Project 0-6979

Developing Deterioration Rates of Texas Bridges Using NBI Data

Research Report 0-6979-1

Bridge and Culvert Deterioration Models Using National Bridge Inventory Data

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August 2020

1. Report No.
FHWA/TX-20/0-6979-2

2. Government Accession No.

3. Recipient's Catalog No.

4. Title and Subtitle
BRIDGE AND CULVERT DETERIORATION MODELS USING NATIONAL BRIDGE INVENTORY DATA

5. Report Date
August 2020

6. Performing Organization Code

7. Author(s)
Jose Weissmann, Angela J. Weissmann, Arturo H. Montoya

8. Performing Organization Report No.
Report 0-6979-1

9. Performing Organization Name and Address
UNIVERSITY OF TEXAS AT SAN ANTONIO
Department of Civil and Environmental Engineering
One UTSA Circle
San Antonio, Texas 78249

10. Work Unit No. (TRAIS)

11. Contract or Grant No.
Project 0-6979

12. Sponsoring Agency Name and Address
Texas Department of Transportation
Research and Technology Implementation Division
125 E. 11th Street
Austin, Texas 78701

13. Type of Report and Period Covered
Technical Report:
September 2018 – August 2020

14. Sponsoring Agency Code

15. Supplementary Notes
Project performed in cooperation with the Texas Department of Transportation and the Federal Highway Administration.
Project Title: Developing Deterioration Rates of Texas Bridges Using NBI Data

This project developed and tested 44 bridge and 12 culvert deterioration models. Out of these, 38 bridge and 8 culvert models were validated and implemented into 9 Excel workbooks, where forecasts can be updated with new inspections. The 3 NBI/PonTex bridge ratings: deck, superstructure and substructure (respectively Items 58, 59 and 60), and the culvert rating (Item 62) were modeled. The models were developed by age groups and by families such as span type, rainfall, or factors such as bridges over water or dry land. Each model is a 2-year Markov transition probability matrix for each age group or family. Matrices contain probabilities that each rating will transition to equal or all possible lesser ratings. The transition probabilities were calculated by counting all actual transitions in a million-record database containing 19 years of NBI/PonTex data. Models were validated and standard errors were calculated. The Markov process extends the 2-year inspection cycle to any desired forecast horizon. Updatable results implemented in Product 2 Excel Workbooks include: 18-year rating and network deterioration tables and curves, and comparisons between the current network condition and the 10-year forecasts. The workbooks with culvert models also include updatable cost forecasts to maintain the culvert network above the rating of 4. Bridge costs are documented in this report. An important finding of this project: contrary to available literature on Markov bridge models, the probabilities of bridge and culvert ratings decreasing by more than 1 in a 2-year inspection cycle were considerably greater than zero in all models.

17. Key Words
Bridge deterioration models, Culvert deterioration models, Bridge and culvert network condition forecasts, Budget forecasts, Markov deterioration models.

18. Distribution Statement
No restrictions. This document is available to the public through NTIS:
National Technical Information Service
Alexandria, Virginia
http://www.ntis.gov

19. Security Classif. (of this report)
Unclassified

20. Security Classif. (of this page)
Unclassified

21. No. of Pages
143

22. Price

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This report is not intended for construction, bidding, or permit purposes.

ACKNOWLEDGMENTS

The research team is grateful to all the Texas Department of Transportation Bridge Division and RTI involved in this project, especially: Chad Dabbs; Drake Builta; Mark Wallace; Tom Yarbrough (retired); Tom Schwerdt.

This project could not have been performed without their prompt assistance with bridge and culvert inspection data, as well as their invaluable insights and advice during project meetings.

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Chapter 1
Introduction

Project Motivation and Objective

Recently, the federal government has initiated several transportation initiatives with the aim of preserving the nation's deteriorating infrastructure. In 2012, the Moving Ahead for Progress in the 21st Century Act (MAP-21) established the National Highway Performance Program (NHPP) to support the condition and performance of the National Highway System (NHS) and ensure that federal funds are used to achieve performance targets established in a State's asset management plan for the NHS (Ref. 41).

In 2015, the Fixing America's Surface Transportation (FAST) Act was passed to guarantee long-term funding for surface transportation infrastructure and planning (Ref. 14, 38). Most recently, in 2017, the Federal Highway Administration (FHWA) established a final rule for State departments of Transportations (State DOTs) and Metropolitan Planning Organizations (MPOs) to carry out the NHPP and assess the condition of pavements and bridges on the National Highway System (NHS) (Ref. 56). Hence, Texas Department of Transportation (TxDOT) is required to make strategic decisions for ensuring the integrity of over 35,300 bridges and over 20,000 culverts, thus achieving the condition targets for their infrastructure assets.

This two-year research project developed, validated and implemented into Excel workbooks, the deterioration models summarized in Table 1. 1 for the 4 major condition ratings in Ref. 13.

Table 1. 1 Summary of Models Developed and Implemented

PonTex/NBI Condition Rating	Data	Number of Models	
		Developed and Tested	*Implemented*
Item 58 Deck	On-System	4	4
	Off-System	9	5
	All Data	4	2
Item 59 Superstructure	On-System	7	7
	Off-System	7	7
	All Data	3	3
Item 60 Substructure	On-System	4	4
	Off-System	6	6
Item 62 Culvert	On-System	6	4
	Off-System	6	4
	Total	**56**	**46**

Models were developed by age groups and, when applicable, by families such as material type or environmental factors such as bridges over water versus bridges over dry land or rainfall regions. Models predict the probabilities that each family will transition from one condition rating to lesser conditions, within any desired time frame, spaced every two years. Results implemented in Product 2 Workbooks include:

- Deterioration curves,
- The following forecasts every 2 years, for 18 years into the future:
    - Deterioration tables,
    - Deterioration curves,
    - Network condition forecasts by number of bridges or culverts,
    - Network condition forecasts by bridge area,
    - Cost estimates to maintain bridges and culverts above ratings of 4.

The Implementation Products automatically update the network condition and the cost forecasts every time the current condition is updated. Network condition forecasts consist of number and percent of bridges (or culverts) at each rating, as well as amount and percent of bridge area at each rating.

Project Summary

This project started by aggregating 19 years of BRINSAP/NBI/PonTex files, provided by TxDOT, into historical bridge and culvert research databases. Climatic variables for rainfall and freezing intensities were mined from other sources and merged into the inspection history databases.

Based on literature review and engineering judgement, extensive statistical analyses of NBI/PonTex variables that may affect bridge and culvert deterioration were prepared and modeling families of culverts and bridges were developed. A Markov-based modeling framework was developed, tested, validated, and applied to model all 3 bridge ratings and the culvert rating by age groups and by families. Project results assist in identifying short-term and long-term budget needs. In addition, future condition forecasts are an indispensable step to meet the remaining requirements of this FHWA Rule dealing with asset life-cycles. According to the methodology developed to calculate the value of this research (VOR), the annualized VOR at 3% discount rate over 10 years, is valued at $106.4 million per year.

Report Organization

This report is organized into 9 chapters, where Chapter 1 is this introduction. Chapter 2 presents the results of a critical literature review of 56 recent references on the subject of bridge and culvert deterioration forecasts.

Chapter 3 discusses the research data preparation. Chapter 4 explains the modeling framework and the exploratory data analysis of all variables that had potential to be used as modeling families. Chapters 5, 6, 7, and 8 respectively discuss the culvert, substructure, superstructure and deck rating models. Chapter 9 presents the methodology used to develop cost forecasts, the value of research, implementation recommendations, and the recommendations for future model updates.

Chapter 2
Literature Review

Background and Objective

Bridge deterioration models predict the future conditions of bridge components over time. Thus, accurate bridge deterioration models will help TxDOT to comply with the federal regulations and develop effective asset management plans. The deterioration models are developed based on historical condition ratings of bridge inventory components. The guidelines for assigning the condition ratings are stipulated by the National Bridge Inspection Standards (NBIS) and require bridge inspectors to assign integer numerical condition ratings based primarily on a visual comparison of the as-is structure to a hypothetical new structure. These condition ratings are scaled from 0 to 9, with 9 representing excellent and 0 representing failed condition (Ref. 13). The ratings reflect the global, rather than local, conditions of the following bridge components: a) decks b) superstructures, c) substructures, and d) culvert (inventory items 58-60, and 62, respectively). In order to maintain compliance with NBIS, all states are required to perform biennial inspection and update the condition rating of core components that are maintained in the National Bridge Inventory (NBI) database.

The output of bridge deterioration models is the prediction of the condition rating of a bridge component over time. However, this is not a trivial statistical task as the deterioration of bridge components is associated with many factors including age, climate, construction material, design characteristics, and average daily traffic (ADT) (Refs. 15; 21; 24; 29). Hence, deterioration models must establish an approach for linking the conditions of the bridge components to a set of explanatory variables (Ref. 5). A conventional approach to include these factors in the deterioration models has been to classify the bridge inventory according to the variable that mostly influences the deterioration rate. For example, if material type is identified as the factor to have the greatest impact on depreciating the condition of bridge superstructures; then, the bridge superstructures will be grouped by materials, i.e. wood, steel, and reinforced concrete. Then, these groups may be subdivided by another explanatory variable, e.g. highway functional classification. Finally, deterioration models will be independently created for each classification group. Nevertheless, certain caution should be taken when increasing the number of bridge categories, as the reliability and applicability of the deterioration models is compromised by reducing the number of bridges in each category.

There are different approaches for developing bridge deterioration models, which can be divided into two main groups: a) deterministic and b) probabilistic. Deterministic models provide a mathematical expression for condition ratings (CR) over time by using simple statistical measures, i.e. mean and standard deviations, and regression analysis. These equations can be formulated for specific classifiers, such as bridge components and material types, and be a function of multiple parameters (Ref. 6). On the other hand, probabilistic models aim to capture the inherent uncertainty in the deterioration process by incorporating random variables to the analysis. Deterministic methods were more privileged in the beginning of the development of Bridge Management Systems (BMS), which are systematic approaches taken by transportation agencies to make optimum decisions in the management of a bridge network. However, it was soon recognized that while these models often provide reasonable estimates within the bounds of available data, they can provide misleading results when extrapolating beyond the bounds of this data set.

Probabilistic methods are categorized into: (a) state-based or Markovian and (b) time-based approaches. Markovian approaches take the condition rating change of the bridge component as a random variable, while time-based approaches model the time elapsed for a bridge component to change condition. Probabilistic methods can incorporate the effect of explanatory variables by defining a hazard rate function rather than recurring to segmentation of the data. The reliability of both methods is dependent on the availability of sufficient data and distribution of such data over the age of the bridges. However, if less than 20 years of data are available, Mauch and Madanat (Ref. 32) recommend employing state-based models.

Deterioration predictions using Markov models have been widely used as a major methodology in the practice management of infrastructure. Markovian methods are more favored by most BMS. AASHTOWare PONTIS, a software application developed by Golabi and Shepard (Ref. 17) for BMS, and BRIDGIT, a software package sponsored by AASHTO for BMS, are good examples of two popular software tools that employ Markovian methods. PONTIS are BRIDGIT are used over forty states. In addition, several researchers, such as Ditlevsen (Ref. 10) and Frangopol et al. (Ref. 16), have strongly favored Markov-based models over other structural deterioration methods.

This project will employ Markov-based models to develop deterioration rates of Texas Bridge components using NBI data. As such, this literature review will focus on: (1) describing the Markov-based method, (2) the approaches taken to classify bridges according to explanatory variables, and (3) the evolution of the deterioration models.

Markov's Process

Markov's Process is the most common probabilistic approach for bridge deterioration models. A Markov process has the assumption of time independence, i.e., the conditional probability *P* of a future condition state depends only on the present state and is independent of the past states (Ref. 8). The change of state is assumed to occur at discrete time intervals equal to the routine inspection period of 2 years. The probabilities that a bridge component would transition from state *i* to another state *j* (e.g. condition rating 9 to condition rating 8) during a specified period are represented in a transition probability matrix. For bridge deterioration models, it has the form:

$$\boldsymbol{P} = \begin{bmatrix} P_{99} & 1-P_{99} & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & P_{88} & 1-P_{88} & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & P_{77} & 1-P_{77} & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & P_{66} & 1-P_{66} & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & P_{55} & 1-P_{55} & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & P_{44} & 1-P_{44} & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & P_{33} & 1-P_{33} & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & P_{22} & 1-P_{22} \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & P_{11} \end{bmatrix} \quad (2.1)$$

In this matrix, each row represents the probability of moving from one state to any other state, including itself. Consequently, the sum of the probabilities in each row should be equal to one. The diagonal matrix terms represent the probabilities of each condition rating remaining unchanged between inspections. The transition matrix has zero values below the diagonal, because it is assumed that no rehabilitation activities are performed within the periods of inspection and therefore, the bridge can only deteriorate further. The bridge component is not allowed to transition more than one state between inspections. The expected condition rating value is simply:

$$\mathrm{E(t,P) = Z_o P^t R} \tag{2.2}$$

where t is the number of prediction cycle, Z_o is the initial state vector for a component, i.e. [1 0 0 0 0 0 0 0 0] for a component in new conditions, P is the transition probability matrix, and R is a column vector containing the rating used in the scale, 9-1. An essential component of the Markov's Process is the derivation of the transition probabilities, P_{ij}. The most common approaches for obtaining the transition probabilities are described next.

Calculation of Transition Probabilities

The expert elicitation method can be used when limited data is available and consists of requesting expert opinion from qualified transportation agencies and engineers. Typically, a group of experts is asked to estimate the transition probabilities of various elements in a bridge inventory based on their judgment and expertise. Although, this method provides a mean of evaluating the transition probabilities when data is limited, the accuracy of this method is questionable as it is not data driven. In general, expert opinion tends to be conservative, overestimating the deterioration rates.

The percentage-prediction method is typically *used when* historic inspection data is available, the simplest approach is to calculate the proportion of components in condition state i that transition to condition state, j, such as:

$$\mathrm{P_{i,j} = \frac{n_{i,j}}{n_i}} \tag{2.3}$$

where n_i is the total number of bridge components in condition state i and $n_{i,j}$ is the number of bridge components that transition from state i to j in one inspection period. This method is easy to compute; however, the deterioration contribution factors, e.g. weather and traffic, are assumed the same in subsequent inspection cycles regardless of the age of the component. The bridge components can be grouped by age groups in order to minimize the age effect.

The Expected Value Method (EVM) is the most used approach for calculating the Markov's transition probabilities. This method follows an iterative approach to determine the transitional probabilities, $P_{i,j}$. First, the average condition rating of the bridge components in a particular zone or age group is determined by applying a polynomial regression to all the bridges in that group. The polynomial regression is of the form:

$$\mathrm{Y_t = \beta_0 + \beta_1 t + \beta_2 t^2 + \beta_3 t^3} \tag{2.4}$$

where Y_t is the bridge component condition rating at age t, and β_0, β_1, β_2 and β_3 are unknown coefficients to be estimated. Then, the transition probabilities, $P_{i,j}$, are estimated by minimizing the distance between the average condition rating and the theoretical expected value $E(t,P)$ of the condition rating,

$$min \sum_{t=1}^{N} \left| \widehat{Y_t} - E(t,P) \right|$$
$$\text{Subject to : } 0 \leq P_{i,j} \leq 1 \text{ and } \sum_{j=1}^{k} P_{i,j} = 1 \text{ for } i,j = 1,2,\ldots,k \tag{2.5}$$

where N is the number of years in one age group. Markov's estimates have shown to most closely mimic the actual deterioration curves when following the EVM. Its drawback is that it is more computationally intensive than the percentage-based derivation approach.

Under the Metropolis Hasting Algorithm (MHA), the transition matrix is obtained by calibrating the model through the Markov chain Monte Carlo (MCMC) method. The Bayesian equation, used to calculate a conditional probability, is a fundamental component of the method:

$$P(\Theta|D) = \frac{P(D|\Theta)P(\Theta)}{P(D)} \tag{2.6}$$

where Θ are the unknown parameter, D is the observed culvert condition, $P(\Theta|D)$ is the posterior distribution of the transition matrix, $P(D|\Theta)$ is the likelihood to observe culvert conditions, $P(\Theta)$ is the prior known probability distribution of Θ, and $P(D)$ the probability of observing a culvert condition, which is a constant value. The theory of MHA is used to generate candidates of transition matrices based on a fix sampling algorithm. The MHA runs a large number of candidates until it converges to an optimum point, where the Markov chain converges to the stationary distribution (Ref. 60).

Some particular examples on how transition probabilities have been estimated by different agencies, include:

a) Florida DOT: Originally, used expert elicitation to estimate the transition probabilities of bridge elements. Recently, with the availability of a robust dataset, FDOT used the EVM approach to determine transition probabilities for element level inspection data (Ref. 46).

b) Colorado DOT: Recently, estimated transition probability matrices form historical data using the percentage prediction method (Ref. 20).

c) Indiana Bridge Management Systems: The EVM approach was used to calculate the transition probabilities (Ref. b43). The life of the bridges were zoned into a 6-year period, and transition probabilities were obtained for those zones. The deterioration rates were assumed constant within in each zone. As the bridge transitions from one age zone to another, it takes the last state vector of the previous zone.

d) Oregon: Yang (Ref. 58) developed a Markov model for predicting the deterioration rate of culverts at the network level based on culvert inspection datasets from three highways in the state of Oregon. The datasets were randomly split into two parts, 80% of the data was used for calibration and 20% for validation of the models.

Bridge Classification and Explanatory Variables

Markov's based models do not account for the effects of various explanatory variables, age, environment, design characteristics and average daily traffic (ADT) (Ref. 28). Hence, in order to increase the accuracy of these models, transition probability matrices have been developed for homogeneous categories, e.g., bridge components under similar environments or made of the same material. The estimation of the transition probability matrices is preceded by a pre-defined classification of the bridges in the network. This section presents an overview of the classifications that have been adopted or suggested by different agencies and researchers for both deterministic and state-based approaches.

North Carolina BMS has developed and updated their bridge models in several occasions, particularly in 1987, 2002, and 2015 (Ref. 7). Figure 2. 1, Figure 2. 2 and Figure 2. 3 illustrate the classification adopted by the North Carolina BMS for the development of bridge deterioration models for the three primary bridge components: (1) deck, (2) superstructure, and (3) substructure. The first level of classification consisted of subdividing the data by material type, e.g. timber, steel, concrete and prestressed concrete. The secondary level of classification varied by bridge component. Decks were subdivided by levels of ADT (0-200, 201-800, 801-2000, 2001-4000, and more than 4000), the superstructures were subdivided by both structural design type (e.g. Multi-beam, T-beam, Truss, slab) and highway functional classification (1: Interstate and 2: Other freeways and expressways), while the substructures were subclassified by geographical region (Coastal, Piedmont, and Mountain regions).

Jiang et al. (Ref. 22) were among the first to employ Markov-based models to study the deterioration of bridge structures. They developed a procedure using a third-order polynomial function to estimate bridge deterioration. They noticed that the deterioration rate changes as the bridge ages, suggesting that transition probability matrices should be developed for various age groups.

Dunker and Rabbat (Ref. 11) analyzed bridges built between 1950 and 1987 and determined that as the quality of bridge material increased from timber to steel to concrete, the structural deficiency percentages decreased. Madanat et al. (Ref. 29) found that bridge condition is a linear function of factors such as current bridge type, volume of traffic, age and many others.

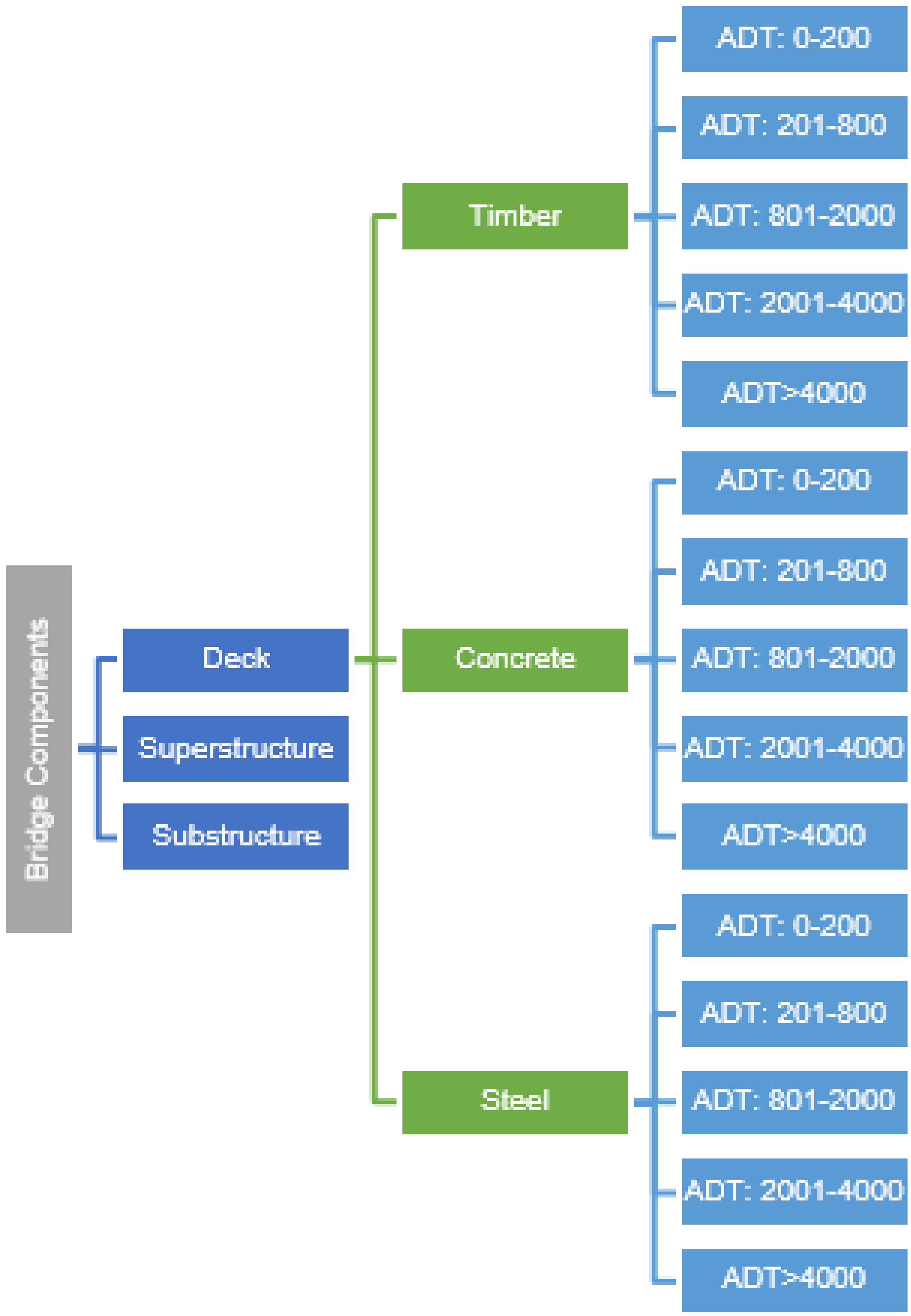


Figure 2. 1 NCDOT Bridge Deterioration Model Classification for Bridge Decks.

Note: ADT stands for average daily traffic.

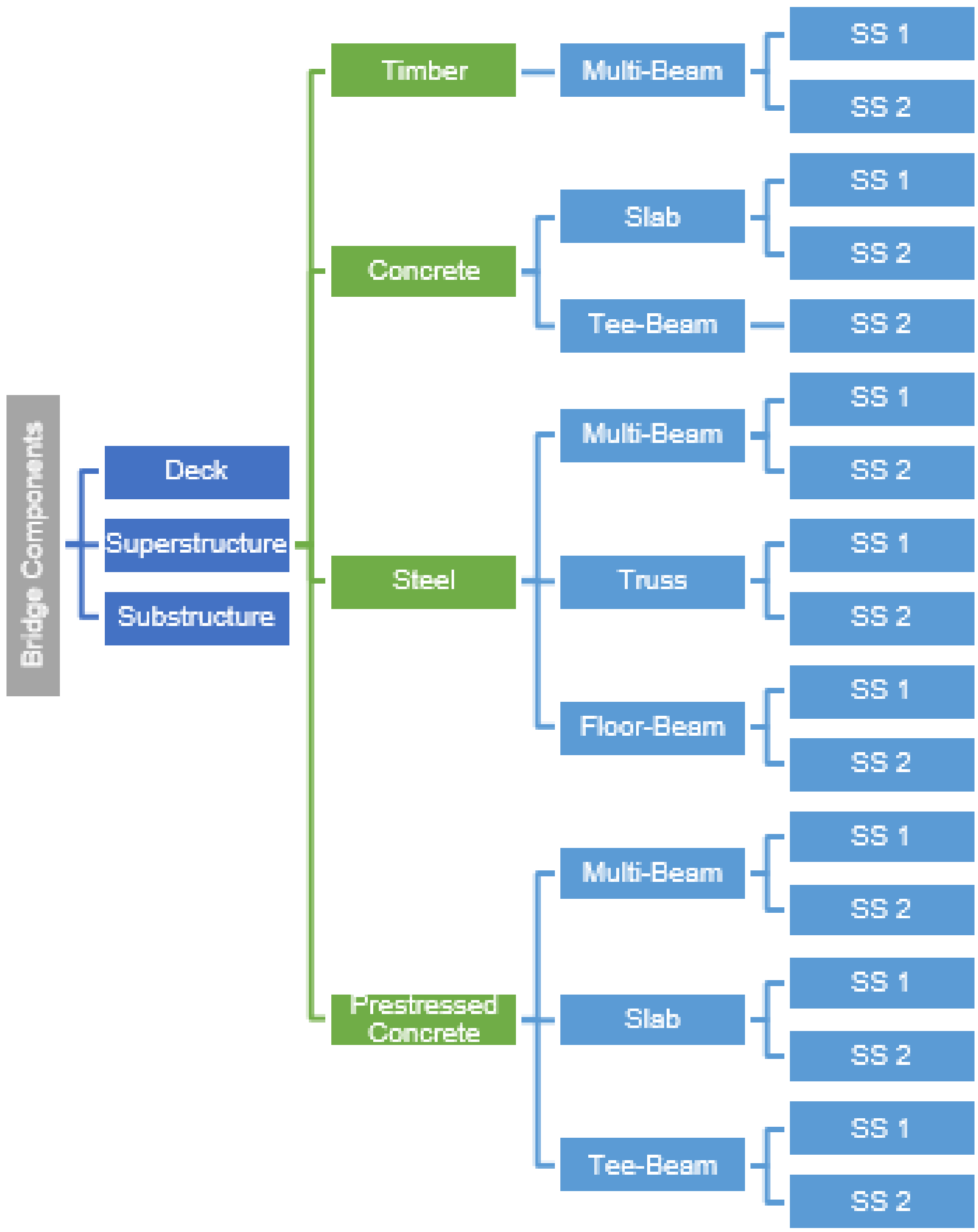


Figure 2. 2 NCDOT Bridge Deterioration Model Classification for Bridge Superstructures.

Note: SS stands for state system

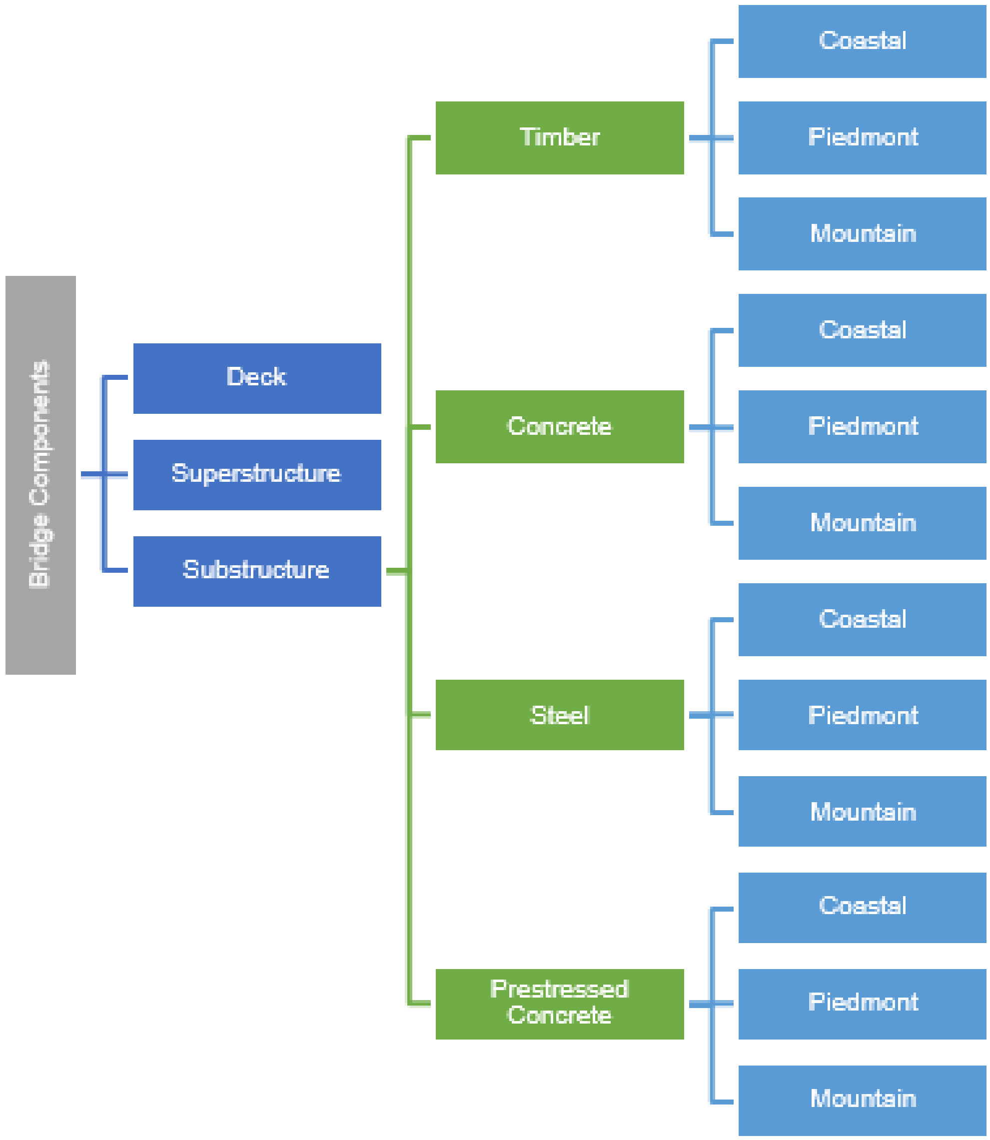


Figure 2. 3 NCDOT Bridge Deterioration Model Classification for Bridge Substructures

PONTIS recognized the role that the environment and climatic exposure play on the deterioration rate of bridge elements. As such, PONTIS requires that each element be assigned to one of four specified environments, i.e. benign, low, moderate, and severe. The description of each environment is provided in Figure 2. 4. As the definition of each environment should be linked to realistic climatic condition in each state, Wells (Ref. 57) presented a systematic strategy for developing a definition of these environments that will be appropriate for each individual state.

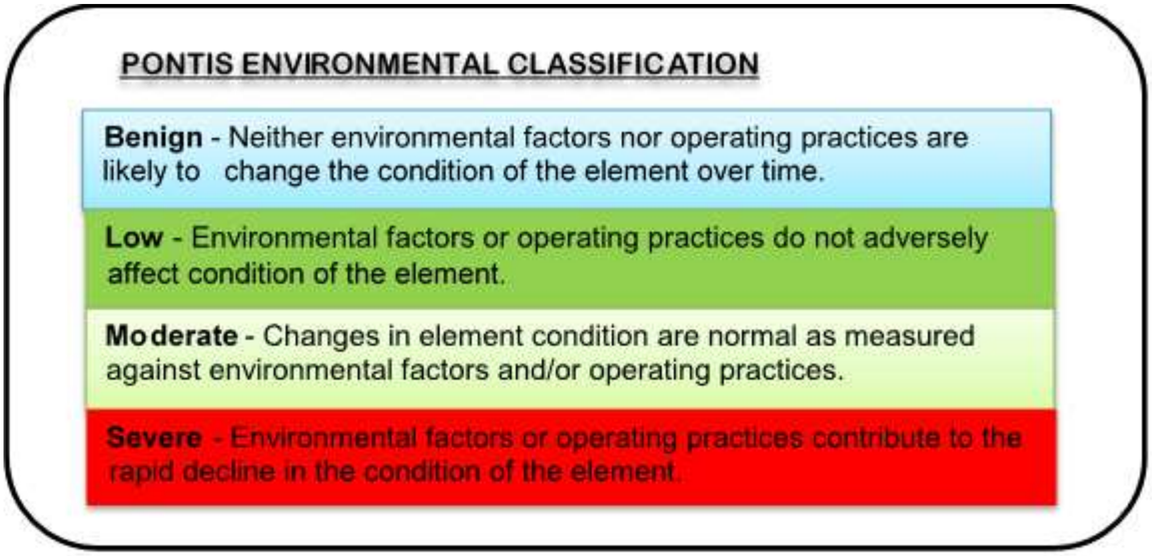


Figure 2. 4 PONTIS Environmental Classifications

Wells (Ref. 57) proposed a survey-based method for defining environmental classes, which consisted of the following 10 steps:

1. Determine the element or group of elements of a structure for which the survey is to be developed.

2. Gather information about climatic conditions and operating practices that may affect the deterioration of the specified element or elements.

3. Determine the applicable, state-specific, quantitative ranges over which the selected factors may vary.

4. Create a survey for the element selected.

5. Distribute the survey.

6. Collect the survey and review the responses.

7. Create a data base of the responses and classify the elements into environmental categories.

8. Analyze the results of the environmental assignments on the basis of the definitions developed.

9. Distribute the results to survey respondents for verification.

10. Use the results to assign defined elements to the appropriate environment.

The environmental classifications can be adjusted based on the accuracy of the predictions over time. If the rate of deterioration is not in agreement with the class assignment, the element can be reassigned to another classification environment.

Kallen et al. (Ref. 23) concluded that the relationship between expected bridge condition and age is a polynomial function and structural deterioration depends highly on age. Kim et al. (2010) found that in cold regions that the structural characteristics of the bridge and traffic volume are the critical contributor factors to deterioration of bridge superstructure after age.

Tolliver et al. (Ref. 52) developed a statistical model with relatively low coefficient of variation by using analysis dataset of the 2009 NBI for the states of Iowa, Minnesota, Nebraska, North Dakota, and South Dakota. The authors' regression model included bridge material, bridge design, operating rating classification, average daily traffic, and the state where the bridge was located. They found the relationship between condition and age is linear up to 65 years. They also indicated that a bridge substructure in these locations loses approximately one-half of a rating point every 13 years until age 65.

Hatami et al. (Ref. 19) developed both deterministic and stochastic deterioration models for the deck, superstructure, and substructure of bridges in Nebraska using visual inspection data from 1998 to 2010. The authors concluded that low-slump concrete overlays had significantly higher deterioration rates than original concrete decks and increase in traffic volume also increased the deterioration rate of concrete bridge decks. They reported 68 years of approximate service life for bridge decks with epoxy coated reinforcement and 40 years with black rebar at fair condition (condition 5). In addition, they indicated that prestressed concrete and steel superstructures had the same performance up to condition 6.

Li et al. (Ref. 27) considered natural, conventional, and recoverable decay circumstances in ten years of bridge data records to verify the deterioration tendency of urban bridges in Shanghai including bridge deck system, superstructure, and substructure. Their results indicated that in the absence of recoverable repair treatments, the bridge conditions drop drastically. On the other hand, deterioration rates slow down if proper repairs are conducted. Enhanced recoverable repairs were found to considerably mitigate the deterioration rate process.

Goyal et al. (Ref. 18) developed a general methodology to identify the critical factors in deterioration process, to test the existing classification categories validation, and develop deteriorations models which are statistically more reliable. They conducted bivariate analyses in order to determine the influence of the explanatory variables on the deterioration rate. The significance of the multivariable models was used using the p-value of the Wald statistics. Only variables that were statistically significant, at 20%-25% level, were included in the multivariable model.

Nelson (Ref. 39) conducted a deterioration rate study on concrete bridge decks in the state of Minnesota. The author concluded that bridges with epoxy coated rebars and more reinforcement cover performed the best, while overlays did not decrease the deterioration as it was expected. It was also concluded that early crack sealing and deck flushing reduced deck deterioration.

Moomen et al. (Ref. 34) developed families of curves representing deterioration models for the three main components of a bridge, i.e. deck, superstructure, and substructure, in order to update the bridge deterioration models that were in use in the Indiana Bridge Management System. The authors developed both deterministic and probabilistic models categorized by administrative region, functional class, and superstructure material type and used traffic volume and truck traffic, design type, climatic condition, and design features as explanatory variables. The results of their probabilistic models indicated that age, current condition rating, transition in last inspection period, and number of years to last transition were the most significant factors in components' deterioration. These models suggested that functional class, region, freeze-thaw cycles, and rehabilitation status variables were influential predictors of deterioration transition probability in all three components while Average Daily Truck Traffic (ADTT), type of wearing surface, and number of cold days were significant for the deck deterioration models. Furthermore, superstructure material type was significant in superstructure deterioration models. The service under bridge (if waterway) was found to be more significant statistically in the substructure than superstructure deterioration models. Furthermore, it was observed that the coefficients of ADTT, service under bridge (if waterway), number of cold days, and freeze-thaw cycle if larger than 60 were influential variables in increasing the probability of transitioning to a lower condition state.

The condition of a culvert can be determined by considering different criteria, including cracking, joint misalignment, and corrosion. It has been found that the deterioration of a culvert is largely dependent on the material type, which are typically reinforced concrete pipe (RCP), corrugated metal pipe (CMP), corrugated aluminum pipe (CAP), high density polyethylene pipe (HDPE), masonry pipe, and culverts classified as mixed or other culverts (Ref. 48). Baik et al. (Ref. 4) obtained transition probability matrices for Markov's chain based deterioration models for wastewater systems by using a condition data set of sewer pipes managed by the City of San Diego's Metropolitan Wastewater Department. Five variables were included in the process, i.e. length, size, type of material, age and slope. Nonetheless, the authors recommended using other data variables if available, including, depth of installation, source of sewer, soils surrounding the pipe, groundwater level, traffic volume above pipe segments, frequency of overflows. Meegoda et al. (Ref. 33) proposed a novel half-life probability method to calculate the transitional probabilities for the Markov chain to predict the remaining service life of corrugated steel culvert pipes.

There exists a variety of multi-variable models for predicting the condition states of culverts. Stoner (Ref. 48) conducted a literature review in which he summarized the physical and environmental variables that have been considered in different deterioration models for culverts. These variables depend on the desired output of the model, i.e. remaining service life, structural performance, hydraulic performance, probability of failure, cracking of pipe, and overall condition. Regardless of the output, age was considered as an important variable in all models. Table 2. 1 summarizes the variables from three studies, Tran et al. (Ref. 53), Baik et al. (Ref. 4), and Najafi and Kulandaivel (Ref. 37), which considered overall condition as the output of the model. Stoner (Ref. 48) concluded that in multi-variable models, the number of the variables and their relevance play a key role in determining the accuracy of the culvert's condition.

Table 2. 1 Input Variables for Culvert Deterioration Models

Model's Input Variable	**Reference**		
	Tran et al. (Ref. 54)	Baik et al. (Ref. 4)	Najafi and Kulandaivel (Ref. 37)
Age	X	X	X
Type of Material		X	
Thickness	X		
Size	X	X	X
Depth	X		X
Slope	X	X	X
Tree Count	X		
Hydraulic Conditions	X		
Exposure	X		
Soil Abrasion	X		
Moisture Index	X		

Source: Stoner (Ref. 48)

Evolution of Deterioration Based Models

Discrete-time Markov chain method is used in deterioration models for the bridge management system in the United States. However, Markov models have two assumptions that can be perceived as unrealistic, which are: a) the stationarity of transition probabilities and b) duration independence. The method assumes discrete transition time intervals, which is contrary to the continuous deterioration process exhibited in bridges. Due to the assumption of time independence, a future facility condition depends only on the current facility condition and not on its history. Due to these inherent limitations associated with Markov models, several researchers have proposed several enhancements and alternatives for the deterioration prediction of bridge components. This section provides a literature review of the recent proposed methods to estimate the deterioration of bridges.

Maheswaran et al. (Ref. 30) presented a continuous-time Markov chains method for management of concrete bridge structures. The authors also developed a Monte Carlo-based simulation method for selecting bridges for maintenance. Morcous et al. (Ref. 35) proposed a new approach by combining a multicriteria optimization model and a Markov chain deterioration model for maintenance management of deteriorated bridge decks. The authors indicated that the proposed approach can consider objective functions, include the bridge deck deterioration's uncertainty, and make efficient and rational decisions for maintenance of network of bridge decks. They concluded that this study showed that the integration of multicriteria optimization and Markov-chain models can develop a more powerful bridge management systems enabling selection of multiple criteria (even conflicting) and considering the uncertainty to optimally decide the maintenance alternatives.

Agrawal et al. (Ref. 3) compared the Markov chains and Weibull distribution approaches using historical bridge inspection data in state of New York to calculate the deterioration rates of different bridge elements. They incorporated both approaches into a computer program and generated the deterioration curves for particular bridge elements. The authors stated that due to inclusion of the duration dependency and right censoring characteristics of data, the Weibull-based approach performed better probabilistically in terms of the observed conditions than Markov chains approach. This conclusion was in agreement with DeLisle et al. (Ref. 9), who had shown that Weibull distribution approach generally gives the best overall fit for structural deck condition data.

Morcous et al. (Ref. 36) presented a two-level maintenance management system for highway bridges by integrating state-based/time-based probabilistic and reliability-based mechanistic models. The probabilistic models predicted the macro-response of bridge components for the network-level analysis while the mechanistic models predicted the micro-response of bridge components for project-level analysis. The authors indicated that balance of accuracy and efficiency in results was achieved through integration of models but several years of detailed condition survey are needed. Furthermore, the available Non-Destructive Evaluation methods could be inapplicable and/or unreliable for different bridge components and construction materials.

Kobayashi et al. (Ref. 25) proposed an analytical methodology to predict the deterioration process of infrastructure through a hidden Markov model considering selection biases as random variables and conducted an empirical study on the Japanese national road system. The hidden Markov model is a special case of Markov chain model with the advantage that it allows the unobserved condition state to be captured, eliminating the noise and bias associated with monitoring data (Ref. 26). They showed the influence of selection biases on deterioration estimations through comparison of their proposed hidden Markov model results and multi-stage exponential Markov model of Tsuda et al. (Ref. 55).

Puz et al. (Ref. 40) presented a stochastic model using homogeneous Markov models considering a finite set of condition states and time as a continuous parameter. The proposed models were intended to predict the probability of the future deterioration in bridge components in any moment of time. Sobanjo (Ref. 45) conducted analysis on bridge conditions using Florida's historical data to estimate different condition states' sojourn times for different bridge categories. The author discussed the semi-Markov model implementation in bridge deterioration and an overall semi-Markov model to predict bridge conditions in the future. It was shown that using arbitrary distributions for the sojourn times could model the bridge deterioration process better than exponential distributions in Markov chain. It was also indicated that due to agencies starting to have longer period data, employing sojourn times in bridge deterioration models is getting more realistic, however, the current formats of bridge condition data collection are not ideal for such.

Saydam et al. (Ref. 43) proposed a methodology using a five-state Markov model accounting for the failure and restoration of the bridges to predict their time-dependent performance. The authors identified direct outcomes based on the individual bridge failure or closure for maintenance while quantified indirect outcomes based on various failure scenarios. The expected loss profiles showed an increasing pattern following a decrease due to the time-variation of the Markov chain state probabilities. The results indicated much higher maximum total expected indirect loss than the maximum total expected direct loss for a highway bridge network. The authors computed the time-dependent risk-based robustness index. They indicated that although these indices give a good measure for long investigation periods, they are not a reliable for shorter time periods. They also indicated that both expected losses and robustness indices are sensitive to Markov models' time-dependent parameters.

Cavalline et al. (Ref. 7) developed a statistical regression methodology using North Carolina Department of Transportation's BMS data and survival analysis approach to improve the existing bridge components' probabilistic deterioration models. The models showed considerable improvements in accuracy of predictions. These advanced models were found to be most suitable for the historical condition rating data, but it was also discovered that a simplified probabilistic deterioration model could achieve the same performance. A software tool to update deterministic and probabilistic deterioration models was developed and user costs computation methodology in NCDOT's BMS were enhanced and updated.

Yianni et al. (Ref. 59) employed a Petri-Net approach to develop an interconnecting multi-module model with each module having its own source of data, calibration methodology, and functionality to provide outputs for railway bridge management. Zhang et al. (Ref. 60) proposed a stochastic Markov chain model with deterioration rates assumed as random variables. They compared the stochastic model's results with the deterministic method's outcomes to forecast the health conditions in offshore structures. The authors found that not only the stochastic Markov chain model could quantify the deterioration process' uncertainties but also it was more flexible. They also indicated that including a long transition period in the model would result in very uncertain predictions, however, a short transition period could generate bias predictions. They concluded that the applied stochastic approach is advantageous in maintenance management for situations such as extreme events in which deterministic approaches cannot predict the deterioration uncertainties.

Lately, with the advancements in computing efficiency, machine learning algorithms, such as artificial neural networks (ANN), have emerged as an alternative for estimating the deterioration of infrastructure systems (Refs. 1, 5). ANNs allow the estimation of outputs based on a series of inputs variables. ANNs are computation systems inspired by the mechanisms of neural networks of living organisms and allow one to create models that learn to performs a task (e.g. predict condition rating) based on input stimuli (e.g. age, ADT, weather, material type) and upon proper training (e.g. historic inspection data). Several researchers have used ANN to predict the condition of storm water pipes and sewers, such as Najafi and Kulandaivel (Ref. 37), Tran et al. (Ref. 53), Duran et al. (Ref. 12), and Tran et al. (Ref. 54).

A neural network is typically composed of an input layer, one or more intermediate hidden layers of neurons, and an output layer. There are two decisions that must be made regarding the hidden layers: 1) how many hidden layers to have in the neural network and 2) how many neurons will be in each of these layers. The selection of the architecture relies on a trial and error approach.

The output provided by each neuron of the network can be summarized as follows:

$$f(\boldsymbol{x},\boldsymbol{w}) = \Phi(\boldsymbol{x},\boldsymbol{w}) = \Phi(\boldsymbol{x},\boldsymbol{w}) = \Phi\left(\Sigma\sum_{i=1}^{n}(x_i w_i)\right) \quad (2.7)$$

where the $\boldsymbol{x}$ vector contains the n -input variables, including physical, environmental, and operational factors, $\boldsymbol{w}$ are the weights of the function, and Φ denotes the activation (nonlinear) function applied at each neuron. Typically, the inspection data is randomly divided into training (60% of the data), testing (20% of the data), and validation (20% of the data) data sets. Training data set is used to determine the weights of the neural network by identifying patterns between the known input and output targets. Then, the validation is used to evaluate how accurately the neural network estimates outputs for inputs that were not used to develop the network. The performance of the model on the validation set is used to tune the weights of the network (Refs. 1, 2). Finally, the test data set is used to assess the final performance of the neural network. Two statistical parameters will employed to evaluate the performance of the network: (1) the correlation coefficient between the predicted output and the measured output, R^2, and (2) the root mean squared error (RMSE). Good predictive models have R^2 and RMSE values close to 1 and 0, respectively. The performance of a neural network can be improved by using alternative training algorithms, including several gradient descent methods, conjugate gradient methods, the Levenberg-Marquardt algorithm (LM), and the resilient back propagation algorithm (Ref. 31).

Stoner et al. (Ref. 48) developed ANNs for a database of approximately 8,000 culverts in South Carolina. The ANN models used physical characteristics of the culverts and associated environmental characteristics as inputs for the model, including historical temperature, precipitation, pH, and estimated runoff coefficient. Also, an ANN was created for each of the six culvert material types found in South Carolina. These models used different combinations of the inputs to rate the culvert in ten categories: cracking, separation, corrosion, alignment, scour, sedimentation, vegetation, erosion, blockage, and piping. The scores for each of these categories were multiplied by predefined weights to give an overall composite score for each of the culverts. The study concluded that in the cases of culvert groups with a reduced number of culverts, the models that had fewer inputs were more successful. There was no concluding evidence to determine an optimum number of neuron layers in the model.

Chapter 3
Data Base Preparation

Background and Objective

This Chapter documents the development of two research datasets: the annual inspection history database, and the bi-annual inspection history database. Both were developed using data from the National Bridge Inventory (NBI)/PonTex (Ref. 51). TxDOT provided 19 PonTex files containing bridge and culvert data from 2001 to 2019, in Access format, with all variables stored as text. Together, these files contain almost a million records.

The research analyses require these individual Access files to be organized onto one file with all numeric data properly stored as numbers, the file year as another variable, missing inspection ratings within a structure's history filled out whenever possible, and other practical data issues solved, as discussed later in this chapter. Given the massive amount of data, and the complexity of the analyses to be performed, the research data files were developed in SAS™ (Ref. 42).

Climatic variables were mined from other sources, summarized by county, then merged onto the annual inspection history file. The annual file was used primarily for data exploration and for model validation and standard error calculations.

The bi-annual inspection history file is a subset of the annual inspection history file in which all records within the same structure are spaced by two years. This file is necessary to correctly derive the Markov transition probability matrices, which age each modeling family by two years. Preparing it required deleting records spaced less than 2 years and, whenever logically possible, inserting records between inspections spaced more than 2 years.

Development of the Annual and Bi-Annual Inspection History Data Bases

This task was performed in the beginning of this project, before 2019 data became available. As such, this section pertains to documentation of the task performed during 2018. The steps were repeated to add 2019 data when it became available in the second year of the project. The data preparation consisted of the following steps:

Step 1-Raw SAS™ historical file.

Procedure: Import into SAS™ 36 on- and off-system data tables provided in Access format, containing inspection data from 2001 to 2019 stored as text. Ensure compatibility of all raw text variables' length as well as names throughout the 18 years of history. Create a variable storing the original file year. Append all data.

Outcome: raw SAS™ historical data set with all on- and off-system structures, containing 207 variables stored as text, for years 2001 to 2019. Each record is one year of data for each structure (bridge, culvert or tunnel). Raw data consists of almost a million records, 321,464 off-system and 615,528 on-system records.

Step 2-Remove tunnels from the raw data

Procedure : PonTex items 5.1 (Structure Function) and 43.5 (Structure Type, Tunnel) were cross-checked and used to identify tunnels. 25 historical records were removed based on Item 5.1= 8. All the remaining records should have Item 43.5 blank, but 6 records pertaining to 4 structures did not. After visual inspection using Google Maps, the tunnel type variable values were set to blank since these records pertained to the following 4 on-system structures:

Culverts 220670008610037 and 071340014201094

Bridges 190190004606015 and 180710AA0537001.

Outcome: raw historical SAS™ data set less 25 records pertaining to tunnels.

Step 3-Format as numeric and adjust as needed all variables relevant for modeling and statistical analyses

Procedure: First, identify all variables originally formatted as text that must be stored as numbers, such as dates and inspection ratings. Compare their values with definitions in the Bridge Inventory, Inspection and Appraisal Files Coding Guide (TxDOT 2010) and ensure consistency. For example, condition ratings' valid values are 0 to 9, and "N" when the rating is not applicable to the structure. However, the raw historical data set had 2,033 records with blank rather than "N" condition ratings. When reformatting the ratings as numeric integers, both "N" and blanks were coded as missing values. Several other variables also had to be reformatted in a similar manner. For example, Item 27, year built, had 282 values less than 1900 or greater than 2018, one record containing "65--" and 734 blanks. The entire history of these structures was visually examined, and most invalid values could be filled in based on data from the rest of the bridge or culvert history. Records with Item 27=2050 did not have any inspection data and were removed. Two structures with Item 27 (year built) in the late 19th century were not corrected to 1900 despite the recommendation in the PonTex coding guide (Ref. 51), since the research data base must contain the actual structure age.

Outcome: Historical SAS™ data set with 936,701 historical records pertaining to 61,996 bridges and culverts, 22,167 of them off-system and 39,829 on-system. All relevant numeric variables previously stored as text were formatted as numeric, and checked for consistency. Inconsistent values were either corrected or set to missing, and structures without any inspection data in their histories were removed.

Step 4: Interpolate missing data based on the existing the history

SAS™ code was developed to identify annual histories containing one or more missing values of the inspection date and of condition ratings, and logically insert as many as possible based on previous and subsequent values in the historical file. This step was necessary to maximize the number of 2-year transitions to be used in the development of the Markov matrices. The left side of Table 3. 1 illustrates this interpolation procedure.

There were 1,029 bridges and culverts with at least one missing inspection date in their history, totaling 1,671 historical records with missing inspection dates; it was possible to logically complete 1,059. Missing ratings found in inspection histories and possible to interpolate based on previous and subsequent ratings: 6,397 deck ratings, 3,076 substructure ratings, 3,076 superstructure ratings, and 3,064 culvert ratings.

Step 5: Subset the annual history into bi-annual ratings

SAS™ code was developed to calculate the interval between consecutive inspections based on PonTex Item 90, Inspection Date. Intervals between 18 and 26 months were considered bi-annual. Intervals below 18 months were deleted in such a way as to ensure an approximate 2-year gap between consecutive records. An intermediate rating was interpolated for inspection frequencies of 4 years, based on values of two consecutive ratings. The right side of Table 3. 1 illustrates is the bi-annual inspection file, extracted from the annual the inspection file.

Table 3. 1 Example of Data Preparation: Off-System Culvert 011170B00223001

Historical (2001 to 2018) Data Set				
PonTex Year	Inspection Date		Culvert Rating	
	New	*Original*	*New*	*Original*
2001	2000	02112000	6	6
2002	2002	05282002	6	6
2003	2002	05282002	6	6
2004	2004	04192004	6	6
2005	2004	04192004	6	6
2006	2006	06122006	6	6
2007	2006	06122006	6	6
2008	2008	03192008	6	6
2009	2008	03192008	6	6
2010	2010	02052010	6	6
2011	2010	02052010	6	6
2012	2012		6	
2013	2012	02102012	6	6
2014	2014	01212014	6	6
2015	2014	1212014	6	6
2016	2015	11192015	6	6
2017	2015	11192015	6	6
2018	2017	11142017	6	6

Inspection Years Data Set			
Inspection Date		Culvert Rating	
New	*Original*	*New*	*Original*
2000	02112000	6	6
2002	05282002	6	6
2004	04192004	6	6
2006	06122006	6	6
2008	03192008	6	6
2010	02052010	6	6
2012	02102012	6	
2014	01212014	6	6
2015	11192015	6	6
2017	11142017	6	6

Climatic Variables

Rainfall precipitation and freeze-related data were obtained, organized and merged into the historical inspection database for analysis. Statistical summaries of the climatic variables were analyzed, and potential families were defined based on the statistical summaries and on the inspection demographics within each group. Special attention was paid to defining typical rainfall precipitation and freezing days by county, in order to facilitate implementation at TxDOT.

Rainfall

Average monthly and annual rainfall precipitation for the climatological period between 1981 and 2010 were obtained from the Texas Water Development Board (TWDB). Data consisted of a shape file with the average annual rainfall precipitation isopleths compatible with ArcMap. The TWDB map was then overlaid with bridge and culvert coordinates from the latest PonTex available at the time (2018), thus assigning bridges and culverts to the different precipitation regions. Figure 3. 1 shows a partial screen capture of the bridges (blue dots) overlaying the rainfall isopleths (curved lines) and County boundaries. Roberts County is highlighted as an example, and a partial screen capture of its corresponding data table is shown. The rainfall averages by County are different for bridges and culverts due to the weighted average procedure explained below, which that takes into consideration the number of bridges (or culverts).

As depicted in Figure 3. 1, rainfall precipitation is not uniform within counties; therefore, meaningful precipitation families had to be defined in terms of geographical boundaries available in PonTex. Two weighted averages were calculated for each county annual precipitation, respectively using the number of bridges and culverts located inside each precipitation region as weights.

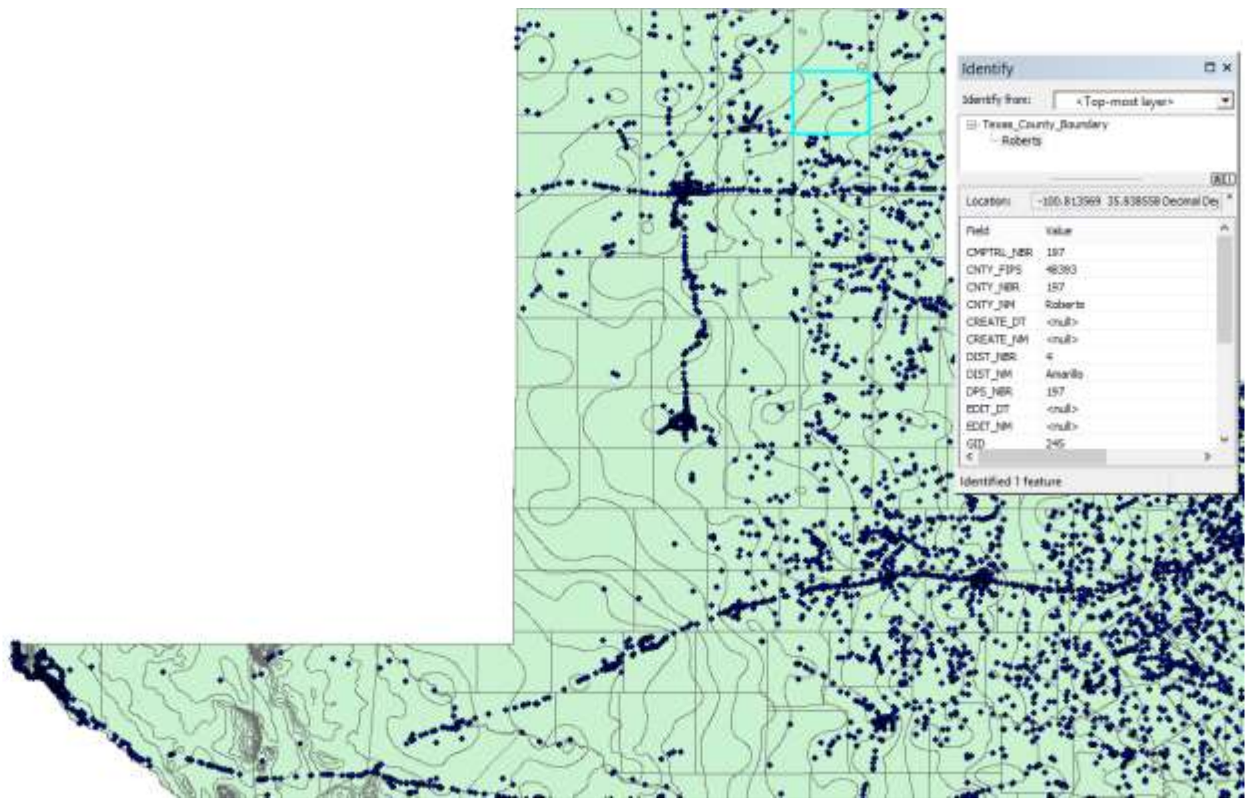


Figure 3. 1 Average Annual Rainfall Precipitation Regions and Bridge Locations

Sources: Texas Water Development Board (https://www.twdb.texas.gov/mapping/gisdata.asp) and 2018 PonTex

Figure 3. 2 and Figure 3. 3 show the histograms of rainfall weighted averages in inches/year, respectively for bridges and culverts. For example, the bottom histogram in Figure 3. 3 indicates that 2.73% of on-system bridges are in locations with weighted average precipitation less or equal to 10 inches, 1.63% in locations with 10 and 15 inches, and so on.

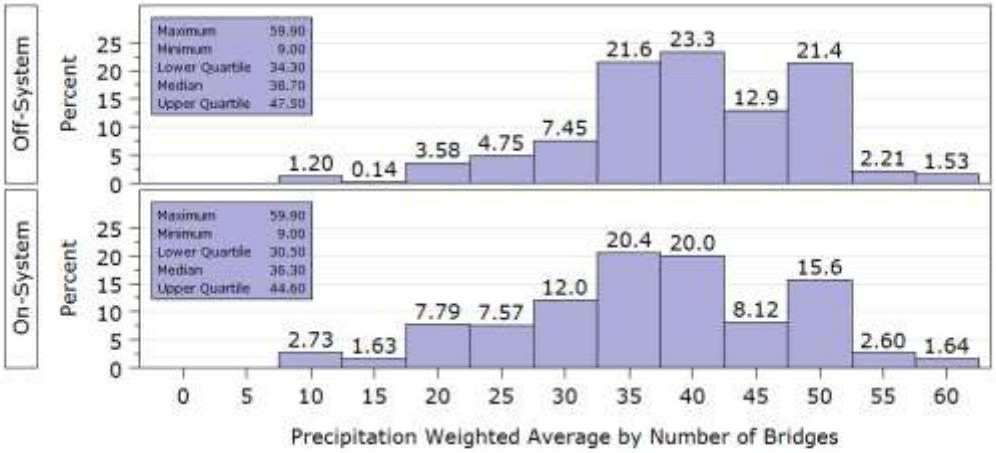


Figure 3. 2 Rainfall Precipitation Weighted Averages by Bridges in Inches/Year

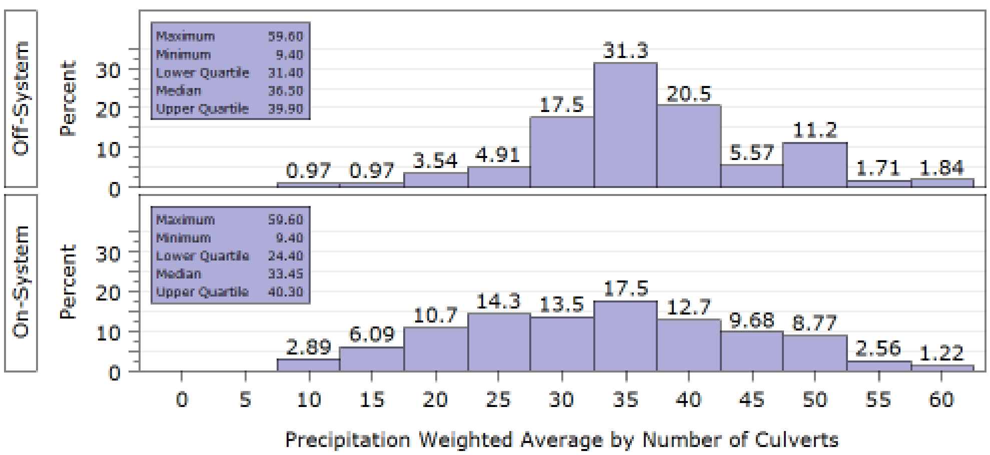


Figure 3. 3 Rainfall Precipitation Weighted Averages by Culverts in Inches/Year

Meaningful rainfall precipitation families could not be defined in terms of in terms of TxDOT Districts, groups of Districts, counties, groups of counties, or Texas climatic regions found in the literature. Therefore, it was decided to define rainfall families in terms of quartiles of the distributions depicted in Figure 3. 2 and Figure 3. 3 above. The potential rainfall families are summarized in Table 3. 2.

Table 3. 2 Rainfall Precipitation Families

		Rain 1	**Rain 2**	**Rain 3**	**Rain 4**
On-System	*Bridges*	Pcpt < 30.5	30.5 ≤ Pcpt < 36.3	36.3 ≤ Pcpt < 44.6	Pcpt ≥ 44.6
	Culverts	Pcpt < 24.4	24.4 ≤ Pcpt < 33.5	33.5 ≤ Pcpt < 40.3	Pcpt ≥ 40.3
Off-System	*Bridges*	Pcpt < 34.3	34.3 ≤ Pcpt < 38.7	38.7 ≤ Pcpt < 47.5	Pcpt ≥ 47.5
	Culverts	Pcpt < 31.4	31.4 ≤ Pcpt < 36.5	36.5 ≤ Pcpt < 39.9	Pcpt ≥ 39.9

Pcpt = average annual rainfall precipitation in inches

These four-level categorical variables representing the four rainfall families, defined in Table 3. 2 according to the indicated ranges were assigned to each culvert and bridge in the inspection data base for further use in the analyses.

However, assigning a rainfall family to each new bridge and culvert would complicate future implementation of the models at TxDOT. Therefore, each county was assigned a culvert and a bridge rainfall family based on a weighted average by number of bridges or culverts. These weighted averages will change as new bridges and culverts are built in each county; however, this classification is expected to last on 10 years on the average, without significant changes in weighted averages, as such change would take a rather large number of new structures within a county.

For future implementation, Table 3. 3 shows the counties assigned to each rainfall region, for culvert and for bridge analyses. There are a few differences due to the differences in number of culverts and bridges. Rain1 is the driest and Rain4 the wettest family.

Table 3. 3 Counties in Each Rainfall Region

Weighted Average by	Rainfall Region	County Number
BRIDGES	Rain1	2, 6, 9, 17, 22, 23, 33, 35, 52, 53, 54, 55, 56, 58, 59, 64, 69, 72, 78, 86, 88, 96, 99, 104, 109, 111, 115, 116, 118, 119, 123, 125, 136, 140, 151, 152, 153, 156, 159, 165, 167, 168, 171, 179, 180, 185, 186, 188, 189, 191, 192, 195, 197, 208, 211, 214, 216, 218, 219, 222, 223, 226, 231, 233, 238, 240, 247, 248, 253, 254
	Rain2	5, 7, 12, 24, 25, 30, 31, 38, 41, 42, 44, 48, 51, 63, 65, 66, 67, 68, 70, 77, 79, 83, 91, 97, 100, 105, 107, 126, 128, 132, 134, 135, 137, 138, 142, 148, 149, 150, 157, 160, 162, 163, 164, 173, 177, 193, 200, 206, 207, 209, 215, 217, 221, 224, 232, 242, 243, 244, 245
	Rain3	4, 10, 11, 13, 14, 15, 16, 18, 21, 26, 27, 28, 39, 43, 46, 47, 49, 50, 57, 61, 62, 71, 73, 74, 76, 87, 89, 90, 95, 98, 106, 110, 112, 120, 127, 129, 130, 131, 133, 141, 143, 144, 147, 161, 166, 169, 175, 178, 182, 184, 196, 198, 199, 205, 213, 220, 227, 235, 246, 249, 252
	Rain4	1, 3, 8, 19, 20, 29, 32, 34, 36, 37, 45, 60, 75, 80, 81, 82, 85, 92, 93, 94, 101, 102, 103, 108, 113, 114, 117, 121, 122, 124, 139, 145, 146, 154, 155, 158, 170, 172, 174, 176, 181, 183, 187, 190, 194, 201, 202, 203, 204, 210, 212, 225, 228, 229, 230, 234, 236, 237, 239, 241, 250
CULVERTS	Rain1	2, 6, 9, 17, 22, 33, 35, 52, 53, 54, 55, 56, 58, 59, 64, 69, 72, 78, 86, 88, 96, 99, 104, 109, 111, 115, 116, 118, 119, 123, 125, 136, 140, 148, 151, 152, 153, 156, 159, 165, 168, 171, 179, 180, 185, 186, 188, 189, 191, 192, 195, 208, 211, 214, 216, 218, 219, 222, 223, 231, 233, 238, 240, 248, 253
	Rain2	5, 7, 12, 23, 24, 25, 30, 31, 38, 41, 42, 44, 48, 51, 63, 65, 66, 67, 68, 70, 77, 79, 83, 91, 97, , 100, 105, 107, 126, 128, 129, 132, 134, 135, 137, 138, 142, 149, 150, 157, 160, 162, 163, 164, 173, 177, 193, 197, 200, 206, 207, 209, 215, 217, 221, 224, 226, 232, 242, 244, 245, 247, 254
	Rain3	4, 10, 11, 13, 14, 15, 16, 18, 21, 26, 27, 28, 39, 43, 46, 47, 49, 50, 57, 61, 62, 71, 73, 74, 76, 87, 89, 90, 95, 98, 106, 110, 112, 120, 127, 130, 131, 133, 141, 143, 144, 147, 161, 166, 167, 169, 175, 178, 182, 184, 196, 198, 205, 213, 220, 227, 235, 243, 246, 249, 252
	Rain4	1, 3, 8, 19, 20, 29, 32, 34, 36, 37, 45, 60, 75, 80, 81, 82, 85, 92, 93, 94, 101, 102, 103, 108, , 113, 114, 117, 121, 122, 124, 139, 145, 146, 154, 155, 158, 170, 172, 174, 176, 181, 183, 187, 190, 194, 199, 201, 202, 203, 204, 210, 212, 225, 228, 229, 230, 234, 236, 237, 239, 241, 250

Freezing

The effect of chemicals (e.g. salts) used for roadway deicing operations on the deterioration rate of bridge components in Texas, particularly of superstructures and decks, was evaluated in this study. The number of days in which trucks were sent to deice the roads of Texas counties in the past five years was inferred through analyzing historic precipitation data in Texas.

Deicing operations are typically performed when two weather conditions coincide: (a) temperatures below the freezing point (T<32˚F), and (b) the presence of precipitation. These conditions favor the creation of slick spots and ice coats on roadways, which can be dangerous for travelers. Bridges in particular are susceptible to icing as the surrounding cold air favors the freezing of liquid raindrops. Precipitation can be differentiated according to its matter state when making contact with the ground surface. The four main precipitation categories are: rain, freezing rain, sleet, and snow, as shown in Figure 3. 4. It was assumed that transportation agencies, including TxDOT, will use deicing chemicals when any of the latter three precipitations occur.

The above-mentioned freezing data were summarized in terms of total number of freezing days in the last five years (2014 through 2018) per Texas County. During the last five years Texas experienced a total of 756 days of freezing.

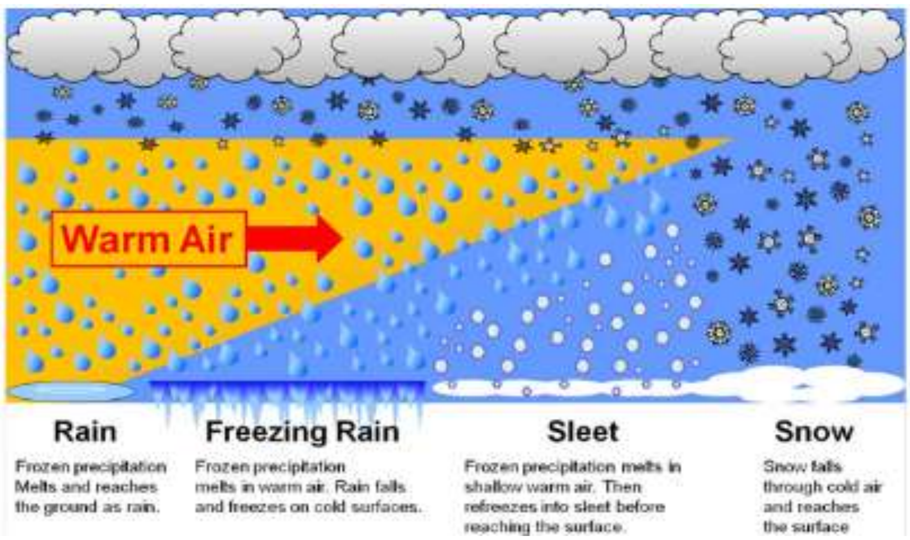


Figure 3. 4 Precipitation Categories

The National Centers for Environmental Information (NCEI) keeps records of the dates in which freezing rain (also known as glaze), sleet (characterized by the presence of ice pellets), and snow have occurred over several years in various stations distributed across Texas. This precipitation information was extracted from NCEI as it was considered useful in determining if bridge deterioration is more drastic in locations where deicing chemicals are most likely to be used. NCEI has an application interface (API) that facilitates data extraction. API provides an identification number for Texas counties, stations, and datatypes, among others. The occurrence of snow, sleet and freezing rain was obtained by requesting datatype ID WT04 (snowfall/pellets) and WT06 (rime/glaze) for every station within the list of counties in Texas. The year range was specified between 2014 and 2018, as it was assumed that a pattern of precipitation occurrences could be extracted by evaluating five years of data.

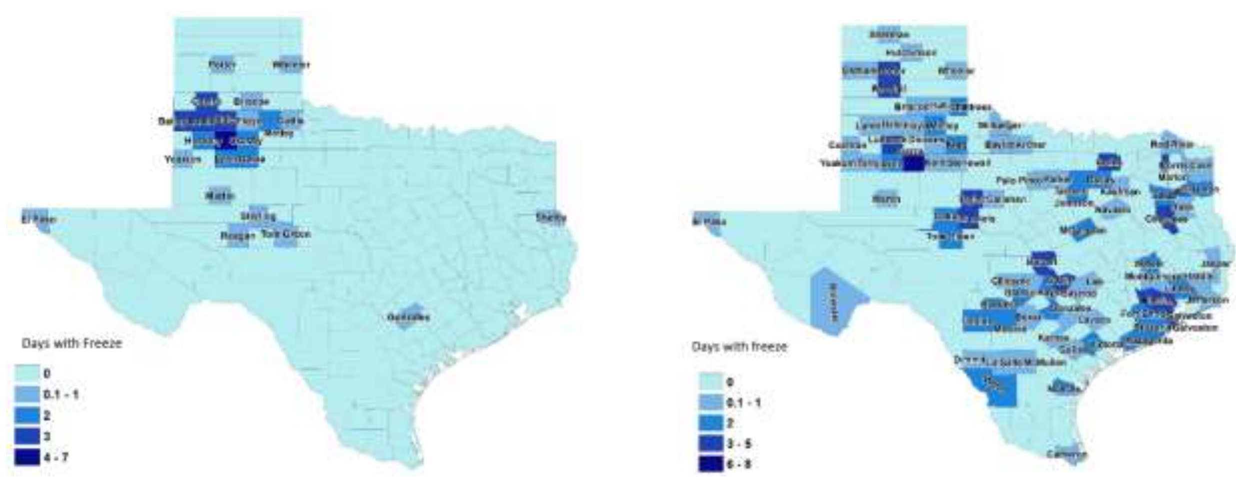
The number of precipitation days that favored icing on roadways in each Texas County was obtained for each of the aforementioned years. This variable was named as “Freeze Days”, and sums the number of days in which rime/glaze or snowfall pellets occurred in each county. The following filtering operations were applied to data in order to find the freeze days per county:

(a) The first filter identified unique dates in each data type (rime/glaze or snowfall/pellets) per county. This operation avoided counting multiple times the same precipitation occurrence, which could have been recorded by different stations in a county. For example, the raw data showed that on 01-16-2018, rime/glaze was recorded in three stations of Harris County, i.e. Houston Hooks Memorial Airport, Houston Intercontinental Airport, and Houston William P Hobby Airport. The filter function identified that on 01-16-2018, there was one rime/glaze event in Harris County.

(b) Another filter identified unique freeze dates, which were defined as those dates in which either rime/glaze or snowfall/pellets occurred. This operation was performed as it was assumed that deicing trucks operated on that date, regardless of the precipitation form, to avoid cars from slipping and sliding on roadways.

High number of freezing days were determined from the statistical analysis to be at least 10 events over the five year data analysis period. As expected, these results encompassed few counties in Texas, primarily are located in the northern part of the state. During the last five years Texas experienced a total of 756 days of freezing. Figure 3. 5 compares the 2016 and 2018 maps of the counties identified as having experienced freezing events. This illustrates the large variation in this particular meteorological condition in Texas.

Since the meteorological data does not make distinction between plowing, deicing, or traffic assistance measures, we attempted to obtain this information to complement the freezing data. We contacted TxDOT Maintenance Department and the Emergency Management Coordinator to obtain data regarding emergency response procedures during freeze days. However, TxDOT has not responded on a timely manner and the analyses were made based on number of freezing days in 5 years.



2016 **2018**

Figure 3. 5 Freezing Events in 2016 and 2018

Table 3. 4 shows the number and percent of counties and of inspection records by freezing days in five years, As expected for the Texas climate, very few counties had a significant number of freezing days in the past 5 years. These data indicate that 80.5% of the counties had 5 or less freezing days in 5 years, i.e., on the average, they have 1 or less freezing day per year. Only 9.2% of the counties experience 10 or more freezing days in 5 years, i.e., an average of at least 2 freezing days per year; 18.4% inspection records are in these counties.

Table 3. 4 Percentage of Counties and Inspection Records by the Number of Freezing Days in Five Years

Number of Freezing Days in 5 Years	Percent Counties	Percent Inspection Data	Number of Freezing Days in 5 Years	Percent Counties	Percent Inspection Data
0	38.6%	27.7%	10	1.6%	0.5%
1	19.5%	15.0%	11	2.0%	1.5%
2	9.2%	8.6%	12	1.2%	8.2%
3	4.8%	8.5%	13	0.8%	0.2%
4	5.6%	4.9%	14	0.8%	0.9%
5	2.8%	2.6%	15	0.4%	0.3%
6	3.6%	10.0%	16	1.2%	2.1%
7	4.0%	2.8%	18	0.4%	4.1%
8	1.2%	0.5%	37	0.4%	0.4%
9	1.6%	1.1%	38	0.4%	0.1%

Truck Traffic Families

Average daily traffic (ADT) and truck percentages were mined respectively from PonTex Items 29 and 109 or 29A/109A, depending on whether the inventory route (Item 5.1) is on or under the bridge. Truck ADTs were calculated for every inspection year. Variable demographics and potential traffic families for on- and off-system truck ADTs are depicted in Figure 3. 6. The numbers of annual data records are shown above the histogram bars.

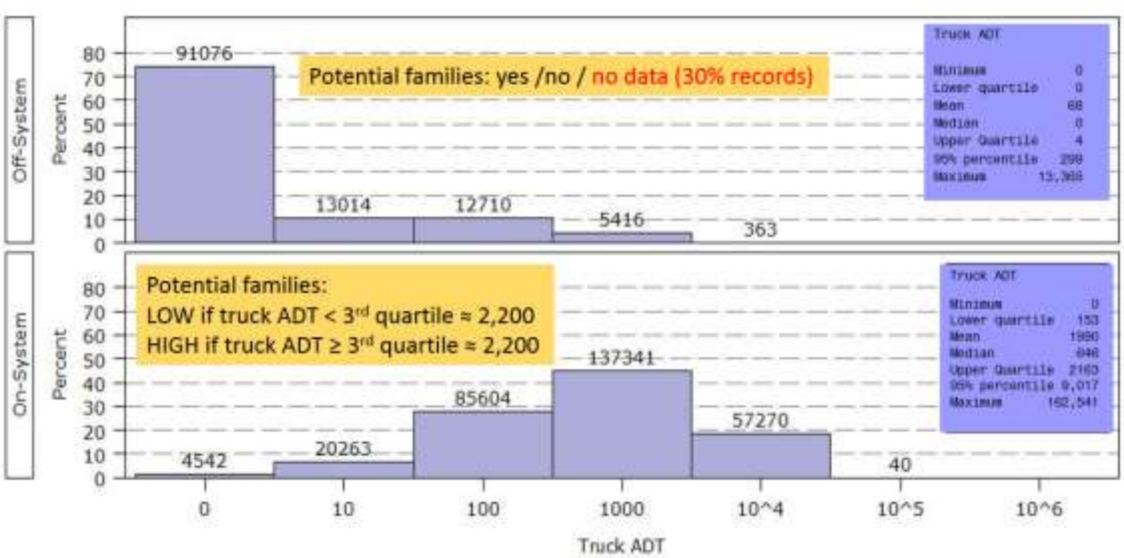


Figure 3. 6 Frequency of Inspection Data by Truck ADT

Truck ADT is available for 99.4% of the on-system inspection years. The missing 0.4% were estimated based on functional class. For off-system, truck ADT is available 69.8% ≈70% of the inspection years. The missing 30% could not be reliably estimated based on other variables.

Implementing on-system traffic families ideally requires assigning families for the 0.6% of the on-system inspections without truck ADT data. Statistical analysis of on-system truck ADT data by functional class indicated that truck ADT families can be assigned to on-system missing data according to Table 3.5. If Item 5.1 is equal to 1, functional class is found in Item 26; otherwise, in Item 26A.

Table 3. 5 Truck Traffic Families Assigned to Missing Truck ADT Data

Functional Class	Assign to Family	Functional Class	Assign to Family	Functional Class	Assign to Family
01	HIGH	13	LOW	25	LOW
02	LOW	14	LOW	26	HIGH
03	LOW	15	LOW	41	HIGH
04	LOW	16	HIGH	42	HIGH
05	LOW	21	HIGH	43	LOW
06	HIGH	22	HIGH	44	HIGH
11	HIGH	23	LOW	45	LOW
12	HIGH	24	LOW	46	HIGH

Summary and Conclusions

PonTex provides nearly all necessary information to reliably model bridge and culvert network performance. Only climatic variables had to be mined from other sources and prepared so that they could be merged onto the data were. However, raw PonTex files are stored in one Access file per year in text format, while modeling requires all data in the same file and in formats conducible to calculations. Moreover, a two-year Markov matrix requires ratings spaced by two years in every structure history.

All this required extensive data mining, analysis and management. The final products of the data preparation task are the following data SAS data sets:

1. Annual inspection history, consisting of PonTex data from 2001 to 2019. The dataset contains 992,119 data records, each with 223 variables. Each record is one year. Used in data exploration and model validation.
2. Bi-annual inspection history, consisting of PonTex data from 2001 to 2019. The dataset contains 537,561 records spaced by 2 years, each with 252 variables. Used in model development and model validation, the latter in conjunction with the annual history.

These databases provided enough data for accurate of transition probabilities estimates. Additional variables to represent model families and age groups were developed and added during model development, and are discussed in the chapters pertaining to each rating models. Chapter 4 documents the modeling methodology.

Chapter 4
Modeling Methodology

Background and Objective

This Chapter documents the development of a methodology to model the deterioration of the four National Bridge Inventory (NBI)/PonTex condition ratings listed below, and to estimate costs to maintain the bridge and culvert network at ratings above 4 (Ref. 51):

- Item 58: deck rating,
- Item 59: superstructure rating,
- Item 60: substructure rating, and
- Item 62: culvert rating.

The ratings consist of integers from 0 (failed condition) to 9 (new condition). The three bridge condition ratings “are used to describe the existing, in-place bridge as compared to the as-built condition.” Culvert ratings also evaluate the overall culvert condition (Ref. 51).

Deck ratings (Item 58) describe “the overall condition rating of the deck. Concrete decks should be inspected for cracking, scaling, spalling, leaching, chloride contamination, potholing, delamination, and full or partial depth failures. Steel grid decks should be inspected for broken welds, broken grids, section loss, and growth of filled grids from corrosion. Timber decks should be inspected for splitting, crushing, fastener failure, and deterioration from rot” (Ref. 51).

The condition of the wearing surface/protective system, joints, expansion devices, curbs, sidewalks, parapets, fascias, bridge rail, and scuppers shall not be considered in the overall deck evaluation. However, their condition should be noted on the inspection form (Ref 51).

Decks integral with the superstructure will be rated as a deck only and not how they may influence the superstructure rating (for example, rigid frame, slab, deck girder or T-beam, voided slab, box girder, etc.). Similarly, the superstructure of an integral deck-type bridge will not influence the deck rating (Ref. 51).

Superstructure ratings (Item 59) “describe the physical condition of all structural members. The structural members should be inspected for signs of distress which may include cracking, deterioration, section loss, and malfunction and misalignment of bearings. On bridges where the deck is integral with the superstructure, the superstructure condition rating may be affected by the deck condition. The resultant superstructure condition rating may be lower than the deck condition rating where the girders have deteriorated or been damaged. Fracture critical components should receive careful attention because failure could lead to collapse of a span or the bridge” (Ref. 51).

Substructure ratings (Item 60) “describe the physical condition of piers, abutments, piles, fenders, footings, or other components. Condition ratings are used to describe the existing, in-place bridge as compared to the as-built condition” (Ref. 51).

Culvert ratings (Item 62) evaluate “the alignment, settlement, joints, structural condition, scour, and other items associated with culverts. The rating code is intended to be an overall condition evaluation of the culvert. Integral wingwalls to the first construction or expansion joint shall be included in the evaluation" (Ref. 51).

Table 4. 1 shows the culvert rating descriptions found in the PonTex Coding Guide, and Table 4. 2 shows the descriptions of bridge condition ratings, used as a guide in evaluating Items 58, 59, 60, respectively deck, superstructure and substructure ratings (Ref. 51).

Table 4. 1 Description of the Culvert Rating Codes

Code	Description
N	Not applicable. *Use if structure is not a culvert.*
9	No deficiencies.
8	No noticeable or noteworthy deficiencies which affect the condition of the culvert. Insignificant scrape marks caused by drift.
7	Shrinkage cracks, light scaling, and insignificant spalling which does not expose reinforcing steel. Insignificant damage caused by drift with no misalignment and not requiring corrective action. Some minor scouring has occurred near curtain walls, wingwalls, or pipes. Metal culverts have a smooth symmetrical curvature with superficial corrosion and no pitting.
6	Deterioration or initial disintegration, minor chloride contamination, cracking with some leaching, or spalls on concrete or masonry walls and slabs. Local minor scouring at curtain walls, wingwalls, or pipes. Metal culverts have a smooth curvature, asymmetrical shape, significant corrosion or moderate pitting.
5	Moderate to major deterioration or disintegration, extensive cracking and leaching, or spalls on concrete or masonry walls and slabs. Minor settlement or misalignment. Noticeable scouring or erosion at curtain walls, wingwalls, or pipes. Metal culverts have significant distortion and deflection in one section, significant corrosion or deep pitting.
4	Large spalls, heavy scaling, wide cracks, considerable efflorescence, or opened construction joints permitting loss of backfill. Considerable settlement or misalignment. Considerable scouring or erosion at curtain walls, wingwalls or pipes. Metal culverts have significant distortion and deflection throughout, extensive corrosion or deep pitting.
3	Any condition described in Code 4, but which is excessive in scope. Severe movement or differential settlement of the segments, or loss of fill. Holes may exist in walls or slabs. Integral wingwalls nearly severed from culvert. Severe scour or erosion at curtain walls, wingwalls or pipes. Metal culverts have extreme distortion and deflection in one section, extensive corrosion, or deep pitting with scattered perforations.
2	Integral wingwalls collapsed, severe settlement of roadway due to loss of fill. Section of culvert may have failed and can no longer support embankment. Complete undermining at curtain walls and pipes. Corrective action required to maintain traffic. Metal culverts have extreme distortion and deflection throughout with extensive perforations due to corrosion.
1	Bridge closed. Corrective action may put back in light service.
0	Bridge closed. Replacement necessary.

Source: Ref. 51

Table 4. 2 Description of the 3 Bridge Rating Codes

Code	Description
N	NOT APPLICABLE
9	EXCELLENT CONDITION
8	VERY GOOD CONDITION — no problems noted.
7	GOOD CONDITION — some minor problems.
6	SATISFACTORY CONDITION — structural elements show some minor deterioration.
5	FAIR CONDITION — all primary structural elements are sound but may have minor section loss, cracking, spalling or scour.
4	POOR CONDITION — advanced section loss, deterioration, spalling or scour.
3	SERIOUS CONDITION — loss of section, deterioration, spalling or scour have seriously affected primary structural components. Local failures are possible. Fatigue cracks in steel or shear cracks in concrete may be present.
2	CRITICAL CONDITION — advanced deterioration of primary structural elements. Fatigue cracks in steel or shear cracks in concrete may be present or scour may have removed substructure support. Unless closely monitored it may be necessary to close the bridge until corrective action is taken.
1	"IMMINENT" FAILURE CONDITION — major deterioration or section loss present in critical structural components or obvious vertical or horizontal movement affecting structure stability. Bridge is closed to traffic but corrective action may put back in light service.
0	FAILED CONDITION — out-of-service beyond corrective action.

Source: Ref. 51

Conceptual Approach

Infrastructure deterioration models' objective is to predict changes in the network condition over time. This is not a straightforward statistical task, since infrastructure deterioration is associated with many factors including age, climate, average daily traffic (ADT), construction materials, design characteristics, and frequency as well type of maintenance. Moreover, the objective of every design, construction and maintenance practices is to reduce deterioration; therefore, infrastructure condition data always minimizes the very phenomenon all infrastructure deterioration models must predict.

A review of the methodologies that have been used to develop bridge deterioration models (see Chapter 2) indicated the Markov process as the best conceptual approach to take full advantage of the availability of 19 years of inspection data. While all Markov models found in the literature assume that a rating can drop only one level in one inspection cycle, this assumption was completely wrong for the inspection data base discussed in Chapter 3. This is discussed below.

Conceptually, the Markov process represents the 10 bridge condition ratings (from 0 to 9) as a row vector of 10 Markovian states. The bi-annual inspection data base, developed as discussed in Chapter 3, was used to calculate probability p_{ij} that each state i will either remain as i or transition to each worse state i-1, i-2, etc., in a certain period. These probabilities were arranged into a 10 by 10 transition probability matrix. The selected transition period was 2 years, the predominant inspection cycle.

Table 4. 3 illustrates one of the many transition probability matrices developed during this project and is used to explain the Markov concept. Rows and columns are numbered according to the ratings. Rows are

initial ratings and columns are future ratings. Each matrix cell is the probability of each rating changing into the rating shown in the columns after 2 years. For example, after 2 years a current rating of 9 has 14.09% probability of remaining as 9, 52.48% probability of decreasing to 8, 32.07% probability of decreasing to 7, and 1.36% probability of dropping to 6. Each probability is calculated as:

$$P_{i,j} = \frac{n_{i,j}}{n_i} \quad [4.1]$$

Where:

$i \geq j$

i = 0, 1, 2,…9

j = 0, 1, 2,…9

P_{ij} = probability of transitioning from condition i to condition j in two years

n_{ij} = number of data points in condition i in year y, that transitioned to condition j in year y+2

n_i = total number of data points in condition i in year y.

The condition i ≥ j means that the calculations do not include rating improvements, since the objective is to estimate deterioration. The calculations must consider all ratings remaining unchanged, even though it is impossible to determine if this means no deterioration in 2 years, or if there was maintenance during the 2-year interval to ensure no change in the rating. Therefore, all models may underestimate true deterioration to an unknown extent. On the other hand, considering only ratings that actually decreased in 2 years would certainly overestimate deterioration, disregard a considerable amount of reliable data, and result in excessive maintenance budgets.

Table 4. 3 Example of a Markov Transition Probability Matrix

	9	**8**	**7**	**6**	**5**	**4**	**3**	**2**	**1**	**0**
9	0.1409	0.5248	0.3207	0.0136	0	0	0	0	0	0
8	0	0.6431	0.3455	0.0108	0.0004	0.0001	0	0	0	0
7	0	0	0.9255	0.0715	0.0029	0.0001	0.0000	0.0000	0	0
6	0	0	0	0.9549	0.0427	0.0021	0.0002	0.0000	0	0
5	0	0	0	0	0.9628	0.0312	0.0057	0.0003	0	0
4	0	0	0	0	0	0.9583	0.0336	0.0071	0	0.0010
3	0	0	0	0	0	0	0.9826	0.0174	0	0
2	0	0	0	0	0	0	0	0.9091	0.0909	0
1	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	1

The program nulls the transition probabilities in matrix rows with less than 9 non-negative transitions, since this would result in unreliable probability estimates. It sets to 1 the probability of rating=0 remaining as zero, since a rating cannot deteriorate any further. The program also sets to zero all probabilities of rating improvements, since the objective is to estimate deterioration.

Elevating the two-year transition probability matrix to the nth power ages the matrix by 2n years. The project calculated predictions every two years, up to 18 years, to stay within the database time range.

Markov matrices are the basis for calculating network condition forecasts and deterioration curves. These calculations are discussed in the next section.

In the Markov approach, variables associated with deterioration are taken into account as modeling families. For example, if the exploratory data analysis indicates that material type appears to impact a bridge or culvert condition rating, each material type, or each group of similar materials, defines a potential modeling family. Each family might be further split by another explanatory variable, and/or by age groups. The selection of modeling families must strike a balance between considering all potential variable combinations, and ensuring enough data points for a meaningful transition probability matrix. Separate model families and/or age groups are recommended for practical implementation if the differences among 10-year network condition forecasts are meaningful for practical infrastructure management purposes.

Conceptual Model Results

Matrices analogous to Table 4. 3 were developed for each viable age group in each family, for each age group in the aggregated on- and off-system subsets, and for aggregated on- and off-system ratings. Then, each matrix was elevated to the 2nd, 3rd, 4th, 5th,6th, 7th, 8th, and 9th power, totaling 9 transition probability matrices, which estimate the probability of deterioration after 2, 4, 6, 8, 10, 12, 14, 16, and 18 years.

For each bridge rating, these 9 Markov matrices were used to calculate two types of forecasts every two years: rating deterioration with time, and network condition forecasts by number of bridges or culverts, and by bridge area. These calculations are explained below. Variables to calculate culvert area are missing for 29% of the on-system and 47% of the off-system culvert data points.

Expected future values of each rating after 2, 4, etc. years were calculated as depicted in Equation 4.2. Results are reported in Product 2 as deterioration tables and as deterioration curves, which are illustrated respectively in Table 4. 4 and in Figure 4.1. Each row in Table 4. 4 corresponds to a graph in Figure 4. 1.

Table 4. 4 Deterioration Table Example

RATING	Expected Value 2 years later	Expected Value 4 years later	Expected Value 6 years later	Expected Value 8 years later	Expected Value 10 years later	Expected Value 12 years later	Expected Value 14 years later	Expected Value 16 years later	Expected Value 18 years later
9	7.793	7.404	7.185	7.027	6.901	6.796	6.704	6.621	6.545
8	7.631	7.367	7.170	7.017	6.894	6.790	6.699	6.617	6.542
7	6.922	6.847	6.773	6.702	6.632	6.564	6.498	6.433	6.369
6	5.952	5.905	5.857	5.810	5.763	5.716	5.669	5.622	5.576
5	4.956	4.913	4.869	4.825	4.781	4.737	4.693	4.648	4.604
4	3.948	3.897	3.846	3.796	3.746	3.696	3.647	3.597	3.548
3	2.983	2.964	2.943	2.919	2.893	2.865	2.836	2.806	2.774
2	1.909	1.736	1.578	1.434	1.304	1.185	1.078	0.980	0.891
1									
0									

Equation 4.2 was used to generate each cell in Table 4. 4.In order to clarify these calculations, below each equation term is an example: the calculation of the 7.793 expected value of rating 9 after 2 years, the first cell in Table 4. 4.

$$E(R,n) = [\mathbf{Z}_R * (\mathbf{M}^{n/2})] * \mathbf{R} \quad [4.2]$$

Where:

E(R,n) is the expected future value of rating R after n years.
Example: E(9,2)= 7.793 in Table 4. 4

$\mathbf{Z}_R$ is a 1 by 10 row vector containing 1 in the column corresponding to the desired rating, and zeroes elsewhere.
Example: $\mathbf{Z}_R$ = [1,0,0,0,0,0,0,0,0,0] since in this example R=9

M is the two-year transition probability matrix
Example: Table 4. 3

n is the number of years of the forecast
Example: n=1→ 2-year forecast

The product $\mathbf{Z}_R$*($\mathbf{M}^{n/2}$) selects the R^{th} row from the transition probability
Example: [1,0,0,0,0,0,0,0,0,0] * Table 4. 3 =[0.1409, 0.5248, 0.3207 ,0.0136, 0, 0, 0, 0, 0, 0]

R is the 10 by 1 column vector of ratings depicted in the first column of Table 4. 3

$$E(9,2) = 7.793 = [0.1409, 0.5248, 0.3207\ ,0.0136, 0, 0, 0, 0, 0, 0] * \begin{bmatrix} 9 \\ 8 \\ 7 \\ 6 \\ 5 \\ 4 \\ 3 \\ 2 \\ 1 \\ 0 \end{bmatrix}$$

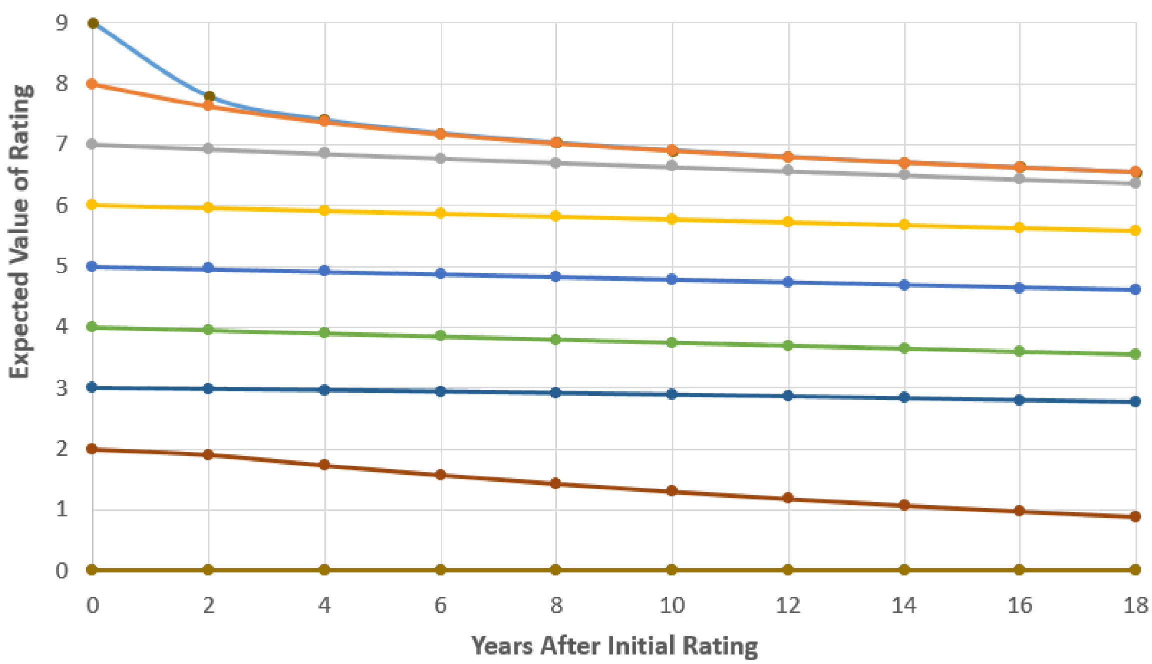


Figure 4. 1 Deterioration Curves Example

Table 4. 5 and Table 4. 6 show examples of network condition forecasts, respectively by number of bridges and by bridge area. In Product 2, the implementable deliverable, these tables automatically update when the number of bridges and the total area at each current rating is updated in the "current number" column.

Table 4. 5 Network Condition by Number of Bridges

		Predicted Bridges for Number of Years Later								
Rating	**Current Number**	**2**	**4**	**6**	**8**	**10**	**12**	**14**	**16**	**18**
9	*118*	17	2	0	0	0	0	0	0	0
8	*1,651*	1,124	731	472	303	195	126	81	52	33
7	*12,210*	11,909	11,415	10,818	10,176	9,523	8,881	8,263	7,675	7,121
6	*6,797*	7,383	7,913	8,380	8,780	9,115	9,387	9,600	9,758	9,867
5	*1,297*	1,575	1,866	2,168	2,476	2,788	3,101	3,412	3,719	4,019
4	*100*	152	213	280	355	438	527	623	725	833
3	*15*	27	42	61	84	110	141	176	215	259
2	*3*	5	7	9	13	17	22	27	34	42
1	*0*	0	0	1	1	1	2	2	2	3
0	*0*	0	0	0	1	1	2	2	3	3

Table 4. 6 Network Condition by Bridge Area

		Predicted Area for Number of Years Later (1000 Sq.Ft)								
Rating	**Current Area**	**2**	**4**	**6**	**8**	**10**	**12**	**14**	**16**	**18**
9	*4,729*	666	94	13	2	0	0	0	0	0
8	*30,285*	21,959	14,472	9,357	6,025	3,876	3,682	1,603	1,031	663
7	*248,391*	241,869	231,653	219,428	206,320	193,034	192,977	167,447	155,528	144,299
6	*128,751*	141,088	152,258	162,105	170,579	177,698	177,901	188,139	191,641	194,128
5	*27,699*	32,893	38,397	44,141	50,054	56,070	56,112	68,169	74,148	80,019
4	*2,133*	3,216	4,441	5,808	7,317	8,964	8,969	12,648	14,670	16,801
3	*447*	699	1,015	1,400	1,859	2,395	2,396	3,713	4,501	5,378
2	*16*	54	103	164	238	326	326	549	686	840
1	*0*	1	5	9	15	22	22	39	50	62
0	*0*	2	5	10	16	23	23	43	56	71

Each cell in Table 4. 5 is calculated by multiplying the current number of bridges by each transition probability in the Markov matrix corresponding to the desired number of years in the future, and adding up the results for each rating. Results are rounded to the nearest integer. For example, 11,909 bridges are predicted for rating 7 two years later. This number was calculated according to Equation 4.3. Analogous calculations are made to obtain results by area depicted in Table 4. 6.

$$11{,}909 = 118 * 0.3207 + 1{,}651 * 0.34552 + 12{,}210 * 0.92551 \qquad [4.3]$$

Where:

11,909 is the number of bridges predicted for rating 7 two years later (see Table 4. 5)

118 is the number of bridges currently at rating 9 (see Table 4. 5)

0.3207 is the probability of rating 9 dropping to 7 in 2 years (see Table 4. 3)

1,651 is the number of bridges currently at rating 8 (see Table 4. 5)

0.3455 is the probability of rating 8 dropping to 7 in 2 years (see Table 4. 3)

12,210 is the number of bridges currently at rating 7 (see Table 4. 5)

0.9255 is the probability of rating 7 remaining as 7 in 2 years (see Table 4. 3)

Exploratory Data Analysis

Prior to developing the transition probability matrices and using them to obtain the type of results discussed in the previous section, it was necessary to select PonTex variables that are good candidates to define modeling families. This section describes the methodology used to select potential modeling families for further analysis.

Methodology

Age, material type, structure type, environmental factors, traffic, etc., may affect infrastructure performance even with the best design and construction practices, and with the best funded maintenance programs. Therefore, their impact must be investigated during the modeling phase. However, it is impossible in this case to use the traditional statistical modeling technique: plotting the data to visualize the trends, then fitting correlations. This is clearly illustrated in Figure 4. 2 and Figure 4. 3, the on- and off-system scatterplots of bridge age versus deck ratings. Data scatter looks even worse when overlaying plots by variables such as rainfall or truck traffic families. Alternative ways to visualize trends were investigated, and the best were boxplots of age at each rating.

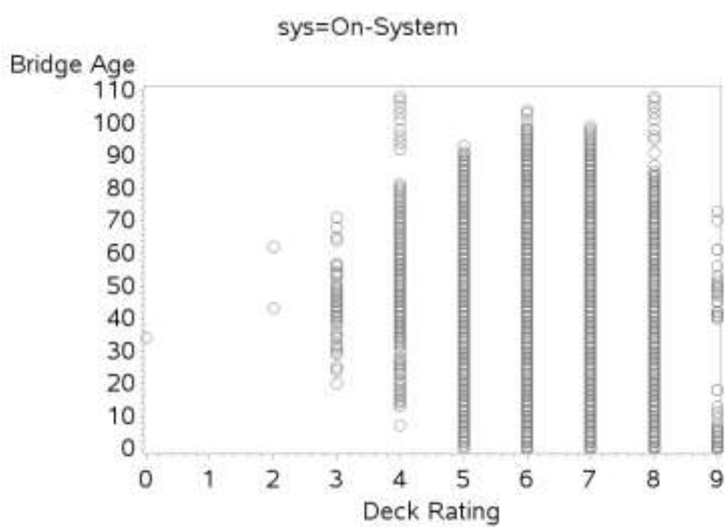


Figure 4. 2 On-System Bridge Age versus Deck Ratings

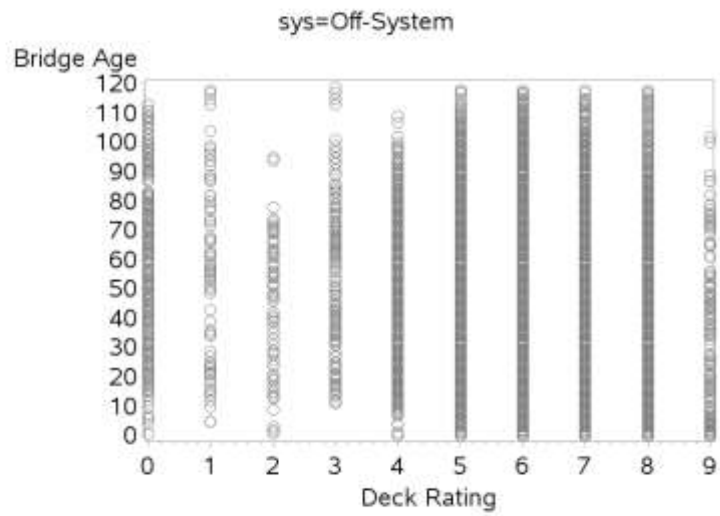


Figure 4. 3 Off-System Bridge Age versus Deck Ratings

Figure 4. 4 depicts the boxplots corresponding to the on-system scatter plot depicted in Figure 4. 2, and is used to explain boxplot symbols. Unlike the scatter plots, Figure 4. 4 assists in visualizing age trends at each rating. One can see that the better the rating, the newer the deck. One can also see that, on the average, ratings of 7, 8, and 9 decrease faster than ratings of 6 or less, possibly due to maintenance. Boxplots of this type, comparing factors such as average daily truck traffic levels, rainfall levels, and material types, were instrumental in evaluating each variable's potential to define modeling families.

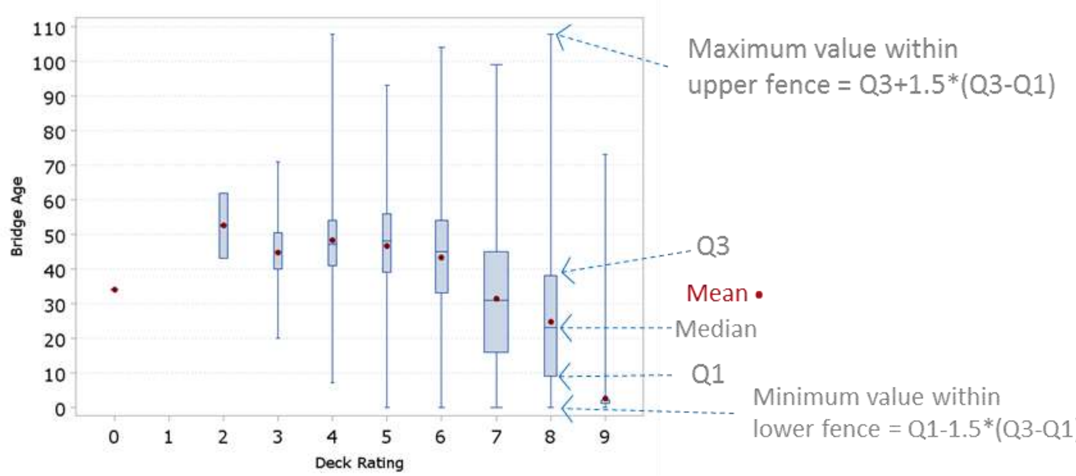


Figure 4. 4 Example of Age Boxplots by On-System Deck Ratings

An example extracted from the discussions in Chapter 6 clarifies this part of the methodology. Figure 4. 5 shows one of the many boxplots used to evaluate potential substructure foundation modeling families. The plots appear to follow logical trends, with drilled shafts performing best, followed by concrete piling. Spread footing, appears to age faster than the other types. All other foundation types were grouped to ensure enough data for meaningful transition probability estimates.

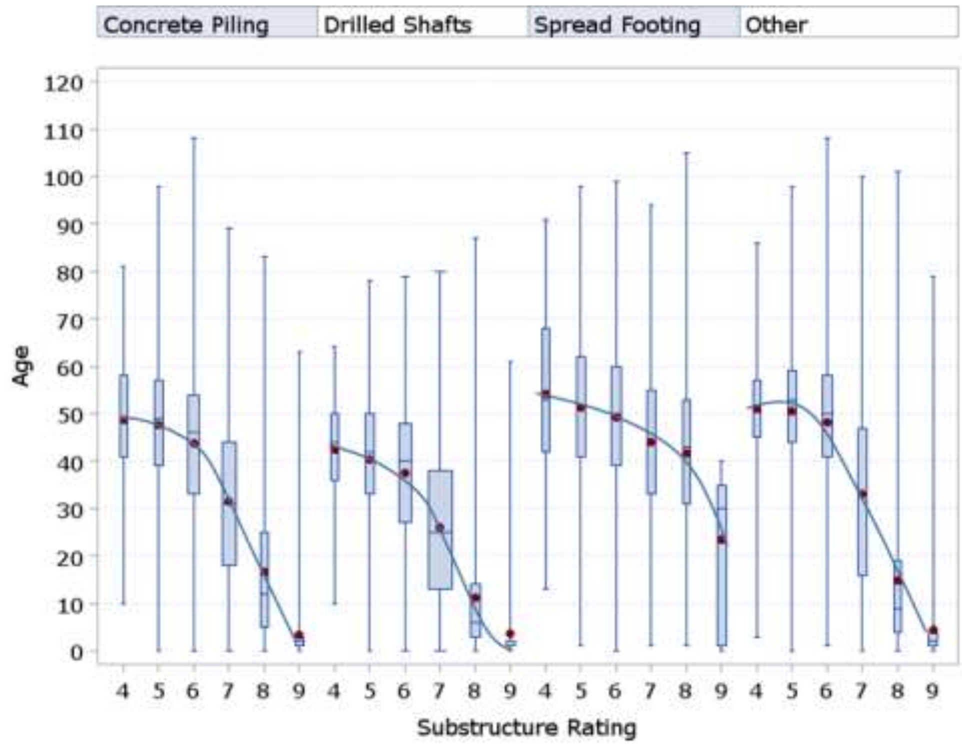


Figure 4. 5 Example of Age Boxplots by Potential Substructure Modeling Family

Note: on system substructure types below ground

In Figure 4. 5 case, the differences in aging for each rating average either less than or close to 10 years. Given the wide data spread and the frequently used 10-year forecast period, these differences are considered too small to justify modeling by families.

When the potential families showed more than 10-year difference in aging for most ratings, they were modeled separately, and statistical summaries of the bridge or culvert age by family were prepared and checked against the boxplots. If the differences among family ages were similar to the differences in the boxplots, age and family effects are clearly confounded, and groups defined based on that particular variable were excluded from consideration as modeling families.

Age Groups

Age was plotted in boxplot format to help investigate potential modeling families, but it is also an important explanatory variable in infrastructure deterioration. Therefore, the next step was to define age groups for modeling. Overall on-system and off-system age groups were defined for bridges and for culverts using the criteria described below. Similar analyses were performed for age groups within families.

Age group thresholds are age percentiles rounded to the nearest integer. Considering the desired 10-year horizon for infrastructure management purposes, and the need to develop unbiased transition probability matrices from scattered data, age groups must:

- Contain enough data to develop a valid transition matrix, and
- Be defined by age thresholds more than 10 years apart, to be consistent with the preferred 10-

year forecast horizon.

Age thresholds defined by quartiles were investigated first, but matrices estimated with only ¼ of the data resulted in increased errors. It was therefore decided to define 3 age groups, with the 33% and 67% percentiles as thresholds. All ages were rounded to the nearest year.

Figure 4. 6 shows the histogram of culvert ages in the inspection data base used to develop the Markov matrices for culvert ratings. On-system culverts as a group are older than off-system culverts. Age thresholds that divide off-system culverts into 3 groups are 0 to 17, 18 to 34 and 35 and older. On-system age thresholds are 0 to 32, 33 to 48 and 49 and older. Additional age groups by families were developed as needed and are discussed in the pertinent chapters.

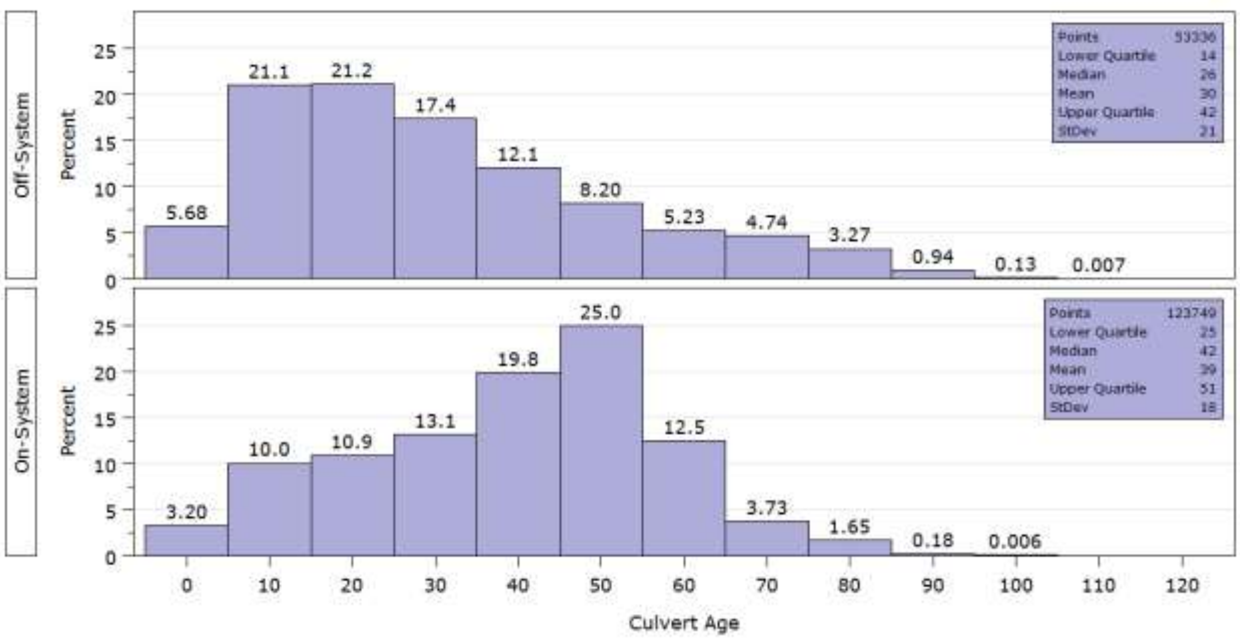


Figure 4. 6 Distribution of Culvert Ages

Figure 4. 8 shows the histogram of bridge ages in the inspection data base used to develop the Markov matrices for deck, superstructure and substructure ratings. On-system bridges as a group are older than off-system. Thresholds that divide on-system bridges into 3 age groups are 0 to 22, 23 to 43, and 44 and older. Off-system age group thresholds are 0 to 16, 17 to 34, and 35 and older. Additional age groups by families were developed when appropriate, and are discussed in the chapters pertaining to substructure, superstructure and deck models. Splitting families by age groups required additional statistical analysis, to ensure that the transition probability matrices do not confound the effects of age and those of the variables defining the families.

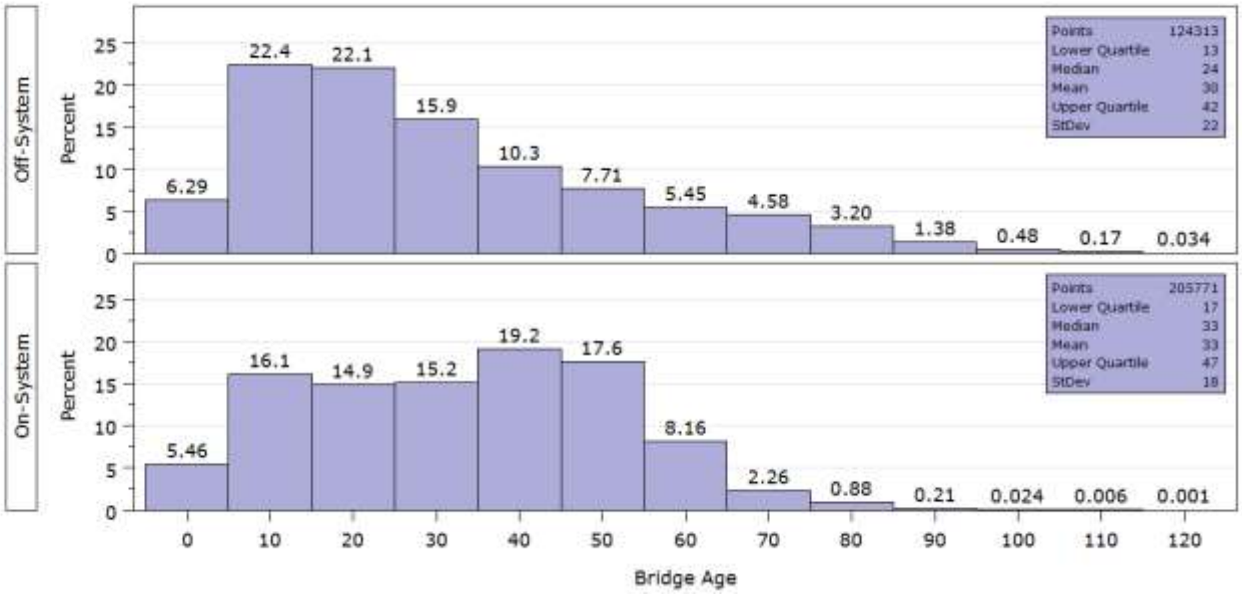


Figure 4. 7 Distribution of Bridge Ages

Modeling by age groups within families is meaningful only when families have approximately the same age distribution. If ages differ significantly among families, the effects of age and the variables defining the families are confounded. Figure 4. 8 shows the histogram of on-system bridge ages by truck ADT families. The Low Truck ADT family is slightly older, but not enough to preclude modeling by truck ADT families by age groups if there are enough data points in each age group by family.

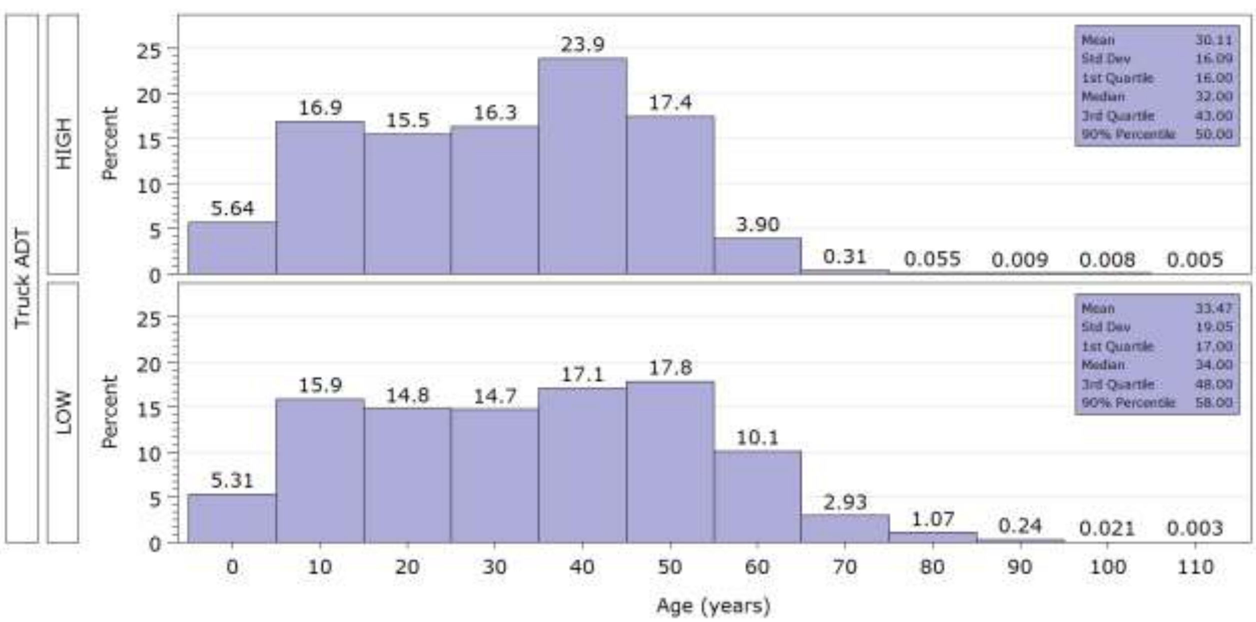


Figure 4. 8 Distribution of On-System Bridge Ages by Truck ADT Families

Rainfall families may have some confounding effects of age, and it may not be possible to develop deterioration models that take into account rainfall and age effects without some confounding. in Table 4. 7 shows the on- and off-system summary statistics of bridge age by rainfall family. While these age differences that do not preclude modeling by rainfall families, careful analysis is necessary and results should be interpreted accordingly. For example, bridges in Rain2 areas are older as a group than all others, while Rain4 bridges are the newest (Rain4 is the wettest areas). If a Rain2 model predicts more deterioration than a Rain4 model, but this would be due to confounding effects of age. These issues are discussed in detail in the Chapters documenting the models.

Table 4. 7 Bridge Age Statistics by Rainfall Family

	Rainfall Family	**Data Points**	**Bridge Age Statistics**						
						Percentiles			
			Mean	*Std. Dev.*	*Skewness*	*25%*	*Median*	*75%*	*90%*
Off-System	*Rain1*	5,876	38.05	21.789	0.538	21	35	53	68
	Rain2	9,320	43.15	26.385	0.078	19	43	67	78
	Rain3	54,876	30.63	23.146	0.999	13	24	44	67
	Rain4	51,845	25.13	17.636	1.126	12	21	34	50
On-System	*Rain1*	24,293	32.77	17.325	0.064	19	34	46	54
	Rain2	25,097	37.16	18.236	-0.144	24	40	50	59
	Rain3	89,382	31.59	18.368	0.170	16	32	46	55
	Rain4	63,921	31.59	18.120	0.187	16	31	46	55

Model Validation Approach

Model validation was implemented using the annual inspection history from 2001 through 2019 in conjunction with the bi-annual inspection history. It was based on the time-honored method of comparing forecasts to observations and estimating the standard error as depicted in Equation 4.4. The transition probability matrices developed from the data age the network by 2 years; therefore, each matrix was validated by comparing 2-year network condition forecasts to the network condition 2 years later, for the same bridges or culverts.

$$STE_y = \frac{\sqrt[2]{\sum_R (Pred_R - Obs_R)^2}}{n-1} \qquad [4.4]$$

Where:

STE_y = standard error of year y forecasts prepared with year y-2 data

$Pred_R$ = predicted rating "R" count in year y

Obs_R = observed rating "R" count in year y for the same structures present in the data used to age year y-2 ratings by 2 years

n = total number of ratings in year y (or in y-2, since they are the same structures)

R = 0 to 9 (ratings).

This comparison was done for every available pair in the data base. For example, 2001 data was used to prepare 2003 network condition forecasts, which was then compared to the 2003 condition of the same bridges or culverts. Analogous comparisons were made for 2002/2004, 2003/2005, etc., up to 2017/2019. These 17 standard errors were averaged to obtain an overall standard error estimate for the transition probability matrix. Table 4. 8 illustrates an example of the yearly standard errors of the network condition forecasts for the aggregated on-system substructure ratings. These intermediate results were saved for illustrative purposes while coding the SAS™ program that calculated the overall standard error of the matrix. All other calculations were automated and the minimum, mean and maximum standard errors were reported in each case.

Table 4. 8 Standard Errors of the 2-Year Transition Probability Matrix, On-System Substructure Rating

Prediction Year	Data Year	Standard Error	Prediction Year	Data Year	Standard Error
2003	2001	3.4%	2012	2010	4.0%
2004	2002	3.2%	2013	2011	4.4%
2005	2003	2.9%	2014	2012	4.8%
2006	2004	3.1%	2015	2013	4.1%
2007	2005	3.8%	2016	2014	3.3%
2008	2006	4.0%	2017	2015	2.9%
2009	2007	3.8%	2018	2016	2.6%
2010	2008	4.5%	2019	2017	2.8%
2011	2009	4.1%			

Minimum: 2.6%
Mean: 3.6%
Maximum: 4.8%

Model Development Methodology

Summary

The overall methodology started with the exploratory data analysis to select potential modeling families, as explained below. Transition probability matrices were then developed for each viable age group in each potential family. Transition probability matrices were also developed for the aggregated on-system and aggregated off-system ratings, as well as for the 3 on-system and the 3 off-system age groups in all 4 ratings. These on- and off-system aggregated models were necessary as a basis for comparison, but they were always implemented in Product 2 workbooks for future convenience. Comparisons among aggregated model results, results by age groups and results by families were performed to recommend the set of models for implementation in infrastructure management. Cost forecasts included in Product 2 workbooks are discussed in Chapter 9.

Stepwise Methodology

The steps below were applied to develop models for substructure, superstructure, deck and culvert ratings. Steps 1 through 4 consisted of the exploratory data analysis to determine potential modeling families. The remaining steps consisted of model development and validation.

Step 1. Based on engineering judgement, select PonTex variables that may affect each rating deterioration and investigate if these variables are fully or almost fully populated. A significant number of missing variables occurred more often in off-system bridges and culverts than on-system.

Step 2. For variables that are fully populated, analyze the number of data points in each value of the variable. Aggregate variable values that represent similar characteristics into one family. Example: below-ground substructure families in Figure 4. 5. These 4 families were grouped from PonTex Item 44.1: Substructure Type, Main Spans, below ground (1^{st} digit). This variable has 9 different main span types, which were grouped into the 4 major types depicted in Figure 4. 5 to ensure sufficient number of points for modeling. Details are discussed in Chapter 6.

Step 3. Check the feasibility of splitting families by age groups. If feasible, define age groups per family. As discussed previously, these age groups must contain enough data points for accurate transition probability estimates. In addition, their thresholds must be significantly greater than 10 years, which according to TxDOT is the most common forecast horizon.

Step 4. Prepare comparative boxplots of bridge or culvert age by rating, and analyze the differences among families and age groups within families when applicable. Select for further analysis families with aging differences greater than 10 years and where family age as a group, and difference in performance by family, are not confounded.

Step 5. Develop a transition probability matrix for each age group in each family. An example is Table 4. 3 in the Conceptual Approach section.

Step 6. Prepare results similar to those discussed in the Conceptual Model Results section: rating deterioration every two years, tabulated and plotted; tables with network condition forecasts every 2 years by number of bridges or culverts, as well as by bridge area. For eaqch rating, these results were developed for:

- Each feasible age group in each family,
- Aggregated by family,
- Aggregated on-system,
- Aggregated off-system,
- On-system by age groups, and
- Off-system by age groups.

Step 7. Calculate the average standard error of the 2-year network condition forecasts, and flag families and/or age groups where the magnitude of the error is close to the magnitude of the differences in forecasts among families and/or age groups.

Step 6. Compare differences among age groups and families, with emphasis in the 10-year forecasts, and select families and age groups for implementation, with emphasis on 10-year network condition forecasts.

Step 8. Develop Product 2 Excel workbooks for implementation, for each selected family and age group in each rating.

Step 9. Apply the methodology discussed in Chapter 9 to forecast costs to keep the existing bridge and culvert network with ratings above 4.

Conclusions

- As discussed in Chapter 2, all Markov-based bridge rating models found in the literature assume that the rating can drop only by one level in one inspection cycle. This research found that such assumption is completely wrong, as previously illustrated in Table 4. 3. Our modeling methodology calculates all observed transitions.
- Data scatter precludes reliable or useful models consisting of equations that correlate ratings to age and other variables. Markov transition probability matrices were developed.
- Data scatter also render scatter plots useless to inspect data behavior.
- Boxplots of bridge or culvert age by rating comparing potential families, used in conjunction with statistical summaries of bridge or culvert age by family, were used to select potential families for further analysis.
- Any infrastructure condition data always reflects design, construction and maintenance practices to counteract or prevent as much deterioration as possible. Therefore, data that represents true deterioration resulting from a do-nothing approach does not exist, and all models are approximations.

Chapter 5
Culvert Deterioration Models

Background and Objectives

This Chapter documents the development of deterioration models for National Bridge Inventory (NBI)/PonTex Item 62: culvert ratingAccording to the NBI/PonTex Coding Guide, Item 62 “evaluates the alignment, settlement, joints, structural condition, scour, and other items associated with culverts. The rating code is intended to be an overall condition evaluation of the culvert. Integral wingwalls to the first construction or expansion joint shall be included in the evaluation” (Ref. 51).

Chapter 9 discusses cost forecasts to maintain the culvert network above rating 4, developed based on the models results. Chapter 4 explains in detail the ratings and the modeling methodology used to develop results presented in this chapter. The underlying methodology is conceptually the same for the culvert rating and the 3 bridge ratings. The next section discusses the results of the Exploratory Analysis of culvert ratings. This analysis was part of this project’s Task 4, which defined prospective families for further analysis during the model development phase.

Exploratory Analysis of Culvert Ratings

Summary of Available Data

As explained in detail in Chapter 3, the culvert modeling database contains 177,085 bi-annual ratings for 20,822 culverts; data were mined from PonTex files from 2001 to 2019, which were provided by TxDOT. Culvert data are split into:

- 6,628 off-system culverts, with 53,336 bi-annual inspection ratings, and
- 14,194 on-system culverts with 123,749 bi-annual inspection ratings.

In addition to the climatic variables obtained and analyzed in this project as discussed in Chapter 3, the following PonTex variables were considered potentially relevant for culvert deterioration and tested as potential families for modeling Item 62, culvert rating:

- Age: calculated from Item 27 (year built) or Item 106 (year reconstructed), and the file year.
- Span type: Item 43.4 first digit
- Material: Item 43.4 second digit
- Truck AADT: calculated from Items 29 (AADT) and 109 (percent trucks), as explained in Chapter 3.
- Length of largest box: Item 48
- Fill/no fill: Item 68 (deck geometry).

Figure 5. 1 shows the histogram of on- and off-system culvert inspection ratings from 2001 to 2019. The graph inset shows the main statistical measures of the distributions. Data comes from the modeling data base containing 177,085 ratings spaced every two years (see Chapter 3 for explanation on development of this database from 19 yearly NBI/PonTex Access files).

The impact of good maintenance is clear for both on and off-system culverts. Both distributions have negative skewness, i.e., they have more high ratings than low ratings; in addition, ratings below 5 are nearly absent. The most frequent rating (mode) is 7 for both on- and off-system. Over 90% of all ratings are either 6 or 7, for both on- and off-system culverts (respectively 93.9% and 90.9%). Mean ratings are between 6 and 7, and 95% of the ratings are 6 or better. Half the ratings are 7 or above (median ratings). Low standard deviations underscore consistency in maintenance quality.

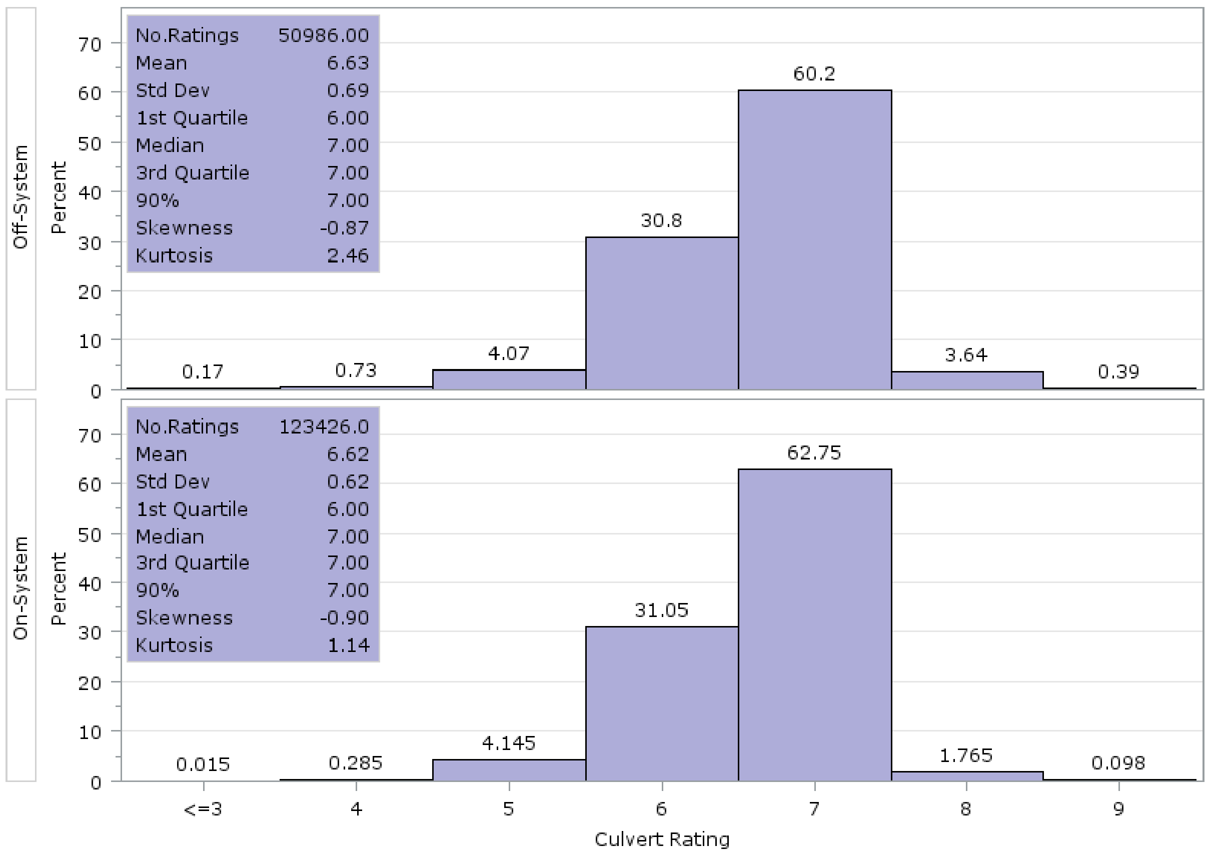


Figure 5. 1 Culvert Ratings Histograms

Culvert Type

Item 43.4—Structure Type, Culvert is a two-digit variable. The first character of this variable is the culvert span type (single or multiple box, single or multiple pipe, and other). The second digit stores the main member type of material, such as steel, concrete, etc. (Ref. 51).

Texas culverts are predominantly multiple concrete boxes: 94.7% of on-system data points consist of multiple box, concrete culverts; and 92.4% off-system data points consist of multiple box, concrete (82.1%) or pre-stressed/precast (10.3%) culverts.

The length of the largest box is stored in Item 48—Length of Maximum Span (Ref. 51). 98.65% of all on system culverts have the longest box of 10ft or less, and 96.24% of all off-system culverts have the longest box 12 ft or less. Conclusion: culverts are basically all the same type, so there are no modeling families.

Climatic Variables

Figure 5. 2 shows the boxplots of on- and off-system culvert ages by rating, comparing the four rainfall families developed as documented in Chapter 3. Rainfall intensity increases in numeric order: Rain1

(driest) to Rain4 (wettest). On-system culverts show no differences among the four groups. Off-system culverts show some difference, but the deterioration does not consistently increase as rainfall increases; Rain1 areas show more deterioration than Rain2, which is wetter. Therefore, it is not possible to develop meaningful deterioration estimates by rainfall families.

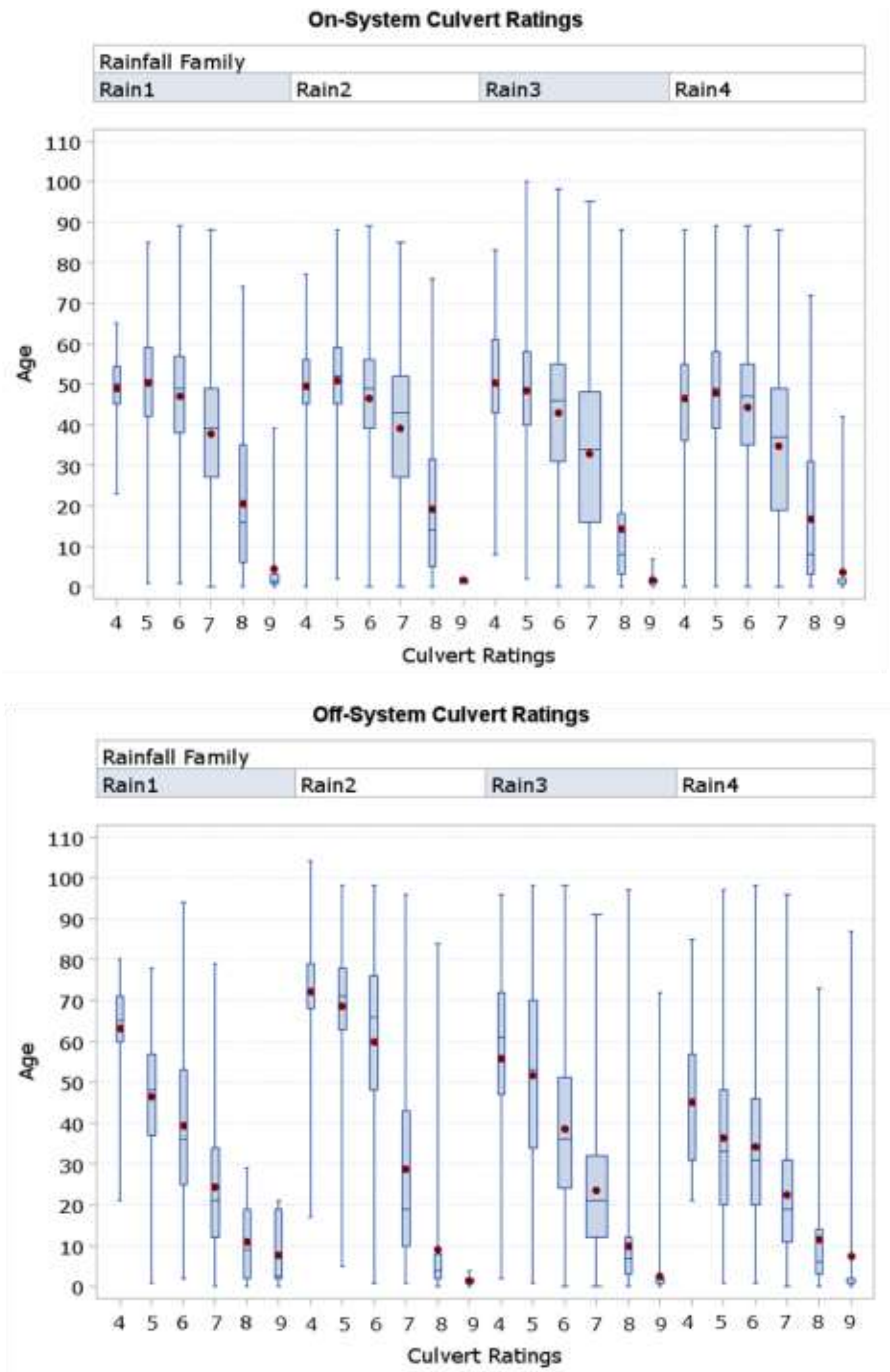


Figure 5. 2 Boxplots of Culvert Age by Rainfall Precipitation

Figure 5. 3 shows boxplots of age by rating, comparing the two families defined by the freezing days' thresholds developed as documented in Chapter 3. Both on- and off-system culverts appear to reach low ratings faster in locations subject to the highest number of freezing days per year. However, counties with 10 or more freezing days per year total less than 1% of all data points, are too few to provide enough transitions to estimate reliable Markov probability matrices.

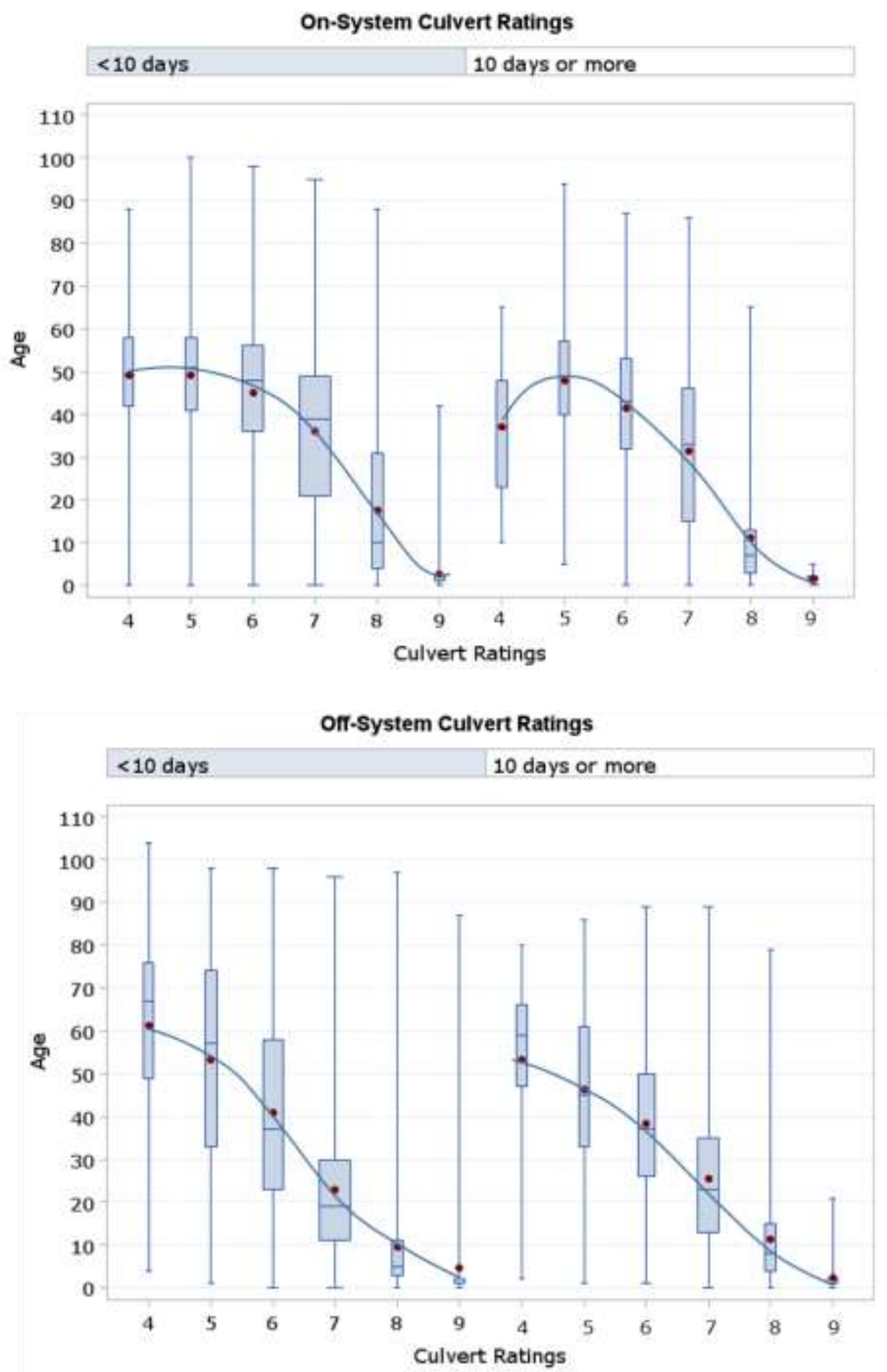


Figure 5. 3 Boxplots of Culvert Age by Ratings and Number of Freeze Days in the Last 5 Years

Average Daily Truck Traffic (ADTT)

As documented in detail in Chapter 3, Item 29 (average daily traffic) and Item 109 (percent trucks) are not populated enough in off-system culverts to allow meaningful modeling by ADTT families: approximately 30% of the data points are missing traffic data.

On-system culverts are almost fully populated with truck traffic data, which were split into "HIGH" and "LOW" Average Daily Truck Traffic (ADTT) according to the criteria documented in Chapter 3. Figure 5. 4 shows the boxplot of on-system culvert ages by ratings and truck traffic families. The high ADTT family decreases ratings about 10 years earlier than the low ADTT group. This result suggests two prospective on-system ADTT families: HIGH (2,200 trucks per day or greater) and LOW. Culverts that do not have on-system truck traffic information (0.3% of the available data points) are displayed in Figure 5. 4 for illustrative purposes: they are basically new culverts, since most data points are less than 10 years old. For modeling purposes, and for subsequent implementation at TxDOT, they can be assigned to an ADTT family based on functional class, as discussed in Chapter 3 and also explained in Product 0-6979-2, Implementation Manual.

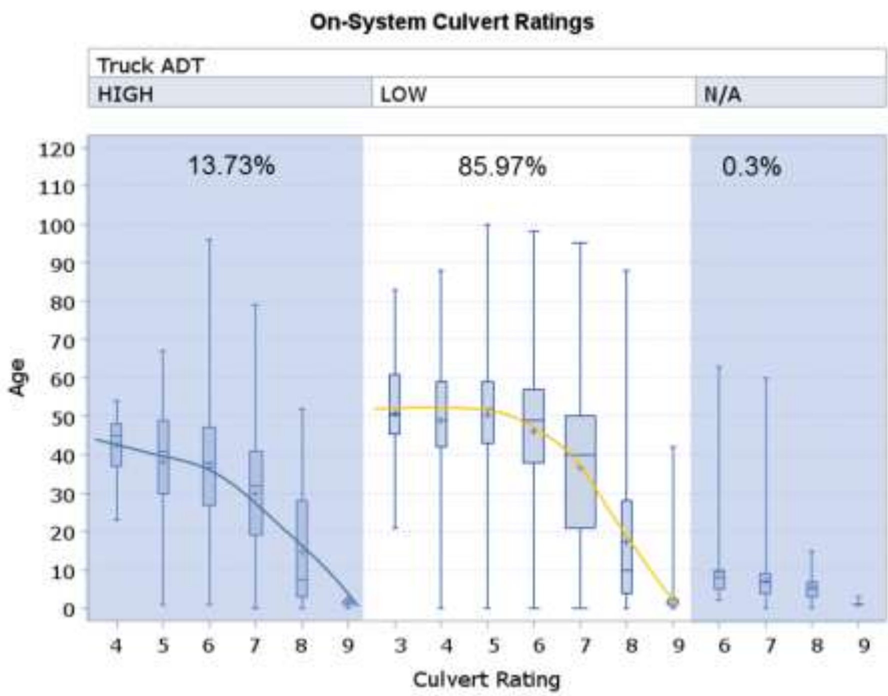


Figure 5. 4 Boxplot of On-System Culvert Age by Rating and Traffic Family

Since nearly 86% on-system culverts are in low truck traffic roads, we examined the impacts of precipitation on this particular subset of culverts. As depicted in Figure 5. 5, there was no difference among the four precipitation families.

Under Fill/No Fill

Item 68—Deck Geometry, takes the value of "N" for culverts under fill, and a code from 2 to 9 that depends on the ADT and the out-to-out measurement of the travel-way surface plus shoulders or face-to-face measurements of the curbs or rails, whichever is more restrictive (Ref. 51). Item 68 was used to create a binary variable for whether or not the culvert is under fill.

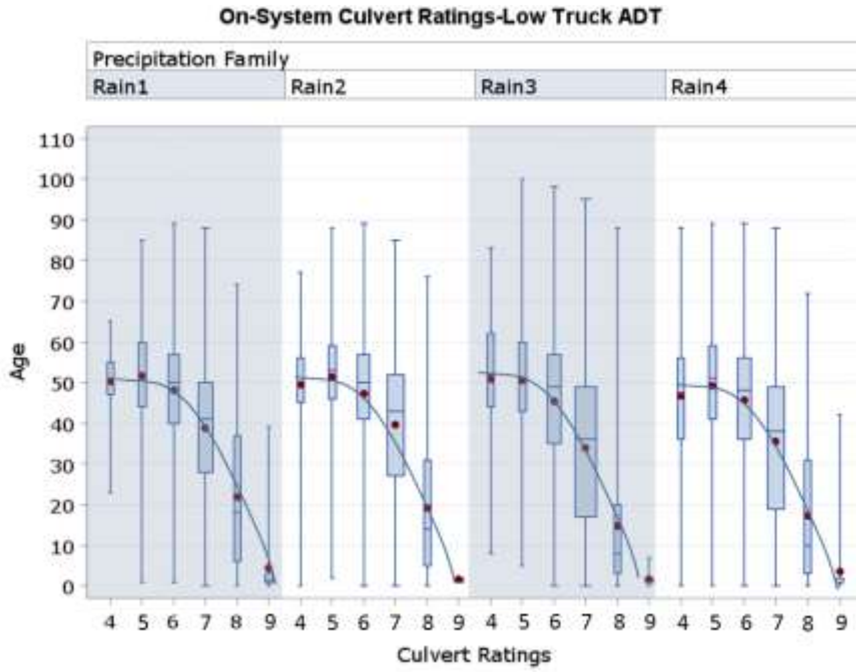


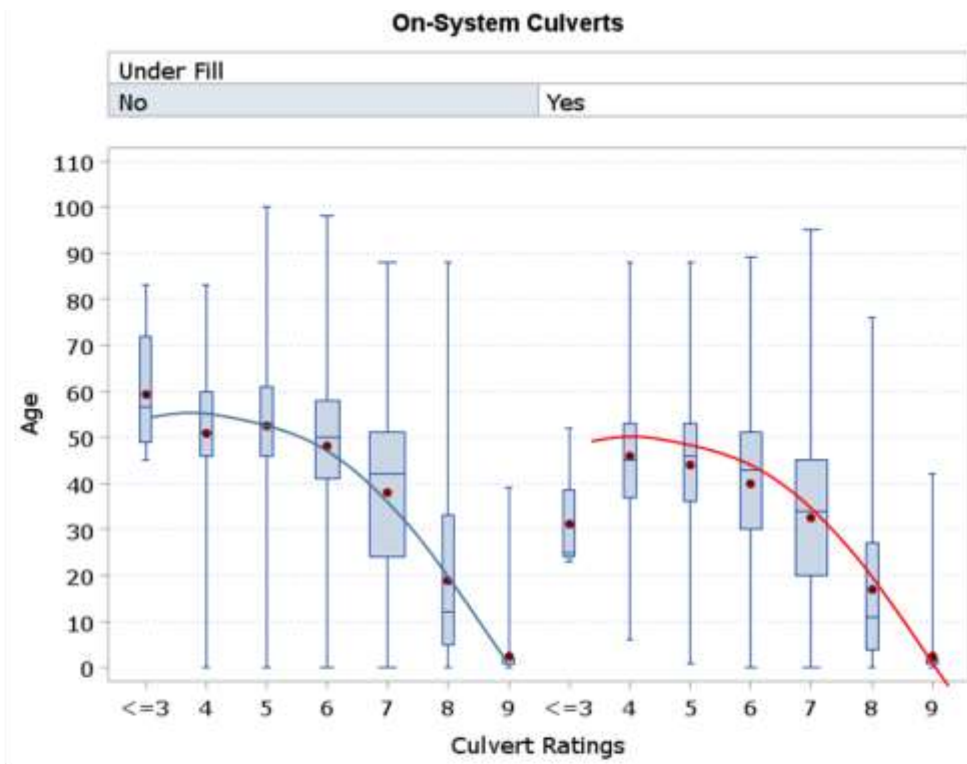
Figure 5. 5 Boxplots of On-System Low Traffic Culvert Age by Rainfall Family

Figure 5. 6 compares under fill versus no fill boxplots of culverts' age at each rating, for on- and off-system culverts. On-system boxplots show difference only for rating=3 and thus were not modeled by under fill/no fill families. Inspection data for off-system culverts are split into 73.32% not under fill and 26.68% under fill. Off-system culverts under fill appear to age faster than those not under fill for all ratings, so transition matrices were prepared and models analyzed for 2 off-system culvert families, under fill and no fill.

Conclusions

- Impact of maintenance in the data is clear for both on and off-system culverts. Both distributions have negative skewness, i.e., they have more high ratings than low ratings; in addition, ratings below 5 are nearly absent. The most frequent rating (mode) is 7 for both on- and off-system. Over 90% of all ratings are either 6 or 7, for both on- and off-system culverts (respectively 93.9% and 90.9%). Mean ratings are between 6 and 7, and 95% of the ratings are 6 or better. Low standard deviations underscore consistency in maintenance quality.
- Over 90% of on- and off-system data are multiple box, concrete culverts (Item 43.4), with length of the largest box (Item 48) of 12ft or less. Therefore, there are no modeling families by culvert type.
- Recommended families to model and analyze (in addition to age groups):
  - On-system culverts: 2 families, HIGH and LOW truck ADT
  - Off-system culverts: 2 families, under fill and no fill.

The next section discusses the Markov deterioration models developed for these families, the analysis of results, and the final implementation product based on model validation and on practical results.



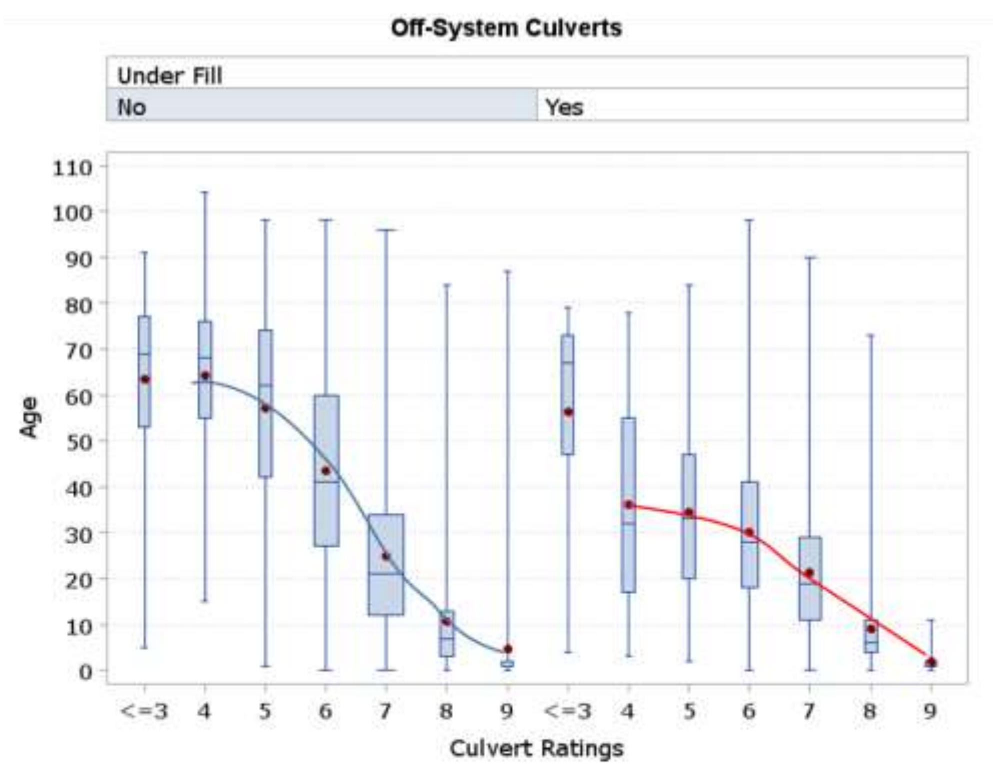


Figure 5. 6 Boxplots of Culvert Age by Under Fill / No Fill Families

Culvert Deterioration Models

Modeling Methodology

The modeling methodology is discussed in detail in Chapter 4 and summarized here for the readers' convenience. A subset of the annual PonTex database (2001 through 2019), prepared to ensure 2-year lags between all consecutive culvert ratings (see Chapter 3), was used to develop Markov transition probability matrices that age the culverts by 2 years, for all families and age groups.

Table 5. 1 illustrates one of the Markov transition probability matrices, showing the matrix calculated for all on-system culverts. Each matrix cell is the probability of the rating shown in the first column either remaining as, or changing into, the rating shown in the blue row, after 2 years. Elevating the two-year transition probability matrix to the n^{th} power ages the probability matrix by 2n years. This is the basis for calculating the network condition forecasts and deterioration curves presented in this section and delivered in Product 2.

Table 5. 1 Two-Year Transition Probability Matrix: All On-System Culverts

Rating Before	No. of Transitions	Rating after 2 Years									
		9	8	7	6	5	4	3	2	1	0
9	121	0.049587	0.32231	0.57851	0.04959						
8	2,069		0.54422	0.43789	0.01643	0.00145					
7	69,205			0.91951	0.07817	0.00212	0.00019				
6	30,314				0.96856	0.02995	0.00145	0.00003			
5	3,625					0.98014	0.01876	0.00083	0.000276		
4	172						0.97093	0.02907			
3	6										
2	-										
1	-										
0	-										1

The program that develops transition probability matrices contains code to null the transition probabilities in rows where the number of valid transitions is less than 9 (see rating=3 in Table 5. 1), due to concerns about reliability of the probability estimates. This generally happened for ratings less then or equal to 4. In older data groups, and/or in families more prone to deterioration, sometimes the rating of 9 did not result in enough transitions. The program assigns a transition probability of 1 for rating=0 remaining a zero, since a structure rating cannot be rated lower than zero.

Before modeling, age distributions by family were analyzed for their statistical properties, as well as to determine whether or not it was possible to disaggregate each family by age groups containing enough data points for a meaningful transition probability matrix by age within families.

Matrices analogous to Table 5. 1 were developed for each viable age group in each family, for each age group in the aggregated on- and off-system subsets, and for all aggregated on- as well as off-system culverts. Standard errors of each matrix were calculated for 17 forecasts and were considered for the validation. Overall maximum, minimum and average values were are reported here. Chapter 4 documents the methodology to calculate these standard errors.

The Markov process was implemented in each viable age group and family, determine rating deterioration tables and curves, as well as and network deterioration forecasts and curves, every 2 years, for 18 years. Results were compared for meaningful differences among age groups and families, with emphasis in 10-

year forecasts, as requested by TxDOT. The comparisons, in conjunction with the standard errors of the matrices, were the basis to determine whether families and/or age groups should be kept separated or aggregated.

Models recommended for implementation and principal model results (updatable) were delivered in 2 Excel workbooks, titled:

- 0-6979 Product2 On-System Culverts.xlsx, and
- 0-6979 Product2 Off-System Culverts.xlsx.

Product 0-6967-2, *Texas Culvert and Bridge Deterioration Models: Implementation Manual,* explains how to update the network deterioration and cost forecasts on Product 2 when new inspection data becomes available.

Culvert Age Groups by Family

Age group thresholds are age percentiles rounded to the nearest integer. Chapter 4 documents an analysis of different criteria to define age groups, which resulted in 3 age groups defined by the 33% and 67% age percentiles. Quartiles were also analyzed and discarded due to increased prediction errors with decreased amounts of data. Table 5. 2 shows the observed age percentiles rounded to the nearest year.

Table 5. 2 Culvert Age Groups by Family

	Off-System			On-System		
	All	*Under Fill*	*No Fill*	*All*	*High Truck ADT*	*Low Truck ADT*
Total Data Points	53,336	14,218	36,768	123,749	17,667	105,759
Age Groups (Quartiles)	0 to 14	0 to 12	0 to 15	**0 to 25**	0 to 22	0 to 26
	15 to 26	13 to 21	16 to 27	**26 to 42**	23 to 35	27 to 43
	27 to 42	22 to 33	28 to 45	**43 to 51**	36 to 44	44 to 52
	43 & Older	34 & Older	46 & Older	**52 & Older**	45 & Older	53 & Older
Data points/quartile	12,747	3,555	9,192	30,857	4,417	26,440
Age Groups (Thirds)	0 to 17	0 to 41	0 to 18	0 to 32	0 to 27	0 to 41
	18 to 34	42 to 49	19 to 38	33 to 48	28 to 33	42 to 49
	35 & Older	50 & Older	39 & Older	49 & Older	34 & Older	50 & Older
Data points/third	16,995	4,739	12,256	41,142	5,889	35,253

~~On-system culverts potential families~~

- Most age group thresholds in the high truck ADT family are less than or close to 10 years apart.
- The age thresholds indicate that the high truck ADT family is newer than the low truck ADT. Age and family effects may be confounded.
- Conclusion: 6 Markov matrices to develop and analyze for on-system culverts:

~~By Age Groups~~	~~By Families~~
0 to 32	High ADTT
33 to 48	Low ADTT
49 and older	All on-system

Off-system culverts potential families

- Most age groups thresholds in all off-system families are either less than or close to 10 years apart.
- The culvert family under fill is newer than the no fill, as indicated by the quartiles and thirds in Table 5. 2. Mean ages are respectively 24 and 34 years. The 90% percentiles are 46 and 67 years, respectively for culverts under fill and no fill. Age and family are confounded and should not be modeled separately.
- Conclusion: 6 Markov matrices to develop and analyze for off-system culverts:

By Age Groups	By Families
0 to 17	Under fill
18 to 34	No fill
35 and older	All off-system

On-System Culvert Models

The modeling task consisted of developing the 6 on-system transition probability matrices previously listed, calculating their standard errors and, if acceptable, using them to calculate deterioration curves and forecast the future network condition for each family and age group. The results for age groups and families were compared for differences considered meaningful in terms of infrastructure management.

Table 5. 1 in the Modeling Methodology section shows the two-year transition probability matrix for all on-system culverts. The other 6 matrices developed for on-system culverts are not shown in this report for the sake of conciseness. The numbers of non-negative transitions extracted from the total biannual inspection data points, and used to develop the 6 on-system Markov matrices were as follows:

Ages 0 to 32	33,751	High truck traffic	14,473
Ages 33 to 38	31,565	Low truck traffic	89,819
Ages 49 and older	31,236	All on-system	105,512

Minimum, mean and maximum standard errors of 17 network condition forecasts were as listed below. All averages were within the acceptable error range.

Ages 0 to 32	1.1%	3.4%	4.9%	High truck traffic	0.8%	3.7%	6.6%
Ages 33 to 38	0.8%	3.0%	4.9%	Low truck traffic	1.1%	3.6%	5.0%
Ages 49 and older	1.5%	4.2%	5.9%	All on-system	1.0%	3.5%	5.1%

Figure 5. 7 shows partial screen captures of rating deterioration curves by age groups, plus the aggregated on-system deterioration curves. Figure 5. 8, compares the culvert rating expected values after 10 years, by age group. Each Figure 5. 8 bar is one 10-year data point in Figure 5. 7.

Differences in expected values are too small for practical purposes, especially in the 10-year horizon. This type of result was consistently observed in all culvert rating deterioration curves. It is likely due to an issue common to every deterioration model of any type of infrastructure: available condition data always embeds maintenance; thus, rating deterioration probabilities are actually low, so future expected values are less useful for infrastructure management than network deterioration tables and curves (discussed next).

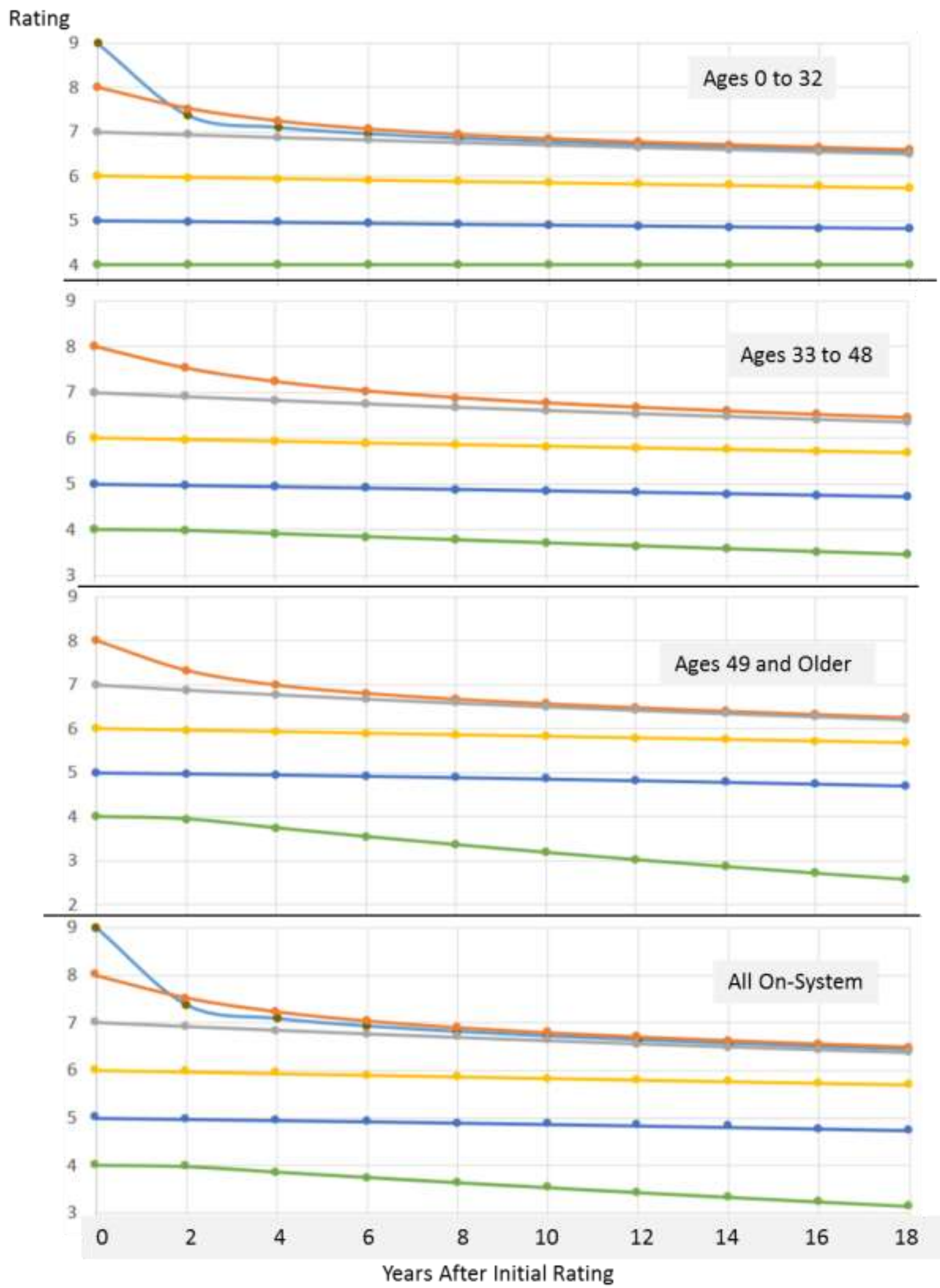


Figure 5. 7 Deterioration Curves for On-System Culverts by Age Groups

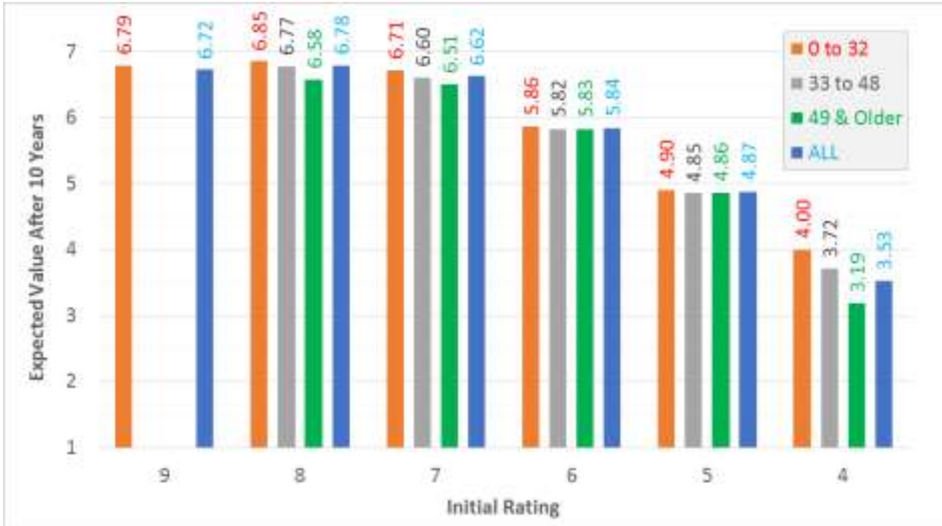


Figure 5. 8 On-System Culvert Ratings Expected Value After 10 Years, by Age Groups

The network deterioration in terms of percent culverts at each future rating, on the other hand, is very helpful for culvert management purposes. Figure 5. 9 shows the aggregated on-system network deterioration curve delivered in Product 2. All curves by age groups are found in Product 2 along with the data tables. This plot provides a more useful forecast than the expected rating values. For example, the 2019 network condition has about 55% culverts at rating 7, predicted to decrease to 36.7% in 2029, while ratings of 6 increase from 39.5% to 41%, and ratings of 5 increase from 4.6% to 11.1% in the same period.

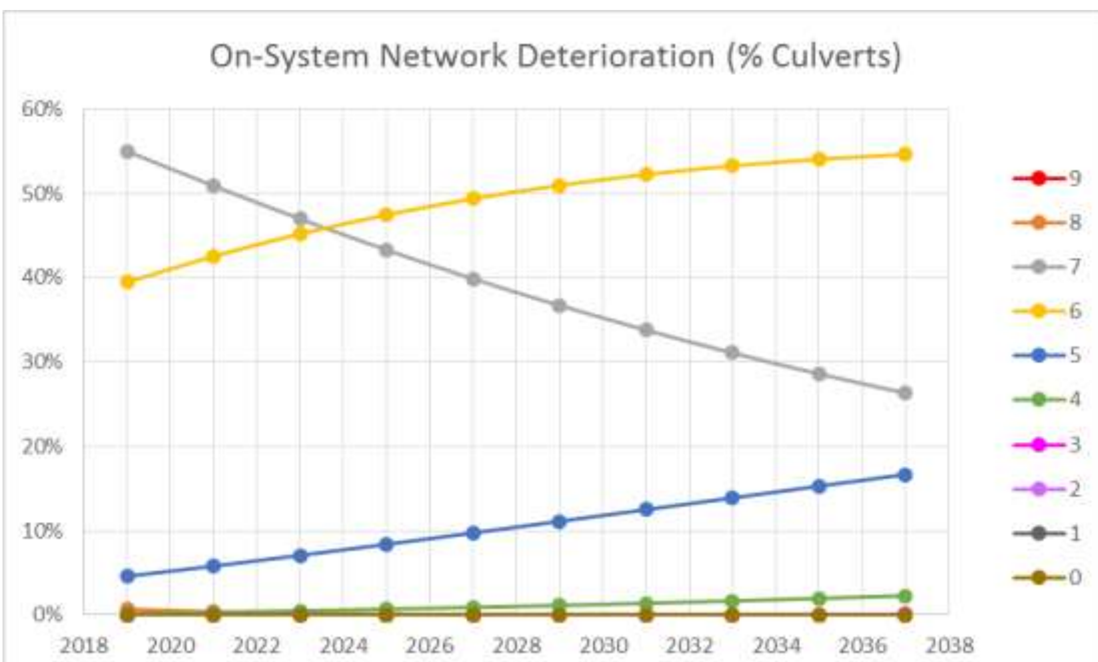


Figure 5. 9 On-System Culvert Network Deterioration Curves

Figure 5. 10 compares the current (2019) network condition to the 10-year forecasts (2029). Newest culverts have the highest percentage of predicted 2029 ratings of 7 (53%). This percentage decreases to 38% the next older age group, and to 23.8% for the oldest culverts. The newest age group is the only one that still retains a small percentage of ratings=8 after 10 years. The percentage of future ratings=5 and 6 consistently increases with culvert age. It is clear f that the age groups have a practical difference in the predicted network condition.

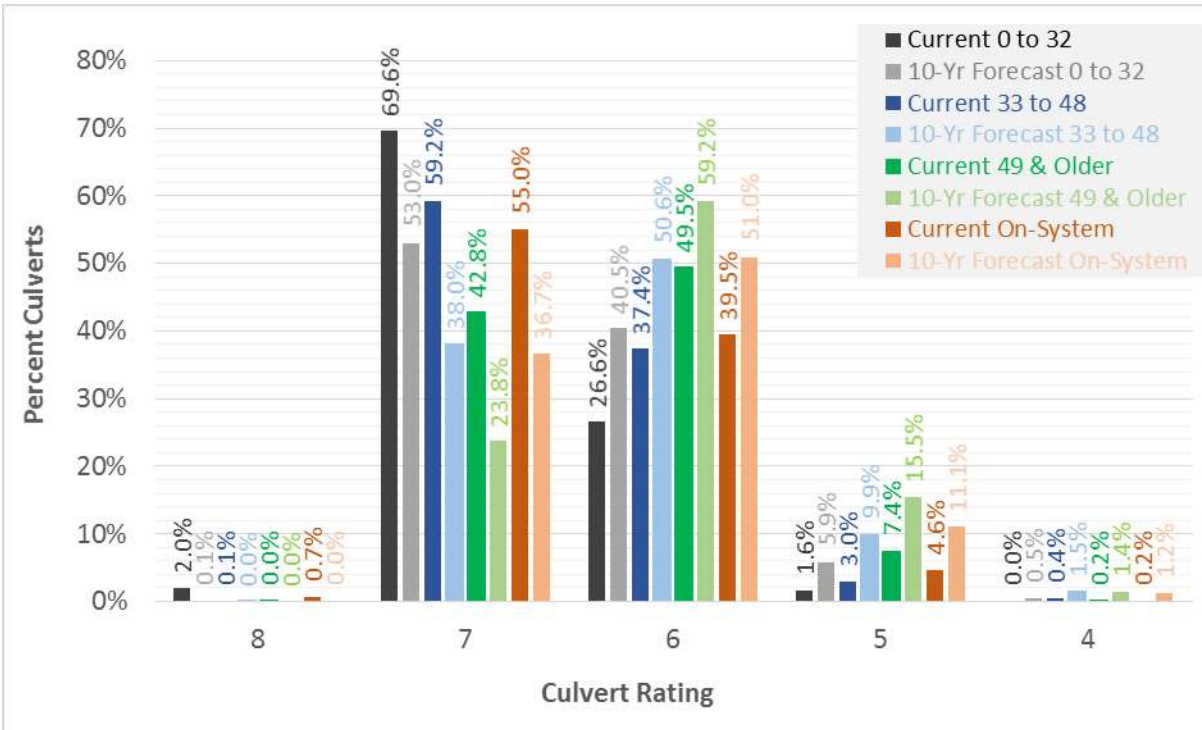


Figure 5. 10 Current On-System Culvert Network Condition and Ten-Year Forecasts by Age Groups

Figure 5. 11 compares the 10-year forecasts by truck ADT families (predicted 2029 network condition for the 2019 culverts). The differences among ADTT families are consistent with more deterioration in high ADTT areas, but are too small for practical purposes. In addition, differences are of the same magnitude as the standard errors associated with the basic transition probability matrix.

This observed rather low impact of ADTT families in culvert deterioration may be due to the fact that over 57% of the high truck ADT data points are in interstate highways, compared to less than 6.2% data points for low truck ADT. Interstate highways by definition are the best in terms of design, construction materials and maintenance, and therefore may be expected to deteriorate less.

Product 2 contains the 3 recommended models by age groups, as well as the aggregated on-system model, the rating deterioration tables and curves, network deterioration tables and curves, charts comparing 10-year forecasts by age group, and cost estimates (discussed in Chapter 9).

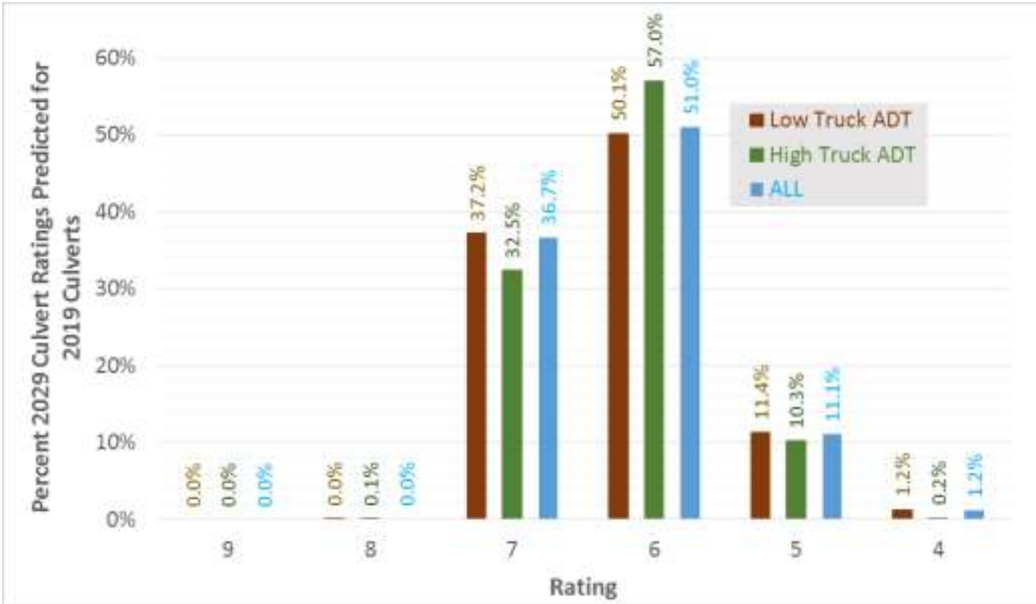


Figure 5. 11 Ten-Year On-System Network Condition Forecasts by Truck ADT Family

Off-System Culvert Models

The numbers of available non-negative transitions extracted from the total data points in Table 5. 2, and used to develop the 6 off-system Markov matrices for analysis were as follows:

Ages 0 to 17	13,223	Under fill	11,454
Ages 18 to 34	12,632	No fill	30,630
Ages 35 and older	14,030	All off-system	43,059

Minimum, mean and maximum standard errors of 17 network condition forecasts are listed below. Average errors were all at the desired 5.0% level or higher. Culverts under fill had the highest standard errors.

Ages 0 to 17	2.3%	6.7%	12.9%	Under fill	3.0%	6.5%	11.9%
Ages 18 to 34	2.4%	5.0%	9.9%	No fill	3.3%	5.1%	8.1%
Ages 35 and older	3.6%	5.4%	8.1%	All off-system	3.5%	5.6%	9.4%

Differences between future expected rating values by under fill/no fill families, were too small for practical purposes and are not shown. Figure 5. 12 compares the 10-year (2029) network condition forecasts by fill/no fill family and aggregated on-system. Differences are too small for practical purposes, as well as too close to the matrices' standard errors, so modeling off-system culverts by fill/ no fill families is not practical.

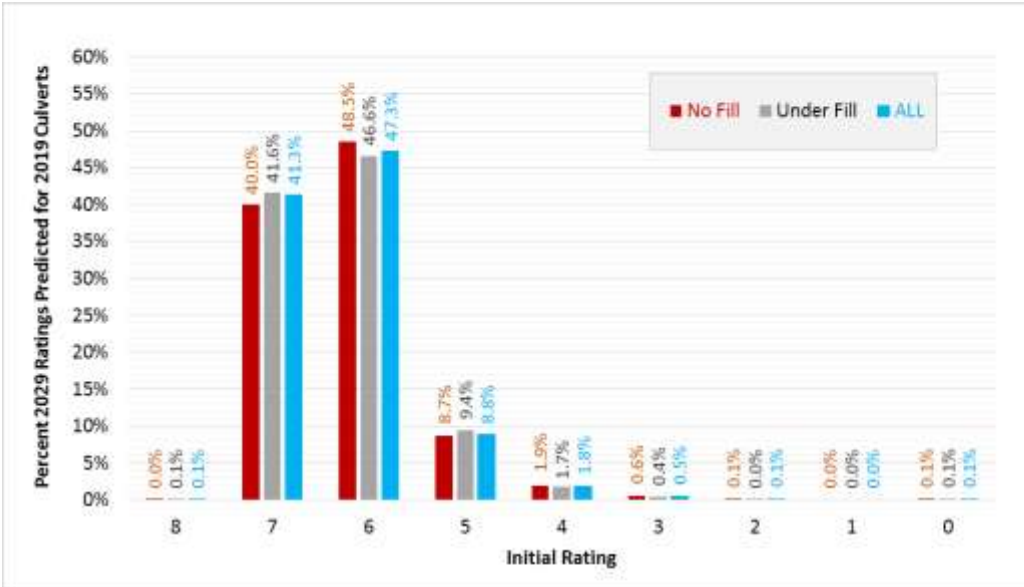


Figure 5. 12 Off-System Ten-Year Network Condition Forecasts by Under Fill/No Fill Family

Figure 5. 13 shows the aggregated off-system rating deterioration curves. Curves by age are available in Product 2. The differences in expected future values are too small for practical purposes, but are larger than the differences observed for the fill/no fill families. However, only the newest age group has ratings=9.

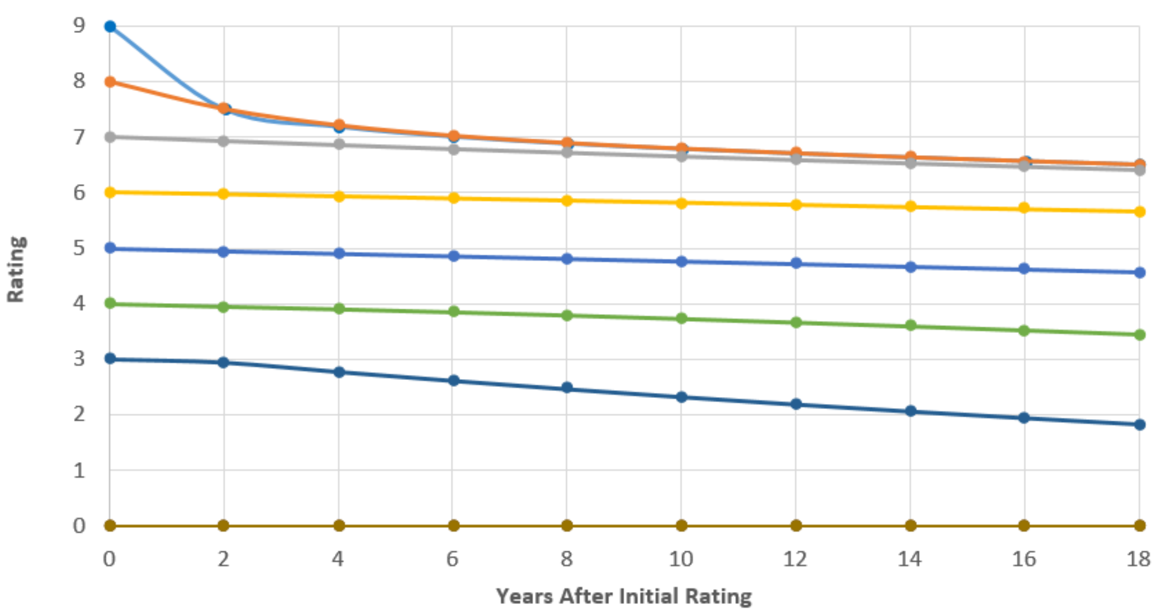


Figure 5. 13 Off-System Deterioration Curves

Figure 5. 14 shows the off-system culvert network deterioration curves. This Markov application is significantly more useful for infrastructure management purposes than Figure 5. 13. The full set of network deterioration curves are delivered in Product 2 along with the data tables.

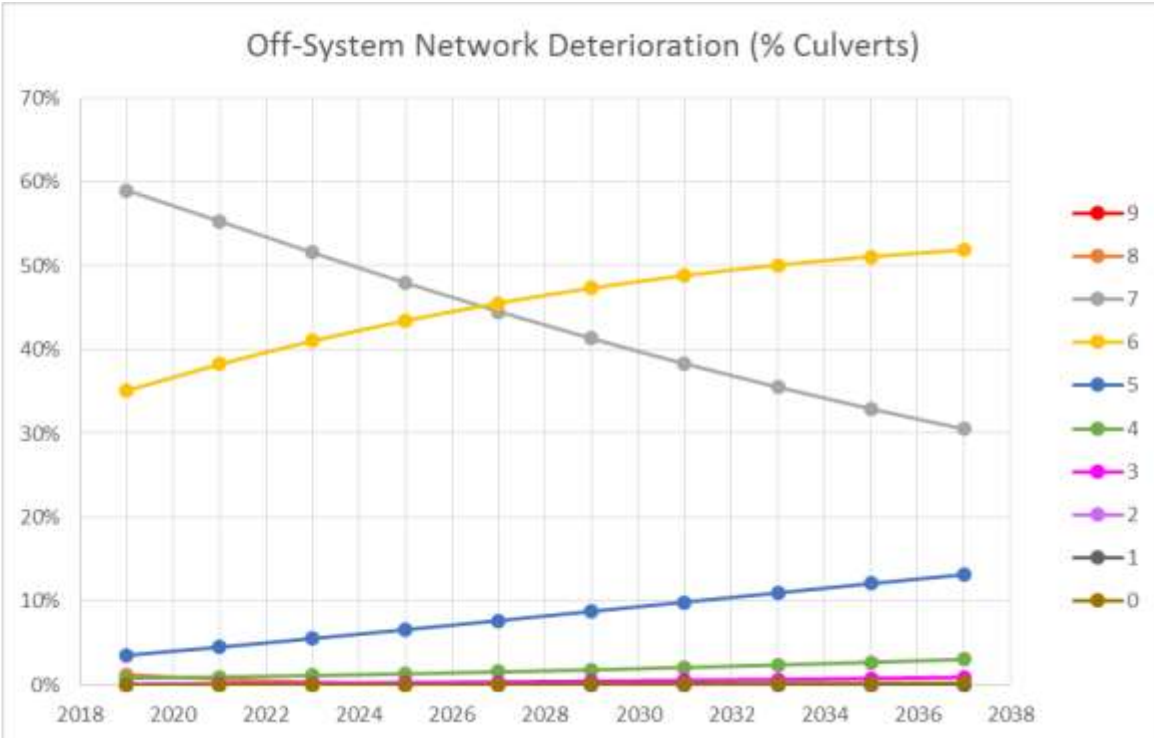


Figure 5. 14 Off-System Culvert Network Deterioration Curves

Figure 5. 15 compares the network condition years 2019 and 2029, by age groups. The newest culverts still retain a small percentage of ratings=8, and have the highest percentage of future ratings=7. The reverse trend is observed for lower ratings. It is clear that the age groups have a practical difference in the predicted 10-year network condition, and should be taken into consideration in Product 2.

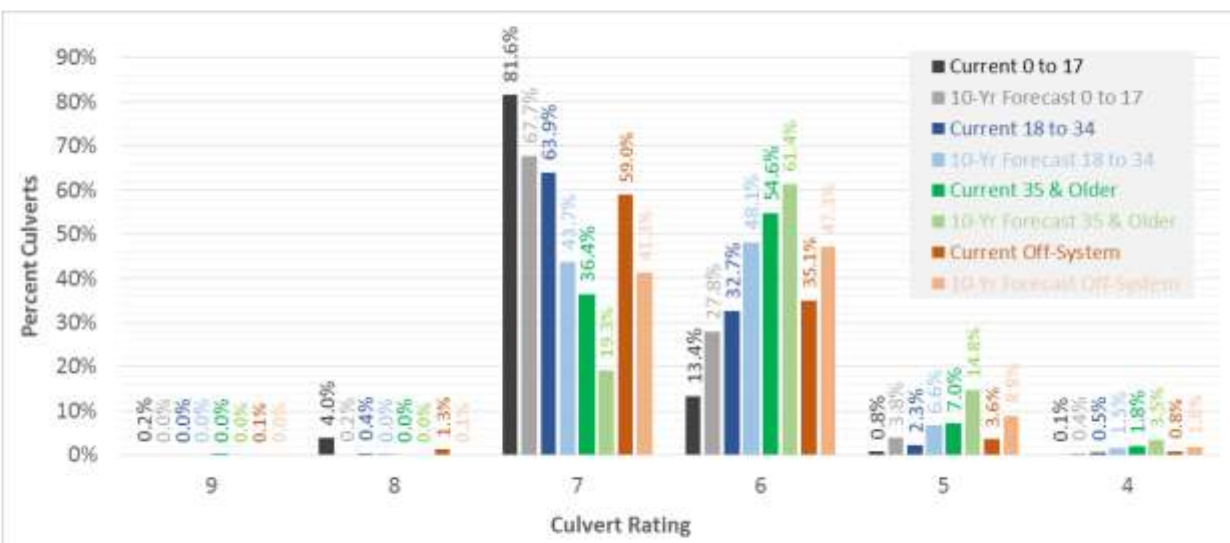


Figure 5. 15 Off-System Ten-Year Network Condition Forecasts by Age

Implementation Considerations

Product 2 consists of two Excel Workbooks, one for on-system culverts and another for off-system culverts. This deliverable implementation and utilization are discussed in Product 0-6976-2, *Texas Culvert and Bridge Deterioration Models: Implementation Manual*.

Rating deterioration tables and curves that predict expected future rating values (such as Figure 5. 7) come from matrix calculations that depend on the Markov transition probabilities. Network deterioration curves (such as Figure 5. 9) will update when the current network condition is updated as indicated in Product 2. They are a very useful infrastructure management application of the Markov transition probabilities.

Given the observed network-level differences in deterioration by age group, it is recommended to retrieve the current year data by age when updating the network deterioration. Nevertheless, general models for all on-system and all off-system culverts are also included in Product 2. Cost forecasts included in Product 2 are discussed in Chapter 9.

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Chapter 6
Substructure Deterioration Models

Background and Objectives

This Chapter documents the development of deterioration models for National Bridge Inventory (NBI)/PonTex Item 60: substructure rating. According to the NBI/PonTex Coding Guide, Item 60 "describes the physical condition of piers, abutments, piles, fenders, footings, or other components. Condition ratings are used to describe the existing, in-place bridge as compared to the as-built condition" (Ref. 51). Condition ratings are discussed in more detail in Chapter 4.

Chapter 4 also explains in detail the modeling methodology used to perform the exploratory data analysis to select potential model families, then develop and validate the deterioration models. The Markov-based methodology is conceptually the same for the 3 bridge ratings and the culvert rating. Chapter 9 discusses the bridge cost estimates delivered with Product 2 workbooks.

The next section discusses the results of the Exploratory Analysis of substructure ratings. This analysis was part of this project's Task 4, which defined prospective modeling families for further analysis during the model development phase.

Exploratory Analysis of Substructure Ratings

Summary of Available Data

The substructure modeling database contains 327,823 bi-annual ratings from 2001 to 2019, for 39,455 bridges. These are split into:

- 15,148 off-system bridges, with 123,204 bi-annual substructure inspection records, and
- 24,307 on-system bridges with 204,629 bi-annual substructure inspection records.

In addition to the climatic variables obtained and analyzed in this project (discussed in Chapter 3), the following PonTex variables were considered relevant and used to test and develop substructure modeling families (Ref. 51):

- Substructure rating: Item 60
- Item 27 (year built) or Item 106 (year reconstructed), and the PonTex file year: used to calculate bridge age.
- Item 44.1: Substructure Type, Main Spans, below ground (1st digit) and above ground (2nd digit): potential substructure type families.
- Item 61, Channel Protection: any value other than "N" indicates a bridge over water. Item 61 was cross-referenced and found consistent with Item 113, where "N" also indicates bridge over dry land.
- Item 113 (scour critical bridges) was discarded as a variable to define potential family, because it consists of another rating to evaluate a specific type of deterioration (scour).
- Item 52, Deck Width (Out-to-Out) and Item 49, Structure Length: used to calculate bridge areas.

Figure 6. 1 shows the histogram of substructure inspection ratings from 2001 to 2019. The graph inset shows the principal distributions' statistics. Data comes from the modeling data base containing ratings spaced every two years (see Chapter 3 for explanation on development of this database from 2001-2019 yearly NBI/PonTex Access files).

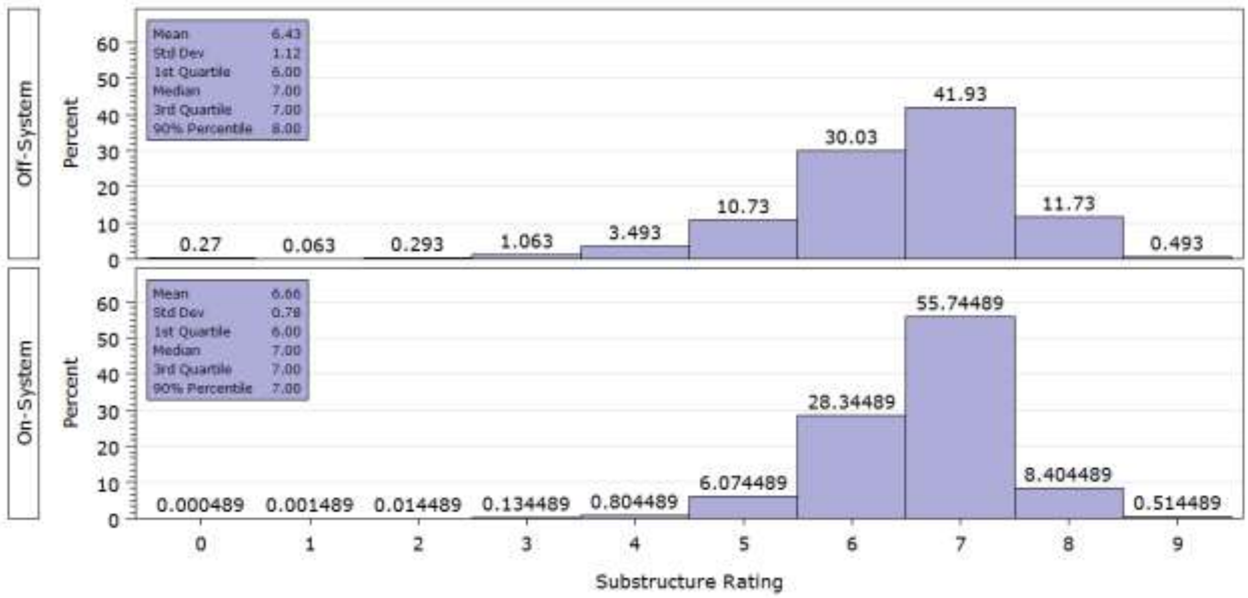


Figure 6. 1 Histogram of On- and Off-System Substructure Ratings

Ratings of 6 and 7 predominate, totaling 72% of all off-system ratings and 84% of all on-system ratings. The impact of maintenance is evident for both on and off-system substructures. Both histograms have negative skewness, i.e., they have more high ratings than low ratings; in addition, ratings below 4 are nearly absent from on-system substructures (0.15%), and total only 1.68% of off-system substructure ratings. The most frequent rating (mode) is 7 for both on- and off-system. Most ratings are 6 or better, for both on- and off-system substructures (respectively 93% and 84%). Mean ratings are between 6 and 7, and the low standard deviations indicate consistency in maintenance quality.

Task 4, Exploratory Data Analysis, was finalized in March 2018; not all charts and tables in the remainder of this section include year 2019 data. The models, however, were updated with data from 2001 to 2019. The analysis consisted of selecting variables that may define prospective families and are either fully or almost fully populated. Boxplots of age by rating were prepared for each family. Variables that apparently caused an impact on the age at which each rating was reached were selected to define prospective families for further analysis.

Climatic Variables

Figure 6. 2 and Figure 6.3 respectively show the boxplots of off- and on-system of bridge age by substructure rating, comparing the four rainfall families developed as documented in Chapter 3. Rainfall intensity increases in numeric order: Rain1 (driest) to Rain4 (wettest). Off-system substructures appear to sustain faster deterioration in Rain4 areas. However, off-system bridges in Rain4 area are the newest group, so bridge age and rainfall impacts are confounded.

On-system substructures show no differences among the four groups. Analogous result was obtained for freezing days. The latter result was expected in Texas, where less than 8% of counties average 2 or more freezing days per year (average of past 5 years). Moreover, superficial freezing affects primarily the bridge deck. Conclusion: neither on- nor off-system substructures can be split into families based on performance difference due to climatic factors.

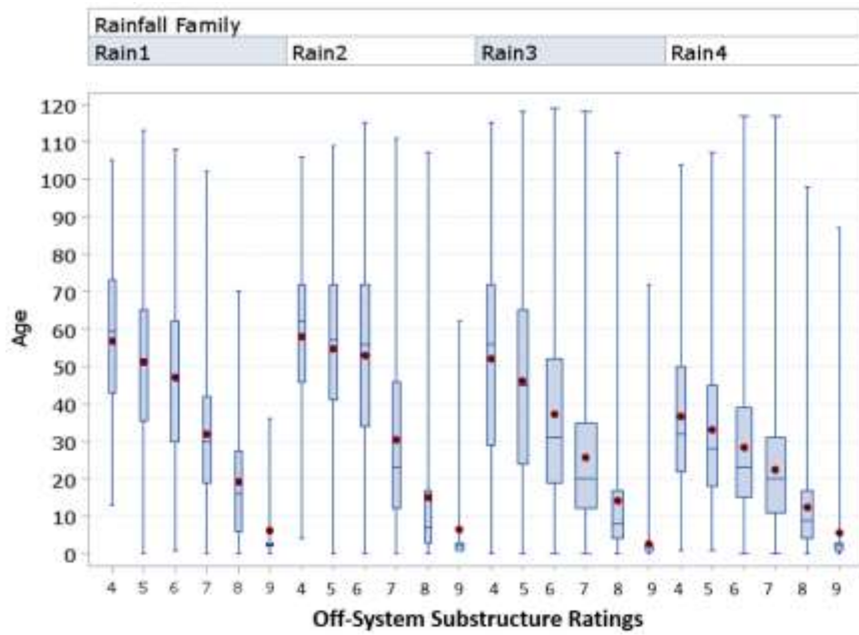


Figure 6. 2 Boxplots of Off-System Bridge Age by Substructure Rating and Rainfall Family

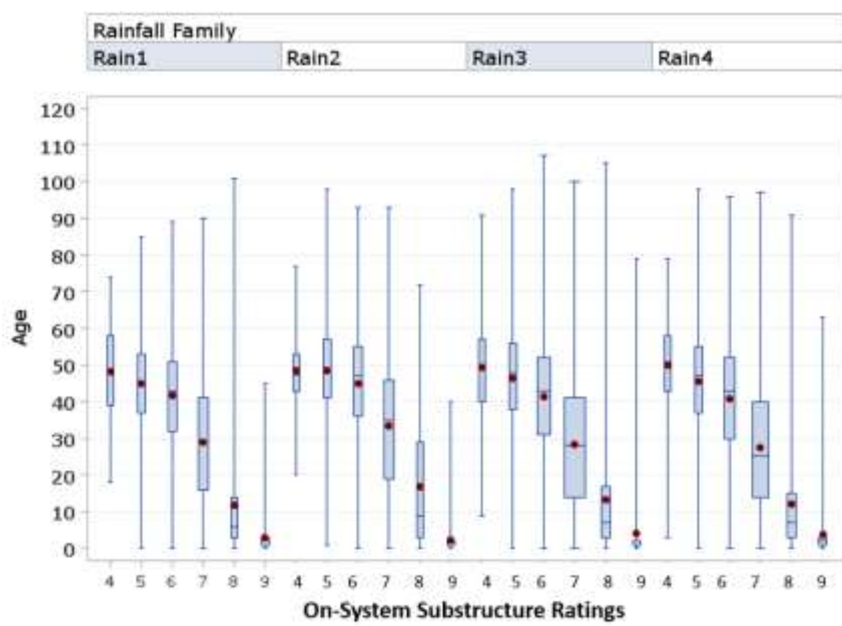


Figure 6. 3 Boxplots of On-System Bridge Age by Substructure Rating and Rainfall Family

Substructure Type

Item 44.1—Substructure Type, Main Span Substructure stores 3 one-digit variables. Each digit takes values from 1 to 9. The first digit is above ground, the second is below ground, and the third is the bent cap type. The first two variables were checked for potential families. Table 6. 1 shows the substructure types coded in PonTex (Ref. 51).

Table 6. 1 Substructure Type Definitions (Item 44)

1st Digit — ABOVE GROUND		2nd Digit — BELOW GROUND		3rd Digit — BENT CAP	
1	Pile Bents	1	Steel Piling	1	Concrete
2	Single Column Bent*	2	Concrete Piling	2	Steel
3	Multiple Column Bent*		(including steel shell	3	Timber
4	Concrete Column Bent		concrete piling)	4	Masonry
	with Tie Beam*	3	Timber Piling	9	Other
5	Concrete Column Bent	4	Drilled Shafts		Leave blank if
	Wall*	5	Spread Footing		no bent cap if
6	Concrete Pier	6	Pile Cap on Steel Piling		no applicable
7	Masonry Pier	7	Pile Cap on Concrete Piling		
8	Trestle (steel, concrete	8	Pile Cap on Timber Piling		
	or timber)	9	Other		
9	Other				

*Could be above ground portions of drilled shafts

Source: Ref. 51

Over 32% off-system data points in the Markov modeling database are missing Item 44.1. For on-system, Item 44.1 is 96.3% populated. Item 44.1 (below-ground), consists primarily of drilled shafts (57.1%), followed by concrete piling (18.7%) and spread footing (8.7%). Item 44.1 (above ground) consists primarily of pile (22.5%) and multiple column (64%) bents. All other types were aggregated into an "Other" prospective family to ensure enough data points per family for the analyses.

Figure 6. 4 shows the on-system boxplots of age by substructure type, below ground. The plots follow the expected trend, with drilled shafts performing best, followed by concrete piling and spread footing. However, the average differences in aging are either less than or close to 10 years. Given the wide data spread and the requested 10-year forecast period, these differences are too small for practical consideration, and no family age analysis is needed.

Figure 6. 5 shows the boxplot of age by substructure type, above ground families, for on-system bridges. Again the differences in age trend are small compared to the data spread and the 10-year forecast horizon. Conclusion: Item 44 does not define practical on-system modeling families.

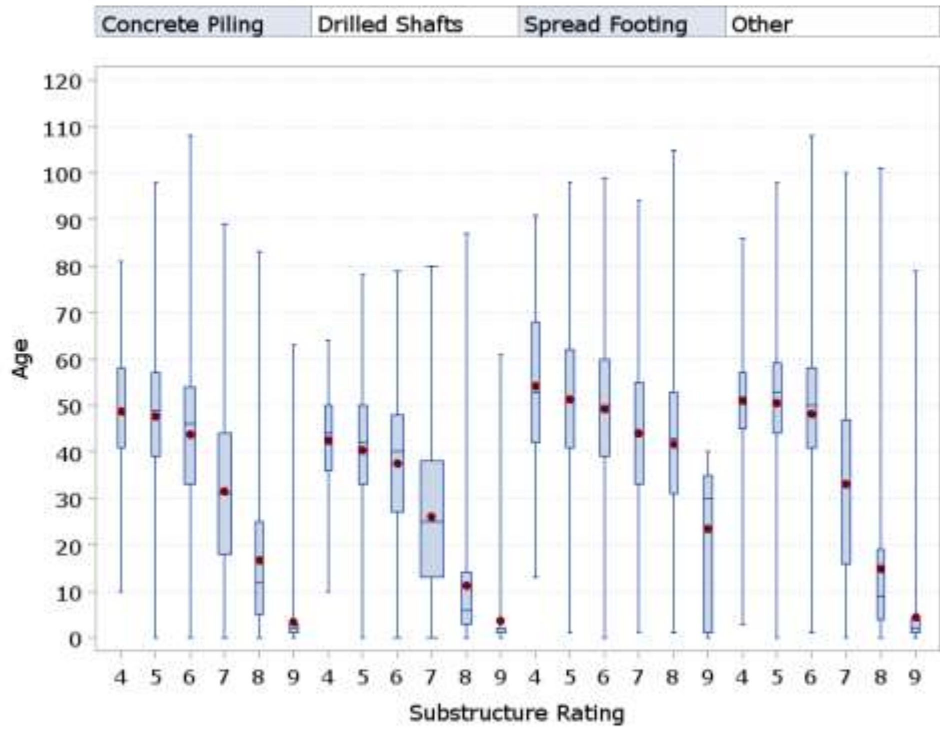


Figure 6. 4 Boxplots of On-System Bridge Age by Rating and Substructure Type, Below Ground

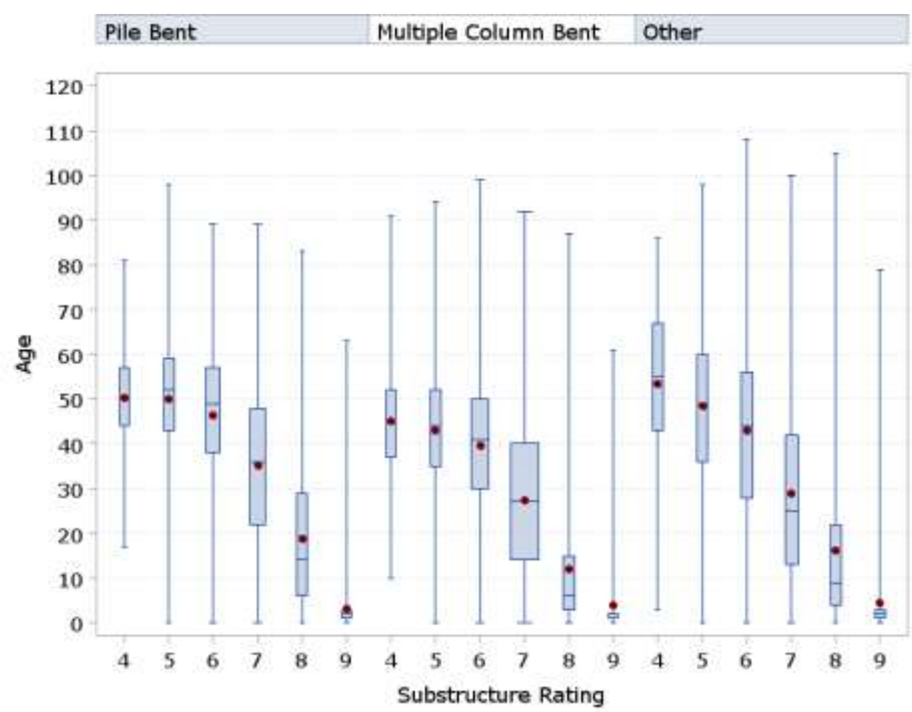


Figure 6. 5 Boxplots of On-System Bridge Age by Rating and Substructure Type, Above Ground

Bridges Over Water / Over Dry Land

After a consistency cross-check with Item 113 (scour critical bridges), PonTex Item 61, channel protection, was selected to define two prospective families: bridges over water and bridges over dry land. Figure 6. 6 and Figure 6. 7 respectively show the boxplots of off- and on-system bridge ages by substructure ratings, for dry land and over water families.

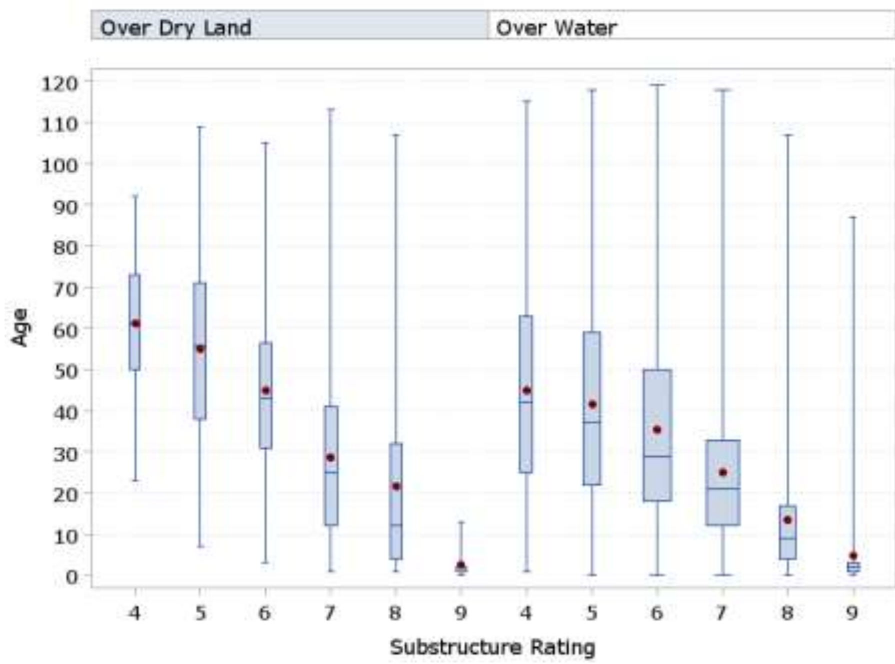


Figure 6. 6 Boxplots of Off-System Bridge Age by Rating and Over Water / Dry Land Families

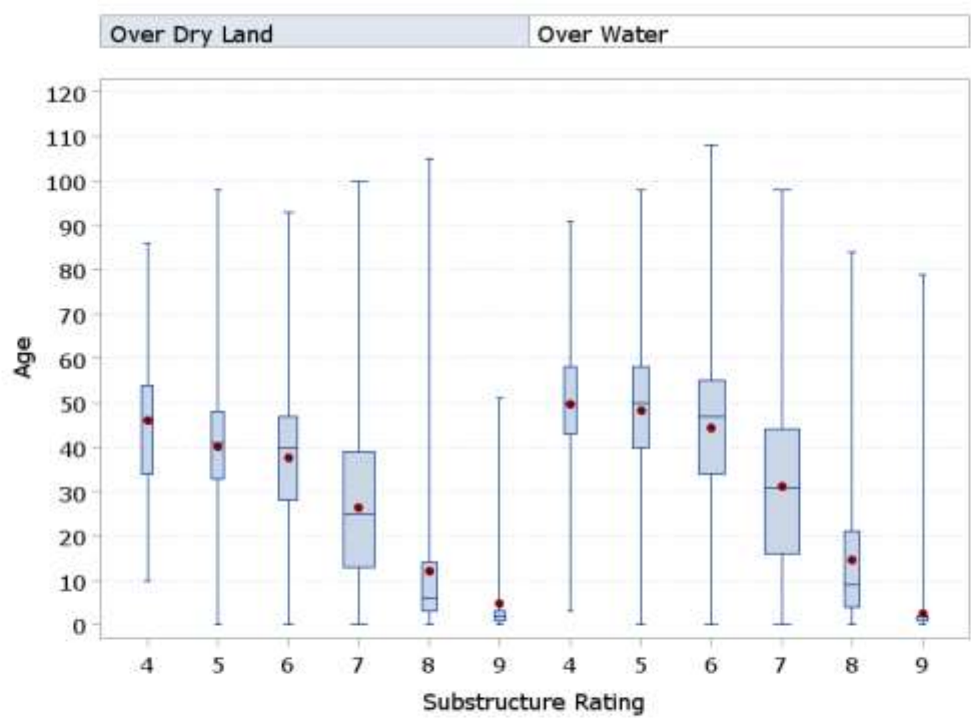


Figure 6. 7 Boxplots of On-System Bridge Age by Rating and Over Water / Dry Land Families

Off-system family over water shows a trend to age somewhat faster than the over dry land family, and the magnitudes of the age differences are greater than 10 years for low ratings. Off-system bridges over water are on the average 5 years newer than those over dry land. Therefore, age differences between the two families does not appear to fully explain the difference in the ages at each rating observed in the boxplots. These two off-system families were investigated further during modeling.

The opposite trend can be seen for on-system bridges over dry land: they appear to deteriorate slightly faster than on-system bridges over water, but the magnitude of the age differences observed in the boxplots are less than the desired 10-year forecast horizon, for all ratings,. Moreover, boxplot age differences and bridge age differences between the two families are of the same magnitude, thus confounding effects of age and family.

Conclusions

- Good routine maintenance is reflected in both on and off-system substructure ratings. Both distributions have negative skewness, i.e., they have more high ratings than low ratings. Low standard deviations underscore consistency in maintenance quality. Ratings below 4 are nearly absent for both on- and of-system bridges, and 99.1% of on-system ratings and 94.8% off-system ratings of 5 or better. The percent of ratings of 6 or better are 84.1% and 93%, respectively for off- and on-system. The most frequent rating (mode) is 7, and mean ratings are between 6 and 7, for both on- and off-system.
- Substructure type impact on deterioration appears too small for practical modeling families.
- There was a difference in deterioration worth investigating further, between off-system bridges over water and over dry land, but not for on-system.
- Recommended families to model and analyze:

  On-system substructures: no families, analyze by age groups.

  Off-system substructures: 2 families, over water and over dry land.

Over water and over dry land off-system families were not split into age groups, due to the fact that the dry land family contains only 6.1% of the off-system data points, thus resulting in too few points per dry land age groups for a reliable transition probability matrix.

The next section discusses the Markov deterioration models developed for these families and for the as age groups, the comparison of results, and the final implementation product after on model validation.

Substructure Deterioration Models

Summary of Modeling Methodology

The modeling methodology is discussed in detail in Chapter 4. It was implemented using the subset of the annual PonTex database (2001 through 2019), prepared to ensure 2-year lags between all consecutive substructure ratings, as discussed in detail in Chapter 3. This bi-annual data set was used to develop Markov transition probability matrices that age the substructure ratings by 2 years. The transition probabilities were calculated based on 327,823 substructure ratings between 2001 and 2019.

Table 6. 2 illustrates the Markov transition probability matrix, calculated for all on-system substructure ratings. Each matrix cell is the probability of the rating shown in the first column changing into the rating shown in the blue row after 2 years. Transition probabilities were calculated from all non-negative two-

year rating transitions (i.e., the rating either deteriorated or remained the same). The program nulls the transition probabilities in matrix rows with less than 9 valid transitions (see column for rating=2). It also sets to 1 the probability of rating=0 remaining zero, since a rating cannot deteriorate any further. As explained in detail in Chapter 4, elevating the two-year transition probability matrix to the n^{th} power ages the matrix by 2n years. These Markov matrices and their n^{th} powers are the basis for calculating the network condition forecasts and deterioration curves discussed in this section.

Table 6. 2 Two-Year Transition Matrix for All On-System Substructure Ratings

On-System Substructure											
TRANSITION PROBABILITY MATRIX- 1 PERIOD (2 YEARS)											
Rating Before	No. of Transitions	Rating After 2 Years: 9	8	7	6	5	4	3	2	1	0
9	1,029	0.14091	0.52478	0.3207	0.01361						
8	15,863		0.64313	0.34552	0.01084	0.00044	0.00006				
7	100,206			0.92551	0.07145	0.00287	0.00013	0.00002	0.00001		
6	46,771				0.95493	0.0427	0.00212	0.00021	0.00004		
5	9,029					0.96279	0.03123	0.00565	0.00033		
4	983						0.95829	0.03357	0.00712		0.001
3	115							0.98261	0.01739		
2	11								0.90909	0.090909	
1	2										
0	0										1
Total	*174,009*										

Matrices analogous to Table 6. 2 were developed for each viable age group in each family, for each age group in the aggregated on- and off-system subsets, and for aggregated on- and off-system. The Markov process was implemented in each case to arrive at deterioration tables and curves, and network condition forecasts every 2 years. Standard errors of each matrix were calculated for 17 network condition forecasts as explained in Chapter 4. Maximum, minimum and average standard errors are reported here and were considered in model validation.

The modeling effort consisted of developing the 10 transition probability matrices listed below, using them to calculate deterioration curves and network condition forecasts every 2-years. The results for age groups within on- and off-system families, and for both off-system families, were compared for meaningful differences in terms of infrastructure management.

<u>On-system substructure rating potential models</u>

- All on-system
- Age group 0 to 22
- Age group 23 to 42
- Age group 43 and older

<u>Off-system substructure rating potential models</u>

- All off-system
- Age group 0 to 16
- Age group 17 to 34
- Age group 35 and Older
- Bridges over water
- Bridges over dry land

Models recommended for implementation and principal model results (updatable) were delivered in 2 Excel workbooks, titled:

- 0-6967Product2 On-System Substructure.xlsx, and
- 0-6967Product2 Off-System Substructure.xlsx.xlsx.

Product 0-6967-2, *Texas Culvert and Bridge Deterioration Models: Implementation Manual,* explains how to update the network deterioration curves and forecasts on Product 2 when new inspection data becomes available.

On-System Substructure Models

The on-system substructure modeling task developed 4 transition probability matrices similar to that depicted in Table 6. 2. The numbers of non-negative transitions extracted from the on-system biannual inspection data points, and the minimum, average, and maximum standard errors calculated from 17 sets of observed versus predicted network condition forecasts by number of bridges are listed below.

~~Transitions~~

Ages 0 to 22	55,182	Ages 44 and older	54,683
Ages 23 to 43	51,613	Aggregated on-system	174,009

~~Standard errors~~

Ages 0 to 22	1.9%	5.3%	8.3%
Ages 23 to 43	1.8%	2.5%	3.0%
Ages 44 and older	3.3%	4.1%	5.2%
Aggregated on-system	2.6%	3.6%	4.8%

Figure 6. 8 shows the deterioration curves developed for on-system substructures. Only the initial ratings of 8 and 9 deteriorated by 1 point or more within the 10-year forecast horizon. Differences among groups are too small for practical purposes. Small changes in expected value with time were consistently observed in all substructure rating deterioration curves.

Network deterioration curves, in terms of percent bridges and percent bridge area, are very helpful for bridge management purposes Figure 6. 9 shows the aggregated on-system network deterioration curves delivered in Product 2. All curves are found in Product 2, along with the data tables. This type of plot provides a more useful forecast than the expected rating values. For example, the 2019 network has about 55% substructure ratings of 7, predicted to decrease to 42.9% in 2029, while ratings of 6 increase from 30.6% to 41.1%, and ratings of 5 increase from 5.8% to 12.6% in the same period.

Figure 6. 10 and Figure 6. 11 compare the current (2019) to the 10-year forecast (2029) network condition, respectively by percent bridges and by percent bridge area. Newest substructures have the highest percent area at predicted ratings of 7 and 8 after 10 years. This percentage decreases as age increases. The reverse trend is observed for predicted ratings of 2, 3, 4, 5 and 6. It is clear from this figure that the age groups have a practical difference in the predicted 10-year network condition.

The differences among age groups for the 10-year network condition predictions are large enough for practical purposes and consistent with expected deterioration behavior. It is recommended to split on-system substructure ratings by 3 age groups: 0 to 22, 23 to 43 and 44 or older. Product 2 contains the 3 recommended models by age groups, and also the aggregated on-system model, which is always included in all Product 2 workbooks.

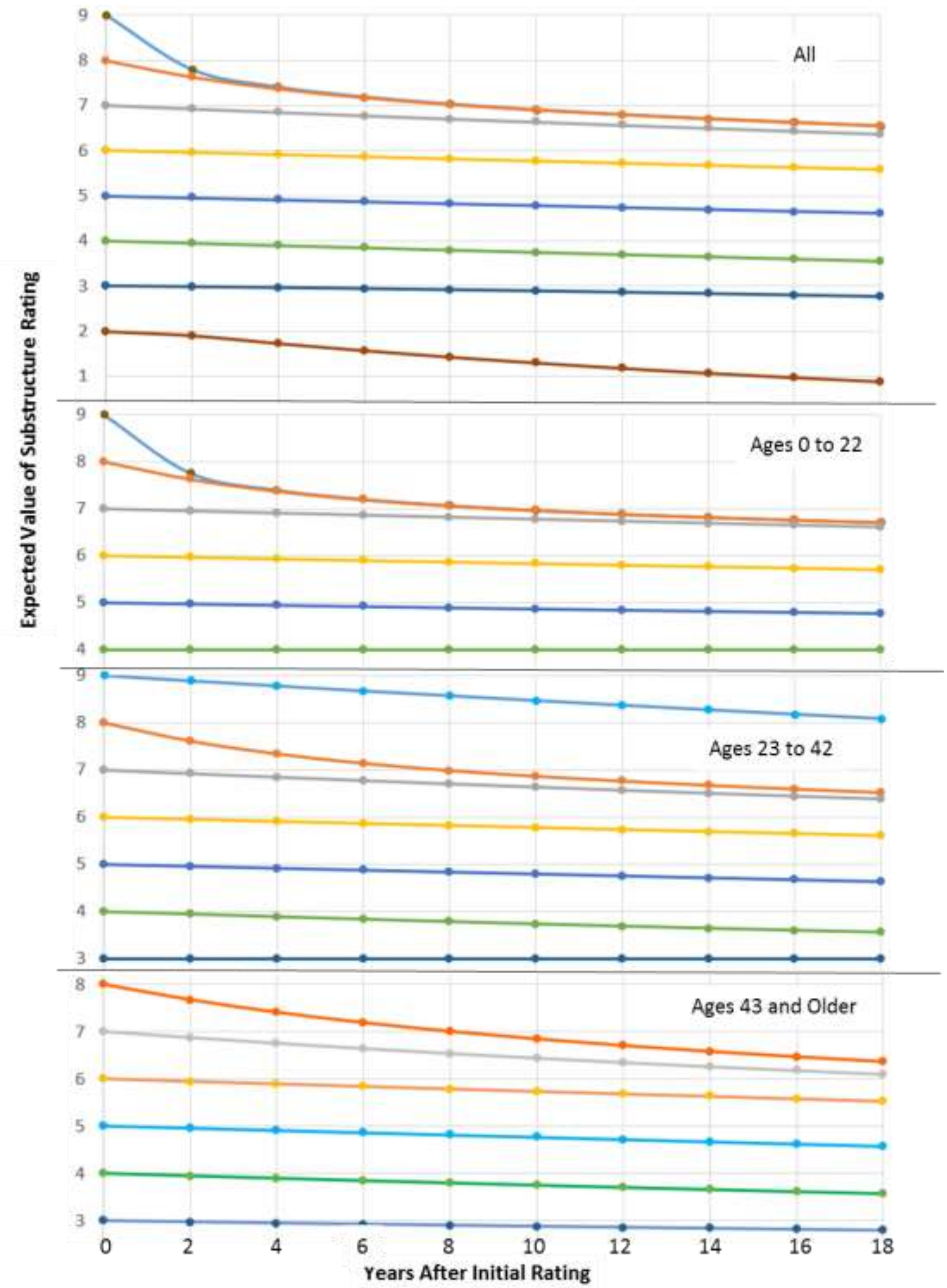


Figure 6. 8 Deterioration Curves for On-System Substructure Ratings

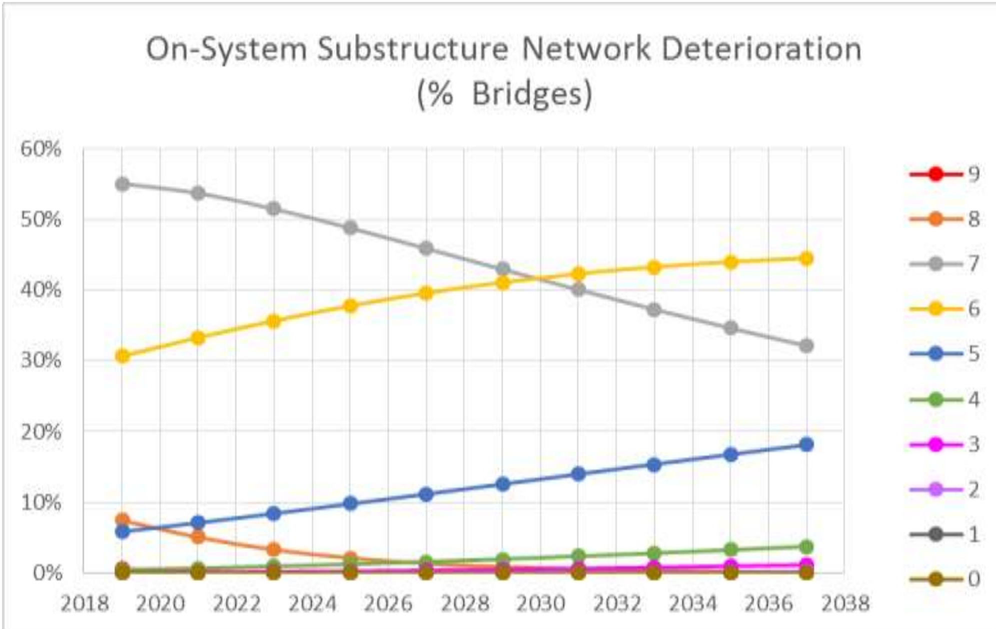


Figure 6. 9 Network Deterioration Curves, On-System Substructure Ratings

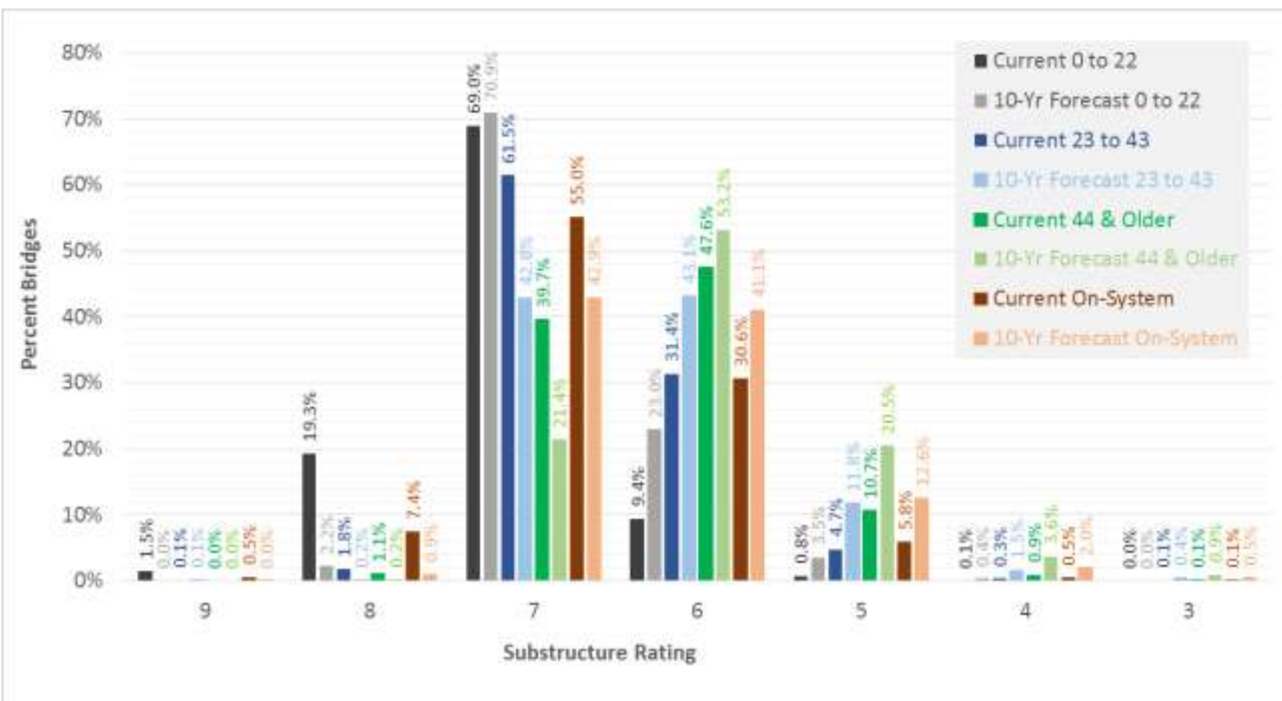


Figure 6. 10 Ten-Year On-System Network Condition Forecasts by Percent Bridges

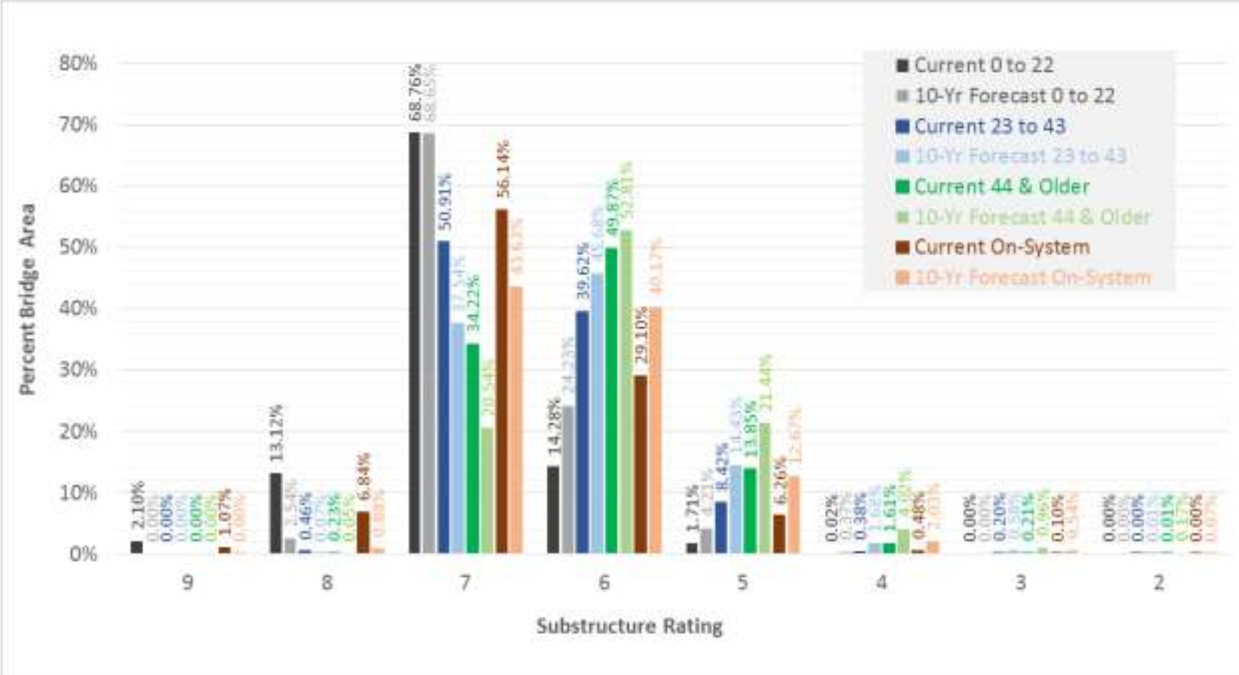


Figure 6. 11 Ten-Year On-System Network Condition Forecasts by Percent Area

Off-System Substructure Models

The numbers of non-negative transitions extracted from the available off-system data and used to develop the 6 off-system Markov matrices for analysis were as follows:

<u>Transitions</u>

Ages 0 to 16	31,053	Over water	96,321
Ages 17 to 34	31,342	Over dry land	6,013
Ages 35 and older	32,423	Aggregated off-system	102,344

<u>Standard errors</u>

Ages 0 to 16	1.9%	5.6%	7.3%
Ages 17 to 34	2.3%	3.3%	5.1%
Ages 35 and older	3.8%	4.2%	5.0%
Aggregated off-system	2.5%	4.1%	4.8%
Over water	4.1%	4.9%	2.6%
Over dry land	1.3%	6.6%	19.8%

The number of non-negative transitions for the off-system over dry land family is considerably smaller than the over water family and the standard errors are the largest. Product 2 has the deterioration tables, deterioration curves, matrices and detailed results for all 6 models. As observed for on-system, expected future values of the off-system substructure ratings have theoretical and mathematical importance but are not a practical infrastructure management result, while the network condition forecasts are useful. Product 2 is programmed to output network condition forecasts every 2 years for 18 years into the future. The 10-year forecasts are discussed here given their practical usefulness.

Figure 6. 12 and Figure 6. 13 compare the current (2019) and 10-year network condition forecast (2029), respectively by number of bridges and bridge area, for the two off-system families and the aggregated off-system. The differences between over water and over dry land are significant, especially for the percentage of substructure ratings of 7. Due to the small number of off-system bridges over dry land, model results for bridges over water and model results for the entire off-system are confounded.

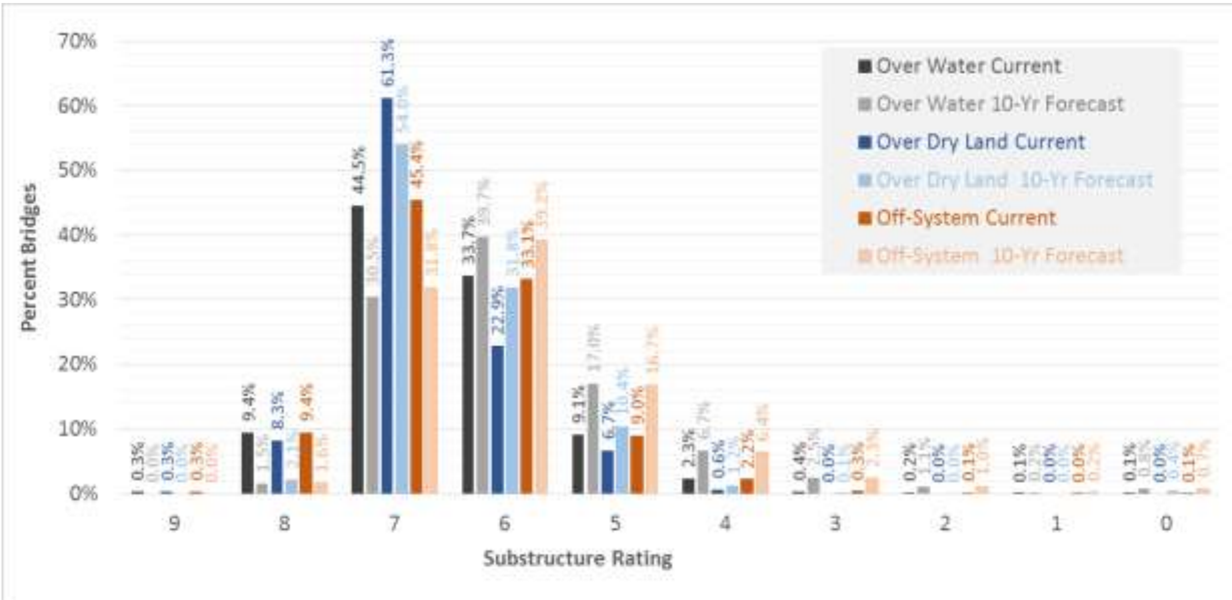


Figure 6. 12 Off-System Current and 10-Year Forecasts of Network Condition by Percent Bridges, Over Water / Over Dry Land Families

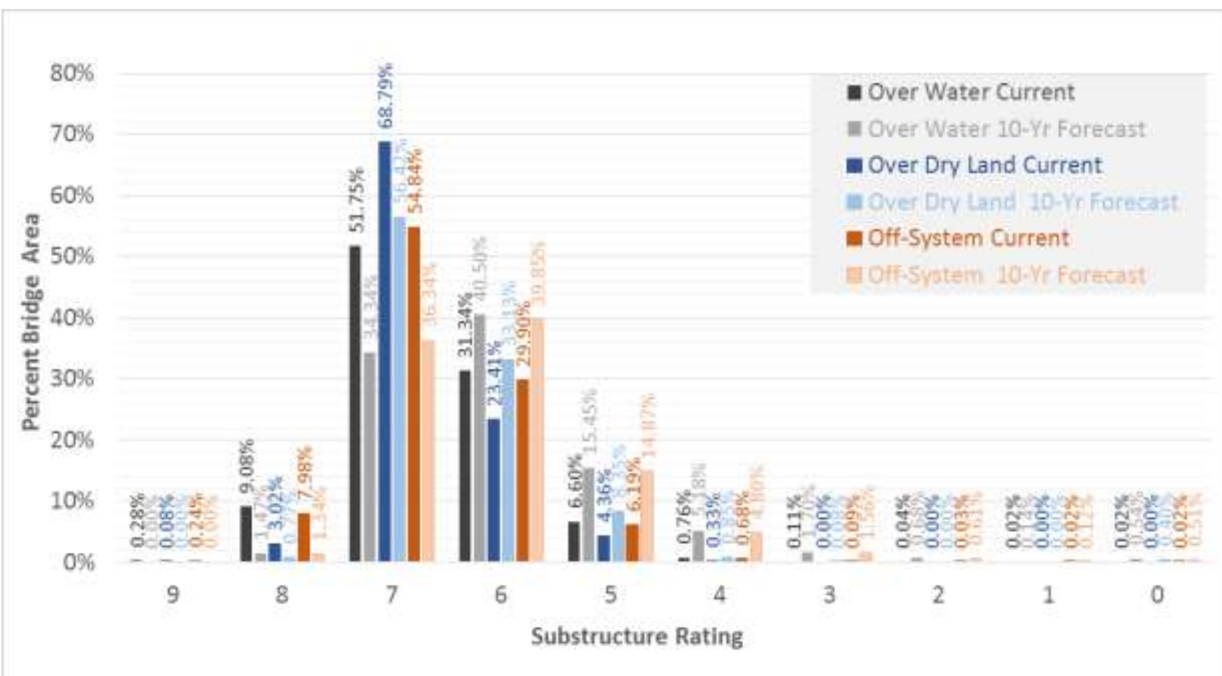


Figure 6. 13 Off-System Current and 10-Year Forecasts of Network Condition by Percent Bridge Area, Over Water / Over Dry Land Families

Figure 6. 14 and Figure 6. 15 compare the current (2019) and predicted 10-year (2029) network condition, respectively by percent bridges and by percent bridge area, by age groups. Differences are consistent with expected deterioration behavior, and are large enough for practical infrastructure management purposes. Differences among age groups ideally should be taken into consideration when using Product 2.

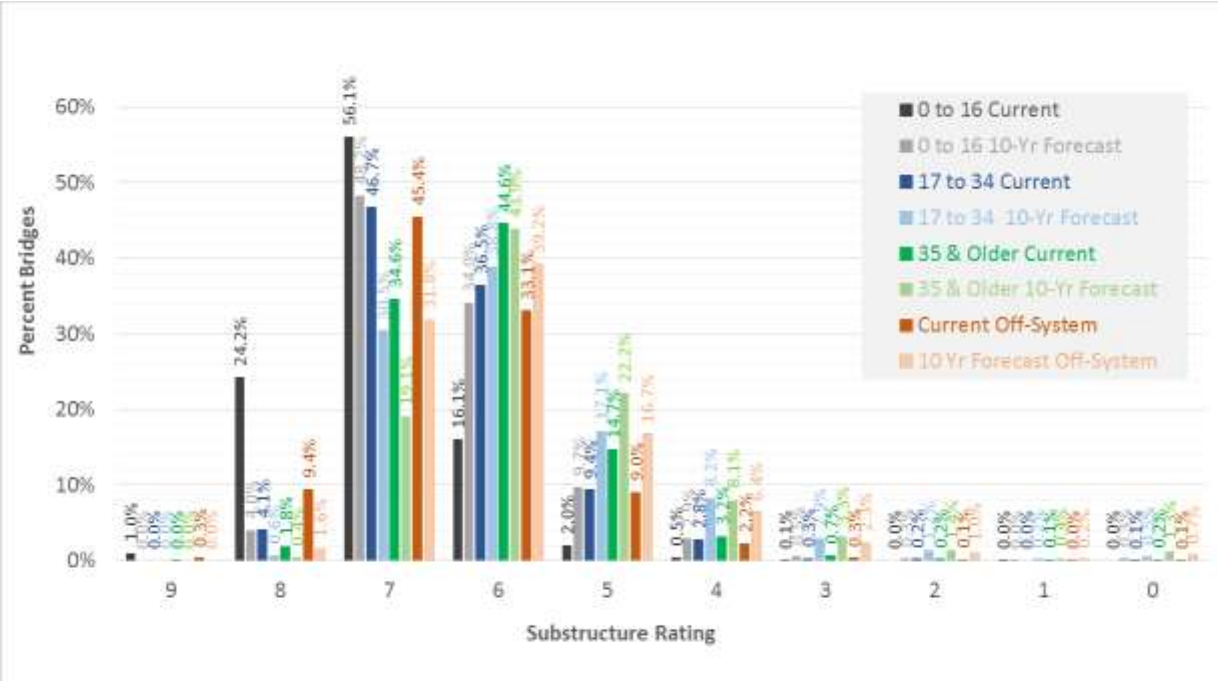


Figure 6. 14 Off-System Current Network Condition and Ten-Year Forecasts by Percent Bridges, Age Groups

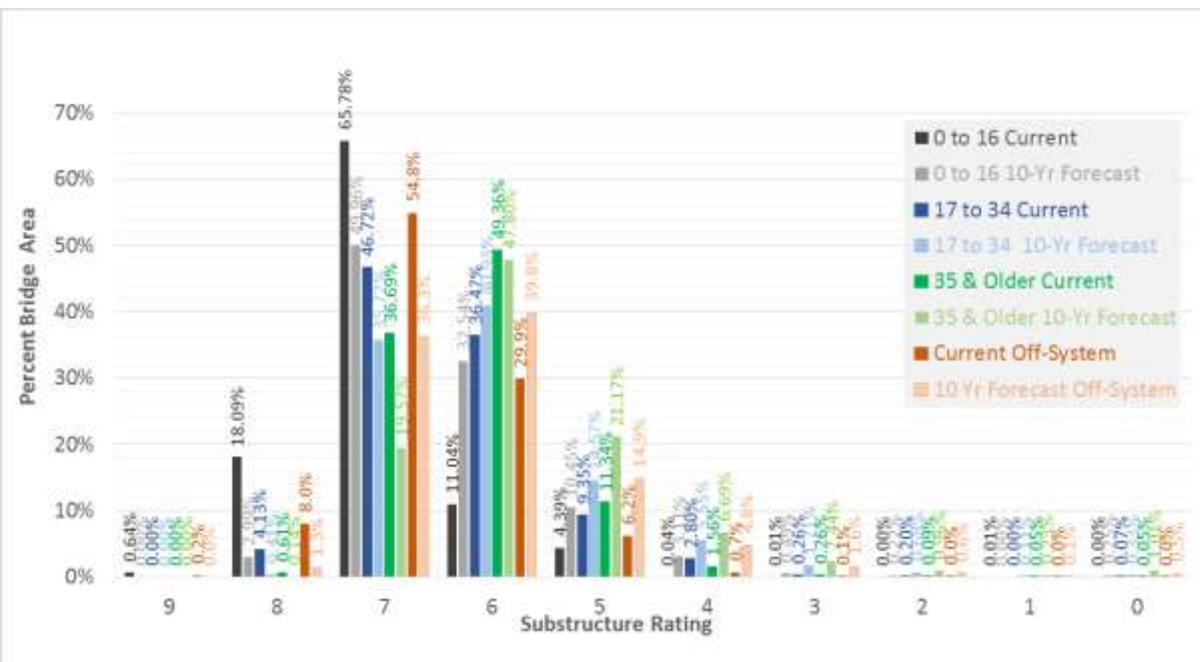
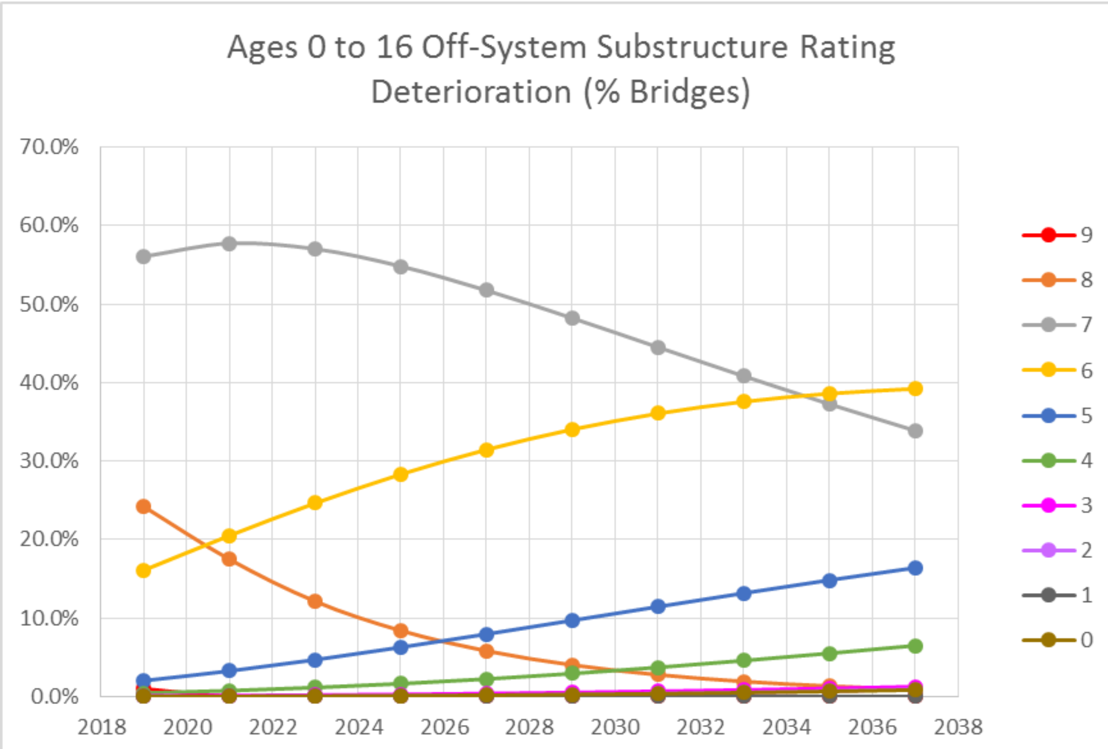


Figure 6. 15 Off-System Current Network Condition and Ten-Year Forecasts by Percent Bridge Area, Age Groups

Figure 6. 16 shows a comparison between deterioration curves of the newest and oldest age groups in the off-system substructure ratings. The full set of network deterioration curves and data tables are found in Product 2.



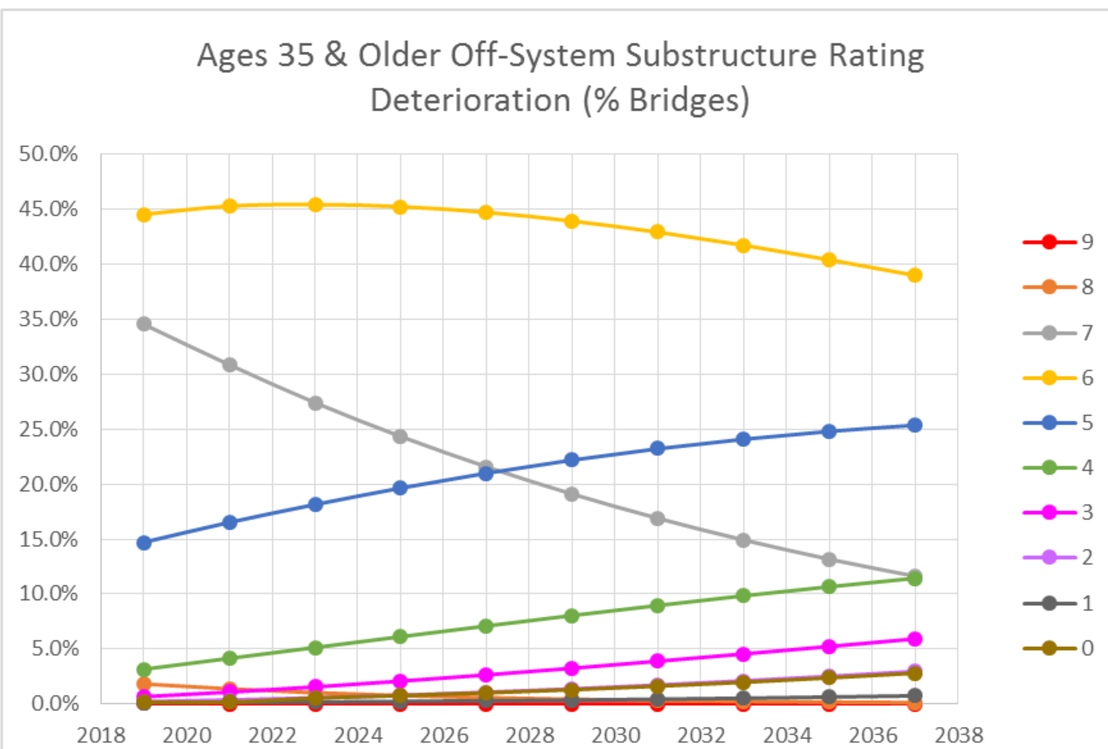


Figure 6. 16 Network Deterioration Curves, Off-System Substructure Ratings

Implementation Considerations

Product 2 consists of two Excel Workbooks, one for on-system and another for off-system substructure models. This deliverable implementation and utilization are discussed in detail in Product 0-6976-2, Texas Culvert and Bridge Deterioration Models: Implementation Manual.

The on-system substructure workbook contains 4 models, one in each worksheet: aggregated on-system, models and one model for each of the 3 age groups. The off-system work book contains 6 models: aggregated off-system, one model for each of the 3 age groups, a model for off-system bridges over water and a model for off-system bridges over dry land.

Updating the off-system substructure deterioration curves by over water/over dry land families can be used when splitting into these families is helpful for infrastructure management purposes, given the considerable difference in performance. However, 93.9% off-system data points are for bridges are over water; therefore, the aggregated model for all off-system bridges and the model for bridges over water are mathematically confounded and therefore both deliver almost the same results.

Chapter 7
Superstructure Deterioration Models

Background and Objectives

This Chapter documents the development of deterioration models for National Bridge Inventory (NBI)/PonTex Item 59: superstructure condition rating. Chapter 3 describes the 2 historical data bases used in model development and validation. Chapter 4 explains the superstructure rating (0 to 9) and the modeling framework, which is conceptually the same for the culvert rating and the 3 bridge ratings and basically has 3 phases: exploratory data analysis, model development, and model validation.

Exploratory Analysis of Superstructure Ratings

Summary of Available Data

The superstructure modeling database contains 313,809 bi-annual superstructure ratings, mined from PonTex files from 2001 to 2019, split into 191,014 on-system and 122,795 off-system. Figure 7. 1 summarizes these data in histograms. The inset shows the main statistical measures of the distributions. The impact of good maintenance is clear for both on and off-system superstructures. Both distributions have more high ratings than low ratings; ratings below 5 are nearly absent, especially for on-system superstructures. The most frequent rating (mode) is 7 for both on- and off-system. Over 90% of all ratings are either 6, 7 or 8, for both on- and off-system superstructures (respectively 94.5% and 90.5%). Mean ratings are between 6 and 7. Half the ratings are 7 or better (median ratings). Low standard deviations underscore consistency in maintenance quality.

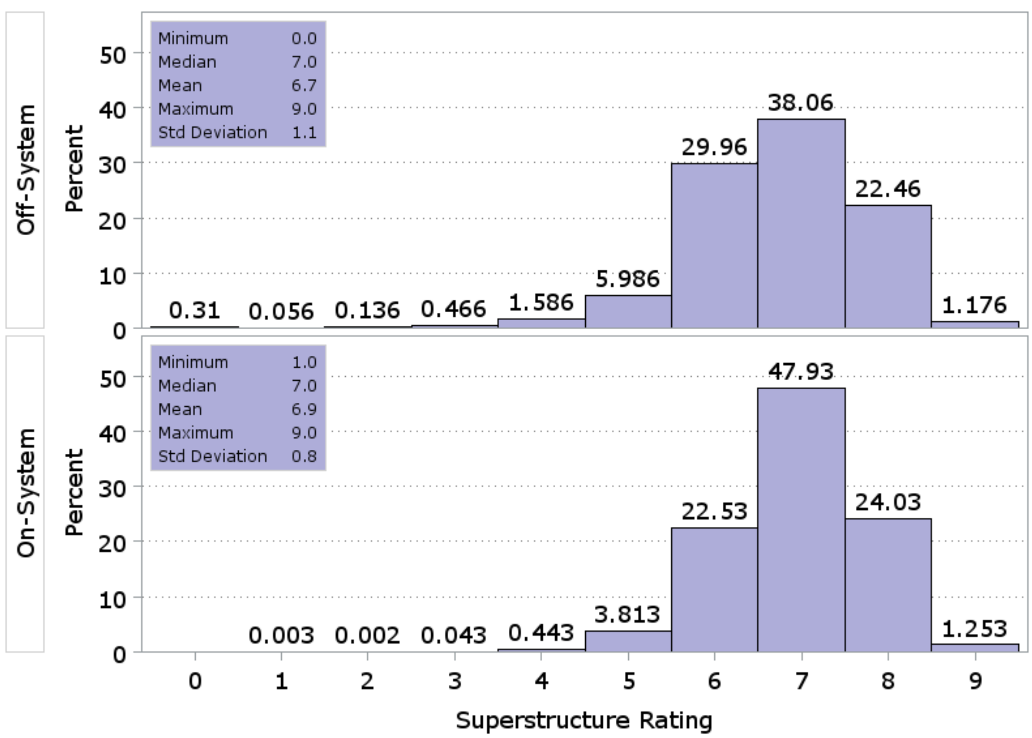


Figure 7. 1 Histograms of Superstructure Ratings

In addition to the climatic variables obtained and summarized as discussed in Chapter 3, the following PonTex variables were considered relevant for superstructure deterioration analysis, and were tested as potential modeling families:

- Bridge age: calculated from Item 27 (year built) or Item 106 (year reconstructed), and the file year. On- and off-system bridge age groups are discussed in Chapter 4. Other families' ages are discussed here.
- Average daily truck traffic (Truck ADT, ADTT): calculated from Items 29 (AADT) and 109 (percent trucks), as explained in Chapter 4.
- Item 43, structure type, discussed in the next section.
- Item 88C, steel type, cross-checked with Item 43.1, 3rd and 4th digits.
- Item 88B, number of fracture critical elements, was investigated and, as expected, resulted in 98.1% on-system, and 96.6% off-system data points, pertaining to structures "with no fracture critical elements."

Superstructure Type

PonTex Item 43 describes the span type and is divided into 3 variables:

- Item 43.1: main span;
- Item 43.2: major approach spans, and
- Item 43.3, minor approach spans.

Items 43.1, 43.2, and 43.3 are similar. They contain 3 variables stored as the 1st digit, the 2nd digit, and last two digits of the item. Item 43.2 (major approach spans) is blank for 90.4% off-system and 75.4% on-system data points. Item 43.3 (minor approach spans) is blank for 99.1% off-system and 97.0% on-system records.

Item 43.1—Structure Type, Main Span is is blank for only 2.9% off-system and 0.13% on-system data points. Item 43.1 first digit is the span type: simple, continuous, cantilever, etc.. Nearly all are either simple or continuous, for both on- an doff-system bridges. Furthermore, over 80% are simple spans, for both off- and on-system. Analogous results were found for the second digit, which describes whether the roadway is "deck", through, part through, etc. Nearly all are "deck," for both on- and off-system bridges.

The 3rd and 4th digits store the main span type as depicted in Table 7. 1 (Ref. 51). These detailed types were grouped into the families as depicted in Table 7. 1. This table also shows the total number and percent of data points available in each family (on- and off-system combined). It is that clear timber, truss and weathering steel cannot be modeled separately for on- and off-system. The "Other" family cannot be accurately modeled for one mathematical reason (too few data points) and one engineering reason: it aggregates dissimilar member types.

Item 88C—Type of Steel, takes the values of 1 (all exposed steel is weathering), 2 (some or all exposed structural steel will require painting), and N (no structural steel) (Ref. 51). In order to check Item 88C's accuracy as means to classify trusses into to material / steel types, Item 88C values were retrieved for the weathering steel and steel families; Item 88C should be equal to 1 for Item 34.1 values of 01 to 09, and equal to 2 for Item 43.1 values of 11 to 19. However, weathering steel bridges Item 88C values were split into 78.8% =1, 7.9%=1, and 13.3%=N. Steel bridges had Item 88C values as follows: 0.83% =1, 85%=2, and

14.2%=N. Conclusion: using Item 88C to classify metal trusses as well as other metal bridges is likely to cause errors in the models.

Table 7. 1 PonTex Item 43.1 Main Span Member Type

3rd & 4th Digits — MEMBER TYPE

01	Weathering Steel (WS) I-Beam	**Weathering Steel**
02	WS Plate Girder — Multiple	2,699
03	WS Plate Girder, Var. Depth — Multiple	0.87%
04	WS Plate Girder w/Floor System	
05	WS Box Girder — Multiple	
06	WS Box Girder — Single or Spread	
08	WS Orthotropic Plate Girder	
09	WS Other	
11	Steel I-Beam	**Steel**
12	Plate Girder — Multiple	64,636
13	Plate Girder, Var. Depth — Multiple	20.85%
14	Plate Girder w/Floor System	
15	Steel Box Girder — Multiple	
16	Steel Box Girder — Single or Spread	
17	Steel Channel Beam	
18	Steel Orthotropic Plate Girder	
19	Other Steel	
21	Concrete Girder — Tee Beam	**Concrete**
22	Concrete Girder, Var. Depth — Tee Beam	100,240
23	Concrete Box Girder — Multiple	32.34%
24	Concrete Box Girder — Single or Spread	
25	Concrete Slab & Girder — Pan Formed	
26	Concrete Flat Slab	
27	Concrete Slab — Variable Depth	
28	Concrete Arch, Open Spandrel	
29	Other Concrete	
30	Segmental Box Girder	**Prestressed Concrete**
31	PS Concrete Girder — Multiple	127,973
32	PS Concrete Girder — w/Floor System	41.28%
33	PS Concrete Box Girder — Multiple	
34	PS Concrete Box Girder — Single or Spread	
35	PS Concrete Slab & Girder — Pan Formed	
36	PS Concrete Slab — Full Depth	
37	PS Concrete Slab — Partial Depth	
38	PS Concrete — U-beam	
39	Other Prestressed Concrete	
41	Timber Stringers — Multiple	**Timber**
42	Timber Girder W/Floor System	10,958
43	Timber Truss	3.53%
49	Other Timber	
51	Metal Arch	**Other**
52	Other Metal	693
53	Masonry Arch	0.22%
54	Movable, Vertical Lift	
55	Movable, Bascule	
56	Movable, Horizontal Swing	
57	Movable, Other	
59	Other Than Metal Truss or Other Metal	
61	Pratt Truss, Parallel Chord	**Truss**
62	Pratt Truss, Half-Hip, Parallel Chord	2,798
63	Warren Truss, Parallel Chord	0.90%
64	Warren Quadrangular Truss, Parallel Chord	
65	Baltimore Truss, Parallel Chord	
66	K Truss, Parallel Chord	
67	Whipple Truss, Parallel Chord	
68	Bedstead Truss, Parallel Chord	
71	Parker Truss, Polygonal Top Chord	
72	Camelback Truss, Polygonal Top Chord	
73	Pennsylvania Truss, Polygonal Top Chord	
74	K Truss, Polygonal Top Chord	
75	Warren Truss, Polygonal Top Chord	
76	Bowstring Truss, Polygonal Top Chord	
77	Lenticular Truss, Polygonal Top Chord	
78	Whipple Truss, Polygonal Top Chord	
79	Pegram Truss, Polygonal Top Chord	
81	Howe Truss, Parallel Chord	
82	Post Truss, Parallel Chord	
83	King Post or Waddell "A" Truss	
84	Queen Post Truss, Parallel Chord	
85	Bollman Truss, Parallel Chord	
86	Fink Truss, Parallel Chord	
87	Fink-Steams Truss, Parallel Chord	
88	Kellog Truss, Parallel Chord	
89	Pratt-Greiner Truss, Parallel Chord	
91	Continuous Truss	
92	Wichert Continuous Truss	
93	Vierendell Truss	
97	Other Truss, Parallel Chord	
98	Other Truss, Polygonal Top Chord	

Note **Family name**
Total number of data points
Percent data points

Table 7. 2 shows the on- and off-system number and percent data points per member type family, as well as the statistical summaries of the bridge ages in each family. As discussed in Chapter 4, families must

have enough points to ensure accurate transition probability estimates. In addition, different families can only be compared to one another when they have similar bridge age distributions in the modeling data; otherwise family and age effects are confounded. For example, the prestressed concrete model predicts less deterioration than the concrete model regardless of material quality, because concrete bridges are considerably older as a group than prestressed concrete bridges.

Table 7. 2 Pontex Item 43.1 Main Span Member Type Families

	Member Type	Data Points		Bridge Age					
		Number	*Percent*	*Minimum*	*1st Quartile*	*Median*	*Mean*	*3rd Quartile*	*Maximum*
OFF SYSTEM	Concrete	29,407	23.9%	0	23	39	41.1	56	118
	Prestressed Concrete	38,174	31.1%	0	9	18	19.5	28	102
	Steel	37,226	30.3%	0	12	20	28.4	42	115
	Weathering Steel	769	0.6%	0	21	32	29.1	37	81
	Timber	10,855	8.8%	0	16	25	31.2	45	117
	Truss	2,381	1.9%	0	52	74	67.4	88	119
	Other	424	0.3%	2	19	49	45.2	65	100
	N/A	3,559	2.9%	0	5	8	15.1	14	96
	TOTAL	122,795		0	12	23	29.4	42	119
ON SYSTEM	Concrete	70,833	37.1%	0	33	45	42.9	53	107
	Prestressed Concrete	89,799	47.0%	0	10	21	22.3	34	88
	Steel	27,409	14.3%	0	26	41	38.5	50	116
	Weathering Steel	1,930	1.0%	0	8	14	14.9	21	44
	Timber	103	0.1%	6	47	52	52.5	63	88
	Truss	418	0.2%	0	52	67	58.8	75	101
	Other	269	0.1%	1	12	31	34.3	53	98
	N/A	253	0.1%	0	8	22	28.2	48	74
	TOTAL	191,014		0	17	33	32.3	46	116

Note: the oldest off-system weathering steel bridge in PonTex is 81 years. According to Ref. 47, weathering steel was first used in construction in Moline, Illinois, in 1964. This outlier does not affect model results, especially because age is included in the models as age groups rather than a continuous variable.

Climatic Variables

Figure 7. 2 and Figure 7. 3 respectively show the boxplots of off- and on-system superstructure ages by rating, comparing the four rainfall families developed as documented in Chapter 3. Rainfall intensity increases in numeric order: Rain1 (driest) to Rain4 (wettest). On-system superstructures show no differences among the four groups. Off-system superstructures show differences, but the deterioration appears inconsistent with the expected behavior of less deterioration in dry areas. This data behavior may reflect design, construction, maintenance and rehabilitation practices emphasizing wet areas, which are known to deteriorate faster. In addition, age and rainfall effects are somewhat confounded, since both on- and off-system bridges in Rain4 areas have the newest ages. Therefore, it is not possible to develop meaningful deterioration estimates by rainfall families.

Figure 7. 4 and Figure 7. 5 respectively show superstructure age boxplots by rating, comparing the two families defined by the freezing days' thresholds developed as documented in Chapter 3. Both on- and off-system superstructures appear to reach low ratings faster in locations subject to the highest number of freezing days per year. However, counties with 10 or more freezing days per year total less than 1% of all data points, are too few to provide enough transitions to estimate reliable Markov probability matrices.

Conclusion: neither on- nor off-system superstructures could be split into meaningful or statistically significant families based on performance difference due to climatic factors.

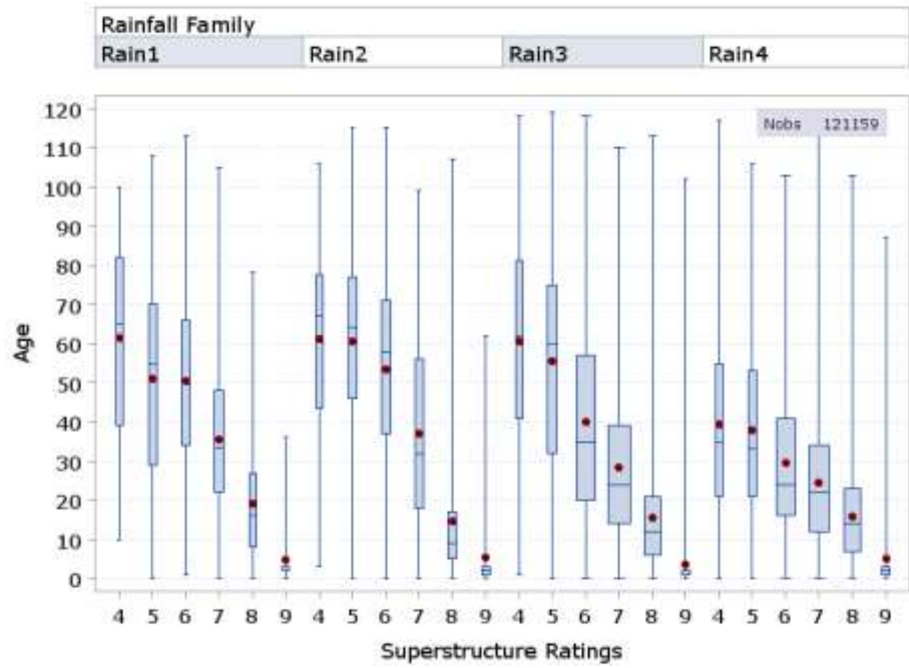


Figure 7. 2 Boxplots of Off-System Superstructure Age by Rainfall Precipitation

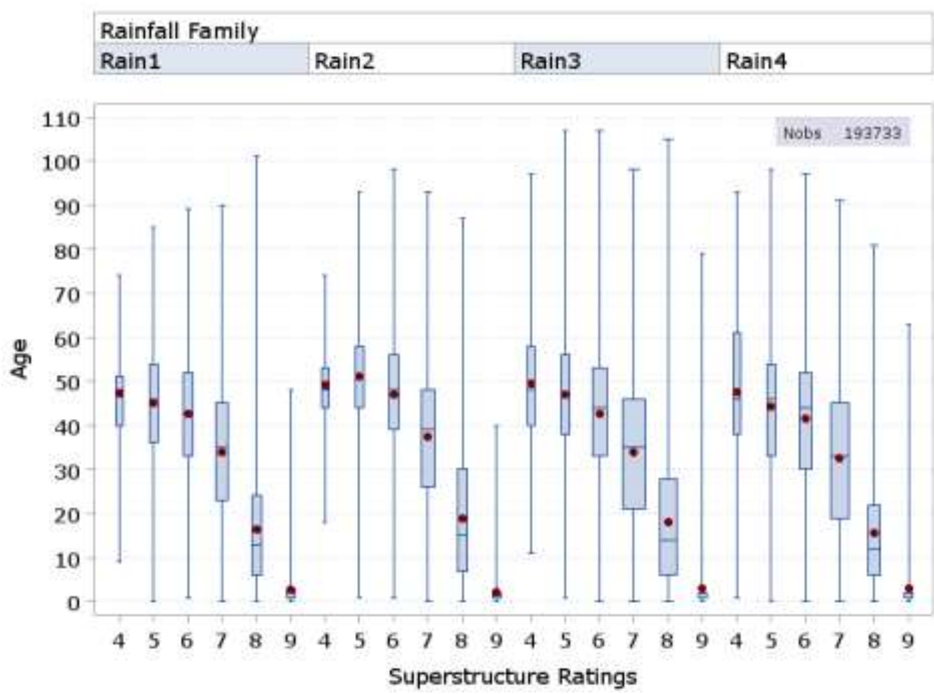


Figure 7. 3 Boxplots of On-System Superstructure Age by Rainfall Precipitation

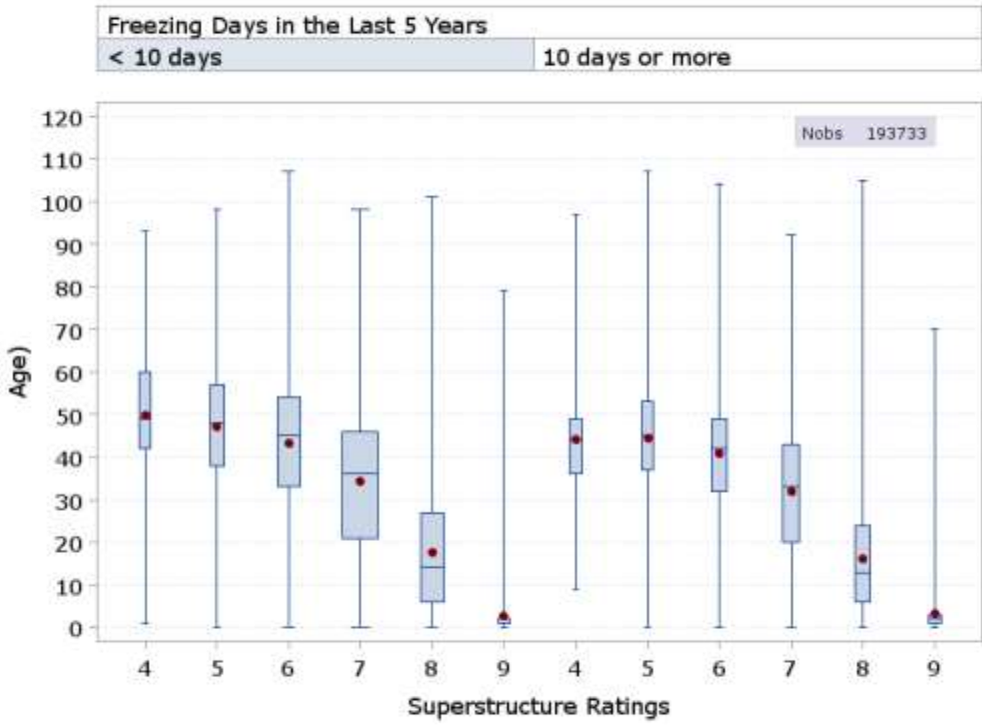


Figure 7. 4 Boxplots of On-System Superstructure Age by Number of Freeze Days in the Last 5 Years

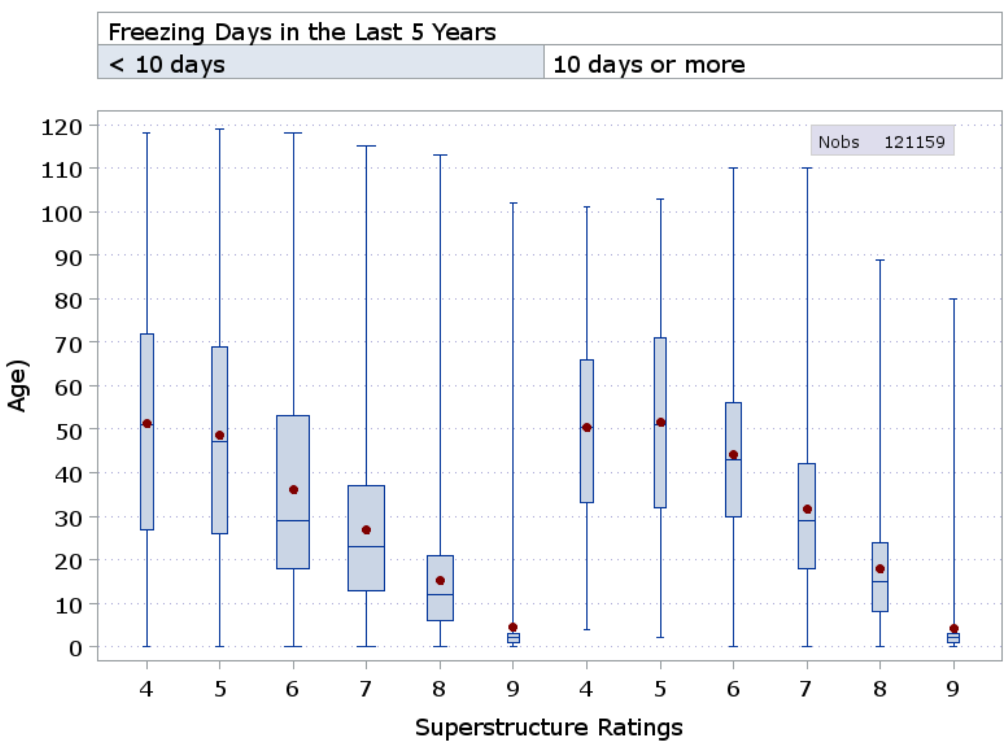


Figure 7. 5 Boxplots of Off-System Superstructure by Number of Freeze Days in the Last 5 Years

Average Daily Truck Traffic (ADTT)

As documented in Chapter 3, Item 29 (average daily traffic) and Item 109 (percent trucks) are not populated enough in off-system superstructures to allow meaningful modeling by traffic families: approximately 30% of the data points are missing traffic data. On-system superstructures are almost fully populated with truck traffic data, and were split into “HIGH” and “LOW” Average Daily Truck Traffic (ADTT) according to the criteria documented in Chapter 3. Superstructures that do not have on-system truck traffic information (0.3% of the available data points) were assigned to an ADTT family based on functional class, as discussed in Chapter 3. The impact of traffic is not significant, as depicted in Figure 7. 6.

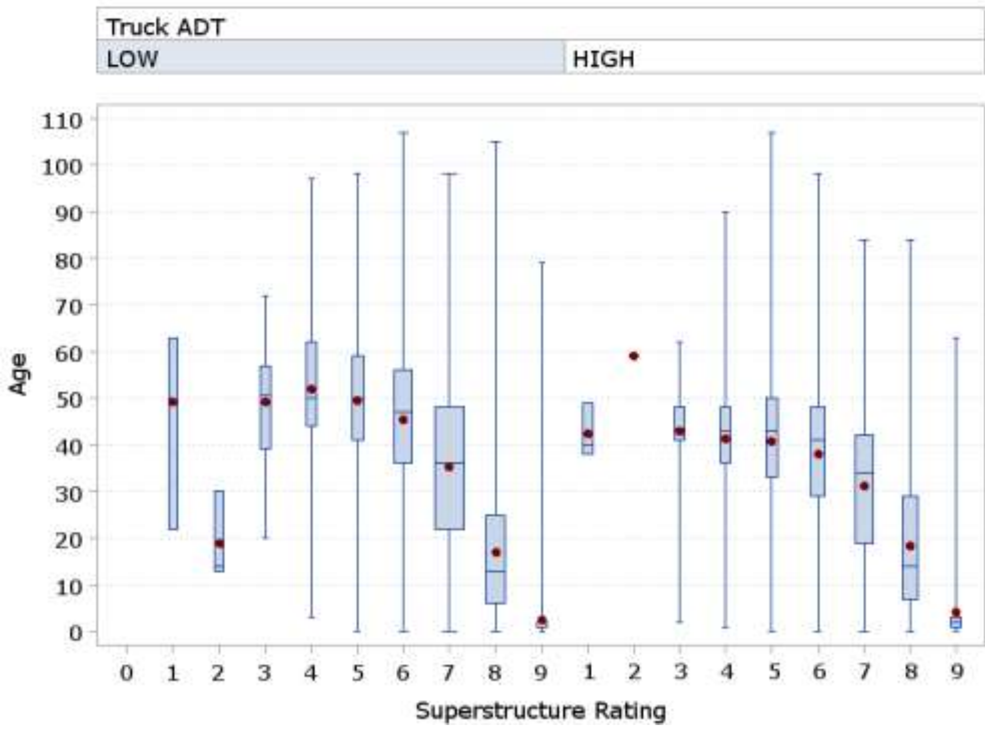


Figure 7. 6 Boxplots of On-System Superstructure Age by Rating and Traffic Family

Conclusions

The following 17 superstructure rating models were developed, validated and analyzed:

- Aggregated on-and off-system: 2 models
- On- and off-system by age groups: 6 models
- On- and off-system by main span type: 6 models each (concrete, prestressed concrete, and steel)
- Aggregated data for on- and off-system: 3 models (weathering steel, truss and timber).

The upcoming sections discuss the Markov deterioration models developed for these families, the analysis of results, and the final implementation recommendations based on model validation and on practical results.

Superstructure Deterioration Models

Modeling Methodology

The modeling methodology, discussed in detail in Chapter 4, is summarized here for readers' convenience. A subset of the annual PonTex database (2001 through 2019), prepared to ensure 2-year lags between all consecutive superstructure ratings was used to develop Markov transition probability matrices that age the superstructures by 2 years (see Chapter 3).

Table 7. 3 illustrates one of the Markov transition probability matrices, showing the matrix calculated for all on-system superstructures. Each matrix cell is the probability that, after 2 years, the rating shown in the first column either will remain as or decrease to the rating shown in the top row. Elevating the two-year transition probability matrix to the n^{th} power ages the matrix by 2n years. This is the basis for calculating the network condition forecasts and deterioration curves discussed in this section and delivered in Product 2 for implementation.

Table 7. 3 Two-Year Transition Matrix for All On-System Superstructures

Initial Rating	Number of Transitions	Rating After 2 Years									
		9	8	7	6	5	4	3	2	1	0
9	2,072	0.125	0.79006	0.08253	0.00145	0.00097	0	0	0	0	0
8	40,328	0	0.83322	0.15976	0.00674	0.00025	0.00002	0	0	0	0
7	78,753	0	0	0.93095	0.06696	0.00192	0.00013	0.00004	0	0.000013	0
6	34,042	0	0	0	0.9654	0.03316	0.00132	0.00009	2.94E-05	0	0
5	5,085	0	0	0	0	0.97719	0.02104	0.00177	0	0	0
4	410	0	0	0	0	0	0.98537	0.01463	0	0	0
3	17	0	0	0	0	0	0	0.94118	0	0.058824	0
2	0	0	0	0	0	0	0	0	0	0	0
1	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	1

The program that develops transition probability matrices contains code to null the transition probabilities in rows where the number of valid transitions is less than 9, due to concerns about reliability of the deterioration probability estimates. This generally happened for ratings less than or equal to 4. In older data groups, and/or in families more prone to deterioration, sometimes the rating of 9 did not result in enough transitions. The program assigns a transition probability of 1 for rating=0 remaining a zero, since a structure cannot be rated lower than zero.

Before modeling, bridge age distributions by family were analyzed for their statistical properties, as well as to determine whether or not it was possible to disaggregate each family by age groups containing enough data points for a meaningful transition probability matrix. Age analysis for aggregated on- and off-system bridges and culverts is discussed in Chapter 4.

Matrices analogous to Table 7. 3 were developed for the 17 age groups and families listed in the previous section conclusions. Standard errors were estimated for 17 sets of observed versus predicted number of bridges in each rating, for each of the 17 transition probability matrix. Minimum, mean and average standard errors of each model are reported here.

The Markov process was implemented in each case to determine rating deterioration curves and tables, and network deterioration curves and tables, every 2 years. Results were compared for meaningful differences among age groups and families, with emphasis in 10-year forecasts, as requested by TxDOT. The comparisons determined how models by families and age groups were implemented in Product 2.

On-System Superstructure Models

The on-system superstructure modeling task developed 7 transition probability matrices similar to that depicted in Table 7. 3. The numbers of non-negative transitions extracted from the on-system biannual inspection data points, and the minimum, average, and maximum standard errors calculated from 17 sets of observed versus predicted network condition forecasts by number of bridges are listed below.

<u>Transitions</u>

Ages 0 to 22 50,724
Ages 23 to 43 51,965
Ages 44 and older 45,754
Aggregated on-system......... 160,707
Concrete 60,585
Prestressed concrete 75,003
Non-weathering steel 22,736

<u>Standard errors</u>

Ages 0 to 22 .... 2.26% .... 5.60% 8.20%
Ages 23 to 43 .... 1.42% .... 2.19% 2.85%
Ages 44 and older .... 2.06% .... 3.17% 4.36%
Aggregated on-system........... 2.44% .... 3.47% 4.42%
Concrete .... 1.81% .... 2.67% 4.41%
Prestressed concrete .... 2.68% .... 5.50% 7.47%
Non-weathering steel .... 2.37% .... 3.99% 5.21%

Figure 7. 7 shows the 3 on-system deterioration curves by age groups. Differences in expected values are too small for practical purposes, especially in the 10-year horizon. Figure 7. 8 shows the network-level deterioration curves in terms of percent bridges at each rating, for the aggregated on-system data. This type of Markov application is more useful for infrastructure management than the expected rating values. It illustrates the decrease in percent bridges with high superstructure ratings while the lower ratings increase. The full set of network deterioration curves are found in Product 2, along with the data tables. These curves will automatically update when the current network condition is updated as indicated in Product 2.

Figure 7. 9 and Figure 7. 10 show the percent ratings predicted for year 2029, for the 2019 population of superstructures, calculated respectively for number of bridges and for bridge area. Newest superstructures have the highest percentage of predicted 2029 ratings of 8 (24.3% bridges and 21.8% bridge area). This percentage decreases to 4.5% and 0.8% bridges, and to 3.5% and 0.8% bridge area for the two older age groups. All other rating trends are consistent with more deterioration in older age groups. Differences among age groups are large enough for practical use in infrastructure management. They are also significantly greater than the average standard errors for most ratings. Forecasts by age group were thus included in Product 2 for implementation.

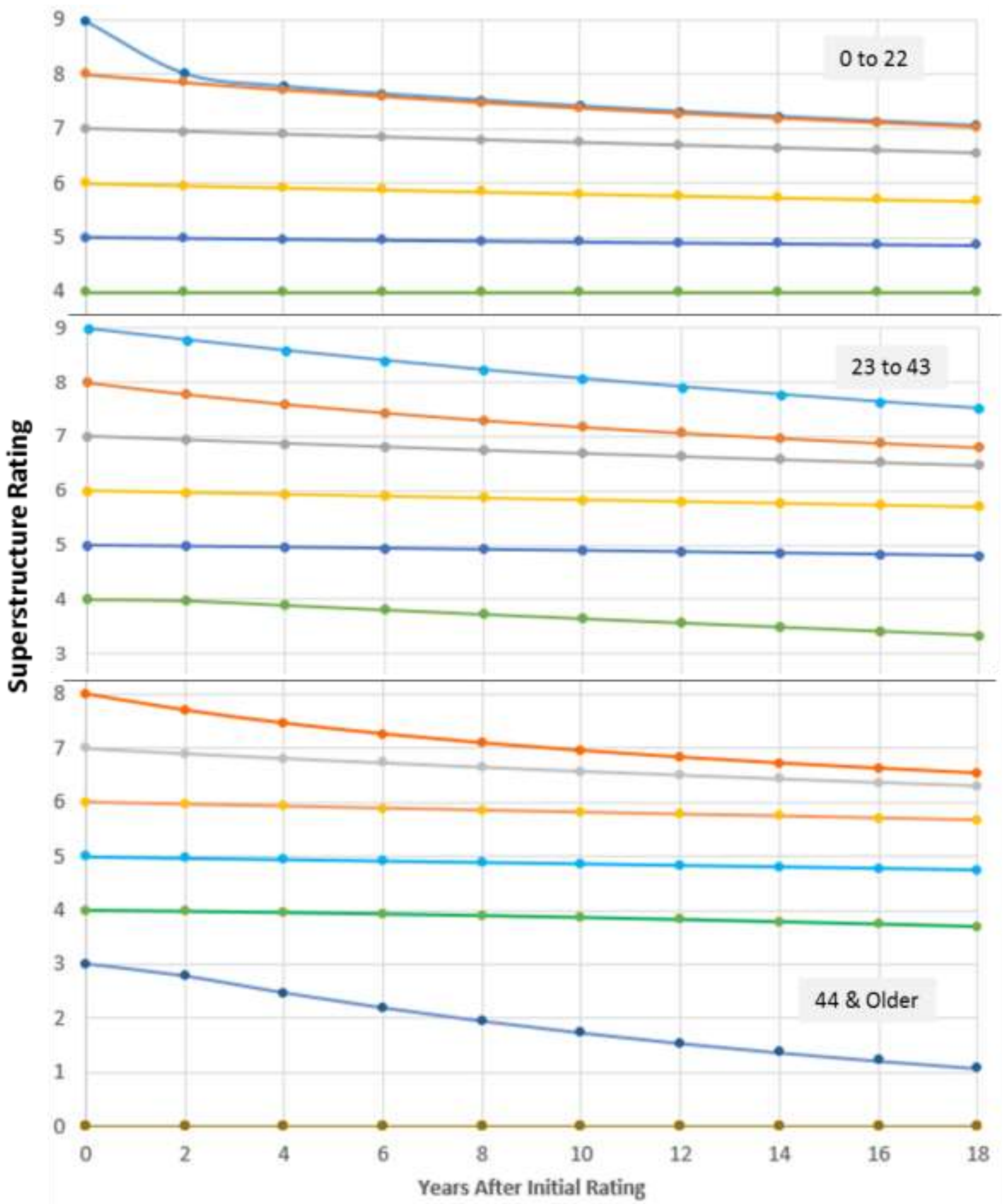


Figure 7. 7 On-System Superstructure Rating Deterioration Curves by Age Groups

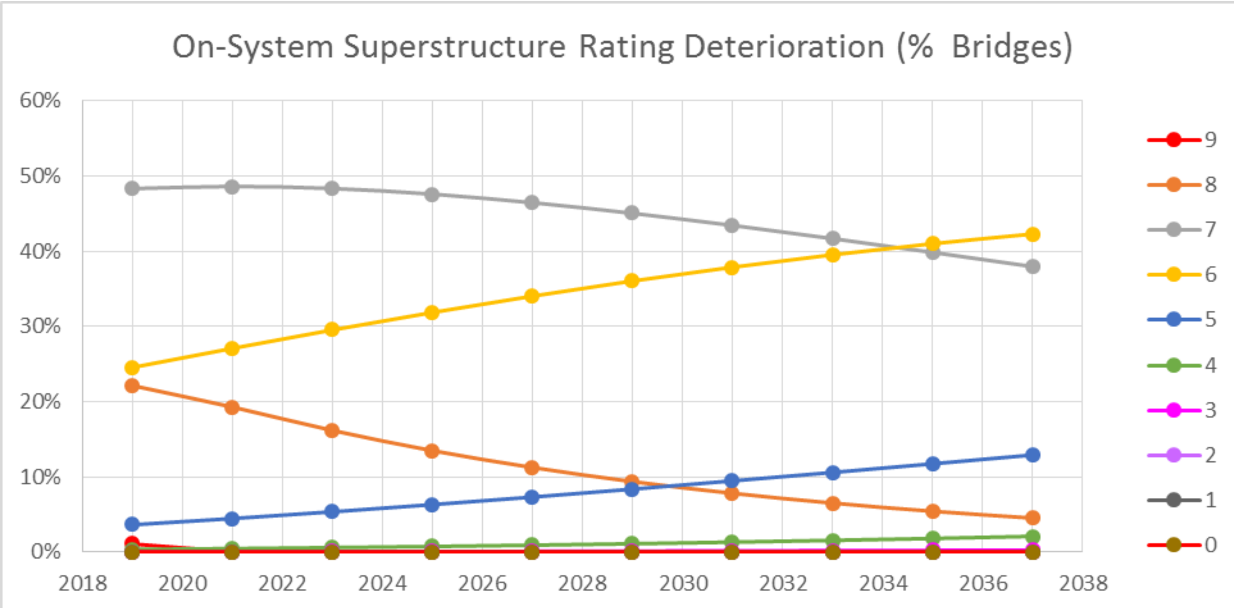


Figure 7. 8 On-System Superstructure Ratings Expected Value After 10 Years, by Age Groups

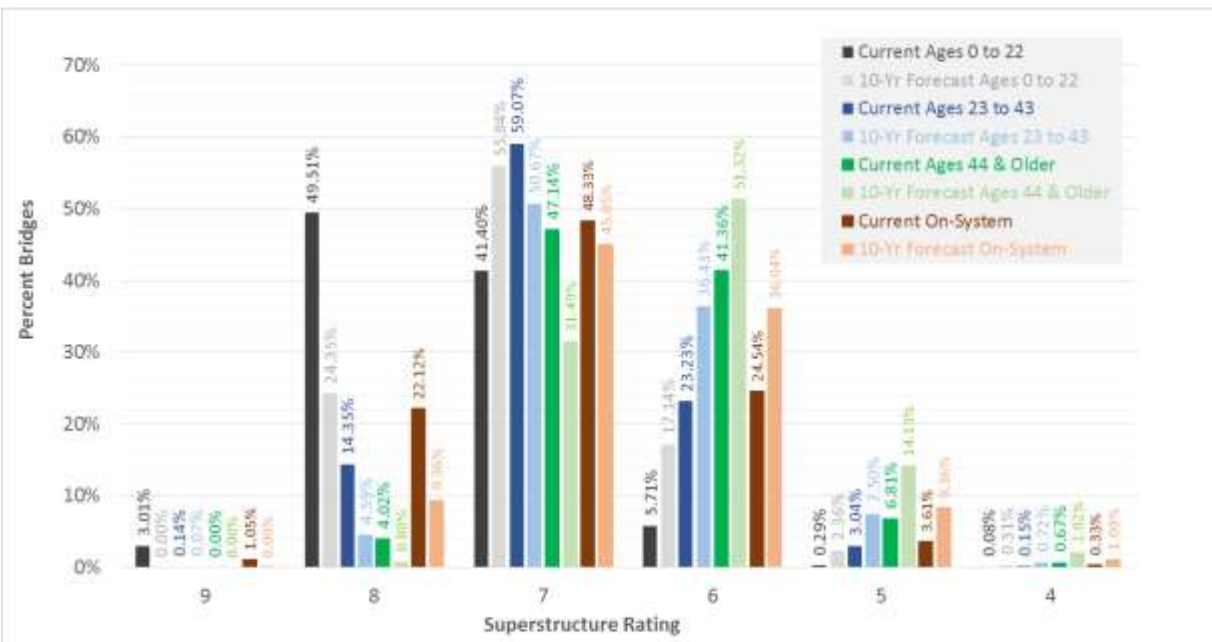


Figure 7. 9 Current and Ten-Year On-System Network Condition Forecasts by Age, Percent Bridges

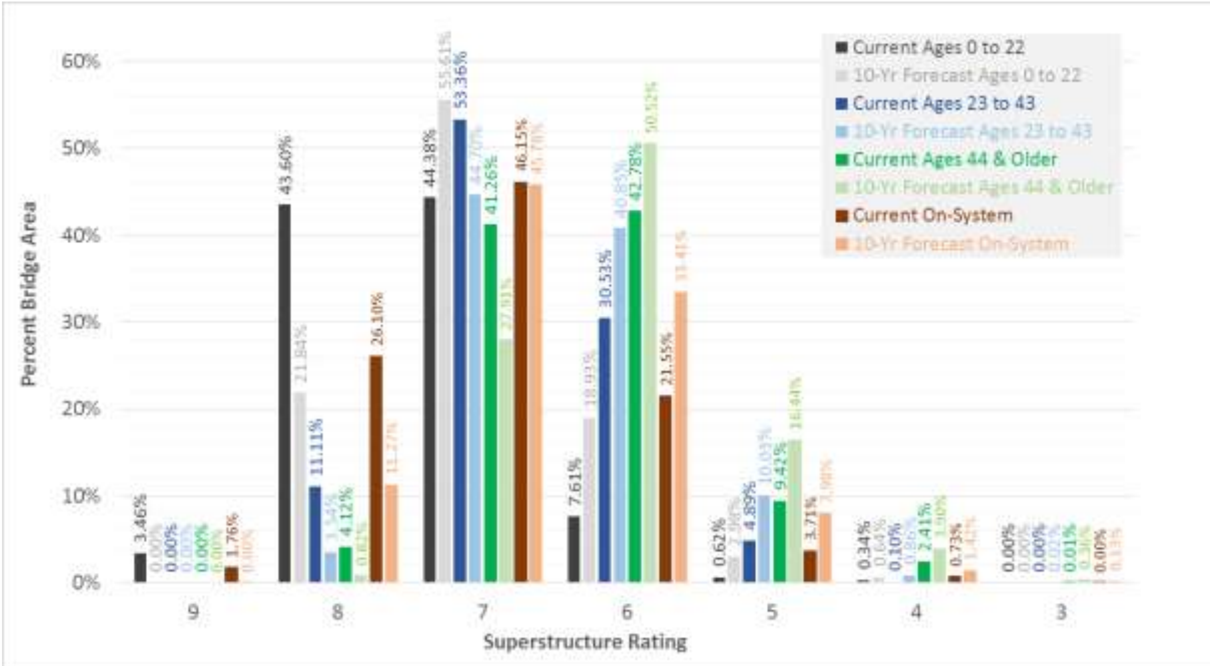


Figure 7. 10 Current and Ten-Year On-System Network Condition Forecasts by Age, Percent Bridge Area

Figure 7. 11 and Figure 7. 12 compare the 2019 network condition to the predicted 10-year forecast (2029), respectively by percent bridges and by percent bridge area. The plots include the 3 main span types that have enough data points to be modeled separately for on- and off-system: concrete, prestressed concrete and non-weathering steel. The 10-year deterioration is evident for all 3 span types, with the percent of higher ratings decreasing and the percent of lower ratings increasing after 10 years.

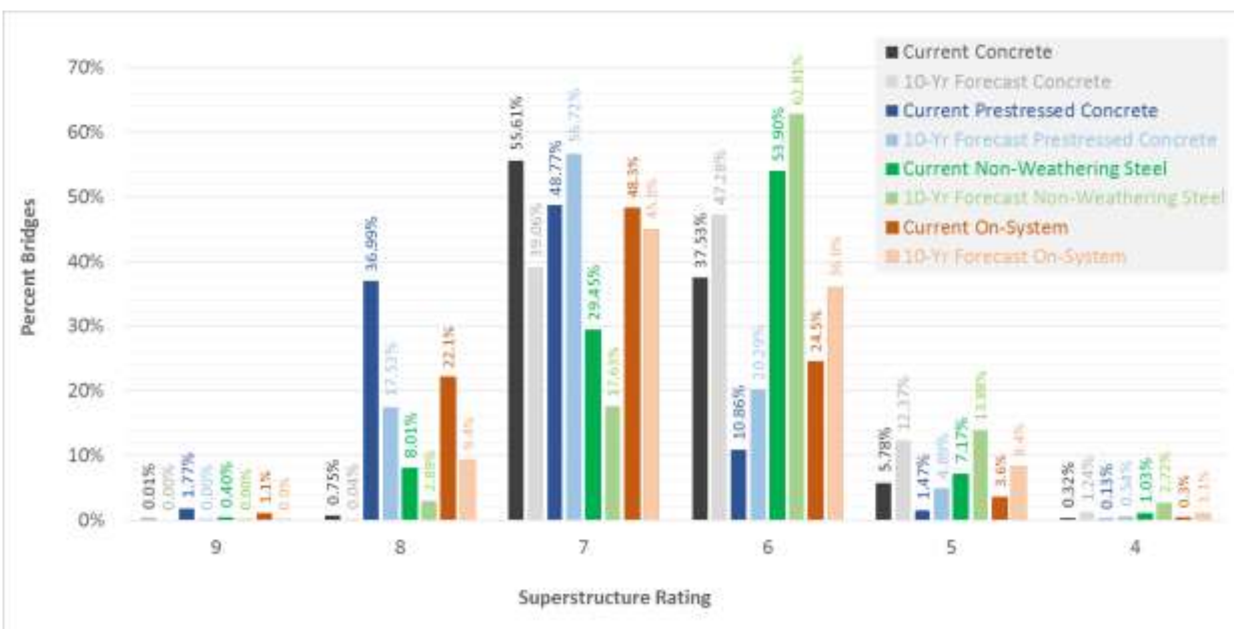


Figure 7. 11 On-System Network Condition Forecasts by Main Span Type, Percent Bridges

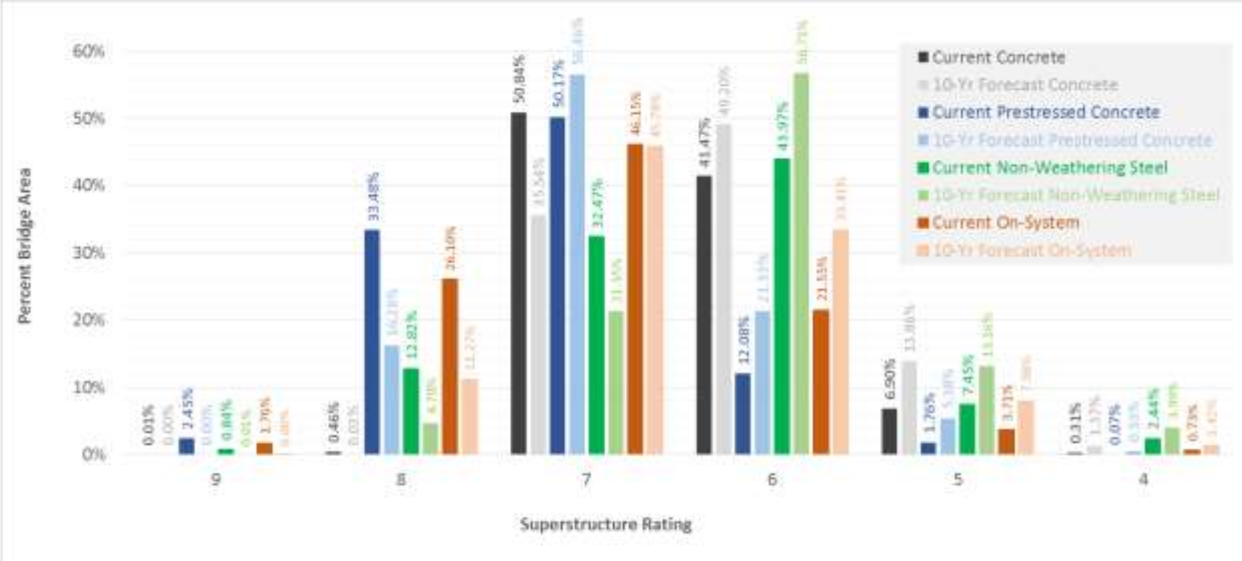


Figure 7. 12 On-System Network Condition Forecasts by Main Span Type, Percent Bridge Area

The 3 span types are depicted in the same graphs for the sake of briefness. Comparing deterioration among these 3 main span types is not recommended due to statistically significant differences in their ages. Prestressed concrete is newer as a group than the other two, as depicted in Table 7. 2. Steel and concrete have similar age means and percentiles in Table 7. 2, so steel and concrete age distributions were compared with three non-parametric homogeneity tests: Cramer-Von Mises, Komolgorov-Smirnov, and Kruskal-Wallis. All 3 tests indicated significantly different age distributions.

Off-System Superstructure Models

The numbers of non-negative transitions extracted from the off-system biannual inspection data points, and the minimum, average, and maximum standard errors calculated from 17 sets of observed versus predicted number of bridges at each future rating are listed below.

<u>Transitions</u>

Ages 0 to 16	30,260	Concrete	25,016
Ages 17 to 34	30,141	Prestressed concrete	31,803
Ages 35 and older	31,097	Non-weathering steel	30,610
Aggregated off-system	98,991		

<u>Standard errors</u>

Ages 0 to 16	2.83%	5.77%	7.57%
Ages 17 to 34	2.16%	2.98%	3.96%
Ages 35 and older	4.29%	4.95%	5.68%
Aggregated off-system	2.69%	4.09%	4.99%
Concrete	2.79%	3.29%	3.95%
Prestressed concrete	2.94%	6.27%	9.50%
Non-weathering steel	4.11%	6.20%	8.76%

Figure 7. 13 compares the expected rating values after 10-years, by age groups. Each bar corresponds to a 10-year expected value point in the rating deterioration curves delivered in Product 2. The differences are too small for practical purposes. Network deterioration curves have more practical utilization, as discussed next.

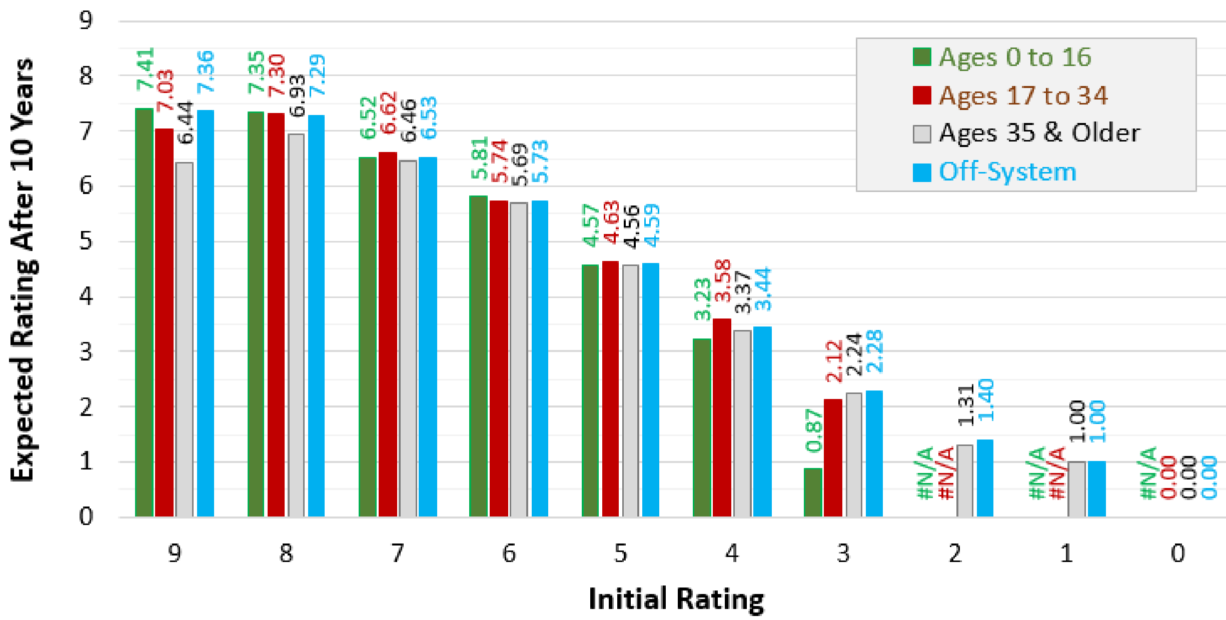


Figure 7. 13 Expected Values of the Initial Rating After 10 Years, Off-System Superstructures by Age Groups

Figure 7. 14 shows the off-system superstructure network deterioration curves developed for the aggregated off-system data. This type of Markov application is more useful for infrastructure management than the expected rating values. It shows the decrease in percent bridges with high superstructure ratings while the lower ratings increase as time passes. The full set of network deterioration curves is found in Product 2, along with the data tables. These curves will automatically update when the current network condition is updated as indicated in Product 2.

Figure 7. 15 and Figure 7. 16 compare the current network condition (2019) to the 10-year forecast (2029), respectively by number of bridges and by bridge area, for the 3 age groups. Comparisons between 2019 and 2029 show deterioration consistent with aging network.

Age groups provide significantly different 10-year forecasts (year 2029 is shown). The newest age group forecast predicts 26.17% bridges and 26.6% bridge area in condition 8 in 2029, dropping to 8.40% bridges and 13% bridge area in the intermediate age group. The oldest age group predicts only 1.4% bridges as well as bridge area in condition 8 after 10 years. Other ratings also show significant changes consistent with age and greater than the matrices average standard errors. Models by age groups were thus implemented as Product 2.

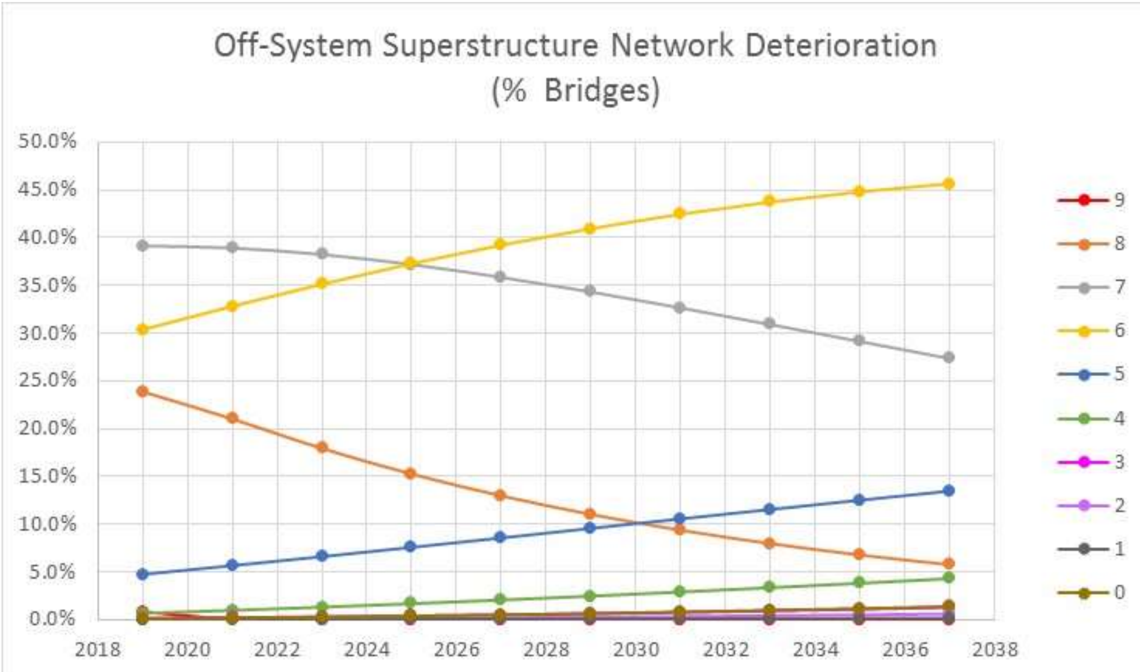


Figure 7. 14 Off-System Superstructure Network Deterioration Curves

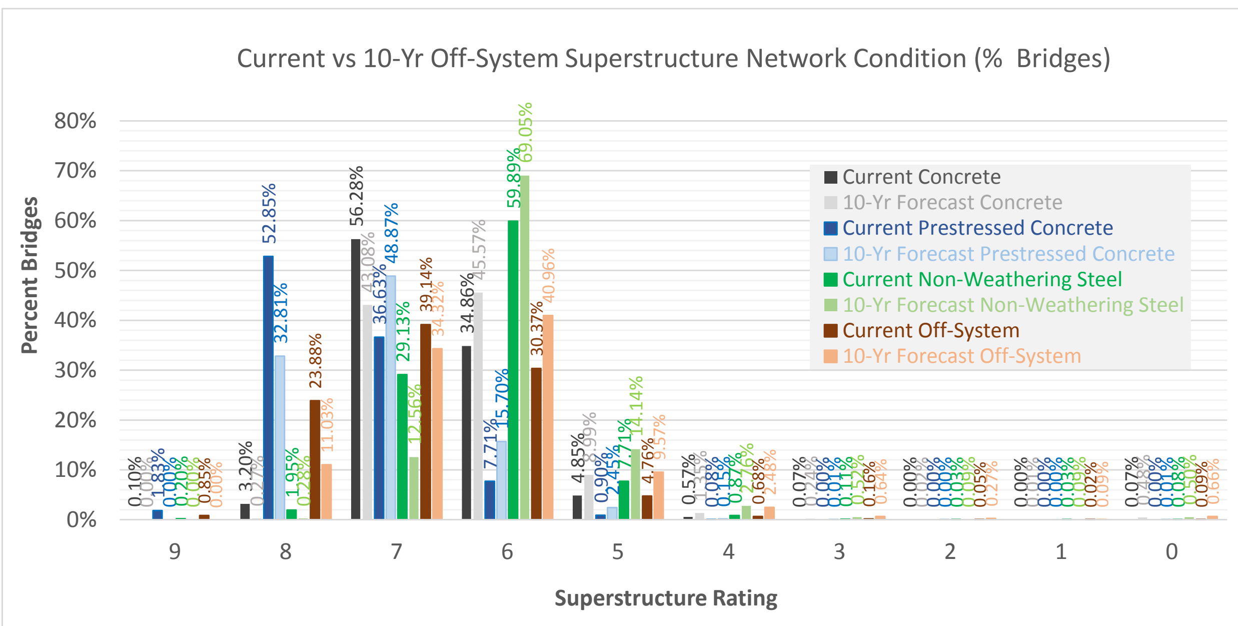


Figure 7. 15 Off-System Ten-Year Network Condition Forecasts by Age Group, Percent Bridges

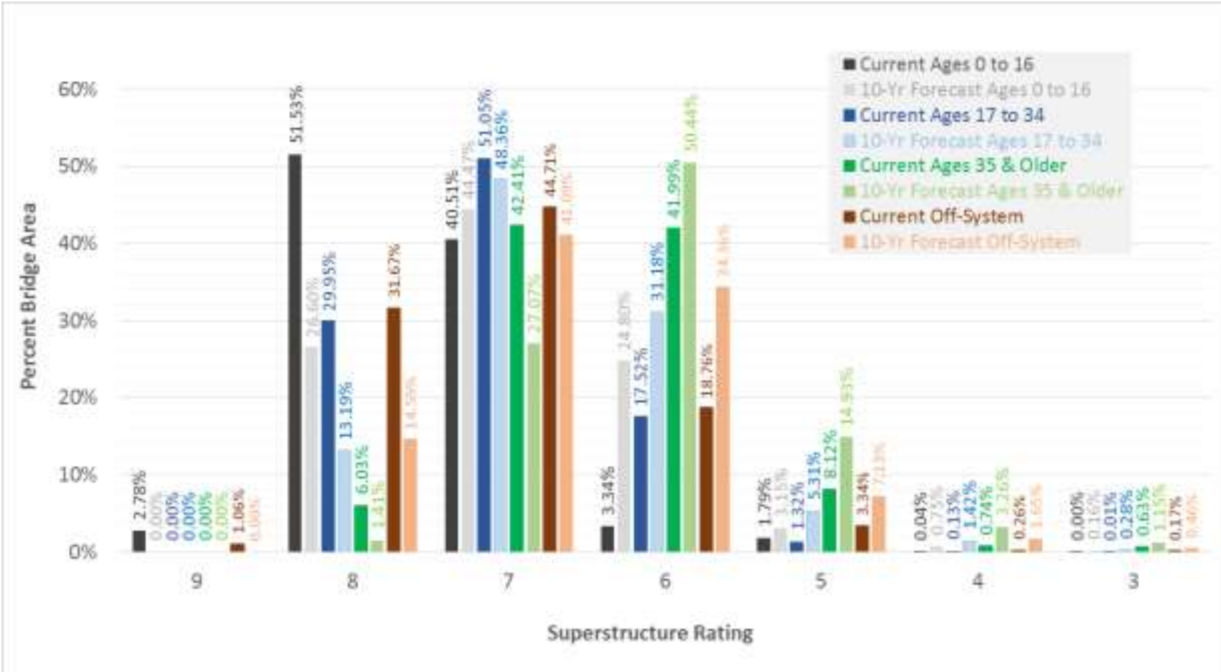


Figure 7. 16 Ten-Year Network Condition Forecasts by Age Group, Percent Bridge Area

Figure 7. 17 and Figure 7. 18 compare the current (2019) network condition to the 10-year forecast (2029) for the 3 main span types that have enough data points to be modeled separately for off-system bridges: concrete, prestressed concrete, and non-weathering steel. The 3 span types are depicted in the same graphs only for the sake of briefness. Comparisons among off-system span types are not recommended, due to statistically significant differences in the bridge age distributions in the modeling data. In this case, age differences are obvious in Table 7. 2, requiring no statistical tests. The deterioration after 10 years is clear for all 3 span types.

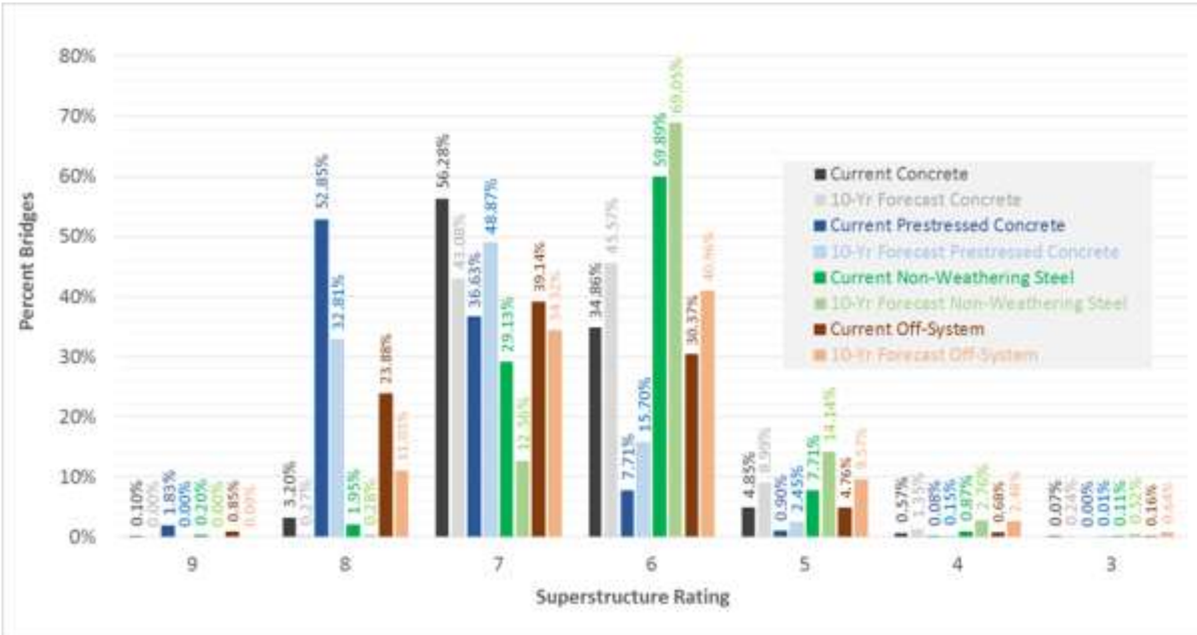


Figure 7. 17 Off-System Ten-Year Network Condition Forecasts by Main Span Type, Percent Bridges

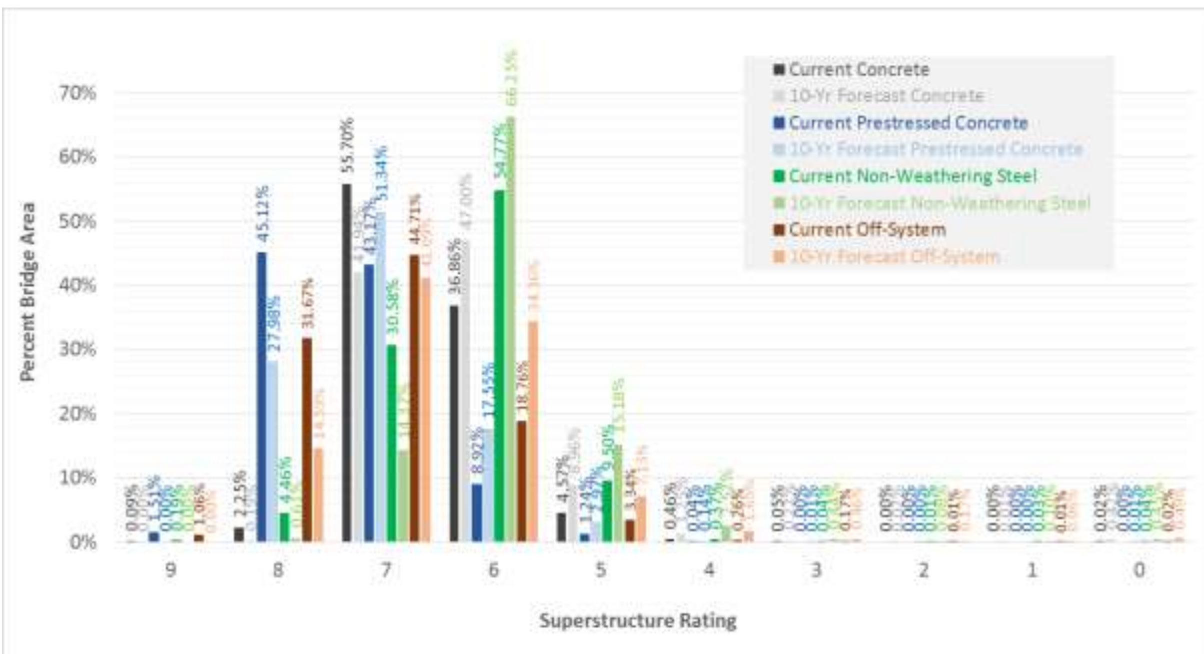


Figure 7. 18 Off-System Ten-Year Network Condition Forecasts by Main Span Type, Percent Bridge Area

Weathering Steel, Timber and Truss Superstructure Models

The numbers of non-negative transitions extracted from the aggregated on and off-system biannual inspection data points are listed below, and so are the minimum, average, and maximum standard errors calculated from 17 sets of observed versus predicted number of bridges at each future rating. The number of available transitions is rather small for all types, thus leading to rather high standard errors of the matrices.

Transitions

Weathering Steel....................2,165
Timber 8,516
Truss 2,060

Standard errors

Weathering Steel...................2.17% ....8.81% 18.69%
Timber ....5.88% ....9.03% 10.85%
Truss ....6.6% ....10.0% 15.2%

Figure 7. 19 and Figure 7. 20 compare timber, weathering steel (WS) and truss current (2019) network condition to the 10-year forecast (2029), respectively by percent bridges and percent bridge area. The deterioration in 10 years is evident for all 3 materials.

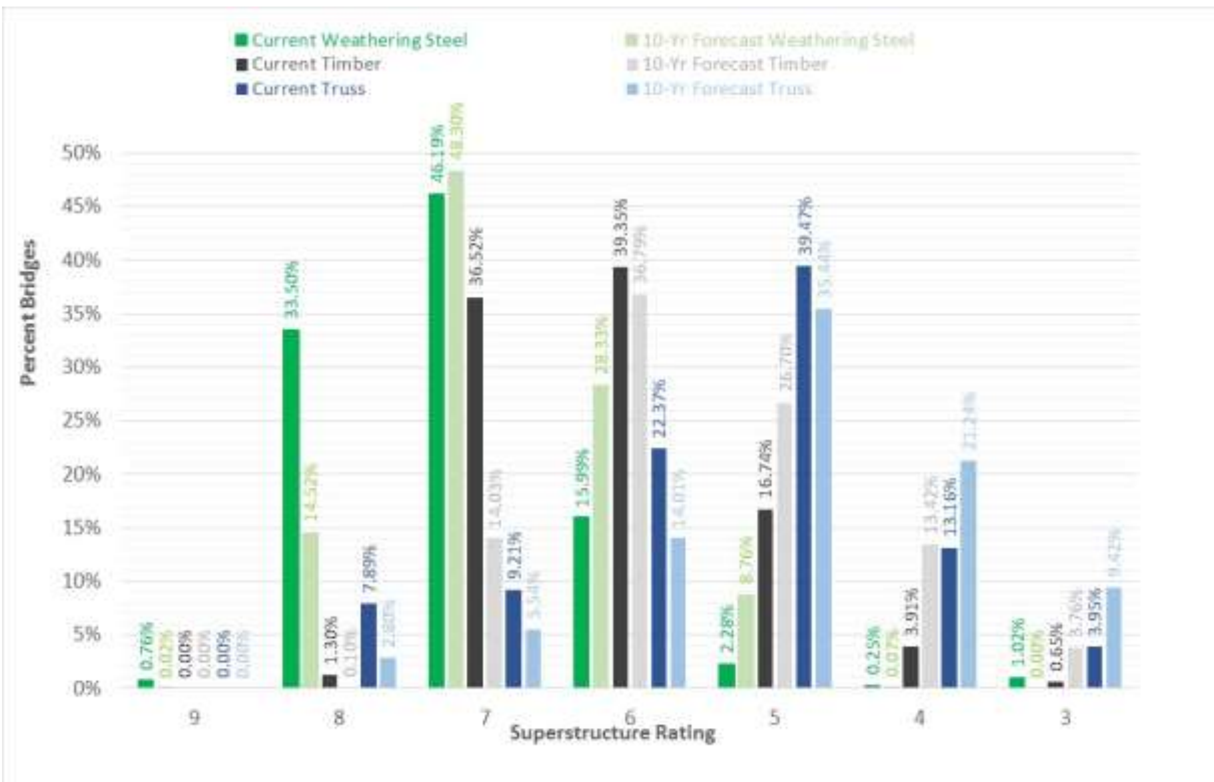


Figure 7. 19 Ten-Year Timber, WS and Truss Network Condition Forecasts, Percent Bridges

These 3 span types are depicted in the same graph only for the sake of briefness. Comparisons among the 3 types are not recommended, due to statistically significant differences in the bridge age distributions in the modeling data. Mean ages are: timber 31, truss 66, and weathering steel 19 years. The mean age differences are large enough to dispense with homogeneity tests of the age distributions.

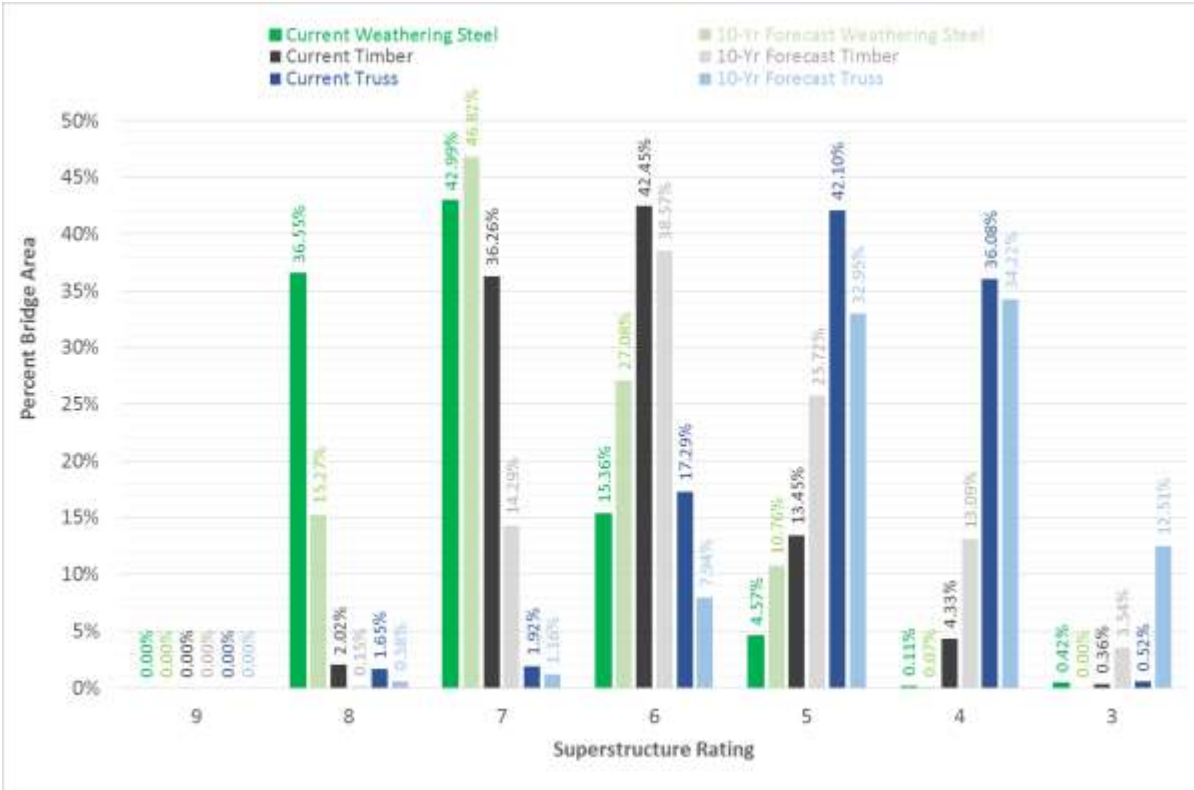


Figure 7. 20 Ten-Year Timber, WS and Truss Network Condition Forecasts, Percent Bridge Area

Product 2 delivers the full set of results, including deterioration curves in terms of expected future rating values, percent bridges at each rating, and percent bridge area at each rating, along with data tables.

Implementation Considerations

Product 2 consists of 3 Excel Workbooks with one model in each sheet, and network condition forecasts every 2 years tabulated and plotted on separate worksheets. The workbooks are: on-system models, off-system models, and a workbook containing timber, weathering steel and truss models. The latter were modeled using aggregated on- and off-system data in order to increase the number of data points. Product 2 workbooks are rather self-explanatory, but are discussed in more detail in Product 0-6976-2: Texas Culvert and Bridge Deterioration Models: Implementation Manual. Aggregated models for all on-system as well as all off-system decks are included in Product 2.

Comparing deterioration among different main span types is not recommended due to age differences among families. For example, on-system prestressed concrete bridges are, on the average, 21 years newer than concrete and 16 years newer than steel. Age and span type effects on deterioration are confounded in the data.

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Chapter 8
Deck Deterioration Models

Background and Objectives

This Chapter documents the development of deterioration models for National Bridge Inventory (NBI)/PonTex Item 58: deck rating (Ref. 51). Chapter 4 explains PonTex Item 58, deck condition rating (0 to 9) and the modeling framework. Chapter 3 describes the 2 historical data bases developed for model development and validation.

Exploratory Analysis of Deck Ratings

Summary of Available Data

The deck modeling database contains 324,621 bi-annual deck inspections, mined from PonTex files from 2001 to 2019. These inspections are split into 202,694 on-system and 121,927 off-system ratings. Figure 8. 1 shows the histogram of deck ratings from 2001 to 2019. The graph inset shows the main statistical measures of the distributions. The impact of good maintenance is clear for both on and off-system decks. Both distributions have negative skewness, i.e., they have more high ratings than low ratings. Ratings of 5 or lower total only 3.36% on-system and 6.28% off-system ratings. The most frequent rating (mode) is 7 for both on- and off-system decks. Over 96.6% of on-system and 93.7% off-system ratings are 6 or higher. Over 79% on-system and 71% off-system ratings are 7 or better. Mean ratings are very close to 7. Low standard deviations underscore consistency in maintenance quality.

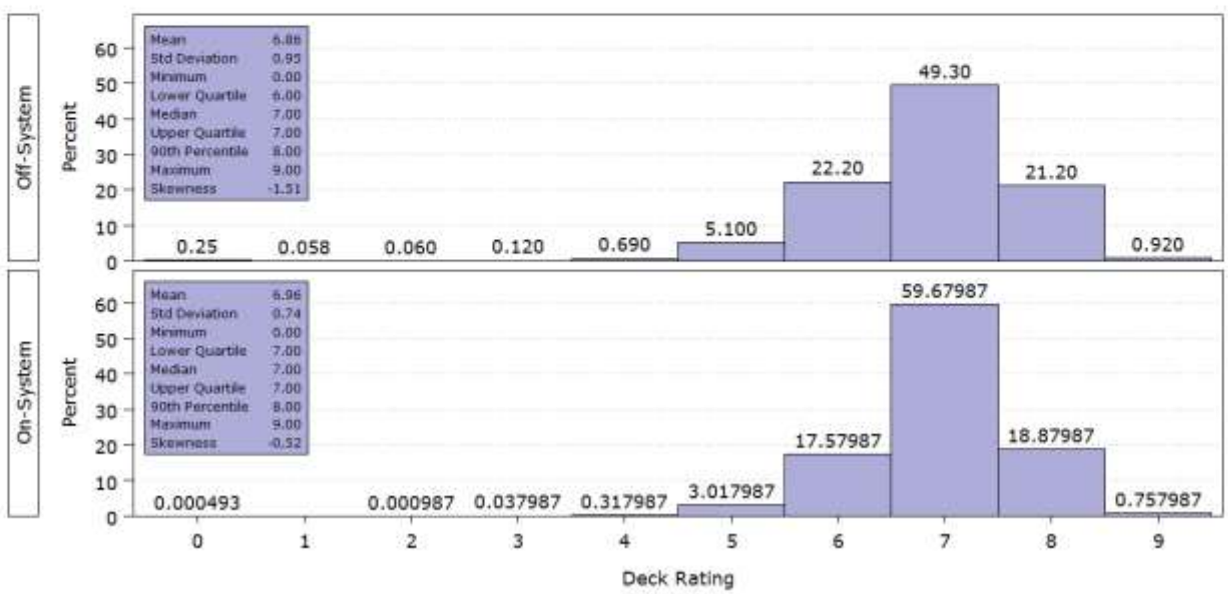

Figure 8. 1 Histograms of Deck Ratings

In addition to the climatic variables obtained and summarized as discussed in Chapter 3, the following PonTex variables were considered relevant for deck deterioration analysis, and tested as potential families for modeling Item 58, deck rating:

- Bridge age: calculated from Item 27 (year built) or Item 106 (year reconstructed), and the file year.
- Average daily truck traffic (Truck ADT, ADTT): calculated from Items 29 (AADT) and 109 (percent trucks), as explained in Chapter 3.
- Item 107, deck structure type.
- Item 108, 1st digit, type of wearing surface.

Deck Type (Item107)

Item 107 stores the "type of deck system on the bridge," according to the first 2 columns in Table 8. 1 (Ref.51). It consists of 3 one-character variables: Item 107.1 — Main Span, Item 107.2 — Major Approach Span, and Item 107.3— Minor Approach Span.

Items 107.2 (major approach span) and 107.3 (minor approach span) respectively have 81.4% and 97.8% data points coded "N" or blank. Item 107.1 (main span) can be considered fully populated: only 0.29% on-system and 0.48% off-system data points are coded "N" or blank. Item 107.1 was therefore analyzed for potential modeling families. The 9 span types coded in PonTex were grouped into the 4 families depicted in Table 8. 2, in order to ensure enough data points in each family. Data points coded "N" or blank are also shown. Table 8. 2 clearly indicates that only concrete decks can be modeled separately for on- and off-system bridges.

Table 8. 1 PonTex Item 107.1, Deck Structure Type, Main Span

Code	Description	Code	Description
1	Concrete Cast-in-Place	6	Corrugated Steel
2	Concrete Precast Panels	7	Aluminum
3	Open Grating	8	Timber
4	Closed Grating	9	Other
5	Steel plate (includes orthotropic)	N	Not applicable or non-vehicular traffic structures

Table 8. 2 Deck Families by Main Span Structure Type (Item 107.1)

Deck Material (Main Span)	Item 107.1	Off-System Ratings		On-System Ratings		Total	
		Number	*Percent*	*Number*	*Percent*	*Number*	*Percent*
Concrete	1,2	92,395	75.78%	200,581	98.96%	292,976	90.25%
Metal	3,4,5,6,7	5,472	4.49%	796	0.39%	6,268	1.93%
Timber	8	21,738	17.83%	91	0.04%	21,829	6.72%
Other	9	1,742	1.43%	627	0.31%	2,369	0.73%
N/A	N or blank	580	0.48%	599	0.30%	1,179	0.36%
All materials		*121,927*		*202,694*		*324,621*	

Notes Item 107.2 — Deck Structure Type, Major Approach Span: 81.4% "N" ratings
Item 107.3 — Deck Structure Type, Minor Approach Span: 97.7% "N" ratings

Figure 8. 2 compares boxplots of deck age at each rating and main span type, for off-system decks. Ratings below 4 are grouped together with 4 and labeled "4" in this figure. They totaled: 0.25% ratings=0, 0.06% ratings=1, 0.06% ratings=2, 0.12% ratings=3, and 0.7% ratings=4.

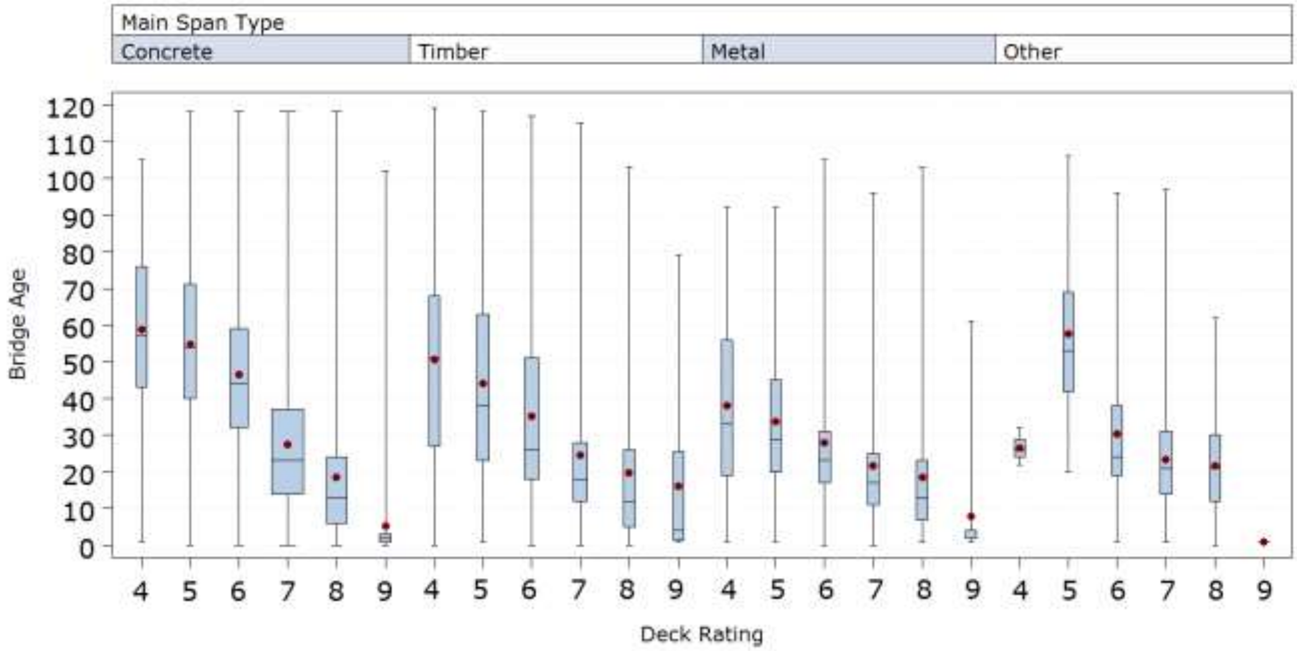

Figure 8. 2 Boxplots of Off-System Deck Age by Rating and Main Span Type (Item 107.1)

Note: Label=4 aggregates ratings of 4 or less

Figure 8. 2 shows metal decks appearing to deteriorate 15-20 years earlier than concrete on the average. This cannot be entirely attributed to age differences by material type since metal decks mean age is 5 years newer than concrete, and the 3rd quartile is 12 years newer. Timber decks appear to deteriorate approximately 10-15 years faster than concrete, and as a group they are only slightly older than concrete. Therefore, metal and timber decks merit separate analysis.

Since nearly 99% on-system main spans are concrete, it is not possible to develop on-system deck models by main span families; on-system deck models are, for all practical purposes, on-system concrete deck models. Metal and timber decks were analyzed using aggregated on- and off-system data, but represent primarily off-system metal and timber decks, since their presence on-system is insignificant.

Deck Wearing Surface / Protective System

Item 108 describes the wearing surface / protective system and was analyzed in conjunction with Item 107.1, main span type. Item 108 includes 3 three-character variables: Item 108.1—main span; Item 108.2—major approach span, and Item 108.3—minor approach span. As discussed in the previous section, approach spans are not populated enough, so this analysis is restricted to Item 108.1.

Item 108.1 first character is the type of wearing surface; the second character is the membrane type, and the third is the deck protection. The membrane type (2nd character) and deck protection (3rd) are populated respectively for only 3.48% and 2.53% data points. The first character, type of wearing surface, is fully populated. Table 8. 3 shows the PonTex codes, their descriptions, and the 4 families for further analysis of Item 108.1: concrete, bituminous, timber, and other.

Table 8. 3 Potential Families by Type of Wearing Surface (Item 108.1, 1st Digit)

Item 108.1 1st Digit	Type of Wearing Surface	% Deck Ratings Item 108.1 %	Family	Family %
1	Concrete	51.63%	Concrete	51.73%
2	Integral Concrete*	0.06%		
3	Latex Concrete	0.00%		
4	Low Slump Concrete	0.03%		
6	Bituminous	39.75%	Bituminous	39.75%
7	Timber	4.65%	Timber	4.65%
9	Other	1.68%	Other	3.87%
8	Gravel	1.27%		
5	Epoxy Overlay	0.00%		
N	Not Applicable (structures with no deck)	0.53%		
0	None	0.38%		
Blank		0.00%		

Table 8. 4 shows the cross-tabulation of Item 107.1 families by Item 108.1 families. Considering that almost 76% off-system and nearly all on-system decks have concrete main spans (Item 107.1); and that 96.83% off-system concrete decks and 98.40% on-system concrete decks have either concrete or bituminous wearing surfaces, concrete decks were divided into 2 wearing surface families: "concrete" and "bituminous + all others."

Table 8. 4 Deck Wearing Surface by Main Span Type

		Main Span Type (107.1) Data Points									
		Number					Percent				
	Wearing Surface (108.1)	Concrete	Metal	N/A	Other	Timber	Concrete	Metal	N/A	Other	Timber
Off-System	Bituminous	19,711	2,346	2	535	4,530	21.33%	42.87%	0.34%	30.71%	20.84%
	Concrete	69,758	438		786	82	75.50%	8.00%	0.00%	45.12%	0.38%
	N/A	313	27	568	24	20	0.34%	0.49%	97.93%	1.38%	0.09%
	Other	2,588	2,604	10	393	2,119	2.80%	47.59%	1.72%	22.56%	9.75%
	Timber	25	57		4	14,987	0.03%	1.04%	0.00%	0.23%	68.94%
	Total by Main Span Type	**92,395**	**5,472**	**580**	**1,742**	**21,738**	**75.78%**	**4.49%**	**0.48%**	**1.43%**	**17.83%**
On-System	Bituminous	101,176	101	2	570	71	50.44%	12.69%	0.33%	90.91%	78.02%
	Concrete	96,197	607		52	11	47.96%	76.26%	0.00%	8.29%	12.09%
	N/A	220		559	3		0.11%	0.00%	93.32%	0.48%	0.00%
	Other	2,988	88	38	2		1.49%	11.06%	6.34%	0.32%	0.00%
	Timber					9	0.00%	0.00%	0.00%	0.00%	9.89%
	Total by Main Span Type	**200,581**	**796**	**599**	**627**	**91**	**98.96%**	**0.39%**	**0.30%**	**0.31%**	**0.04%**

Figure 8. 3 and Figure 8. 4 respectively show the on- and off-system boxplots of concrete decks' age by rating and type of wearing surface. On-system bituminous wearing surfaces apparently remain 15 to 20 years longer than concrete at ratings of 7 and 8. Analogous behavior, although less prominent, is seen off-system. Since bituminous surfaces are generally less durable than concrete, this performance is probably indicating routine maintenance of bituminous surfaces, and therefore was not considered in deterioration models.

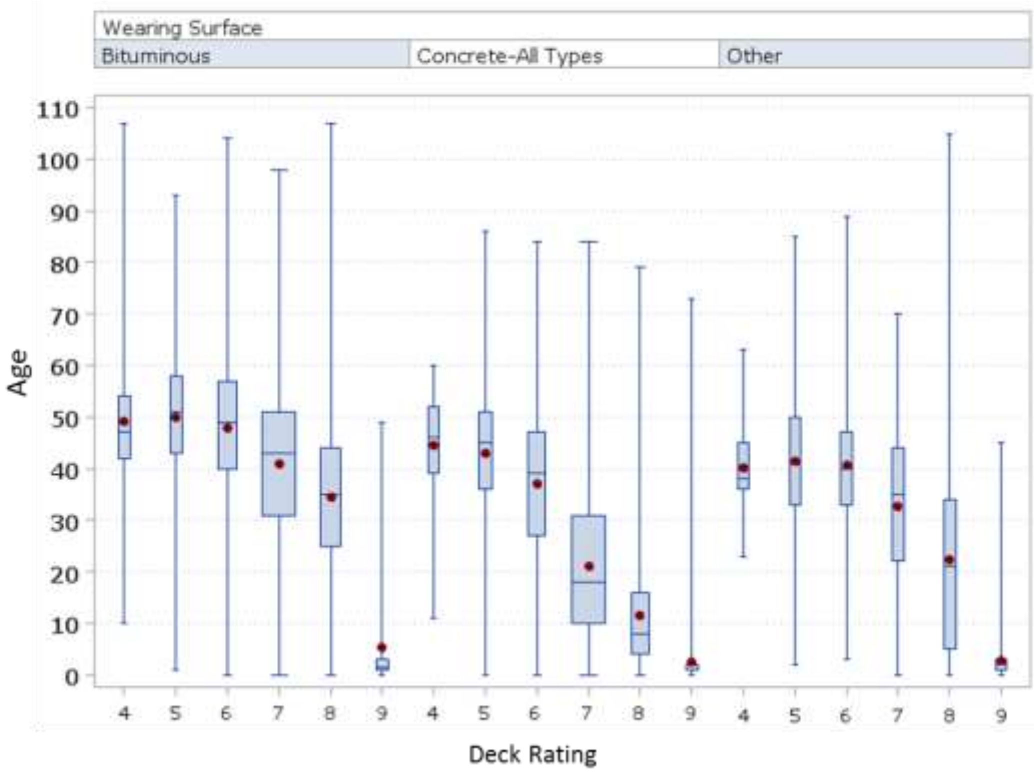

Figure 8. 3 Boxplots of On-System Concrete Decks' Age by Rating and Type of Wearing Surface

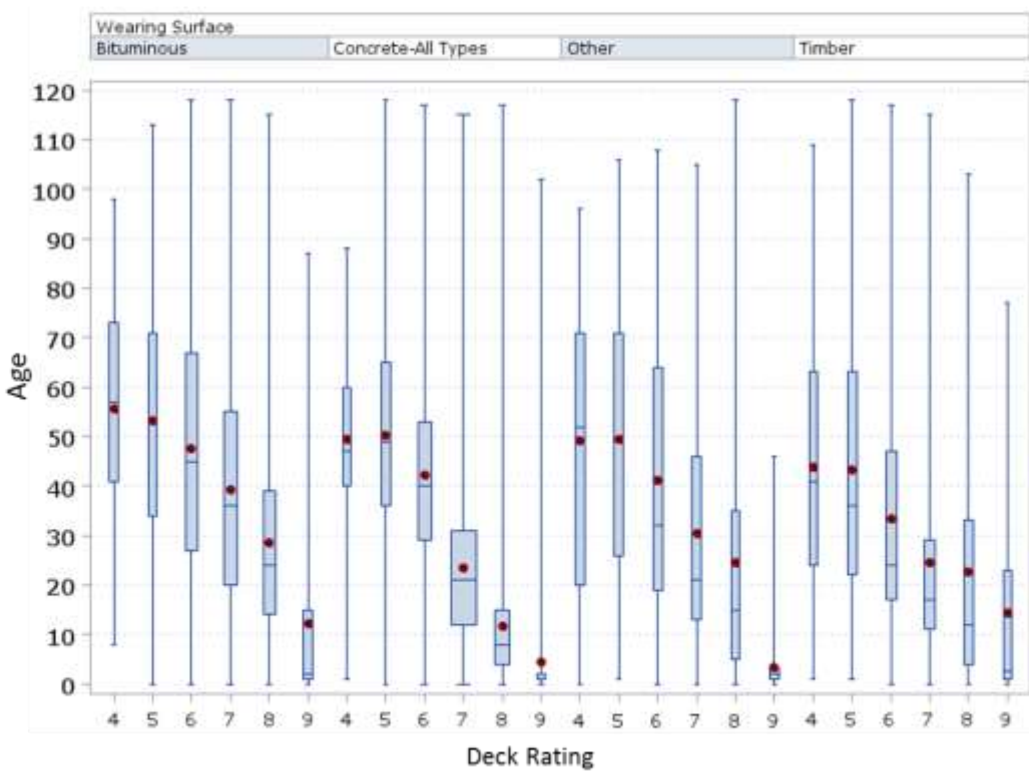

Figure 8. 4 Boxplots of Off-System Concrete Decks' Age by Rating and Type of Wearing Surface

Climatic Variables

Figure 8. 5 and Figure 8. 6 respectively show the boxplots of on- and off-system deck ages by rating, comparing the four rainfall families developed as documented in Chapter 3. Rainfall intensity increases in numeric order: Rain1 (driest) to Rain4 (wettest). On-system decks show little differences among rainfall families. There is little to no difference due to rainfall.

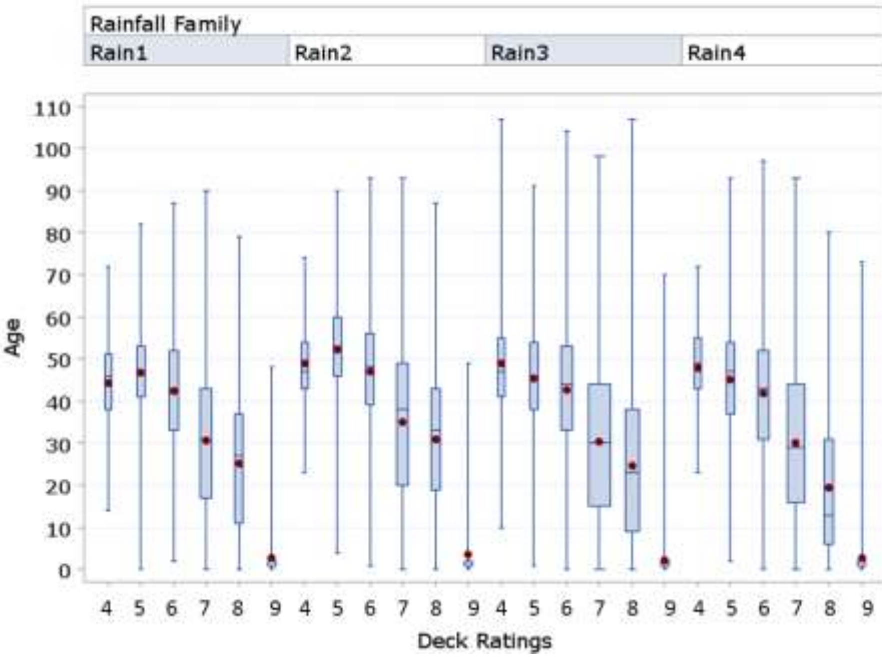

Figure 8. 5 Boxplots of On-System Deck Age by Rainfall

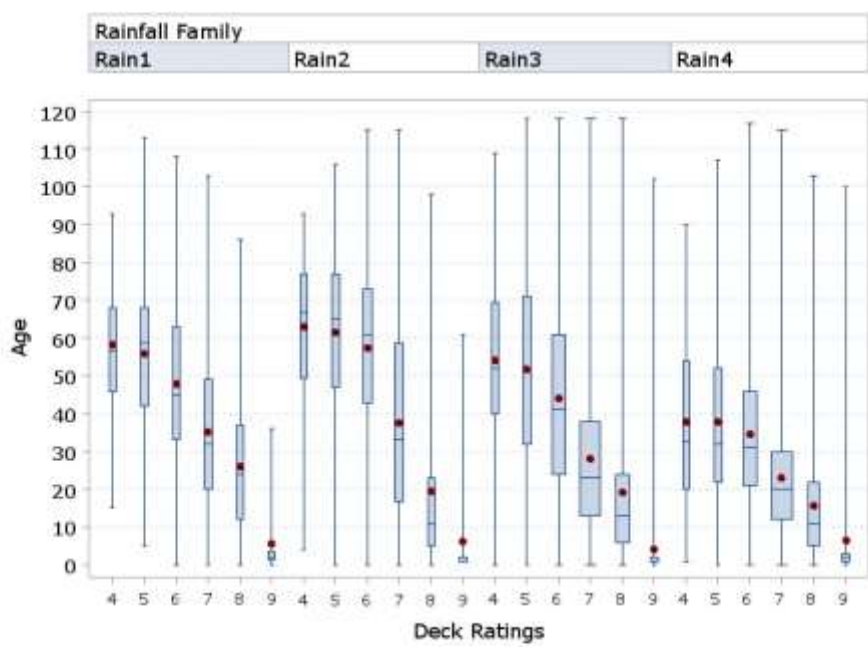

Figure 8. 6 Boxplots of Off-System Deck Age by Rainfall

Off-system decks show differences, but the data behavior is inconsistent with more deterioration in wetter areas. While this may include the effects of design, construction, maintenance and rehabilitation practices geared at counteracting deterioration in wet areas, it definitely reflects bridge ages in different rainfall areas. Average off-system ages in Rain1, Rain2, Rain3 and Rain4 areas are respectively 38, 43, 31 and 25 years. The newest off-system bridges on the average are in Rain4 areas, and the oldest, in Rain2 areas. These age differences are clearly reflected in the boxplots. Therefore, modeling off-system decks by rainfall families is not indicated.

Metal decks total only 0.39% of on-system deck ratings, and nearly 4.5% of off-system ratings. They appear to deteriorate faster in wet areas, as depicted in Figure 8. 7. It is noteworthy that the two drier areas (Rain1 and Rain2) do not differ significantly from each other, and neither do the two wetter areas (Rain3 and Rain4). The two wet areas appear to reach lower ratings between 20 and 30 years earlier than the two dry areas. This is partly due to the fact that the metal bridge population is newer in the wet areas. Rain 1 and Rain2 mean ages are both 39 years, while Rain3 is 22 and Rain4 is 19 years. Even more significant are the 3rd age quartiles: 56, 59, 26 and 24 years, respectively in Rain1, Rain2, Rain3 and Rain4 areas. The boxplots are clearly reflecting age differences, but since rainfall may be important in metal deck deterioration, it was investigated during modeling.

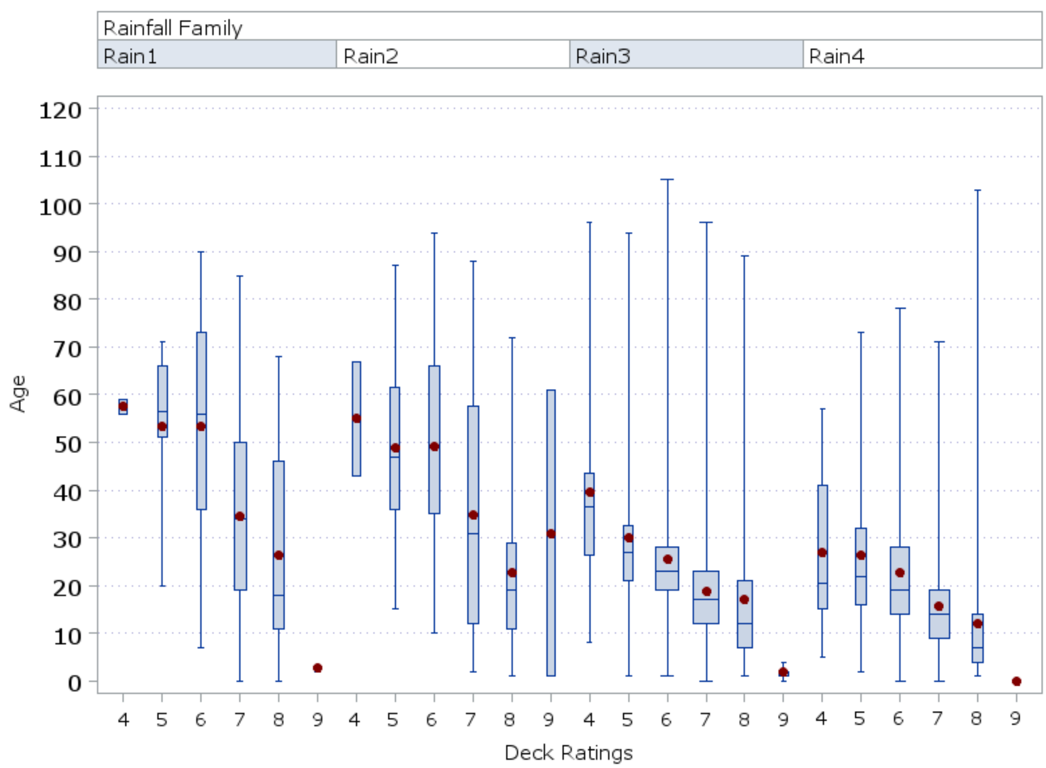

Figure 8. 7 Boxplots of On- and Off-System Metal Decks' Age by Rainfall

Timber decks also appear to deteriorate faster in wet areas, but less than metal decks, as shown in Figure 8. 8. Nearly all timber decks are off-system, comprising almost 18% of the available off-system data points, and only 0.04% of on-system data points. Timber decks in the wettest area (Rain4) appear to deteriorate between 20 and 35 years earlier than those in the other 3 areas. Timber bridges in Rain4 areas are respectively 22, 30 and 16 years newer than those in Rain1, Rain2 and Rain3 areas, so age is a confounding factor; nevertheless, timber decks were modeled by rainfall in an attempt to capture some of the effects of rain, since timber tends to deteriorate faster in wet climates.

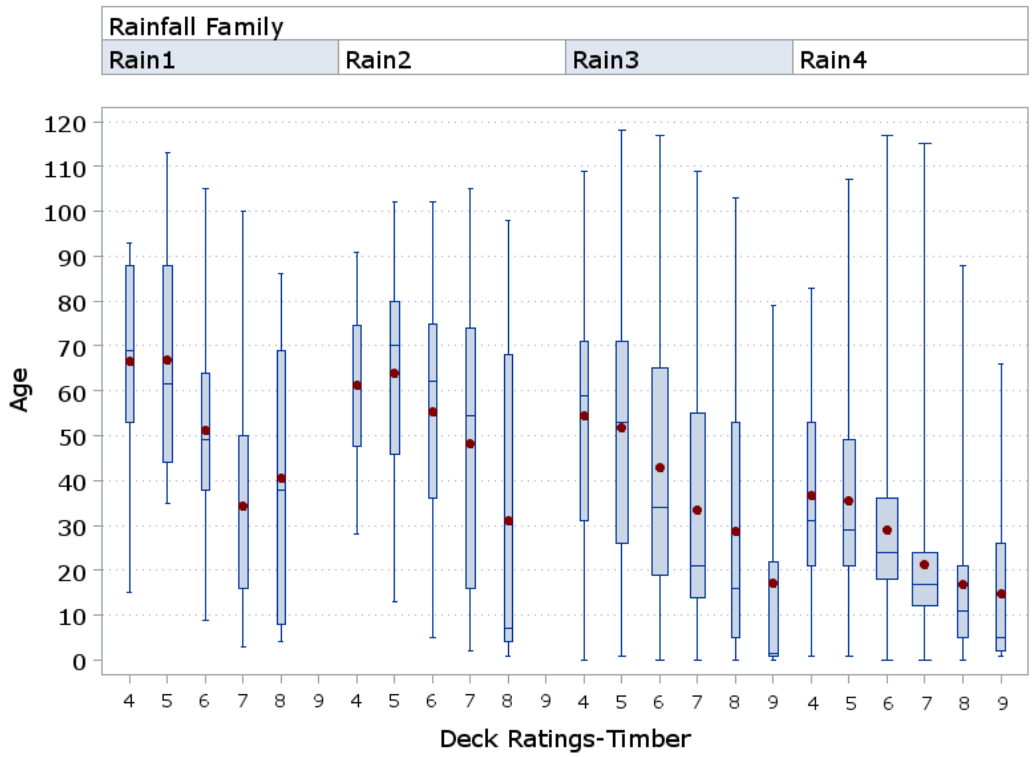

Figure 8. 8 Boxplots of On- and Off-System Timber Decks Age by Rainfall Family

Metal and timber decks were further analyzed during modeling, aggregating on- and off-system ratings, by the rainfall families listed below. Model results were compared to models by age groups.

- Metal: Rain1 + Rain2 (18% data points) and Rain3 + Rain4 (82% data points).
- Timber: Rain1 + Rain2 + Rain3 (36% data points), and Rain4 (64% data points).

Figure 8. 9 and Figure 8. 10 respectively show on- and off-system boxplots comparing the two families defined by the freezing days' thresholds developed as documented in Chapter 3. Neither on- nor off-system decks appear to present significant differences in deterioration depending on freezing. Moreover, counties with 10 or more freezing days in 5 years total less than 1% of the available data points, and this is not enough for reliable estimates of freezing effects on Markov probability matrices.

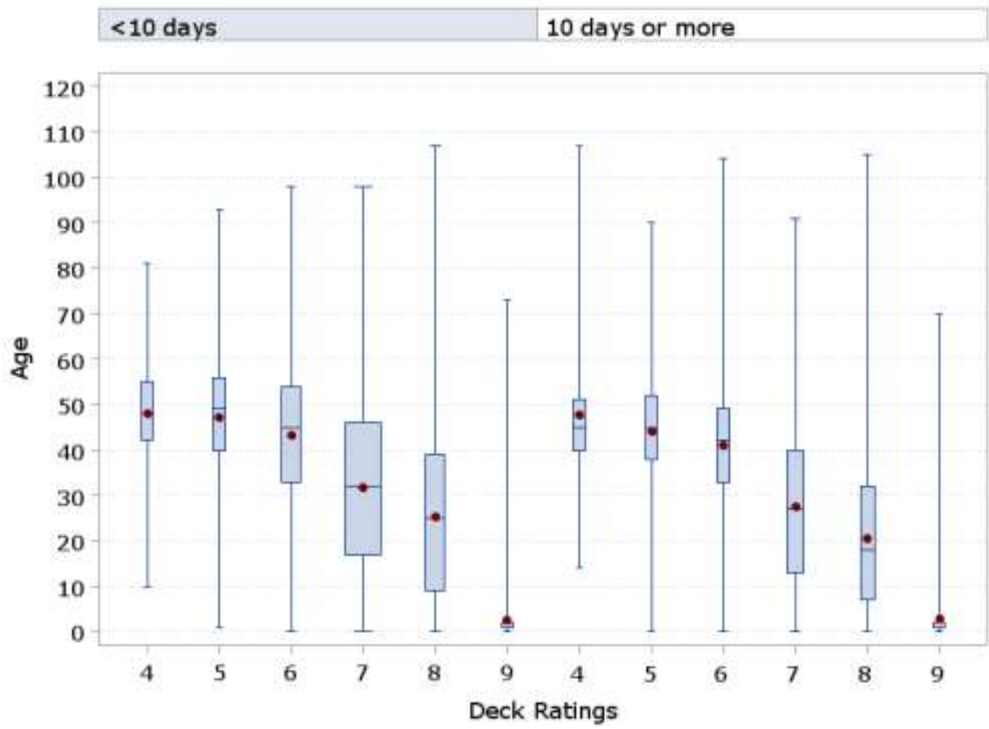

Figure 8. 9 Boxplots of On-System Deck Age by Freezing Families

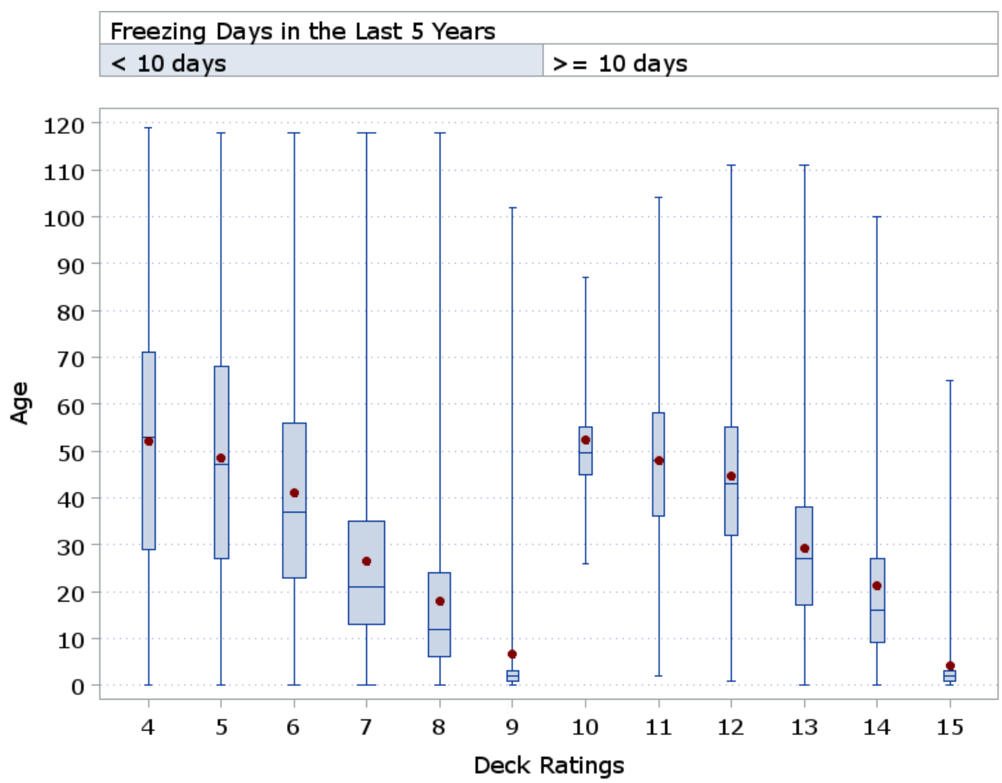

Figure 8. 10 Boxplots of Off-System Deck Age by Freezing Families

Average Daily Truck Traffic (ADTT)

As documented in Chapter 3, Item 29 (average daily traffic) and Item 109 (percent trucks) are not populated enough in off-system decks to allow modeling by traffic families. On-system decks, on the other hand, are almost fully populated with truck traffic data, and were split into "HIGH" and "LOW" ADTT families according to the criteria documented in Chapter 3. Figure 8. 11 shows the boxplots of on-system deck ages by ratings and truck traffic families. The difference between high and low ADTT families is generally less than 10 years, the preferred forecast horizon. Considering that nearly all on-system decks are concrete, this result is not surprising. As depicted in Figure 8. 12, on-system decks with bituminous wearing surfaces show some effect of traffic, but not enough to warrant modeling by traffic families.

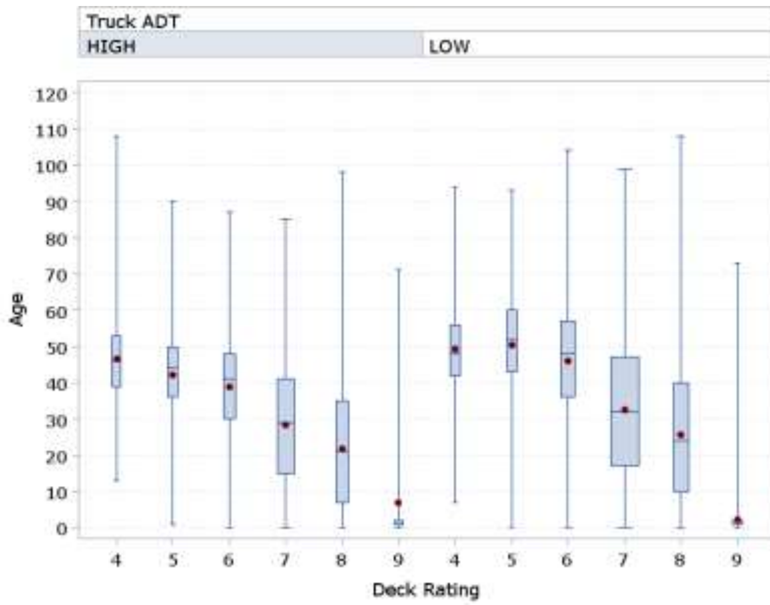

Figure 8. 11 Boxplots of On-System Deck Age by Rating and ADTT Family

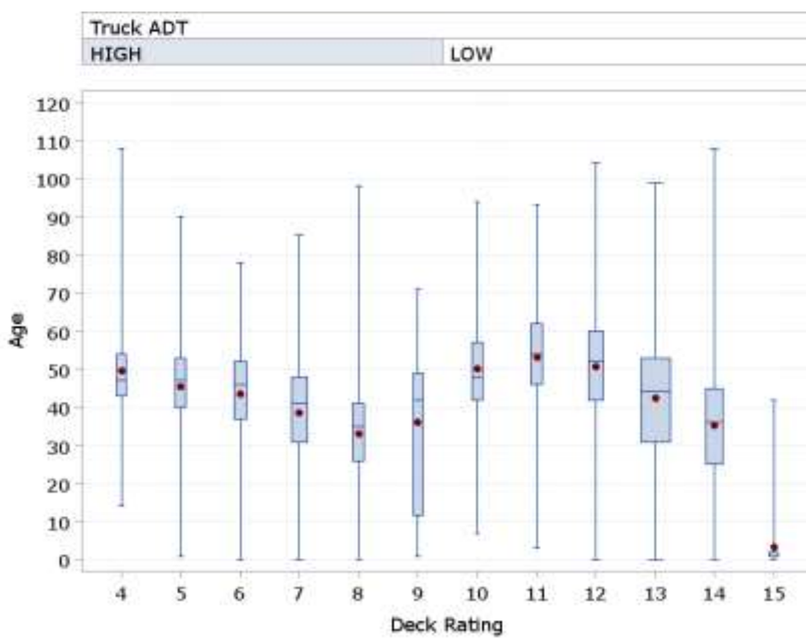

Figure 8. 12 Boxplots of On-System Decks with Bituminous Wearing Surfaces by ADTT Family

Summary of Conclusions

- Impact of maintenance in the data is clear for both on and off-system decks. Both distributions have negative skewness, i.e., they have more high ratings than low ratings; in addition, ratings below 5 are nearly absent. The most frequent rating (mode) is 7 for both on- and off-system. Nearly 80% off-system and over 86% on-system ratings are 7 or better. Mean ratings are close to 7, and low standard deviations underscore consistency in maintenance quality.
- Nearly all on-system and almost 76% off-system main spans are concrete (Item 107.1). Nearly all concrete decks have either concrete or bituminous wearing surfaces.
- Boxplots of concrete decks with bituminous surfaces seem to indicate that they remain at high (7 and 8) ratings longer than concrete. Since concrete surfaces are generally more durable than bituminous, these differences can be attributed to maintenance, so modeling deterioration by wearing surface families is not indicated.
- There was little impact of freezing on decks, both for on- and off-system; moreover, less than 1% data points are in locations subject to 10 or more freezing days in the past 5 years.
- Truck ADT families had little impact on on-system decks, even the subset with bituminous wearing surfaces. This is not surprising, since nearly all are concrete. Off-system bridges lack traffic data for over 30% of data points.
- There was impact of rainfall on metal and timber decks. They are a negligible percent of on-system data points, but comprise respectively 4.5% and 17.8% off-system data points. Therefore, timber and metal decks were modeled by rainfall families using aggregated on- and off-system data.

Conclusion: the 13 deck rating models listed in Table 8. 5 below were recommended for development and analysis of results.

Table 8. 5 Deck Rating Model Families

On-system (4)	Off-system (9)	
1. All on-system	1. All off-system	6. Metal, Rain1 & Rain2
2. Age group 0 to 22	2. Age group 0 to 16	7. Metal, Rain3 & Rain4
3. Age group 23 to 42	3. Age group 17 to 34	8. Timber, Rain1, 2 & 3
4. Age group 43 and older	4. Age group 35 and older	9. Timber, Rain4
Note: on-system decks are nearly all concrete.	5. Concrete	Note: Metal and timber deck models include on-system data points.

The next section discusses the Markov deterioration models developed for these families, the analysis of results, and the recommended models, based on model validation and on practical results.

Deck Deterioration Models

Modeling Methodology

The modeling methodology is discussed in detail in Chapter 4 and summarized here for readers' convenience. A subset of the annual PonTex database (2001 through 2019), prepared to ensure 2-year lags between all consecutive deck ratings (see Chapter 3), was used to develop Markov transition probability matrices that age the decks by 2 years.

Table 8. 6 illustrates one of the 13 Markov transition probability matrices developed for deck ratings. It shows the matrix calculated for aggregated on-system decks. Each matrix cell is the probability of the rating shown in the first column either remaining as or decreasing to the rating shown in the blue row, after 2 years. Elevating the two-year transition probability matrix to the n^{th} power ages the transition probability matrix by 2n years. This is the basis of the Markov Process for calculating the network condition forecasts and deterioration curves presented in this section and delivered in Product 2.

Table 8. 6 Two-Year Transition Matrix for All On-System Decks

Rating Before	Number of Transitions	Rating After 2 Years									
		9	8	7	6	5	4	3	2	1	0
9	1506	0.033201	0.60757	0.35525	0.00398						
8	35925		0.70898	0.27758	0.0123	0.00097	0.00017				
7	103382			0.94582	0.0524	0.00173	0.00004	0.00001			
6	27584				0.964	0.0348	0.00105	0.00015			
5	4424					0.97785	0.0208	0.00113	0.000226		
4	380						0.97632	0.02368			
3	39							1			
2	0										
1	0										
0	0										

The program that develops transition probability matrices contains code to null transition probabilities in rows where the number of available transitions is less than 9 due to concerns about reliability of the deterioration probability estimates. This generally happened for ratings less than or equal to 4. In older data groups, and/or in families more prone to deterioration, sometimes the rating of 9 did not result in enough transitions. The program assigns a transition probability of 1 for ratings=0 remaining as zeroes, since a rating cannot be lower than zero.

Before modeling, bridge age distributions by family were analyzed for their statistical properties, as well as to determine whether or not it was possible to disaggregate each family by age groups containing enough data points for a meaningful transition probability matrix. This methodology is discussed in detail in Chapter 4.

Matrices analogous to Table 8. 6 were developed for each age group and family, totaling 12 matrices. The Markov process was implemented in all 13 cases to determine 18-year deterioration curves and network condition forecasts every 2 years. Standard errors of each matrix were calculated for 17 pairs of observed versus predicted network conditions, documented in Chapter 4. Standard errors were considered in model validation and the overall maximum, minimum and average values are reported here.

All network condition forecasts were developed by number of bridges and by deck area. Results were compared for differences among age groups and families, with emphasis in 10-year forecasts, the horizon mentioned as the most important for TxDOT. The comparisons determined which families and/or age groups should be recommended for implementation in Product 2, together with aggregated on- an off-system models.

On-System Deck Models

Table 8. 6 in the Modeling Methodology section illustrates the two-year transition probability matrix for all on-system decks. The other 3 on-system matrices by age groups (see Table 8. 5) are documented only

in Product 2, together with deterioration curves, deterioration tables, and network condition forecasts every 2 years. The number of non-negative transitions extracted from the total biannual inspection data points, and used to develop the 4 on-system Markov matrices were as follows:

Ages 0 to 22 55,027	Ages 23 to 43 55,173
Ages 44 and older.................50,452	All on-system 173,240

Standard errors associated with each of these four transition probability matrices were calculated using the methodology documented in Chapter 4. The minimum, mean and maximum standard errors for 17 pairwise comparisons were respectively:

Ages 0 to 22 .... 1.5%....................... 5.9% 12.1%

Ages 23 to 43 .... 1.0%....................... 2.0% 3.6%

Ages 44 and older .... 1.9%....................... 3.8% 7.7%

All on-system .... 1.9%....................... 3.7% 6.9%

Figure 8. 13 compares the expected deck rating values after 10 years, by age group and aggregated by on-system. Figure 8. 14 shows partial screen shots of the 4 on-system deterioration curves: the 3 on-system deck age groups, and the aggregated on-system deterioration curves. All 4 rating deterioration curves are fully documented in Product 2. Each Figure 8. 13 bar corresponds one 10-year data point in Figure 8. 14.

Differences in expected values are too small for practical purposes. This type of result was consistently observed in nearly all deterioration curves developed in this project. The most likely explanation is an issue common to every deterioration model of any type of infrastructure: available condition data always embeds maintenance.

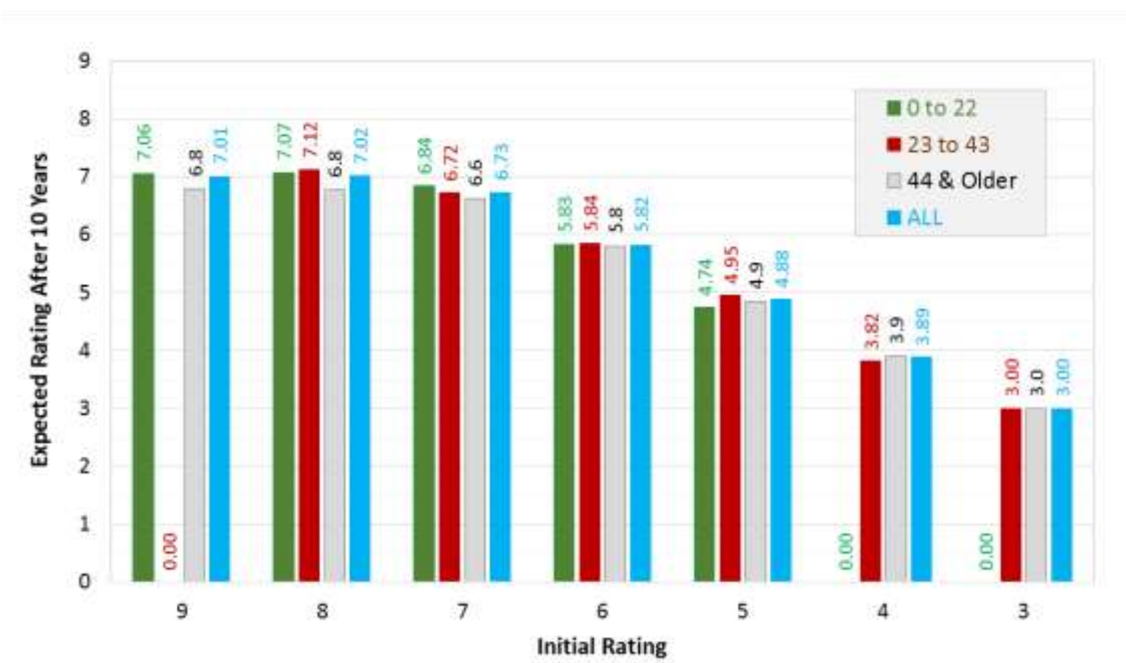

Figure 8. 13 On-System Deck Ratings Expected Value After 10 Years

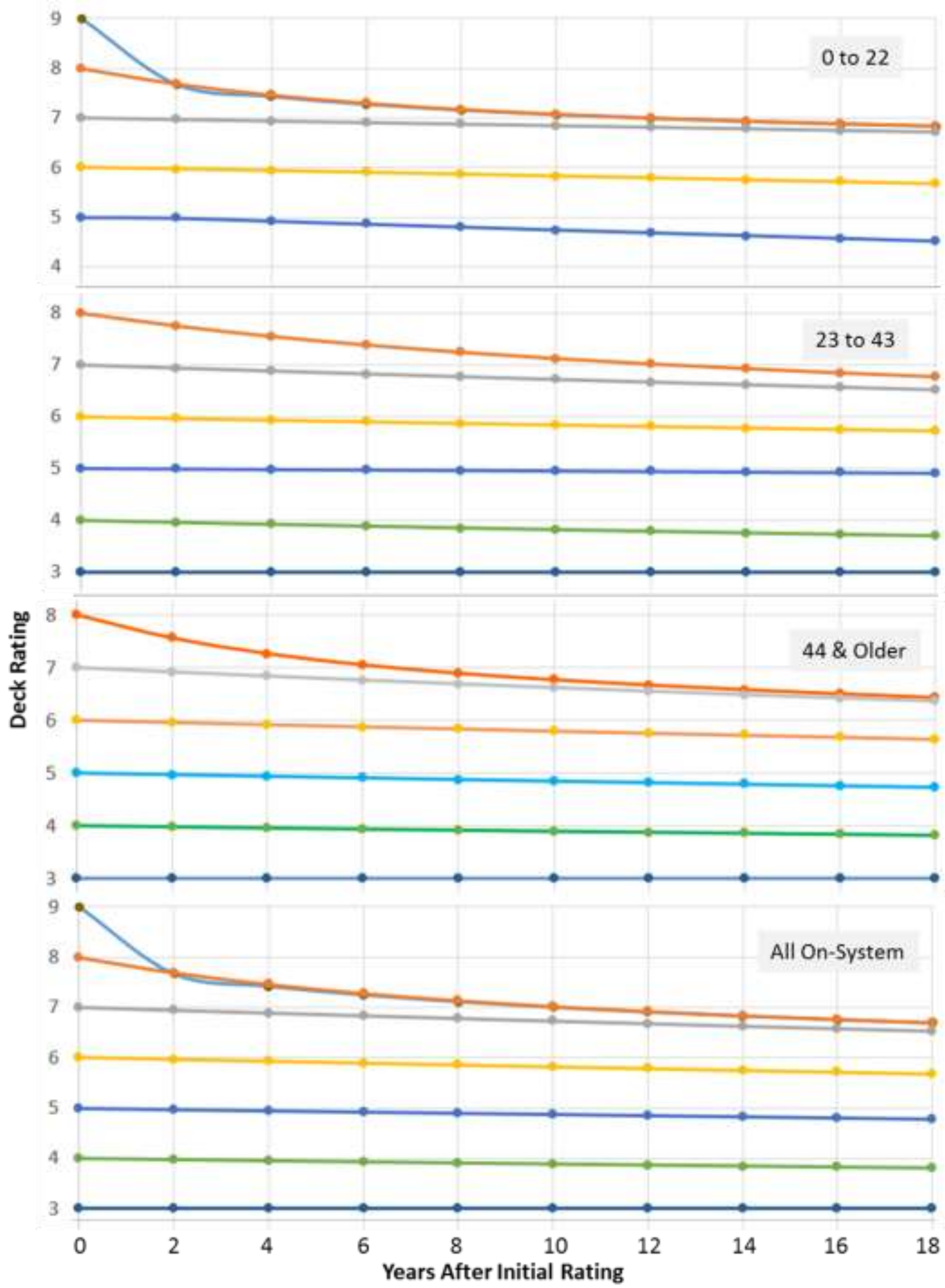

Figure 8. 14 Rating Deterioration Curves for On-System Decks

The network condition forecasts, on the other hand, are clearly helpful for infrastructure management purposes. Figure 8. 15 depicts the deck network deterioration curves for the aggregated on-system network. Product 2 delivers the complete set of 8 curves, for percent area and percent bridges, together with the data tables.

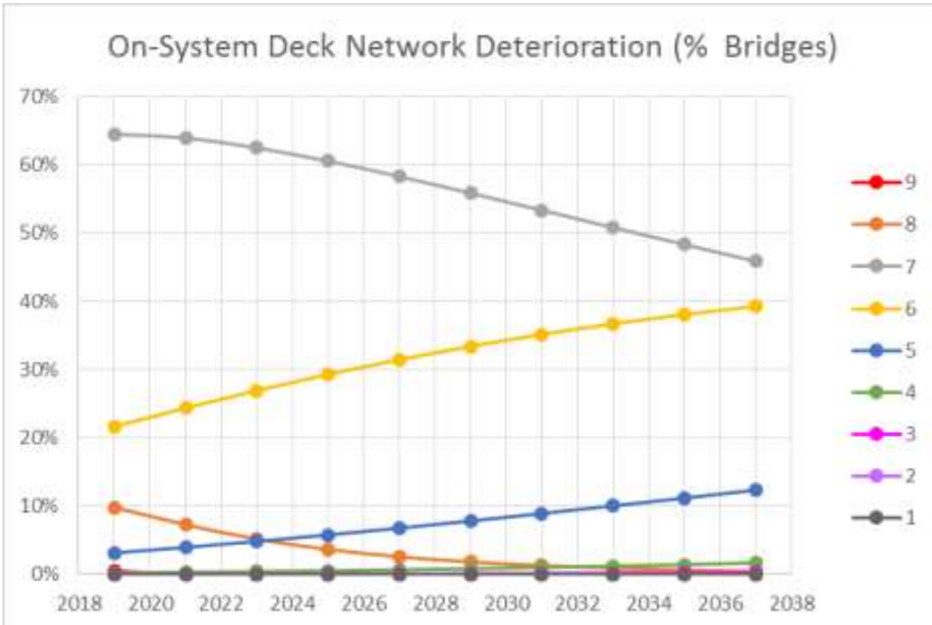

Figure 8. 15 On-System Deck Network Deterioration Curves

Figure 8. 16 shows the percent bridge decks predicted at each deck rating in year 2029, for the 2019 population of decks (10-year forecasts). Figure 8. 17 shows analogous forecasts in terms of percent deck area. Each bar in Figure 8. 16 corresponds to the 10-year (2029) data point in Figure 8. 15 and its equivalent for each age group. Likewise for the bars in Figure 8. 17.

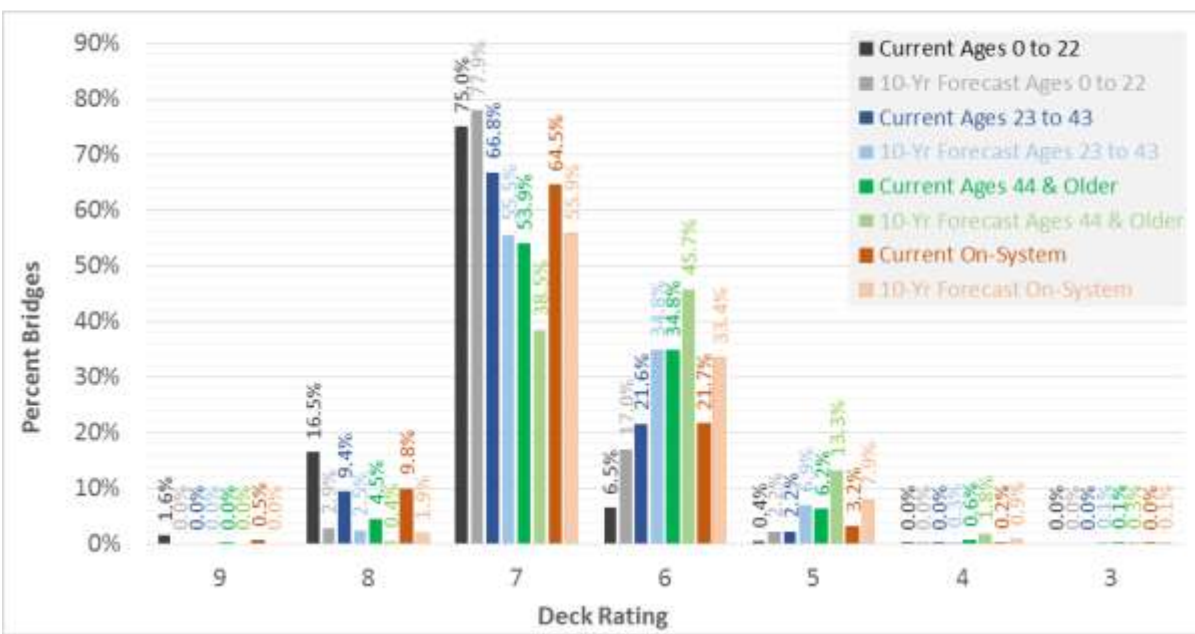

Figure 8. 16 Ten-Year On-System Network Condition Forecasts by Age Groups (Percent Bridges)

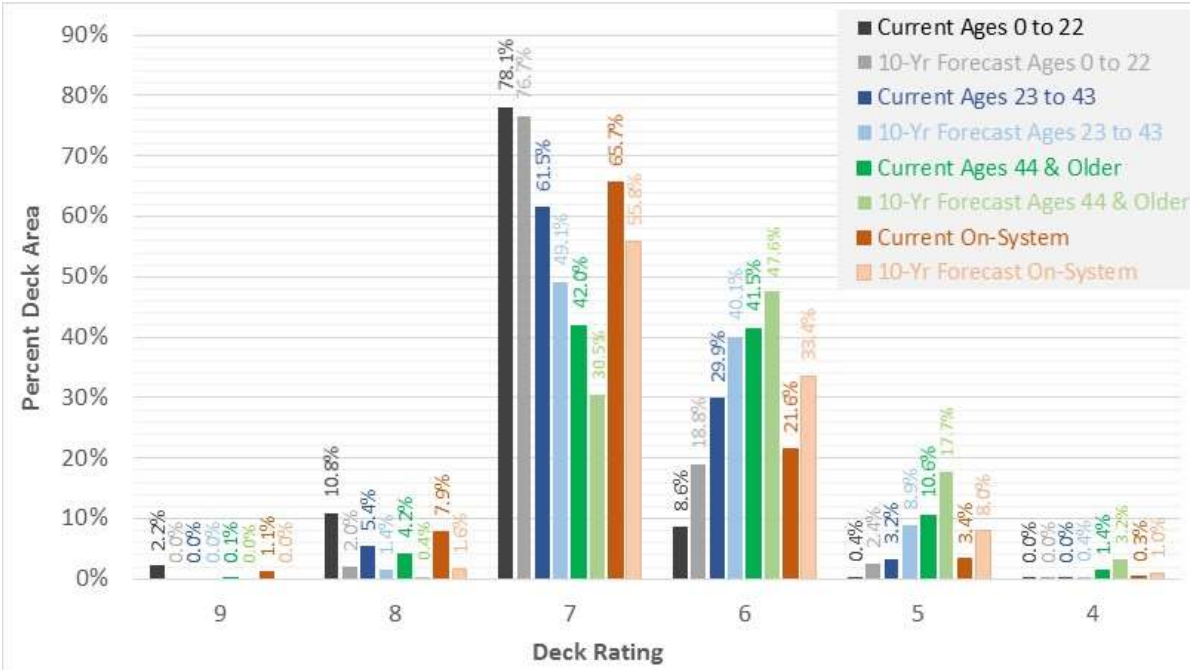

Figure 8. 17 Ten-Year On-System Network Condition Forecasts by Age Groups (Percent Deck Area)

Figure 8. 16 and Figure 8. 17 both show a considerable difference in network deterioration among age groups. Over 78% of the newest deck area remain at rating=7 after 10 years, a minimal change from the initial 78.1%. This percent drops to 49% in the intermediate age group, and 30% in the oldest age group. The reverse situation is observed for ratings of 6 or less. The newest age group is the only one without any ratings of 3 or 4 after 10 years.

Off-System Deck Models

The numbers of available non-negative transitions extracted from the off-system data points in Table 8. 5 and used to develop the 5 off-system Markov matrices for analysis were as follows:

Age group 0 to 16 31,205

Age group 17 to 34 31,413

Off-system concrete decks 78,182

Age group 35 and older 31,772

All off-system 101,993

The standard errors associated with each of these 5 transition probability matrices were calculated with 17 pairwise predicted versus observed network condition forecasts by number of bridges. The minimum, mean and maximum standard errors are listed below:

Ages 0 to 16 .... 2.5%....................... 6.0% 9.1%

Ages 17 to 34 .... 2.5%....................... 3.5% 5.9%

Ages 35 and older .... 3.9%....................... 5.5% 7.3%

Off-system concrete .... 2.1%....................... 3.3% 4.5%

All off-system .... 2.7%....................... 4.5% 6.0%

Figure 8. 18 illustrates one of the deck network deterioration curves for the aggregated off-system data. This type of deterioration plot is informative, clearly showing the increase in low ratings as the high ratings decrease with time. The complete set of off-system transition probability matrices, deterioration curves, deterioration tables, network condition curves and data tables are fully documented in Product 2.

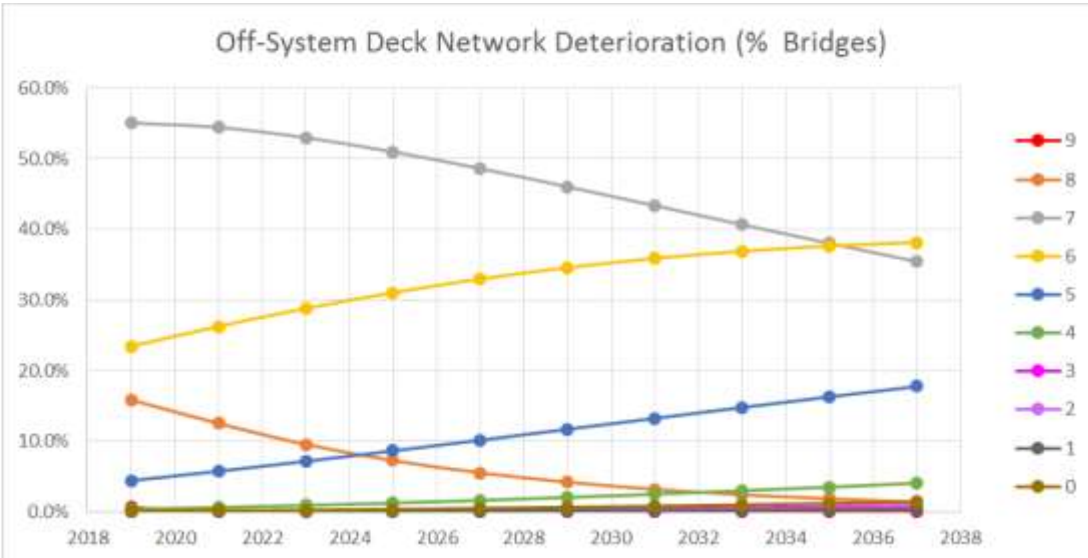

Figure 8. 18 Off-System Deck Network Deterioration Curves

Figure 8. 19 and Figure 8. 20 compare the network condition in years 2019 (current condition) and year 2029 (10-year forecasts), respectively by percent bridges and percent deck area. Each bar corresponds to the 2019 data point in the tables that generated the network deterioration curves similar to Figure 8. 18.

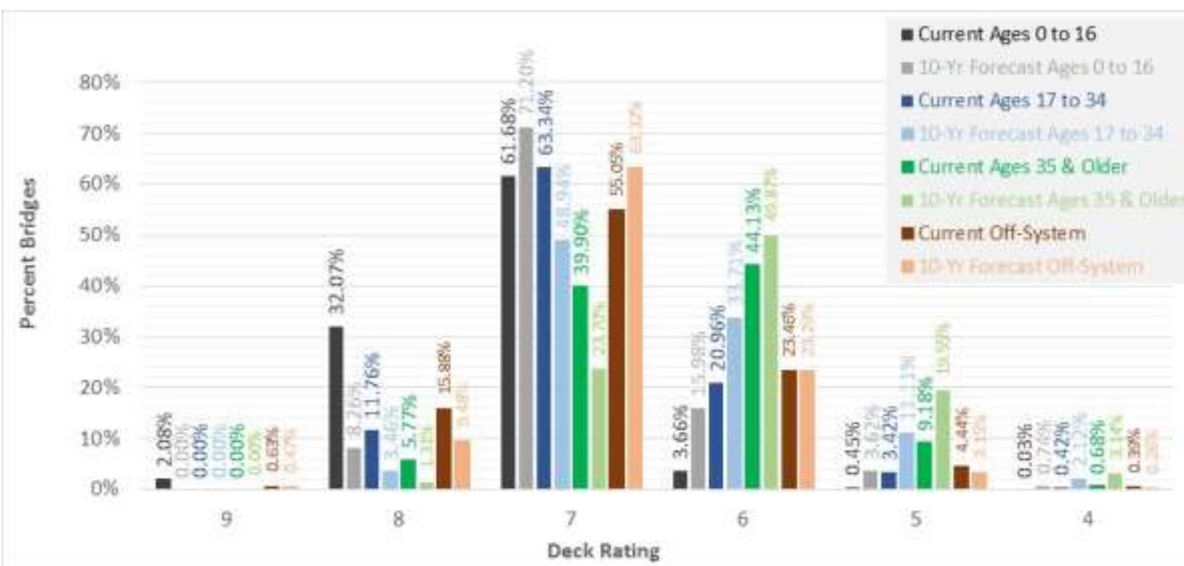

Figure 8. 19 Ten-Year Off-System Network Condition Forecasts by Age Groups (Percent Bridges)

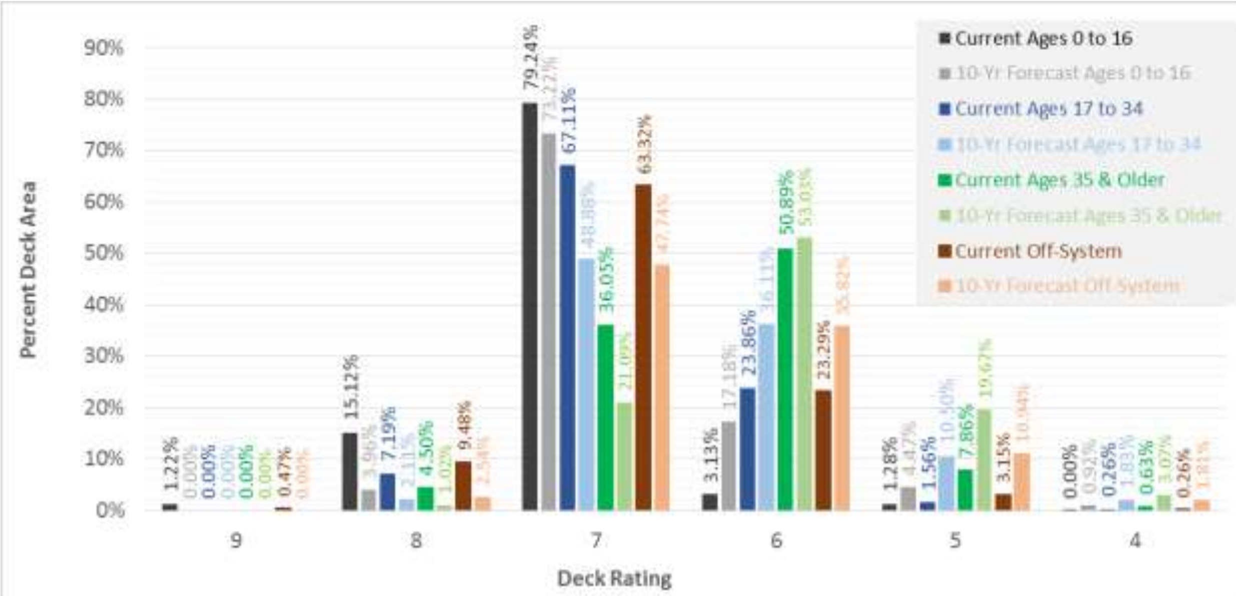

Figure 8. 20 Ten-Year Off-System Network Condition Forecasts by Age Groups (Percent Deck Area)

Figure 8. 19 and Figure 8. 20 both indicate considerable differences in off-system deck deterioration by age groups, with ratings . Over 8% of the newest bridge decks remain at rating=8 after 10 years and over 71% remain at rating=7. The rating=7 percentages drop to 48.9% in the intermediate age group, and over 23.7% in the oldest age group. The reverse situation is observed for ratings of 6 or less. In the oldest age group, ratings of 5 more than double after 10 years, and ratings of 4 increase almost fivefold.

Timber and Metal Decks by Rainfall

The numbers of available non-negative transitions extracted from the total data points in Table 8. 5 and used to develop the 3 Markov matrices for timber and metal decks, were as follows:

Timber decks		Metal Decks	
All timber decks	16,936	All metal decks	4,818
Rain1, 2 and 3 areas	5,957	Rain1 and 2 areas	849
Rain4 areas	10,979	Rain3 and 4 areas	3,969

The standard errors associated with these 3 transition probability matrices were calculated as discussed in Chapter 4. The minimum, mean and maximum standard errors were respectively:

Timber

All timber decks	9.4%	10.5%	12.5%
Rain1, 2 and 3 areas	10.8%	13.1%	15.6%
Rain4 areas	7.5%	9.5%	11.5%

Metal

All metal decks	3.4%	7.5%	11.0%
Rain1 and 2 areas	3.8%	7.4%	11.1%
Rain3 and 4 areas	2.3%	7.9%	12.8%

Timber and metal deck models were developed using aggregated on and off-system data, in order to maximize the number of transitions used in developing the Markov matrices. However, these models were delivered in Product 2 off-system workbook, since 87% metal decks and 99.8% timber decks data points are off-system.

Figure 8. 21 and Figure 8. 22 compare current (2019) to 10-year forecast (2029) network condition by rainfall families, respectively for timber and metal decks. Differences in timber 10-year forecasts are of the same magnitude as the matrices standard errors; therefore, only the aggregated timber deck model is recommended for implementation.

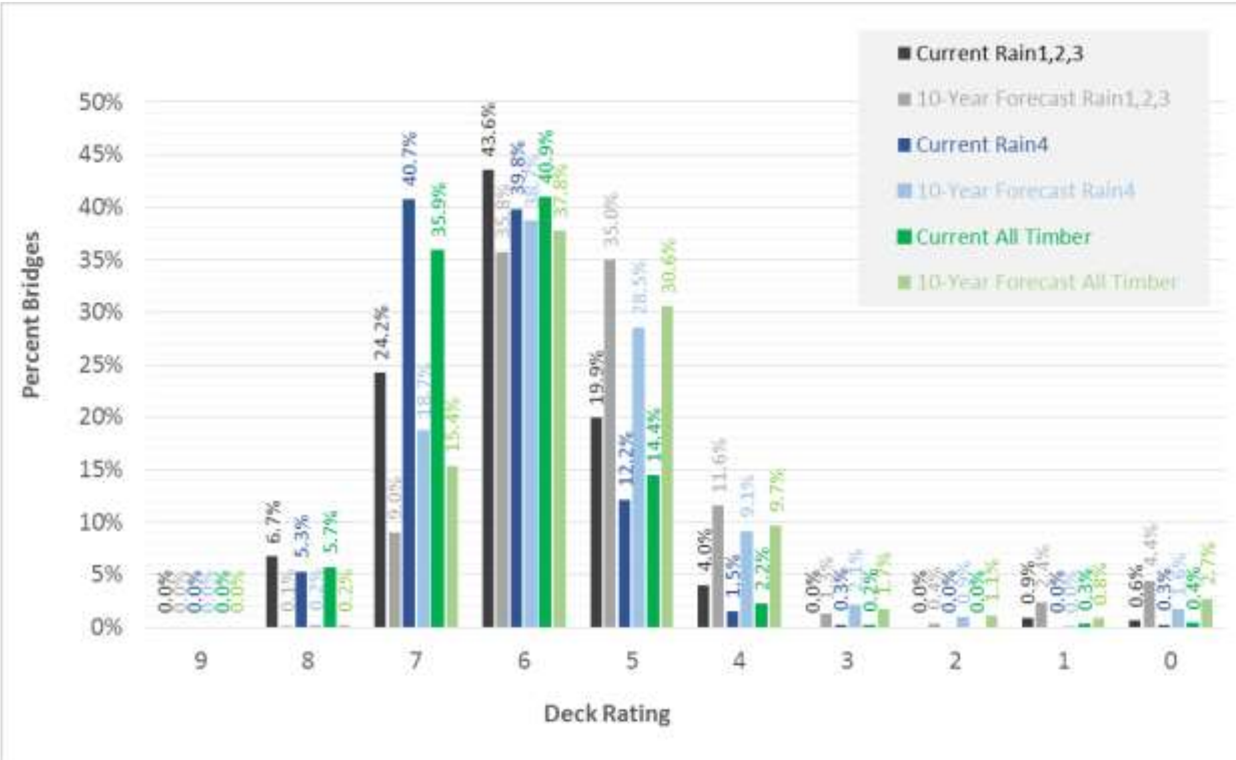

Figure 8. 21 Current Network Condition and 10-Year Forecasts, Timber Decks

Metal deck models differences in 10-yr forecasts by rainfall families are considerably greater than the standard errors for ratings of 6 and 7 (the most numerous), substantiating the expected result of more deterioration in wet areas. However, 82% metal deck data points are in Rain3+Rain4 families; furthermore, the model for Rain1+Rain2 families was developed from only 849 transitions. Given these facts, only aggregated metal deck models were recommended for implementation.

Off-System Decks by Main Span Type

Models by main span type (Item 107.1) are delivered for in Product 2 Off-system workbook because metal and timber decks are predominantly off-system. Figure 8. 23 and Figure 8. 24 respectively show the comparison between the current (2019) and 10-year forecast (2029) deck network for the 3 different span types.

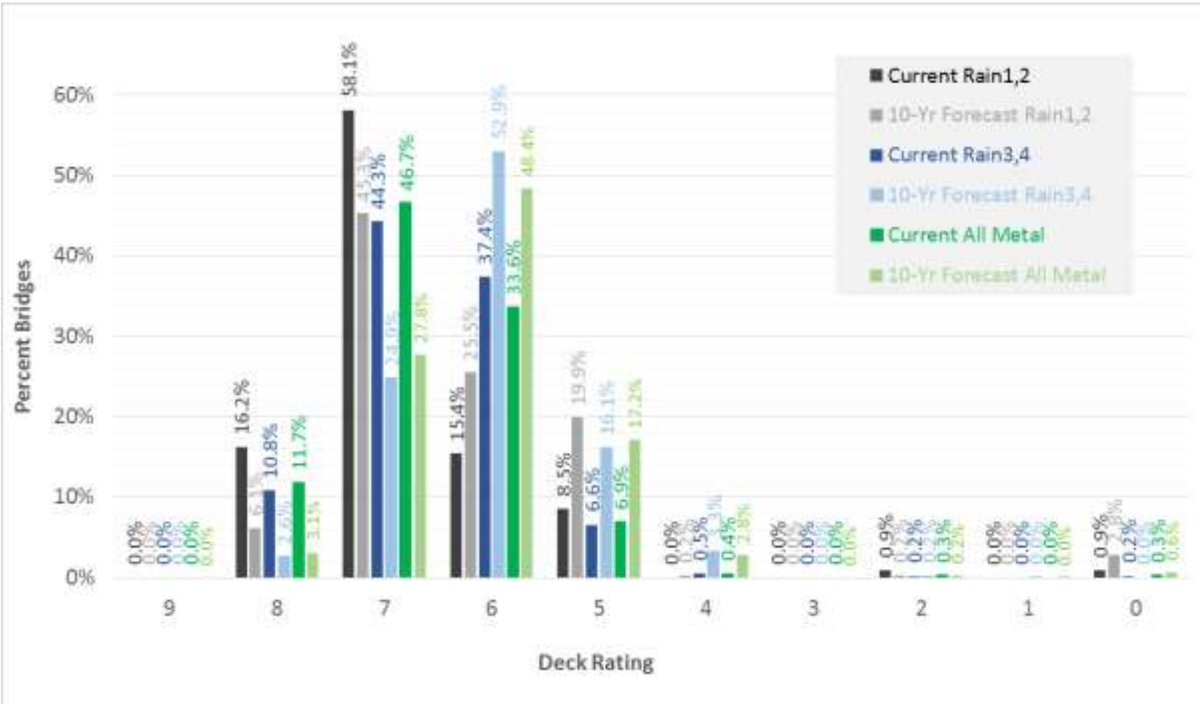

Figure 8. 22 Current Network Condition and 10-Year Forecasts, Metal Decks

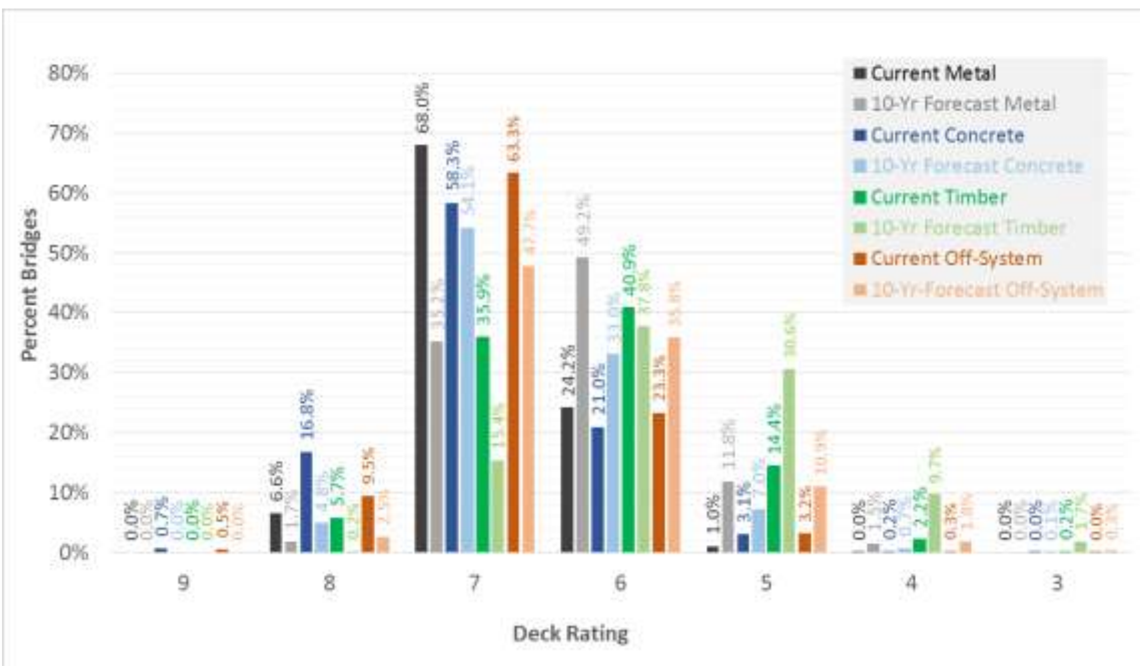

Figure 8. 23 Current vs. 10-Yr Network Condition Forecast, Deck Main Span Type, % Bridges

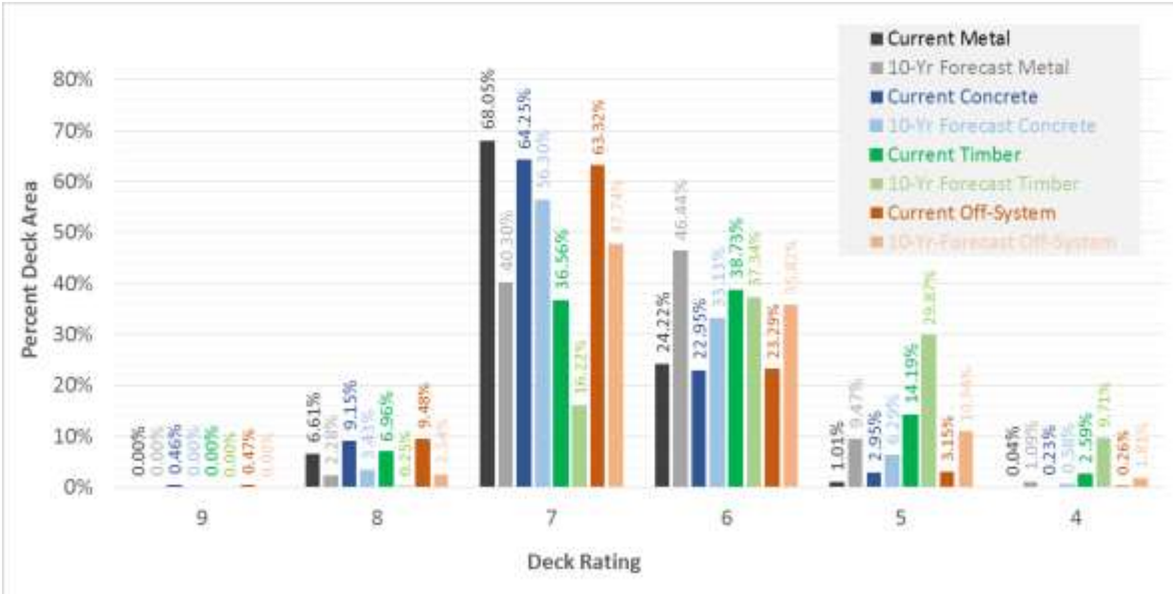

Figure 8. 24 Current vs. 10-Yr Network Condition Forecast, Deck Main Span Type, % Deck Area

The 3 types are plotted in the same chart for the sake of briefness only. Valid comparisons are the changes between current network condition and 10-year forecasts for each individual type. Aggregated off-system is also presented to assist in results analysis.

Comparisons of among the 3 span types deteriorations requires considering the age distributions of each family.. Means are not very different but, the distributions failed all pairwise homogeneity tests. As shown in Figure 8. 25, metal decks as a group are newer than timber, so their better performance is partly due to age and partly due to span type. However, metal decks are rather newer than off-system concrete, so concrete can be interpreted as outperforming metal.

Implementation Considerations

Product 2 consists of 2 Excel Workbooks with one model in each sheet, and network condition forecasts plotted on separate worksheets. The on-system workbook contains 4 models, the aggregated on-system model and the 3 models by the age groups. Product 2 workbooks are rather self-explanatory, but are discussed in more detail in Product 0-6976-2: Texas Culvert and Bridge Deterioration Models: Implementation Manual.

The off-system workbook contains 7 models: aggregated off-system, 3 off-system models by age groups, off-system concrete, timber and metal decks. The latter were modeled using aggregated on- and off-system data in order to increase the number of data points. They are included in the off-system workbook because 87% metal and 99.8% timber deck data points are off-system.

Given the observed network-level deterioration differences by age group, it is recommended to update the current year data by age groups, as explained in Product 0-6979-2, Texas Culvert and Bridge Deterioration Models: Implementation Manual.

Aggregated models for all on-system as well as all off-system decks are included in Product 2. Bridge cost estimates included in Product 2 are based on the overall on- and off-system models outputs. Costs are explained in Chapter 9.

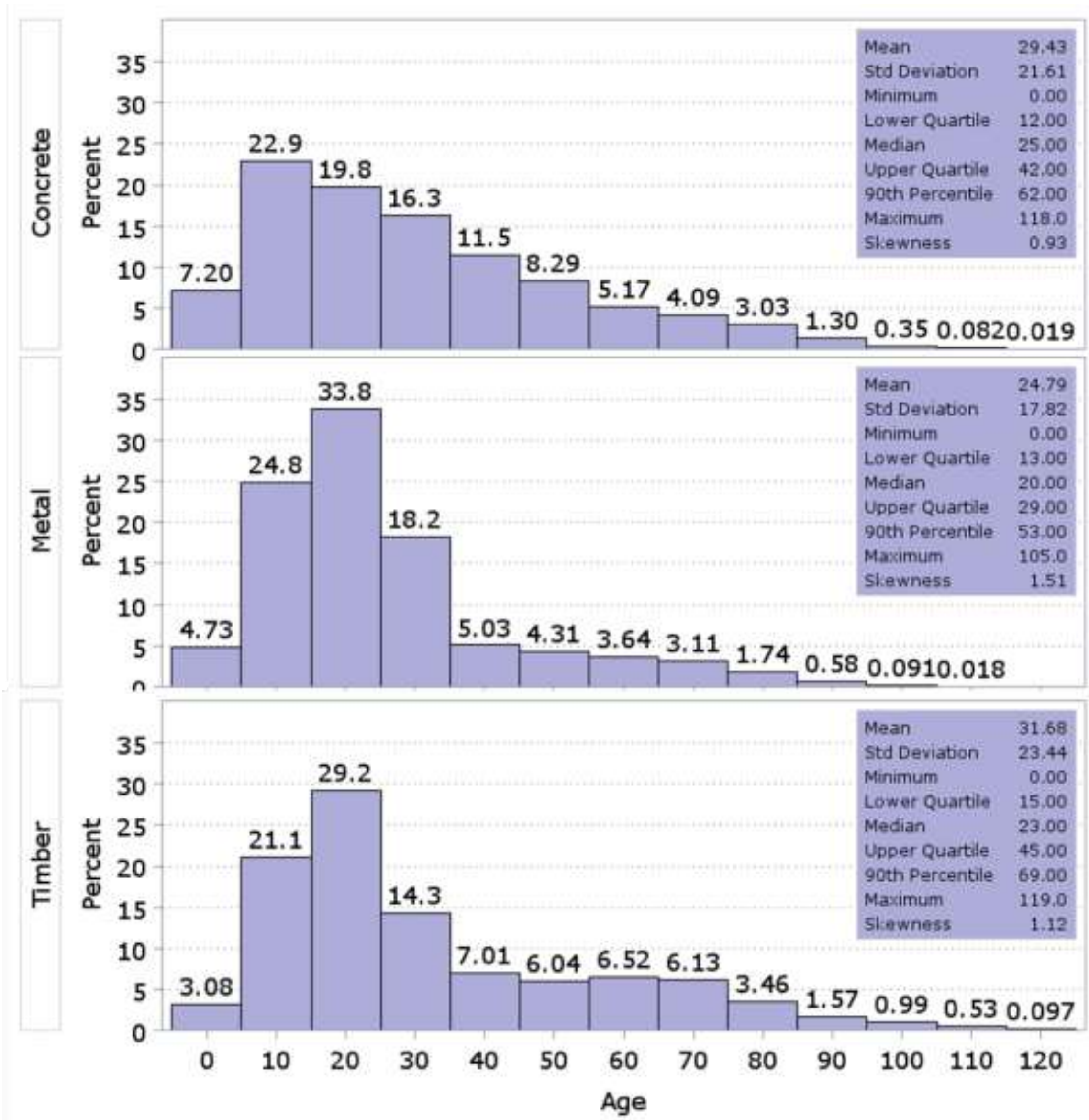

Figure 8. 25 Age Distribution of Off-System Deck Types

Chapter 9
Value of Research, Conclusions, and Recommendations

Introduction

This Chapter presents a framework developed and recommended to forecast repair costs for maintaining the culvert and bridge network in good or better condition (above 4). Culverts cost forecasts are implemented in Product 2, since culverts are evaluated with only one condition rating. Bridges, on the other hand have 3 different condition ratings, and it is necessary to forecast costs after considering all possible combinations of deck, substructure and superstructure ratings of 4 and below.

The chapter also presents the Value of Research, the recommendations for future model updates, further implementation and Product 2 improvements, and recommendations for future research.

Background

Federal law requires that most bridges in the United States be regularly inspected by the State Departments of Transportation (DOTs) for functionality and structural condition. Texas reports these data for inclusion in the National Bridge Inventory (NBI).

The NBI specifications classify a bridge as "structurally deficient" if any one of the following bridge components are rated less than or equal to 4 or in poor or worse condition:

- NBI/PonTex Item 58: Deck condition
- NBI/PonTex Item 59: Superstructure condition
- NBI/PonTex Item 60: Substructure condition
- NBI/PonTex Item 62: Culvert condition

The NBI specifications use four factors in determining the "sufficiency rating" of a bridge, which translates into its sufficiency to remain in service. Each bridge is assigned a numerical percentage rating between zero and 100, with 100 being the ideal.

Effective January 1, 2018, the Federal Highway Administration (FHWA) changed the definition of structurally deficient as part of the final rule on highway and bridge performance measures, published May 20, 2017, pursuant to the 2012 surface transportation law Moving Ahead for Progress in the 21st Century Act (MAP-21). Two measures that were previously used to classify bridges as structurally deficient are no longer used. This includes bridges where the overall structural evaluation was rated in poor or worse condition, or with insufficient waterway openings The new definition classifies as structurally deficient culverts that have ratings in poor or worse condition (4 or less), and bridges where one of the key structural elements (deck, superstructure, or substructure) is rated in poor or worse condition (also 4 or less).

The Annual Report on Texas Bridges published by the Texas Department of Transportation (TxDOT) defines management targets in terms of Good or Better (GB) structures (Ref. 50). A Good or Better (GB) structure meets current federal and Texas requirements. It is not structurally deficient, functionally obsolete, or substandard for load only. Desirable change in GB structures from year to year is reflected by an increasing number of structures in GB condition.

According to TxDOT's Annual Report on Texas Bridges (Ref. 50) a bridge is classified as structurally deficient if it meets the FHWA criteria previously discussed (rating of 4 or less), or any of the following additional criteria:

- It has an extreme restriction on its load-carrying capacity.
- It has deterioration severe enough to reduce its load-carrying capacity beneath its original as-built capacity.
- It is closed.
- It is frequently over-topped during flooding, creating severe traffic delays.

A bridge is classified Functionally Obsolete (FO) if it fails to meet current design criteria in any one of the following areas:

- Deck geometry
- Load-carrying capacity
- Vertical or horizontal clearances
- Approach roadway alignment

In the TxDOT Annual Report on Bridges, structures that are both functionally obsolete and structurally deficient are counted only as structurally deficient (Ref. 50).

Project 0-6979 results forecast the deterioration of the culvert, deck, superstructure, and substructure NBI/PonTex ratings. These models forecast rating as well as network deterioration in terms of percent bridges or culverts, and percent bridge area, at each future rating. Therefore, the models can be used to forecast the number of bridges and culverts that are in good or better condition, thus assisting TxDOT in its management goals.

Objective

From the previous background, it is evident that TxDOT's Bridge Division can considerably benefit from a computerized tool to forecast bridge deterioration at the network level. Project 0-6979 developed Markovian deterioration models for the deck, superstructure, substructure and culvert ratings. These deterioration models forecast bridge and culvert network condition, i.e., the percent bridges and percent bridge area at each rating, every 2 years.

One of the primary functions of a Bridge Management system (BMS) is to be a data-driven decision making support system that forecasts future network-level needs and anticipates the costs and benefits of bridge replacement, rehabilitation, and preservation actions. Of these actions, bridge replacement projects account for a significant part of the current funding needs and annual TxDOT allocations. Consequently, shortcomings in cost forecasting models used within bridge management systems can impose serious and potentially costly errors affecting financial needs projections as well as project selection and prioritization. Project 0-6979 developed Markov-based deterioration models for deck, superstructure, substructure and culvert ratings, and its implementation Product assists TxDOT Bridge managers in forecasting network level needs to maintain “good or better” goals for the on- and off system Texas bridges. Reliable condition ratings forecasts add a significant value to the research developed by project 0-6979. Every dollar that is not anticipated by TxDOT bridge managers may lead to budget shortcomings for bridge and/or culvert rehabilitation and replacement, causing heavy financial costs for TxDOT and consequently to Texas citizens. Forecasted budgets needs using this project’s Implementation Products is the major cost benefit of this research project.

Bridge and Culvert Cost Forecasts

This section discusses a methodology developed to use the 0-6979 models to predict budgetary needs, over a planning horizon. The methodology was then applied for a ten year planning horizon, starting with the on and off system 2019 bridge network condition (the latest available PonTex). A modified cost forecast analysis was developed for the culverts.

Bridge Costs Forecast

The deterioration models developed in this project forecast the network deterioration separately for the three bridge ratings: deck, superstructure and substructure. However, if only one of these ratings is 4 or less the bridge is considered deficient. Therefore, one cannot simply add the forecasts for each rating. A cross-tabulation methodology was developed to eliminate double and triple counting of structures where two or three of these ratings have a value of four or less.

Table 9. 1 (on-system) and Table 9. 2 (off-system) compare the current (2019) network condition to the 10-year forecast (2029) for each rating, in terms of deck area (in 1000 ft^2). The last row summarizes the amount of deck area with ratings of 4 of less for deck, superstructure and substructure ratings. The totals forecast by the models in 1000 ft^2 are:

On-system 2019: 7,497.86 Off-system 2019: 1,149.37
On-system 2029: 23,569.55 Off-system 2029: 9,605.3

However, as mentioned before, these values cannot be simply added due to the bridges that have more than one rating at 4 or less. Duplicates and triplicates need to be subtracted from these totals. A methodology was developed to estimate future duplicates and triplicates based on the current condition.

Table 9. 3 and Table 9. 4 present the total area for all combinations of ratings of 4 less observed in 2019, respectively for the on- and off-system bridges. Using Table 9. 3 as an example, the on-system correction factor of 0.872 was calculated as follows (see “Totals” row of Table 9. 3):

$$6{,}537.92/ (1{,}673.98 + 3{,}228.74 + 2{,}595.15) = 0.872$$

Applying this correction factor on the forecasted area not in “good or better” condition for a ten-year planning horizon for the on-system results in 20,553 or 23,569.55x0.872 thousand square feet of on-system bridges not in “good or better” condition in the year 2029. Using the correction factor in Table 9. 4, the 2029 total off-system bridge area not in “good or better” condition is 9,605.3x0.876 or 8,405 thousand square feet.

Table 9. 1 Current (2019) and 10-Year (2029) Forecast: On-System Network Condition by Area (1000 ft^2)

RATING	Superstructure 2019	Superstructure 2029	Substructure 2019	Substructure 2029	Deck 2019	Deck 2029
9	7,777.49	0.24	4,729.36	0.26	5,019.13	0.00
8	115,480.00	49,861.42	30,285.47	3,875.63	34,791.41	7,040.54
7	204,188.87	202,542.85	248,390.56	193,033.51	290,688.48	247,079.22
6	95,367.62	147,826.47	128,750.50	177,697.79	95,545.18	148,037.41
5	16,407.76	35,285.85	27,699.44	56,070.09	14,926.78	35,511.88
4	3,216.89	6,285.24	2,132.60	8,964.20	1,442.23	4,206.45
3	11.84	563.81	446.74	2,394.69	231.75	744.59
2	-	4.06	15.81	326.33	0.00	6.98
1	-	28.18	-	21.65	0.00	0.00
0	-	-	-	23.37	0.00	0.00
Total 4 or less	**3,228.74**	**6,881.29**	**2,595.15**	**11,730.25**	**1,673.98**	**4,958.02**

Table 9. 2 Current (2019) and 10-Year (2029) Forecast: Off-System Network Condition by Area (1000 ft^2)

RATING	Superstructure 2019	Superstructure 2029	Substructure 2019	Substructure 2029	Deck 2019	Deck 2029
9	757.10	0.00	175.26	0.00	333.56	0.00
8	22,703.07	10,457.50	5,723.09	960.78	6,792.60	1,820.51
7	32,050.03	29,457.95	39,324.63	26,055.59	45,393.00	34,221.78
6	13,444.22	24,631.41	21,443.04	28,574.37	16,698.00	25,680.53
5	2,393.99	5,109.97	4,439.95	10,660.61	2,261.70	7,842.02
4	184.25	1,182.76	490.70	3,445.09	187.98	1,294.37
3	125.41	326.40	63.04	1,118.58	3.17	197.32
2	6.51	123.42	24.63	440.62	1.82	130.28
1	4.17	40.76	13.08	88.48	4.32	88.59
0	14.31	352.91	13.45	364.13	12.54	411.60
Total 4 or less	**334.65**	**2,026.24**	**604.89**	**5,456.91**	**209.83**	**2,122.17**

Table 9. 3 On-System Correction Factor

Combinations	2019 area with ratings of 4 or less (1000 ft^2) Deck	Superstructure	Substructure	Corrected Area
Deck+Sub	-	-	-	
Deck+Super	105.32	105.32	-	105.32
All Three	22.62	22.62	22.62	22.62
Deck Only	1,546.04	-	-	1,546.04
Substr Only	-	-	1,763.14	1,763.14
Superstr Only	-	2,291.41	-	2,291.41
Sub+Super	-	809.39	809.39	809.39
Totals	**1,673.98**	**3,228.74**	**2,595.15**	**6,537.92**
Correction factor			**0.872**	

Table 9. 4 Off-System Correction Factor

Combinations	2019 area with ratings of 4 or less (1000 ft^2)			
	Deck	Superstructure	Substructure	Corrected Area
Deck+Sub	15.23	-	15.23	15.23
Deck+Super	19.68	19.68	-	19.68
All Three	32.89	32.89	32.89	32.89
Deck Only	142.03	-	-	142.03
Substr Only	-	-	514.42	514.42
Superstr Only	-	239.74	-	239.74
Sub+Super	-	42.35	42.35	42.35
Totals	**209.83**	**334.65**	**604.89**	**1,006.34**
Correction factor			**0.876**	

Assuming a 2019 replacement cost of \$200/ft^2, based on values reported in the Texas 2030 Committee Report (Ref. 49) and corrected for inflation, the forecasted needs for the year 2029 to maintain the network condition of on-system bridges in "good or better condition" would be about 4.11 billion dollars. A similar calculation may be developed for the off-system based on the values summarized in Table 9. 2 and in Table 9. 4. The 2029 off-system budget forecast is 9,605 thousand square feet multiplied by a correction factor of 0.876 and by the \$200 per square feet of bridge replacement cost, totaling 1.68 billion dollars. The total estimated amount to erase the backlog of bridges that are not in "good or better" condition for the year 2029 for both the on and off-systems would be 5.79 billion dollars (in 2019 dollars). This total may be reduced if some bridges with ratings of 4 or less get rehabilitation or replacement during this ten year planning horizon.

The area correction factors discussed in this section, ideally should be updated before future budget forecasting exercises by recalculating the area correction factors for the new starting year.

Culvert Costs Forecast

The process for forecasting culvert costs for the ten-year planning horizon is simplified due to the single rating associated with culverts. While Ref. 49 reports culvert costs as \$80/ft^2, variables to calculate culvert area are missing in nearly 30% on-system and over 45% off-system culverts, so the models developed in this project output results in terms of number of culverts. Thus, a distribution of the areas for both the on- and off-system culverts was developed based on the 2019 NBI/PonTex data, and used to estimate an average cost per on- and off-system culvert.

A weighted average of all culvert areas available for on and off systems culverts was calculated using the 2019 PonTex data, resulting in 2,418 ft^2 and 2,087 ft^2, for the on and off-systems respectively. Using an average cost of \$80 / ft^2 for culvert replacement, it is possible to estimate an average cost per culvert replacement of \$193,440 and \$166,960, respectively for on- and off-system.

The number of culverts predicted to be rated 4 or less in 2029 is 163 and 159, respectively for on- and off-system. Applying the average cost per culvert replacement calculated previously, the budgeted amount for culvert replacement in the year 2029 should be 31.5 and 26.7 million dollars for on- and off-system respectively. The total estimated amount to erase the backlog of culverts that are not in "good or better" condition for the year 2029 for both the on and off-systems would be 58.2 million dollars in 2019 dollars.

This total may be reduced if some culverts with ratings of 4 or less get rehabilitation or replacement during this ten year planning horizon.

Value of Research

The calculations previously discussed, predict a total budget amount forecasted for the ten-year planning horizon spanning from 2019 to 2029 is 6.09 billion dollars to maintain a rating greater than or equal to 4, for all bridges and culverts in Texas' on and off-systems.

These forecasted financial needs have to be met by a combination of federal and state funds for the on-system structures, and a combination of federal, state and local agencies funds for the off-system structures. Failure to plan and budget accurately for these funds will certainly increase the number of bridges and culverts that have a potential to be closed or load posted, significantly increasing the costs borne by the motoring public, which places a potential burden on TxDOT's public image as a good steward of the State of Texas road infrastructure.

A financial analysis of the Net Present Value (NPV), Equivalent Uniform Annual Costs (EUAC) and Benefit Cost Analysis (B/C) was carried out using the values of the forecasted budgets as benefits and the cost to fund the research for Research Project 0-6979 as the cost. This analysis assumes that the results of Project 0-6979 will increase the accuracy of the budget forecasts and reduce budget shortfalls by twenty percent.

Figure 9. 1 depicts the cash flow for the project over the ten year planning horizon spanning 2019 to 2020. First year and second year budgets for 0-6979 were $125,144 and $128,219 respectively. The twenty percent of the forecasted budgets for maintaining good or better conditions for the bridges and culverts in the on and off-systems amounts to 1.17 billion dollars.

Using a 3% discount rate on the cash flow depicted in Figure 9. 1, one can calculate the NPV for this project as being $870.3 million dollars. Using the same cash flow we determine the EUAC over the ten year planning horizon as being $102.0 million dollars per year. Finally, the B/C ratio is calculated to be 3,488.

Figure 9. 1 Cash Flow for Calculating the Value of Research

Recommendations for Future Model Updates

Ideally, all infrastructure deterioration models should be updated as more data becomes available. Considering the network deterioration curves, and the fact that TxDOT usually works with 10-year forecast horizons, it would be appropriate to update the models around 2030, if the modeling age group thresholds do not significantly change in the next 10 years.

Age percentiles used to define the modeling age groups will change as the road network develops: existing structures age, new structures are added, old structures are rehabilitated, culverts are replaced with bridges, etc.. In order to verify the recommendation to update the models in 2030, we analyzed changes in bridge and culvert 33% and 67% age percentiles in 10 years, using the available 19-year database. Table 9. 5 shows a comparison among bridge age group thresholds calculated using all data (the thresholds used in the models), data from 2001 to 2010, and data from 2011 to 2019.

It is clear that there are changes in age group thresholds in 10 years for both bridges and culverts. However, the changes are not large and do not affect all age group thresholds. Therefore, we are comfortable recommending updating the models in 2030.

Table 9. 5 Changes in Age Group Thresholds as Bridge and Culvert Populations Age

		Data used in calculations	Age Group		
			Newest	*Intermediate*	*Oldest*
Bridges	**Off-System**	2011 to 2019	0 to 16	17 to 34	35 & older
		2001 to 2010	0 to 16	17 to 35	36 & older
		2011 to 2019	0 to 17	18 to 33	34 & older
	On-System	2011 to 2019	0 to 22	23 to 43	44 & older
		2001 to 2010	0 to 22	23 to 40	41 & older
		2011 to 2019	0 to 22	23 to 45	46 & older
Culverts	**Off-System**	2011 to 2019	0 to 17	18 to 34	35 & older
		2001 to 2010	0 to 17	18 to 31	32 & older
		2011 to 2019	0 to 18	19 to 35	36 & older
	On-System	2011 to 2019	0 to 32	33 to 48	49 & older
		2001 to 2010	0 to 31	32 to 45	46 & older
		2011 to 2019	0 to 32	33 to 52	53 & older

Conclusions and Recommendations for Future Research

- The NBI/PonTex condition ratings are a tried and true measure of bridge and culvert deterioration. The models developed and implemented in this project can be a valuable bridge and culvert management tool. Standard errors of the Markov basic matrices were low, and the Markov process provided useful network condition forecasts, which in turn can be readily used to improve future budgets required to support TxDOT's management goals. Model updates are recommended for year 2030.

- The extensive literature review conducted in this project (see Chapter 2) did not find any Markov transition probabilities estimated from 19 years of inspection history, and a database with nearly a million records. Some references estimated the probabilities based on experience and expert opinions, others based on considerably more limited data.

- All Markov matrices found in the literature were simplified to only 2 probabilities per rating: the rating either did not change, or decrease by 1. All the other probabilities were assumed equal to zero. This project clearly demonstrated that this assumption is wrong; probabilities assumed as zero in all projects that used Markov transition probabilities were considerably different when calculated based on actual inspection histories. Below are two examples of results from basic 2-

year Markov matrices developed in this project:

1. On-system culverts. Culverts with initial rating of 9 had 4.9587% probability of remaining a 9, 32.231% probability of dropping to 8, 57.851% probability of dropping to 7, and 4.959% probability of dropping to 6.

2. On-system decks. Bridges with initial deck ratings of 8 had 70.898% probability of remaining at 8, 27.758% probability of dropping to 7, 1.23% probability of dropping to 6, 0.097% probability of dropping to 5, and 0.017% probability of dropping to 4.

- Element-based inspections measure both severity and extent of bridge deterioration. We recommend developing Markov models for these inspections. This would refine the network condition forecasts, thus improving future budget allocations for maintenance, rehabilitation and replacement.

- Budget forecasts and allocations would be considerably improved by developing unit cost models based on material types, span lengths, roadway functional class, instead of using an average cost for all bridges or culvert types as discussed in this Chapter.

Recommendations for Implementation Product Improvements

The implementation Product 2 developed in this Project relies on NBI/PonTex data retrieval and organization to update the current network condition in the model worksheets. Instructions are provided in Product 0-6979-2 Manual. While these updates are rather straightforward, a more practical bridge and culvert management system would include macros that retrieve the data and update the relevant fields in the spreadsheet models, thus fully automating all network forecasts updates.

This proposed fully automated bridge and culvert management system could be further improved by including cost estimates based on the cost research mentioned in the 3rd recommendation for future research above.

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