ P_{3,8} & P_{3,7} & P_{3,6} & P_{3,5} & P_{3,4} & P_{3,3} \end{pmatrix} \tag{9}$$

The TPM elements along the diagonal are the probabilities of staying in that CR, and the elements with different subscripts (e.g., $P_{7,6}$) show the probability of transitioning from one CR to another. For example, $P_{8,4}$ is the probability of transitioning from CR 8 to CR 4.

The TPM power *n* is the number of inspection cycles desired to predict the future CRs of the bridge family. The TPM could be determined either by using the K-M reliability and deterioration graphs or plugging the median TICR from the K-M reliability graphs for each CR to the Pontis equation - $P_{Stay} = 0.5^{1/T}$, where T is the median TICR for each CR.

The median TICR for Missouri decks is provided in the matrix shown below and the probability of transitioning to the lower CR is $1 - P_{stay}$:

$$TPM_{Median\_TICR} = \begin{pmatrix} 0.906 & 0.094 & 0 & 0 & 0 & 0 \\ 0 & 0.939 & 0.061 & 0 & 0 & 0 \\ 0 & 0 & 0.952 & 0.048 & 0 & 0 \\ 0 & 0 & 0 & 0.917 & 0.083 & 0 \\ 0 & 0 & 0 & 0 & 0.871 & 0.129 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{pmatrix} \tag{10}$$

As an illustration, data for the current distribution of CIP decks in Missouri is shown as the initial distribution in Table 38. As shown in the table, the current distribution of CIP deck condition in Missouri shows there are 11.3% in CR 8, 39.3% in CR 7, and so on. The TPM matrix (8) was used in equation (5) to calculate the distribution in 10 years (*n* = 5 inspection cycles) based on the initial distribution of CIP bridge deck conditions. These data show that initially there was 4.1% of CIP decks in CR 3, and in 10 years that number would be expected to increase to 8.1% (without repair). Decks in CR 4 would increase from 5.4% to 7.1%, again assuming no repair during the 10-year interval. The anticipated rate of repair could also be

integrated into the model, although this was not shown here for simplicity. In this way, future needs for repair and rehabilitation can be forecast with a relatively simple model that can be implemented with commonly available software.

Table 38. Example data for using a Markov model to predict future bridge deck conditions.

Case	CR 8 (%)	CR 7 (%)	CR 6 (%)	CR 5 (%)	CR 4 (%)	CR 3 (%)
Initial distribution	11.3	39.3	26.9	13.2	5.4	4.1
Distribution in 10 years	6.9	32.5	31.1	14.5	7.1	8.1

The Markov model has a number of limitations. It is based on a power law that results in a deterioration forecast that assumes more rapid deterioration initially with a decreasing rate, which, as shown in this research, is actually the opposite of the observed behavior of structures historically. Also, the Markov approach does not consider the age of a structure or the number of years a structure may have already been in a given CR. For example, a component that just transitioned to CR 6 is considered to have the same probability of transitioning to a CR of 5 in a given inspection cycle as a component that has been in CR 6 for 10 years. Regardless, this is a common method of forecasting future deterioration trends and could be used to implement the results of the research. The quality of the models would be improved through the use of the results of the research in terms of calculating transition probabilities directly from the K-M reliability curves, either by using the median TICR values or using the transition probabilities directly. If using the transition probabilities directly, the user would have to select a value to use.

The results from the Cox regression analysis are more complicated to implement for practicing engineers. Curves like those shown in Figure 11 and Figure 15 show the hazard ratios developed through Cox regression applied to the K-M modeling results. These data show the deterioration over time for one covariate value as compared to another, based on the hazard calculated through Cox regression. The development of these types of curves could be used to quantify the anticipated deterioration patterns for one value of covariates as compared to another, such as shown in Figure 15 that illustrates the effect of different span lengths. These data could also be used to illustrate the effect of changing policies such as the rate of salt application, as shown in Figure 11. However, these curves are not simple to form and generally require the use of specialized software, and several steps are needed to develop the curve.

The Cox regression data could also be used more qualitatively to improve the quality of future predictions by modifying the deterioration rates such as those shown in Figure 21, modifying the K-M reliability curves, or modifying the transition probabilities used for a Markov model. For example, the Cox regression showed that the effect of salt had an average hazard ratio of 2.13. This means that at any point in time, the likelihood of transitioning to the next lower CR is twice as large for a structure with one ton of salt per mile more than another structure. Given that the fundamental data from which the salt application rates were found have some limitations, this result could be used qualitatively to simply increase the deterioration rate for

structures where salt use is high as compared to other areas. For example, those districts in the northern part of the state should use an increased deterioration rate as compared with those in lower salt-use areas. Other covariates had smaller effects but could be used in a similar manner, where the Cox regression results are used to provide a relative weight or importance to a certain covariate and used to modify the existing deterioration curves qualitatively. Attributes like those used for risk models such as ADT, materials, superstructure type, span length, etc. can be characterized qualitatively using the Cox regression results to guide the weight given to each attribute. In this way, the estimate could be improved in a rational way using the risk model developed for Risk-Based Inspection (RBI) and to estimate the appropriate weights to give different attributes (i.e., covariates)[16].

Results from the current study reported herein could also be used to determine if a specific bridge or family of similar bridges is likely to have a service life greater than or less than the median value. The relative influence of covariates such as the effect of span length, age in TICR, or number of snow days are reported and can be used to estimate future deterioration patterns. The most significant covariate found in the study was salt application; components exposed to relatively high rates of salt application can be expected to have a shorter service life and therefore would transition sooner than the median value. In this way, the Cox regression results can be used more practically for future predictions.

Recommendations

One of the objectives of the research was to provide recommendations for cost-effective bridge types identified through the research. The results of the research provided some insight into the past performance of different bridge types, but did not provide a clear preference for any one bridge type. For the primary bridge materials and types, including steel girders (simple and continuous spans), RCC beam bridges, and PSC continuous structures, the median service life between CR 8 and 4 were essentially the same (see Figure 14). PSC box beams had significantly shorter estimated median service life, and RCC slab had significantly longer estimated median service life. These data indicate that the primary bridge types currently being constructed in Missouri have had very similar past performance and deterioration patterns. However, the research did illustrate some tendencies for cost effective bridge types. The following recommendations are made based on the results of the research.

Recommendation 1: Implement preservation strategies to maintain bridges in good condition.

Deterioration rates increase for CR 5 and lower.

Rate of salt application has the most significant impact on deterioration.

The results of the K-M analysis to determine the TICR data and median service life estimates illustrated a change in the deterioration rate once a bridge reaches CR 5. This can be observed in the median service life

estimates for each bridge component and for culverts. Therefore, maintaining structures in CR 6, 7 or 8 would presumably result in decreased deterioration rates and longer service lives.

Although not specifically studied within this research project, other research conducted with MoDOT and other states, combined with practical experience, indicates that the primary damage mode affecting steel bridges is corrosion damage[16, 17]. The corrosion damage most commonly occurs in the area below joints that are leaking, causing coatings to fail and initiating corrosion damage. As a result, the CR drops over time as corrosion damage becomes more advanced.

It was also shown in the research that the application of deicing chemical (salt) increases the deterioration of structures significantly. Consequently, one of the most impactful actions that could be taken would be to reduce the amount of salt used OR reduce exposure of structural components to salt. Preservation strategies such as maintaining leak-free joints and spot or zone painting to repair deteriorating coatings would help maintain structures in the fair to good condition and avoid the rapid deterioration. Previous research also illustrated that zone maintenance painting with Calcium Sulphonate, a coating that can be easily applied in the field, was effective in preventing corrosion damage if the joint was also repaired to prevent water and deicing chemicals from coming in repeated contact with the superstructure [17].

Preservation strategies that would be beneficial include many that MoDOT is already performing on at least a portion of the inventory. Application of penetrating sealers for bridge decks, sealers or protective coating for concrete components as shown in Figure 23, and protective overlays on bridge decks are suitable preservation strategies. Regular bridge washing on an annual basis in the spring to clean away residual salts, and repair and sealing of all joints would also be suitable preservation strategies. The timely repair of bridge joints would likely be the among the most beneficial actions to prevent deterioration of the superstructure and substructure of a bridge. It is notable that the effect of salt application was most pronounced for the deterioration of substructure components. Substructure components are directly exposed to salt as a result of deck drainage, either through leaking joints or inadequate deck drainage systems. The results of the study suggest that the concentration of deck drainage onto substructures has a measurable deleterious effect. Superstructure components were significantly affected by salt application, which may also be the result of exposure to deicing chemicals through poor drainage or leaking joints. Zone and spot painting of steel to prevent corrosion damage would allow for preservation treatments in the area leading joints or other drainage issues exposing the superstructure components to deicing chemical. This is likely to provide measurable near-term benefits by slowing the deterioration of superstructure components.

Figure 23. Example of a concrete coating applied to beam shelf under expansion joint to protect concrete substructure, Fulton, MO.

In addition, improved data collection regarding preservation treatments or surface protecting coating systems would be beneficial for quantifying the effectiveness of preservation strategies. The research provided good rationale for preservation actions to prevent the CR decline into the 5 – 3 range. An improved tracking system for various treatments and exactly what is done when, and considering the district weather conditions and salt applications in combination with the treatment, would allow for optimization of preservation strategies looking forward. The impact of the new data collection would be to demonstrate the effectiveness of the policy or practice, or the ineffectiveness, and the impact on the CR and subsequent decision making could be quantified.

Recommendation 2: Perform a best-practices survey for PSC box beam bridges.

PSC box beams and CIP decks on box beams have the most rapid deterioration characteristics of any structure studied.

PSC box beam bridges had poor performance characteristics, both in terms of superstructure deterioration and deterioration of decks constructed on PSC box girders. The research showed that PSC box beam bridges and CIP decks on PSC box beam bridges deteriorate more rapidly than any other components or culverts. To improve the performance, MoDOT may want to conduct a survey of other states to determine the best practices for the construction of these bridge types. It may be that specific details or technologies are available to improve the performance of these types of bridges and a best-practices study could reveal methods or specifications to improve the performance of these structures. The RT notes that problems with

PSC box beam bridges are neither new nor unique to Missouri, and such a study may not provide effective solutions.

Recommendation 3: Consider impact of parameters studied for bridge type and geometry selection during preliminary design.

It was found that span length has a negative impact on reliability.

Substructures over water deteriorate more rapidly than substructures not on waterways.

Exposure to deicing chemical presents the greatest hazard.

Selection of bridge type and geometry at the design level is a complex interaction of many different needs and options to design an economical and efficient combination of materials and geometry. . Although the results of this research did not provide clear guidance on one bridge type over another, the results should be included as a consideration at the early design phases when selecting materials and geometry. Specifically, increasing the span length results in an increased rate of deterioration, and this should be considered as a factor in the life-cycle cost estimation. Substructures over waterways deteriorated more rapidly than substructures not on waterways, so avoiding placing abutments and piers in the water rather than adjacent to the water, where practical, should be a consideration. Finally, exposure to deicing chemical (salt) is the greatest driver for deterioration. Consequently, jointless bridges would be preferred to reduce exposure. Efficient and maintainable drainage systems for decks are also an important factor for the design of durable structures, as well as reliable bridge joints that prevent leakage.

It should be noted that this recommendation is consistent with some current MoDOT practices and not completely new information. The quantitative analysis included in this research verifies engineering experience and judgement. Increasing use of jointless bridges, extending scuppers below the bottom flange, and coating the bearing areas of weathering steel bridges would be examples of current practices that are supported by the data from this study.

Recommendation 4: Improve monitoring of salt application.

Application of deicing chemical (salt) is the most significant driver for deterioration of all structures studied.

As detailed in this report, the application of salt to components such as the bridge deck was a key player in long-term performance and the life of the deck before maintenance or replacement was required. In this study several assumptions were taken into account as previously detailed regarding the use and application of salt equally over respective lane miles in each county and district based on salt storage data provided by MoDOT. The RT encourages MoDOT to consider the use of technology to more precisely monitor when highway salts and other treatments used to prevent or limit ice buildup are applied to both bridge decks and

highway pavements. The use of a mobile app that tracks the date, time, and route that the driver is applying salt or other treatment to the deck/highway surface will allow future NBI-related deterioration work to further refine deterioration modeling. More sophisticated techniques that also monitor the application rate and surface temperature may allow future research studies and researchers to further understand the most effective use of salt application in terms of timing, and cost optimization, while minimizing long-term deterioration to bridge decks, components, and highway pavement. This proposed work is a recommended follow up study that also examines improvements in the NBI deterioration study undertaken in this study.

Some existing applications that can track driving routes and time frames work with GPS-enabled phones that MoDOT salt application crews likely carry are shown below:

- Protrack GPS
- Route4Me Route Planner
- In Route Planner & GPS Navigator
- Waze GPS Navigation, Maps and Social Traffic
- Footpath Route Planner
- Map My Customers – Pin Mapping and Route Planning

Many of these existing applications that can track routes in real time have route-saving features where MoDOT could save and download the routes that drivers have taken. This could improve the understanding of where and when salt applications have occurred, and result in the total usage being more precisely known. Such data could improve the quality and accuracy of bridge deterioration models.

An in-house developed app in combination with a monitoring process could also be developed by MoDOT to more precisely monitor drop rates (i.e., salt concentration levels), surface temperatures, and more. Certainly, a pilot study using a commercially available app could be step one. In the RT's literature review, the team found no readily available information on monitoring salt application to bridge decks or highway pavement at any significant level. While the data provided by MoDOT to the RT was very valuable and the team found that salt is a major player in bridge deterioration, particularly the bridge deck, extrapolating the storage tonnage usage of salt and assuming even distribution over lane miles certainly lacks precision and improved monitoring methods of salt usage is warranted. These data could provide insight into where preservation actions would yield that highest cost/benefit ratio and be most effective for extending the life of structures.

It should also be noted that other states have begun to collect more specific information on the rates of salt application across their inventory. A study of best practices in other states may provide some practical solutions for tracking salt application more closely.

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